Discrimination Against Housing Vouchers: Evidence from Online Rental Listings*

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Abstract

The Housing Choice Voucher program provides substantial rental subsidies to low-income households, yet many recipients struggle to secure housing with their vouchers, particularly in low-poverty areas. This paper examines a key bottleneck in the program: landlord discrimination against voucher holders. Using a nationwide dataset from a major online rental platform, we identify listings that explicitly seek or reject voucher holders. We find significant variation across metropolitan areas, with voucher-seeking listings ranging from nearly zero to 18 percent and voucher-rejecting listings ranging from nearly zero to 28 percent. Within metros, landlords in high-poverty neighborhoods with larger Black and voucher populations are more likely to seek voucher holders, while rejection of voucher holders is relatively more common in low-poverty neighborhoods. Using a difference-in-differences design, we provide causal evidence that statewide prohibitions on source-of-income discrimination significantly reduce explicit rejection of vouchers. This reduction is particularly pronounced in low-poverty neighborhoods and can eliminate cross-neighborhood disparities in discriminatory behavior.

Keywords: affordable housing, vouchers, landlords, discrimination, neighborhoods

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1 Introduction

The Housing Choice Voucher (HCV) program is the largest rental assistance program in the United States, serving 2.3 million low-income households as of 2022.[1] This program provides low-income households with a subsidy (voucher) to rent a unit in the private rental market while paying only 30 percent of their income towards rent and utilities.[2] Policymakers often argue that the HCV program can facilitate the relocation of program recipients (henceforth, 'voucher holders') to areas with more favorable economic opportunities compared to other housing support programs, such as public housing, where designated subsidized housing is often located in high-poverty areas. This is particularly important given previous research indicating that these relocations can lead to positive effects on subsidized households and their children's long-run outcomes (Katz et al., 2001; Kling et al., 2007; Chetty and Hendren, 2018a,b; Chyn, 2018).

Despite the potential benefits of the program, the share of voucher holders successfully leasing units with their voucher remains surprisingly low (Ellen et al., 2024) and, when they do, voucher holders tend to live in high-poverty neighborhoods (Galvez, 2010; Lens, 2013; Horn et al., 2014; Collinson et al., 2019).[3] Prior research shows that landlord discrimination is in part responsible for the low lease-up rates, particularly in low-poverty areas (Garboden et al., 2018; Aliprantis et al., 2022), and that interventions increasing landlord engagement can boost lease-up rates in those areas (Bergman et al., 2024). Since voucher holders must secure a unit within a specified time frame to maintain their subsidy, landlord discrimination directly affects the program's take-up rates and locational outcomes of voucher holders.

In this paper, we study explicit discrimination by landlords in online rental listings, focusing on two key research questions. First, how prevalent is explicit discrimination against voucher holders in online rental listings, and in which areas? Second, how do Source of Income laws prohibiting discrimination against voucher holders impact landlord discrimination?

[1] *Source*: The Picture of Subsidized Households by the U.S. Department of Housing and Urban Development. 53 percent of households receiving housing subsidies from the federal government are in the HCV program.

[2] While this subsidy is generous, the HCV program includes restrictions on the maximum rents of the units that the government will subsidize. These are known as payment standards, partly determined by Fair Market Rents (FMRs).

[3] Ellen et al. (2024) reveals that only 60 percent of voucher holders leased up a unit between 2015 and 2019.

To answer these questions, we collect data from Craigslist, one of the United States' largest online rental platforms, covering all rental listings posted between September 2022 and August 2024. Our dataset includes search-result page information, such as price and unit characteristics, along with listing-specific details, including listing descriptions. By analyzing listing descriptions, we identify listings referencing vouchers and classify them as either *voucher-positive*, actively seeking vouchers with phrases such as "Section 8 welcome," or *voucher-negative*, rejecting vouchers with phrases such as "No Housing Choice Voucher." We fine-tune an AI for the classification task, achieving 97 percent accuracy. In our analysis sample of over 4 million cleaned and deduplicated rental listings, 2.2 percent of all listings include references to vouchers. Among these listings, 73 percent are voucher-positive, while 27 percent are voucher-negative.

We document the prevalence of discriminatory language towards vouchers and analyze how it varies across and within metropolitan areas. We find substantial variation across metros: in places such as North Port-Sarasota-Bradenton, FL, Lincoln, NE, and Tulsa, OK, 6.8 percent to 28 percent of listings explicitly reject vouchers, while in 80 percent of metropolitan areas in our sample, such occurrences are less than 1 percent. Within metros, we find that landlords in high-poverty neighborhoods with larger Black and voucher populations are more likely to actively seek voucher holders. Relatively, discrimination against voucher holders is more frequent in low-poverty neighborhoods. These differences in landlords' attitudes towards vouchers may limit voucher holders' ability to find housing, particularly in low-poverty areas.

We then examine the impact of Source of Income (SOI) legislation prohibiting discrimination on landlord discrimination. These laws, which have been adopted by an increasing number of state and local jurisdictions, often include voucher holders as a protected class. To estimate the causal effect, we focus on the adoption of a statewide SOI law in Hawaii, implemented in May 2023. Using a difference-in-differences (DID) design, we compare changes in discriminatory listings in Urban Honolulu, where the pre-SOI law discrimination rate was 11.2 percent, to other metropolitan areas without an SOI law as of August 2024. Our DID results indicate that Hawaii's SOI law led to a 67 percent reduction (7.5 percentage points) in voucher-negative rental listings. This reduction was particularly pronounced in low-poverty neighborhoods with high baseline discrimination rates, effectively equalizing voucher-negative listing shares between high- and low-poverty neighborhoods. Both individual landlords and property management companies reduced explicit voucher discrimination in response to the law, with property management achieving nearly perfect compliance.

Our findings suggest that SOI laws can significantly reduce landlord discrimination against voucher holders in online rental listings, especially in low-poverty areas, potentially broadening neighborhood choice for voucher holders. To validate our research design, we show a compelling parallel trend in the pre-treatment period and demonstrate that these results are robust to using synthetic DID (Arkhangelsky et al., 2021) as an alternative identification strategy. Additionally, we note that Hawaii's SOI law may be more stringent than other SOI laws as it explicitly identifies discriminatory rental listings as violations and contemplates penalties. To complement the Hawaii study, we examine Boise City, ID, whose SOI law does not contemplate penalties, and find a substantial reduction in voucher-negative rental listings, suggesting the broader applicability of our findings.

This paper is most closely related to the literature on housing market discrimination. Previously, correspondence experiments and audit studies have documented that landlords and real estate agents are more likely to discriminate against racial minorities in various contexts (Yinger, 1986; Page, 1995; Ondrich et al., 2000, 2003; Zhao, 2005; Zhao et al., 2006; Ahmed and Hammarstedt, 2008; Hanson et al., 2011; Christensen et al., 2021; Chan and Fan, 2023).[4] This literature also finds evidence of landlord discrimination against voucher holders (Phillips, 2017; Cunningham et al., 2018; Aliprantis et al., 2022; Faber and Mercier, 2022). Notably, Aliprantis et al. (2022) show that a policy encouraging voucher holders to move to low-poverty areas does not change landlords' screening behavior in those areas. We contribute to this literature in three ways. First, we focus on explicit discrimination in online rental listings, which complements the common correspondence and audit studies. Second, we provide a comprehensive picture of landlord discrimination against voucher holders across most major U.S. rental markets, while existing studies are often limited to a few geographic areas. Third, to our knowledge, we are the first to document, with national data, the prevalence of voucher-positive behavior of landlords in high-poverty, high-minority neighborhoods.

[4]This behavior is more prevalent in areas with greater economic opportunity and lower pollution exposure (Christensen and Timmins, 2022; Christensen et al., 2022) and often reflects statistical discrimination (Ewens et al., 2014).

This paper also contributes to the growing literature examining the impact of SOI laws on outcomes for voucher holders, finding that these laws are generally associated with a higher likelihood of securing a rental unit (Finkel and Burron, 2001; Freeman, 2012; Ellen et al., 2024) and moving to lower-poverty areas (Freeman and Li, 2014; Ellen et al., 2023). Hangen and O'Brien (2023) document that SOI laws are uncorrelated with explicit discrimination against voucher holders using online rental listings data from 77 mid-size U.S. metro areas. We add to this literature by broadening the coverage to 155 metro areas, employing an AI to infer discriminatory practices, and providing the first causal estimates of the effect of SOI laws on explicit landlord discrimination.

Finally, this paper is also related to the public finance literature on welfare program take-up, which often highlights informational barriers and transaction costs to explain low participation rates (Bettinger et al., 2012; Bhargava and Manoli, 2015; Alatas et al., 2016; Deshpande and Li, 2019; Finkelstein and Notowidigdo, 2019). A distinctive aspect of the HCV program is its reliance on the private market, a feature shared with some other programs (e.g., food vouchers), though discriminatory practices are particularly pervasive in housing markets, potentially exacerbating low take-up rates. In this paper, we provide nationwide evidence of landlord discrimination, its associated impacts on neighborhood quality for voucher holders, and an evaluation of the effectiveness of legislation in addressing these challenges.

2 Institutional Background

2.1 The Housing Choice Voucher Program and Landlords' Incentives

The Housing Choice Voucher (HCV) Program, commonly known as Section 8, supports low-income families, the elderly, and disabled individuals in securing affordable housing in the private rental market. Participants typically contribute 30 percent of their adjusted gross income towards rent, while the local Public Housing Agency (PHA) covers the remainder of the rent, up to a specified limit known as *payment standard*.[5] Most PHAs set their payment standards between 90 and

[5] If the rent exceeds this limit, participants may choose to pay the difference, but they cannot contribute more than 40 percent of their income towards rent in the first year of the lease.

110 percent of Fair Market Rents (FMR), which are an estimate of the 40th percentile gross rents within a metropolitan area and are published annually by the U.S. Department of Housing and Urban Development (HUD).[6]

The HCV program is highly popular, with demand for vouchers often far exceeding the supply. Waitlists for vouchers are typically long and, in many cities, remain closed for extended periods of time due to an overwhelming number of applicants. Once a household receives a voucher, they must find a rental unit in the private rental market that meets HUD's housing quality standards and falls within the payment limits set by the local PHA. Voucher holders have a limited timeframe to secure suitable housing, which varies by PHA and must be a minimum of 60 days. If the voucher holder is unable to find a unit within this period, they may request an extension from the PHA, though these extensions are not always granted.

From the landlords' perspective, there is a trade-off to accept voucher holders. On the one hand, the program provides economic incentives such as (partially) guaranteed income, potential for charging higher rents up to payment standards (Rosen, 2014; Garboden et al., 2018; Desmond and Perkins, 2016), and an expanded tenant pool (Greenlee, 2014), which are particularly compelling in markets with high vacancy and delinquency rates (Rosen, 2014). On the other hand, administrative burdens due to unit inspections and paperwork may deter landlords from participating (Greenlee, 2014; Garboden et al., 2018; Aliprantis et al., 2022; Bergman et al., 2024). Some landlords may also be biased against voucher holders due to perceived risks of missed payments or property damage or correlated tenant demographics, especially in markets where landlords have easier access to a lower-risk pool of tenants.[7] Consequently, landlords may be more likely to accept vouchers in high-poverty, low-rent, low-demand areas where the financial benefits outweigh the costs, but they may discriminate against voucher holders in low-poverty, high-rent, high-demand areas where opportunity costs and the appeal of market-rate tenants are higher.

[6]Since 2018, HUD mandates PHAs in 24 metropolitan areas to implement Small Area Fair Market Rents (SAFMR), for which the FMR is computed at the zip code-level instead of the metropolitan area level.

[7]Yet, Aliprantis et al. (2022) finds no significant evidence that landlords use voucher holders to proxy for race.

2.2 Source of Income Laws

In recent years, a growing number of state and local jurisdictions have enacted Source of Income (SOI) laws, which prohibit discrimination based on a tenant's lawful sources of income. According to the Poverty & Race Research Action Council (PRRAC), which tracks SOI laws across federal, state, and local jurisdictions, the percentage of voucher holders protected by these laws rose from 34 percent in 2018 to 57 percent in 2022 (Appendix Figure C.1 shows SOI coverage as of 2023). However, SOI laws differ in both their explicit inclusion of voucher holders and their enforcement mechanisms. While some SOI laws explicitly mention vouchers, others explicitly exclude them as a protected class (e.g., Delaware and Wisconsin).[8] Regarding enforcement, some jurisdictions impose fines on landlords for SOI violations, while others do not.

Hence, SOI laws affect landlords' incentives to discriminate as they would consider the potential penalties when deciding whether to reject vouchers. Empirically, however, there is no causal evidence linking the passing of these laws to changes in explicit landlord discriminatory behavior. Prior research primarily focuses on the impact of SOI laws on voucher holders' locational outcomes (Freeman and Li, 2014; Ellen et al., 2023), and only provides descriptive evidence that voucher holders in jurisdictions with SOI laws have higher success rates in securing a suitable unit (Ellen et al., 2024). Hangen and O'Brien (2023) shows that explicit discrimination against voucher holders in Craigslist listings still exists in jurisdictions with SOI laws in their cross-sectional analysis.

3 Data

To identify discriminatory language in online rental markets, we scrape the titles and descriptions of Craigslist rental listings in addition to other listing details. We then use language-processing methods to identify phrases referencing voucher holders.

[8] Even when voucher holders are explicitly mentioned, their protection may not be guaranteed. Maine's SOI law exemplifies such a case: while it explicitly mentions voucher holders, a court interpretation in 2014 weakened the interpretation of the law by suggesting that discrimination against vouchers may be based not on the voucher holder's status but on the administrative burden that contracting with HUD under the HCV program imposes on the landlord.

3.1 Data Sources

We scrape the universe of Craigslist listings in the 'apartments/housing for rent' section on all 504 regional websites in the U.S. on a weekly basis between the last week of August 2022 and August 2024. We collect both the front-page information, including the listing identifier, asking rent, title, number of bedrooms, square footage, and the date when it was posted, as well as listing-specific details, including the listing's description, number of bathrooms, street address, and approximate geographic coordinates. Most existing Craigslist data do not include listing-specific details, which are critical in our analysis to detect explicit discriminatory language in rental listings. We exclude the first week of scraping so that the analysis captures only newly posted listings.

We clean and deduplicate 20.5 million raw rental listings to obtain 4.12 million unique rental listings (see Appendix A.1 for details). This data cleaning procedure removes spam listings and outlier listings and defines a unique listing observation at the geographic coordinates, number of bedrooms and bathrooms, square footage, and initial listed price level each week. The resulting analysis sample spans 1,989 cities and 155 CBSAs (see Appendix Figure C.1 for the coverage). Appendix A.1 provides summary statistics of our analysis sample and shows supportive evidence that median rental prices in our sample are fairly representative of median population rents as measured by Census.

We merge this dataset with several HCV program features and neighborhood characteristics. First, we gather information on Fair Market Rents (FMR) and the number of voucher holders by Census tract from HUD. Because PHAs can set the payment standard, the maximum rent covered by the HCV program, between 90 and 110 percent of FMR, we also show descriptive results and check the robustness of empirical findings using a subsample of listings with a rental price equal to or smaller than 110 percent of FMR, consisting of 68.2 percent of our sample. Second, we merge Census tract-level characteristics from the 2019 5-year American Community Survey, including several demographic, socioeconomic, and housing characteristics. These neighborhood characteristics are used as control variables, as well as for heterogeneity analyses.

3.2 Textual Analysis of Rental Listing Descriptions

We identify rental listings with language that either seeks or rejects voucher holders using a fine-tuned GPT-4o mini model. First, we filter listings containing voucher-related keywords in either their title or the description, such as “voucher,” “Section 8,” and “HCV.” Next, we design a prompt to classify listings as either positive (actively seeking out voucher holders, e.g., “Section 8 welcome”) or negative (specifying that they do not accept vouchers, e.g., “no Section 8”), which we set as a system message for GPT-4o mini. We fine-tune the AI model parameters with 250 manually classified listings to improve the task-specific accuracy. Finally, we validate the classification outcomes using another 253 manually classified listings. Our classification with the fine-tuned GPT-4o mini has 97 percent accuracy, while the accuracy of other GPT models ranges from 82 percent to 92 percent.[9] See Appendix A.3 for more details about the textual analysis and validation.

In our analysis sample, we observe such keywords in roughly 90,959 deduplicated listings (2.21%); in the subsample with prices lower than 110 percent of FMR, we observe them in approximately 67,757 listings (2.50%). Among listings with voucher-related keywords, 72.6 percent are positive, and 27.4 percent are negative in the analysis sample. Restricting listing prices to be below 110 percent of FMR, 69.4 percent are positive, and 30.6 percent are negative. The most common expressions in voucher-positive listings include “section 8 accepted" and “section 8 welcome". The most common ones in negative listings include “no section 8” and “not accept section 8".

Lastly, we identify rental listings with terms such as “property management” or “leasing office” to distinguish listings posted by property management companies from those posted by landlords themselves, which we use to examine differences in discriminatory practices by management type.

4 Descriptive Analysis of Landlord Discrimination

We document that landlords who either seek out or discriminate against voucher holders are concentrated within a subset of metropolitan areas. Within these markets, landlords are more likely

[9] Users can access our fine-tuned AI via OpenAI API using the model code “ft:gpt-4o-mini-2024-07-18:university-of-colorado::A2iujFDC.”.

to target vouchers in neighborhoods with larger Black populations and higher poverty rates, while the opposite pattern holds for landlords who discriminate against vouchers.

4.1 Cross-Metro Variation in Discrimination

The prevalence of voucher-negative listings, those explicitly rejecting voucher holders, varies widely across CBSAs. Figure 1 shows the shares of voucher-negative listings across the 40 CBSAs with the highest rates. Appendix Table C.1 further provides a list of the top 25 metros along with their shares of voucher-negative listings. Among the top five metros, the share of voucher-negative listings ranges from 6.2 to 28 percent, with the highest share in North Port-Sarasota-Bradenton, FL. Discrimination against vouchers is higher among listings priced below 110 percent of the Fair Market Rent (FMR), the primary market segment for voucher holders. In this segment, the top five shares of voucher-negative listings range from 8.1 percent to 37.4 percent. In contrast, many metros show almost no voucher-negative listings: 126 CBSAs have less than 1 percent of them.

Source of Income (SOI) laws do not strongly correlate with a reduced likelihood of negative listings. In Figure 1, we indicate CBSAs with state or local-level SOI laws. Metros with SOI laws are equally represented on the right-hand side of the percentage of negative listings distribution as those without SOI laws. For instance, Hawaii, Maryland, Oklahoma, and Virginia have high shares of voucher-negative listings despite the existence of statewide SOI laws.[10] This observation suggests that a cross-sectional evaluation alone may not provide sufficient evidence of SOI laws' effectiveness, likely due to selection in SOI adoption and differences in penalties and enforcement across jurisdictions.

We also find high shares of voucher-positive listings, those actively seeking out voucher tenants, in several CBSAs, often in those with low shares of voucher-negative listings. Appendix Table C.2 provides a list of the top 25 metros along with their shares of voucher-positive listings. The top

[10] Washington-Arlington-Alexandria, DC-VA-MD-WV illustrates another interesting case. 5.7 percent of listings in this metropolitan area contain negative mentions, and 8.6 percent contain positive mentions. Washington, DC, has a SOI law, and 0 percent of its listings contain negative mentions, while 30 percent of them contain positive listings. That is, negative mentions are solely driven by listings in Maryland, Virginia, and West Virginia, where 7.1 percent of listings contain negative mentions and only 3.7 percent contain positive mentions despite the fact that Maryland and Virginia also have SOI laws in place.

five metros, including Springfield, MA, Washington, DC, and Akron, OH, show voucher-positive listing rates ranging from 5.1 percent to 18 percent of all listings.

4.2 Within-Metro Variation in Discrimination

We describe the correlation between the prevalence of discriminatory listings and neighborhood characteristics within a rental market. We study three dependent variables: whether a listing contains a positive mention of vouchers, whether it contains a negative mention of vouchers, and whether it contains a negative mention conditional on the presence of a voucher-related keyword. Table 1 presents the results. In each column, we estimate a linear probability model that separately regresses the corresponding outcome variable on each listing characteristic. The regressions control for year-by-month and CBSA fixed effects, as well as listing characteristics such as the number of bedrooms, bathrooms, and square footage.

Generally, voucher-positive listings appear much more frequently than voucher-negative listings (see the 'Y mean' row at the bottom of the table). This finding suggests that the financial benefits of vouchers are large enough to motivate a significant number of landlords to seek out voucher holders. These positive mentions are more common in tracts with larger voucher populations, larger Black populations, higher poverty rates, higher vacancy rates, and older housing stocks. In contrast, the share of positive mentions is negatively correlated with the white population share, median household income, and median rent. This pattern is consistent with prior literature documenting that landlords in less profitable, higher-poverty areas often specialize in voucher holders (Rosen, 2014; Garboden et al., 2018), though it had not been yet documented at a national scale. It also aligns with the hypothesis in Section 2.1. Landlords have a stronger financial incentive to accept vouchers in areas with high poverty rates, where the value of secured rental payments is higher, and the typical tenant base is more likely to miss rent, and in low-rent areas, where landlords have more room to increase rents up to the voucher limit.

The prevalence of voucher-negative listings correlates with neighborhood characteristics in the opposite way, though many coefficients are not statistically significant due to the sparseness of voucher-negative listings. A comparison of the estimates in Columns 1 and 2 supports the hypothesis that landlords have stronger incentives to discriminate against voucher holders in high-demand markets where the demographics of the typical tenant differ significantly from those of voucher holders. The differences between neighborhoods where landlords seek vouchers and those where they discriminate against them become starker when we restrict the sample to listings with any voucher-related keywords in Column 3.

Lastly, the likelihoods of positive and negative mentions also correlate with listing-level characteristics, such as unit quality and property management type. We construct a unit quality index using the residuals from a price hedonic regression that includes tract fixed effects and observed listing characteristics. Voucher-positive listings are typically associated with lower-quality rental units, while voucher-negative listings are linked to somewhat lower-quality units. Notably, we find that rental listings posted by property management companies are more likely to be voucher-positive than those posted by individual landlords.

5 Effects of Source of Income Laws on Discrimination

We examine whether the adoption of Source of Income (SOI) protections can mitigate landlord discrimination against voucher holders, focusing on Hawaii as a case study. Hawaii enacted Act 310, a statewide SOI law, in July 2022, which became effective in May 2023. The law explicitly lists "*discriminating against current and prospective tenants based on participation in Permanent Supportive Housing Programs or the HCV program*" as a violation, with fines ranging from $2,000 for the first offense to $2,500 for subsequent violations.

Hawaii provides a particularly compelling empirical setting for studying landlord discrimination. First, Hawaii ranks among the most unaffordable states in the U.S., with 58 percent rent-burdened households as of 2022, making the HCV program particularly important for low-income rental housing in Hawaii. Second, Urban Honolulu has one of the highest shares of voucher-negative listings nationwide, as shown in Figure 1. Prior to Act 310, 11.23 percent of rental listings explicitly included discriminatory language against voucher holders.

5.1 Empirical Strategy: Difference-in-Differences

We adopt a difference-in-differences (DID) design to causally estimate the impact of Hawaii's SOI law on landlord discrimination. We compare the presence of voucher-negative listings in Urban Honolulu, the only Hawaiian metropolitan area in our analysis sample, to a comparison group that includes all other 761 local jurisdictions in our sample that had not passed any SOI laws as of August 2024. The identifying assumption is that had Hawaii not passed the SOI law, landlord discrimination in Urban Honolulu would have evolved similarly to the comparison group. While Hawaii may have a unique housing market compared to the contiguous United States, we alleviate this concern by including Census tract fixed effects to control for time-invariant neighborhood-specific characteristics and estimating event studies to discuss the validity of the parallel trends assumption. Our results are also robust to using the synthetic difference-in-differences method in Arkhangelsky et al. (2021) (see Appendix Figure C.3).[11]

Using our sample of online rental listings for the treated and comparison jurisdictions from September 2022 to August 2024, we estimate the following equation at the listing i level:

$$Y_i = \alpha_{m(i)} + \phi_{l(i)} + \beta\left(\text{Post}_i \times \text{Treated}_i\right) + \gamma' \mathbf{X_i} + \varepsilon_i \tag{1}$$

where Y_i is an indicator variable for whether listing i contains negative terms towards vouchers. β captures the treatment effect, i.e., the impact of the SOI law on landlord discriminatory language. More specifically, β is the coefficient on the interaction of an indicator variable for whether the listing was posted after the SOI took effect in May 2023 (Post_i) with an indicator variable for whether the listing is in Urban Honolulu (Treated_i). We include year-by-month ($\alpha_{m(i)}$) and Census tract fixed effects ($\phi_{t(i)}$) to control for aggregate time trends and time-invariant neighborhood character-

[11] We implement synthetic DID by collapsing the dataset at the metropolitan area-by-month level, where Urban Honolulu is the treated unit and the 61 metropolitan areas without an SOI law that have a monthly average number of listings greater than 150 constitute the donor pool. Synthetic DID is a useful alternative empirical strategy in our setting for two reasons. First, it reduces our reliance on the parallel assumption by matching the pre-treatment trends of Urban Honolulu to a convex combination of metropolitan areas in the control group, placing more weight on both donor units and pre-treatment periods that are more similar to the Urban Honolulu. Second, it allows for unit-level shifts, unlike traditional synthetic controls. This second point is particularly important given that only a few metropolitan areas have voucher-negative listing shares as high as Urban Honolulu.

istics, respectively. We also control for a vector of listing characteristics $\mathbf{X_i}$, including the number of bedrooms, number of bathrooms, and square footage.

5.2 Results: Effects of SOI Law on Discrimination

We find that Hawaii's SOI law substantially reduced landlords' explicit discrimination against vouchers after it became effective in May 2023. Column 1 of Table 2 presents the baseline estimates of β_1 in Equation (1).[12] After the law took effect, the share of voucher-negative listings in Urban Honolulu decreased by 7.5 percentage points, equivalent to a two-third reduction from the pre-treatment level of 11.2 percent. In contrast, we find no statistically significant effect when using an indicator variable for voucher-positive listings as the dependent variable (see Column 5). We interpret this result as a placebo test since the SOI law should not have affected landlords' financial incentives to actively seek out voucher holders as tenants.

To assess the validity of our empirical strategy, we estimate a dynamic version of Equation (1), where we interact the Treated$_i$ variable with month indicator variables. Figure 2 presents the results. The coefficient estimates remain stable and statistically insignificant during the pre-treatment period, supporting our parallel trend assumption. Panel (a) shows a distinct and statistically significant drop in voucher-negative listings immediately following the SOI law's effective date. Panel (b) further suggests that the prevalence of voucher-positive listings remained relatively stable before and after the law's implementation.

In Columns 2 and 3 of Table 2, we examine the effectiveness of the SOI legislation by neighborhood poverty rates and voucher holder density. To do this, we divide Census tracts within each metropolitan area into quartiles based on each variable and estimate Equation (1) separately for each quartile. First, note that voucher-negative listings were particularly concentrated in low-poverty neighborhoods in Urban Honolulu before the SOI law took effect, listings in Census tracts with the lowest quartile of poverty rates were 60 percent more likely to reject vouchers explicitly. These listings were only slightly more prevalent in neighborhoods with lower shares of voucher holders at baseline (See 'Y mean' rows at the bottom of the table).

[12] Appendix Figure C.2 and Table C.3 present the results for the sample of listings priced below 110 percent of FMR.

We find that the SOI law was particularly effective in reducing discrimination in the lowest poverty quartile of Census tracts, where it decreased the share of voucher-negative listings by 12.3 percentage points (73 percent of the baseline). In fact, the SOI law nearly equalized discrimination rates across poverty quartiles, leaving all quartiles with a similar share of voucher-negative listings (3.5-4.5 percent) after May 2023. We observe a similar pattern of equalization after May 2023 across quartiles for voucher-holder presence, with each ending up at roughly 3.5-3.9 percent of voucher-negative listings. These findings suggest that the SOI law may have expanded opportunities for voucher holders in lower-poverty neighborhoods with previously slightly lower voucher presence. This evidence aligns with the slight improvements in neighborhood outcomes for voucher holders after SOI adoption found in prior literature (Freeman and Li, 2014; Ellen et al., 2023), supporting the idea that these gains may be due to reductions in landlord discriminatory practices.

In Column 4 of Table 2, we present the differential responses by listing poster type, distinguishing between property management companies and individual landlords. This distinction serves as a proxy for landlord type (institutional vs. mom-and-pop), as 83 percent of small landlords do not hire property management, while most institutional investors rely on internal management operations (Coven, 2025). Prior to the implementation of the SOI law, property management companies exhibited a lower likelihood of explicit discrimination, with a pre-SOI voucher-negative share of 3.2 percent, compared to a higher pre-SOI share of 12.5 percent for listings posted by landlords. This pre-SOI disparity suggests that mom-and-pop landlords show higher levels of discrimination in the rental market than large landlords, even in the absence of SOI laws.

The share of voucher-negative listings by property management companies decreased by 3 percentage points following the implementation of the SOI law, effectively eliminating nearly all voucher-negative listings posted by them. We also find that the SOI law reduced discriminatory listings posted by individual landlords by 8 percentage points (64 percent from the baseline). Although this represents a larger absolute reduction, it is relatively smaller in percentage terms. That is, the SOI law was effective in reducing explicit discrimination among individual landlords, who exhibited higher levels of discrimination prior to the law, though it did not eliminate discriminatory practices entirely. These findings align with prior research suggesting that property managers tend to be more law-abiding compared to individual landlords by their use of algorithms for tenant screening and their greater awareness of legal changes (Rosen et al., 2021).

Lastly, we find consistent results in a complementary case study of Boise City, ID, detailed in Appendix B. Unlike the Hawaii study, this case examines a city-level SOI that does not explicitly contemplate penalties for violations. Boise City enacted its SOI law in late 2023, which was subsequently repealed in March 2024. Using a similar DID methodology, we find a substantial reduction in voucher-negative listings following the adoption of the city-level SOI law. After its repeal, however, we find suggestive evidence of a recovery of discriminatory listings to the pre-SOI rate. This pattern further reinforces our conclusion that SOI laws significantly affect landlords' discriminatory practices in online rental listings.

In summary, our empirical findings suggest that SOI laws can be an effective tool for reducing explicit landlord discrimination against voucher holders. The impact is particularly pronounced in low-poverty areas, eliminating across-neighborhood variation in voucher-negative listing shares. This is especially relevant for policy discussions, as prior research highlights that voucher holders predominantly live in high-poverty areas (Galvez, 2010; Horn et al., 2014; Lens, 2013). Additionally, we find that SOI laws influence both mom-and-pop landlords, who typically handle tenant searches themselves, and larger landlords, who often rely on property management companies.

6 Concluding Remarks

Low lease-up rates and the concentration of voucher holders in high-poverty areas remain major challenges of the Housing Choice Voucher program, the largest federal rental assistance program in the U.S. In this paper, we study a primary factor contributing to these outcomes: landlord discrimination, which limits voucher holders' housing options and restricts their access to low-poverty neighborhoods.

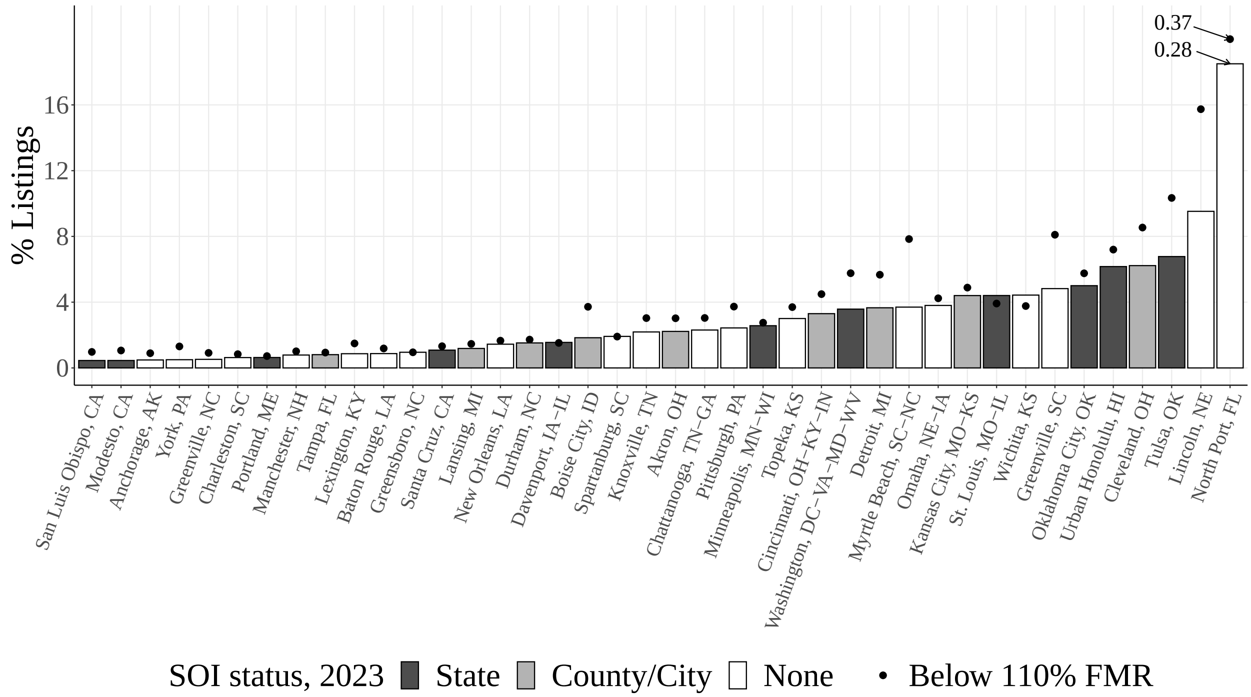
Using a novel dataset of online rental listings, we quantify the explicit discrimination faced by voucher holders in the online rental markets. Our findings reveal that such discrimination is frequent, particularly in specific metro areas and in low-poverty neighborhoods with larger Black and voucher-holder populations. Additionally, we document that a substantial share of landlords actively advertise to voucher holders, suggesting that some landlords specialize in renting to voucher holders, taking advantage of the stable income partially guaranteed by government subsidies.

We then provide a causal estimate of the effects of Hawaii's Source of Income law (Act 310) on discriminatory listings. Our DID analysis shows a significant reduction in explicit discrimination immediately following the implementation of the law: the share of discriminatory listings decreased by 67 percent from the pre-SOI law share of 11.2 percent. This reduction was particularly pronounced in low-poverty neighborhoods, where pre-treatment discrimination rates were notably high.

Our analysis underscores the presence of explicit discrimination in rental listings that deter voucher holders from applying and demonstrates the effectiveness of Source of Income laws in reducing this form of discrimination. However, we acknowledge a limitation: our study does not capture landlord discriminatory practices that may occur later in the application and leasing process after voucher holders contact landlords, as highlighted in prior literature. Thus, we cannot rule out the possibility that landlords who no longer display discriminatory language in their rental listings may still discriminate against vouchers at subsequent stages.

Figures and Tables

Figure 1: Percentage of voucher-negative listings for top negative CBSAs



Note. The figure reports the percentage of listings with negative mentions of vouchers by CBSA. Only the 40 CBSAs with the highest share of voucher-negative listings are included. The bars indicate the percentage of negative listings among the full sample of listings, and the dots indicate the percentage of negative listings among listings with a price below 110 percent of the Fair Market Rent (FMR). Shaded colors indicate whether a state SOI law (dark gray) or a county/city SOI law (light gray) applies to *any* locality within the CBSA.

Table 1: Pairwise regressions of voucher-related keywords on Census tract characteristics

	Positive	Negative	Neg | Any
	(1)	(2)	(3)
Panel A: Census tract-level characteristics			
Voucher holders in tract, share	0.121***	-0.010	-0.723**
	(0.019)	(0.021)	(0.309)
White, share	-0.012*	0.017	0.594**
	(0.007)	(0.020)	(0.236)
Black, share	0.031***	-0.015	-0.554***
	(0.010)	(0.019)	(0.205)
Hispanic, share	0.008	-0.002	-0.137
	(0.005)	(0.006)	(0.099)
Median household income, log	-0.008***	-0.001	0.073**
	(0.003)	(0.001)	(0.029)
Poverty rate	0.054***	0.001	-0.679***
	(0.008)	(0.008)	(0.198)
Vacancy rate	0.047***	-0.024	-1.438**
	(0.015)	(0.028)	(0.688)
Median home value, log	-0.003	-0.005***	-0.075
	(0.002)	(0.001)	(0.093)
Median contract rent, log	-0.018***	-0.001	0.185***
	(0.003)	(0.003)	(0.037)
Median building age, log	0.006***	-0.001	-0.050*
	(0.002)	(0.001)	(0.028)
Panel B: Listing-level characteristics			
(Unobserved) quality index	-0.008**	-0.002***	-0.097
	(0.003)	(0.001)	(0.076)
Property management	0.006***	0.002	-0.122**
	(0.002)	(0.002)	(0.059)
CBSAs	155	155	154
Observations	3,886,170	3,886,170	87,342
Y mean	0.016	0.006	0.273

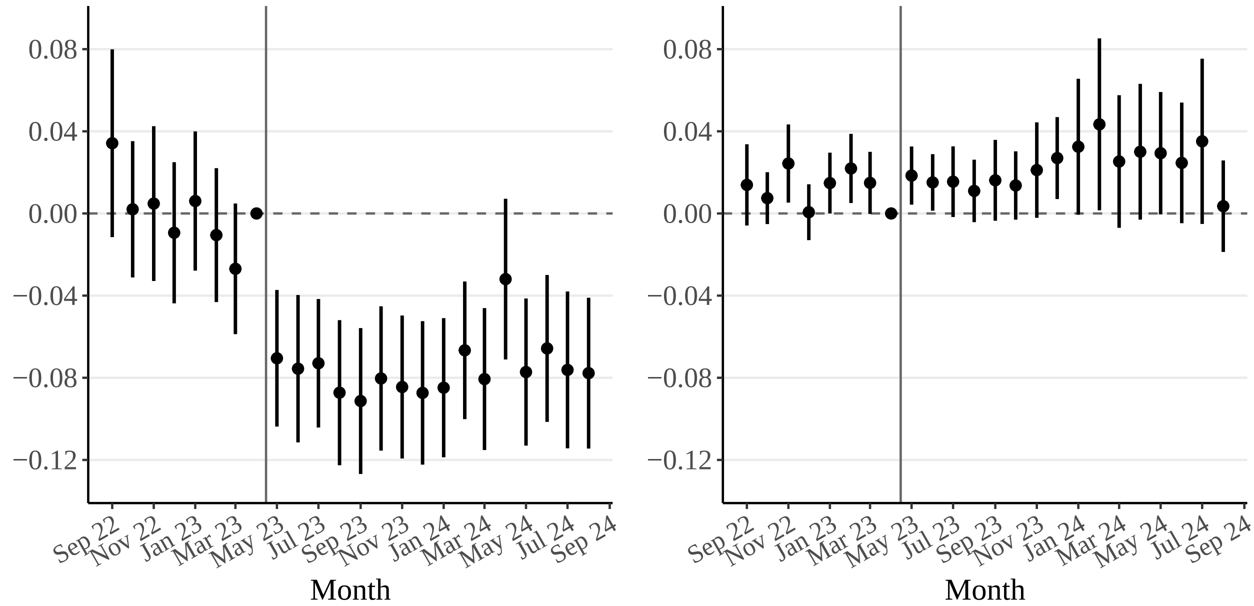
Note. This table reports the regression results of linear probability models using 3.9 million observations with the complete set of neighborhood characteristics. The outcome variable in column (1) is whether the listing contains positive mentions of vouchers; in columns (2) and (3), whether the listing contains negative mentions of vouchers. Column (3) is restricted to listings with any voucher-related keywords. The share of voucher holders is calculated as voucher units in a Census tract in 2022 (reported by HUD) over housing units in that tract in 2019. All Census tract characteristics are obtained from the 2019 5-year ACS. The (unobserved) quality index is defined as the residual of a regression of the listing price on census tract fixed effects and the interaction of CBSA indicators with the following variables: year-by-number of bedrooms FE, month FE, number of bathrooms FE, and square footage. All regressions include CBSA and year-by-month fixed effects and control for the number of bedrooms, bathrooms, and square footage of the listing. Standard errors are clustered at the census tract level and are reported in parentheses. Significance codes: ***: 0.01, **: 0.05, *: 0.1

Table 2: Effect of Hawaii's SOI law on voucher discrimination, total and by heterogeneity variables

	(1)	(2)	(3)	(4)	(5)
	Baseline		**Heterogeneity**		**Placebo**
	Negative	Poverty	Voucher share	1(Manag.)	Positive
Panel A: Total effect					
Post×Treated	-0.075***				0.009
	(0.009)				(0.008)
Panel B: By Census tract quartiles					
Post×Treated×Q1		-0.123***	-0.086***		
		(0.023)	(0.022)		
Post×Treated×Q2		-0.066***	-0.097***		
		(0.014)	(0.015)		
Post×Treated×Q3		-0.070***	-0.054***		
		(0.018)	(0.013)		
Post×Treated×Q4		-0.062***	-0.088***		
		(0.013)	(0.017)		
Panel C: By property management					
Post×Treated×Manage=0				-0.080***	
				(0.009)	
Post×Treated×Manage=1				-0.030***	
				(0.009)	
Observations	993,000				993,000
Y mean (Treated, Pre-SOI)	0.112				0.027
Y mean Q1 (Treated, Pre-SOI)		0.168	0.124		
Y mean Q2 (Treated, Pre-SOI)		0.105	0.135		
Y mean Q3 (Treated, Pre-SOI)		0.105	0.093		
Y mean Q4 (Treated, Pre-SOI)		0.1	0.123		
1(Manag.) mean (Treated, Pre-SOI)				0.138	
Y mean, Manage = 0 (Treated, Pre-SOI)				0.125	
Y mean, Manage = 1 (Treated, Pre-SOI)				0.032	

Note. This table reports regression estimates of β in Equation (1). The outcome variable in Columns 1-4 is whether the listing contains a negative mention of vouchers; in Column 5, whether the listing contains a positive mention of vouchers. Each cell in this table represents a different regression: Columns 1 and 5 use the full sample of listings, and each heterogeneity result uses the sample of listings within the corresponding heterogeneity group. All regressions include census tract- and year-by-month fixed effects, as well as controls for the number of bedrooms, bathrooms, and square footage. Standard errors are clustered at the census tract level and are reported in parentheses. Significance codes: ***: 0.01, **: 0.05, *: 0.1

Figure 2: Event study of the impact of Hawaii's SOI law on landlord discrimination



(a) Voucher-negative

(b) Voucher-positive

Note. The figures depict coefficient estimates and 95% confidence intervals on the interaction of Treated_i with month indicators (instead of Post_i) in a regression analogous to Equation (1). The interaction with April 2023 is omitted from the regression. Each panel uses one of the following indicator variables as the outcome variables: whether the listing includes (a) negative mentions of vouchers and (b) positive mentions of vouchers. Standard errors are clustered at the census tract level. The vertical lines depict when the SOI law took effect.

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Supplementary Appendix

"Discrimination Against Housing Voucher Holders:
Evidence from Online Rental Listings"

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A Data Appendix

A.1 Craigslist rental listing data cleaning and summary statistics

We eliminate duplicated listings and remove outliers in our sample since listings are often posted multiple times with the exact same or very similar content on Craigslist. First, we remove listings if any of the property characteristics (listed price, geographical coordinates, number of bedrooms, number of bathrooms, and square footage) are missing, the listing description contains less than 27 words (dropping the lowest percentile), or if listed prices change for more than three times. Second, each week, we take listings that have never appeared in previous weeks and deduplicate them by geolocation, number of bedrooms, number of bathrooms, square footage, and initial listed price. Third, we restrict the analysis to metropolitan areas with a minimum level of activity on Craigslist by restricting our sample to Core-Based Statistical Areas (CBSA) where at least 5 (de-duplicated) listings are posted each day on average (i.e., 3,650 listings over our sample period) and cities with at least 50 listings a year (i.e., 100 listing over our sample period). Finally, we remove daily and weekly rentals and price outliers, defined as the lowest and highest 0.5th percentiles, excluding listed prices lower than 100 dollars or higher than 10,000 dollars. These de-duplication and outlier removal steps leave us with 5.04 million listings among 20.5 million raw listings.[13] Table A.1 provides summary statistics of our analysis sample.

A.2 How representative is Craigslist of rental housing markets?

We investigate to what extent rental prices on Craigslist are representative of the distribution of rents of U.S. rental housing markets. In the past, Boeing and Waddell (2017) find a high correlation between median listing prices in Craigslist and median rent estimates reported by the Department of Housing and Urban Development (HUD) using 5-year ACS data.

We perform a similar exercise to that paper. Given that HUD reports median rents at the metropolitan area level (defined by HUD) by number of bedrooms, we also compute median rents

[13] We apply stringent de-duplication steps to prevent over-counting spam listings and exclude posts that are not from landlords or property managers, such as those from tenants seeking rentals or roommates.

Table A.1: Summary statistics of listing characteristics in the analysis sample

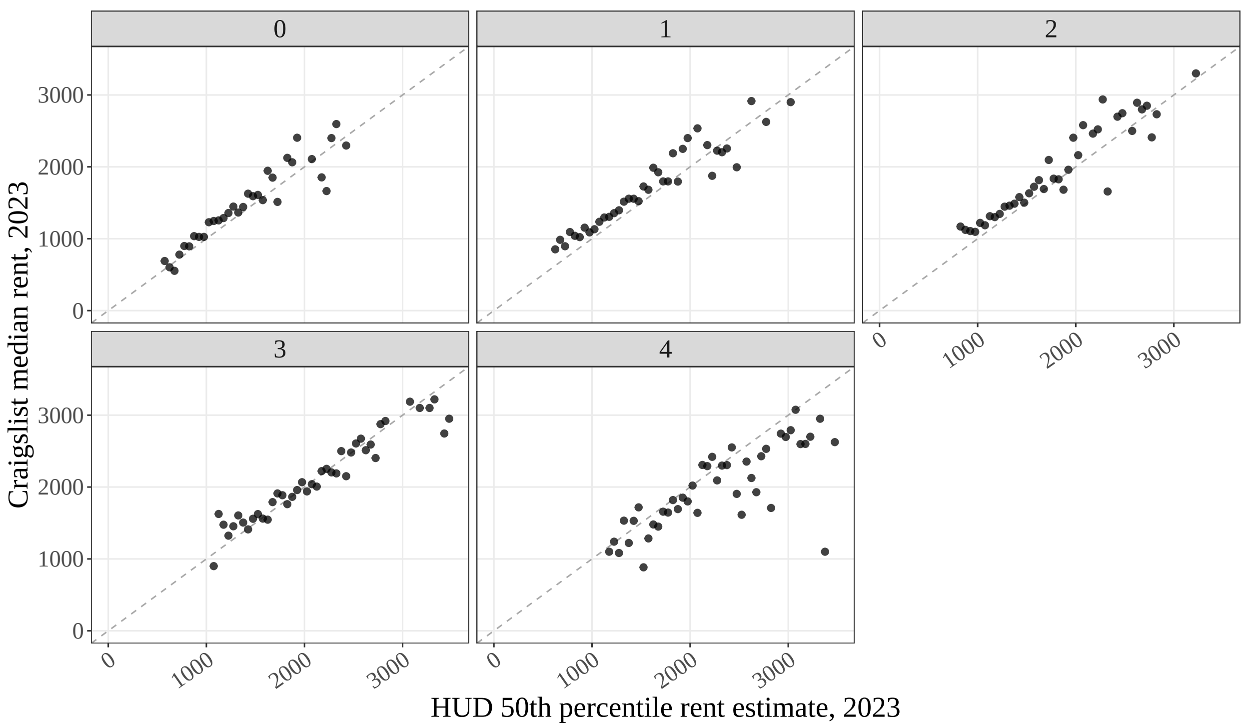
Panel A. Studio units ($N = 282,559$)					
Variable	Mean	SD	Q1	Q2	Q3
Listed rent	1693.1	589.8	1295	1620	2000
Square footage	497.3	136.0	415	478	549
# Bathroom (excl. $N = 272$ with shared/split)	1.0	0.1	1	1	1
Panel B. 1-Bed units ($N = 1,614,438$)					
Variable	Mean	SD	Q1	Q2	Q3
Listed rent	1786.6	681.8	1299	1658	2175
Square footage	706.6	141.4	620	700	777
# Bathroom (excl. $N = 1,223$ with shared/split)	1.0	0.1	1	1	1
Panel C. 2-Bed units ($N = 1,713,819$)					
Variable	Mean	SD	Q1	Q2	Q3
Listed rent	2125.4	895.6	1500	1895	2587
Square footage	1003.1	178.6	890	987	1100
# Bathroom (excl. $N = 719$ with shared/split)	1.7	0.5	1	2	2
Panel D. 3-Bed units ($N = 451,814$)					
Variable	Mean	SD	Q1	Q2	Q3
Listed rent	2456.1	1097.2	1715	2200	2910
Square footage	1315.9	250.1	1149	1280	1450
# Bathroom (excl. $N = 270$ with shared/split)	2.0	0.5	2	2	2
Panel E. 4-Bed units ($N = 54,001$)					
Variable	Mean	SD	Q1	Q2	Q3
Listed rent	2705.8	1336.9	1750	2400	3400
Square footage	1582.6	305.1	1359	1586	1831
# Bathroom (excl. $N = 71$ with shared/split)	2.3	0.7	2	2	2.5

Note. The table provides summary statistics of main listing characteristics, including listed monthly rent, square footage, and number of bedrooms in our analysis sample by number of bedrooms.

on Craigslist at that level using the number of bedrooms reported in the listing. We can do so for 274 HUD metropolitan areas. Figure A.1 is a binned scatter plot representing the relationship between our estimated median rents in Craigslist (y-axis) and HUD's median rents (x-axis) by number of bedrooms. Each dot represents a 50-dollar bin of the x-axis.

The plot shows that Craigslist is fairly representative of U.S. rental housing markets. Across all bedroom sizes, all data points are close to the 45-degree line. If anything, Craigslist's median rents for units with two or fewer bedrooms are slightly above median rents. There are two reasons why Craigslist's median rents may overestimate market rents. First, Craigslist captures asking rents. Asking rents are likely above contract rents, given that prospective tenants may be able to negotiate downwards with landlords. Second, Craigslist only reflects the flow of new rental units. Rental units coming out on the online marketplace update their price and are also likely higher-priced than the stock of existing rental housing captured by HUD's estimates.

Figure A.1: Price Representativeness of Craigslist Rental Listings



Note. This figure plots the relationship between the median rent in Craigslist in 2023 at the metropolitan level estimated by the authors and the 2023 median rent estimates reported by HUD. Each panel reports the results by the number of bedrooms. Dots are combined in 50-dollar bins.

A.3 Textual analysis details

We begin the textual analysis by searching for voucher-related keywords in the listing titles and descriptions, including 'voucher', 'hcv', 'section 8', 'section-8', 'section8', 'sec 8', 'sec8', 'housing authority', and 'housing authorities'. For rental listings that include voucher-related keywords, we fine-tune GPT-4o mini to classify them into voucher-positive and voucher-negative listings. To do so, we provide the following system message to GPT-4o mini: "*You need to identify whether the provided rental listing accepts Housing Choice Voucher/Section 8, for example, by including positive language towards vouchers (e.g., voucher accepted, section 8 welcome), or not, for example, by including negative language towards vouchers (e.g., no section 8, we do not accept vouchers)?*" Additionally, we upload 250 manually classified listing descriptions as a training set and 253 listings as a validation set on the OpenAI fine-tuning interface with GPT-4o mini as the baseline model to achieve an improved task-specific performance.[14] Both training and validation sets are formatted in JSONL and include the concatenated text of the listing title and description and the desired output (1 if voucher-positive listing, -1 if voucher-negative listing, and 0 if unclear) for each listing. Users can call the fine-tuned AI via OpenAI API using the model code "ft:gpt-4o-mini-2024-07-18:university-of-colorado::A2iujFDC."

We apply the fine-tuned GPT-4o mini model to classify all 309,537 unique listing descriptions that include voucher-related keywords. Table A.2 demonstrates our classification accuracy in comparison to alternative AIs. The fine-tuned GPT-4o mini shows the highest accuracy, with over 97 percent accuracy in both training and validation sets, while the accuracy of other models ranges from 81.8 percent to 92.1 percent. At the same time, the fine-tuned GPT-4o mini is the most cost-efficient model: as of September 2024, fine-tuned GPT-4o mini costs \$0.3 per 1M input tokens and \$1.2 per 1M output tokens, with additional \$3 per 1M training tokens, while the most expensive GPT-4 costs \$30 per 1M input tokens and \$60 per 1M output tokens, with no fine-tuning options. Given its best performance and cost efficiency, the fine-tuned GPT-4o mini is our preferred method for analyzing the texts of over 300,000 listing descriptions.

As we de-duplicate raw listings by geolocation, number of bedrooms, number of bathrooms, square footage, and initial listed price, each observation may have multiple listing descriptions. We define that if any of the listing descriptions at the geolocation, number of bedrooms, number of bathrooms, square footage, initial listed price, and listed week includes positive phrases towards voucher holders, we define them as voucher-positive. Similarly, if any of them include negative phrases towards voucher holders, we define them as voucher-negative. Of 90,959 de-duplicated listings that include voucher-related keywords, only 9 of them show conflicts in their attitudes towards voucher

[14] Fine-tuning parameters were set at # epochs = 3, batch size = 1, and learning rate multiplier = 1.8.

holders. That is, these 9 de-duplicated listings are the only cases where 1(voucher-positive) and 1(voucher-negative) are both equal to one.

Table A.2: Classification Accuracy of Fine-Tuned GPT-4o mini

Panel A. Accuracy Comparision with Other GPT Models

	(1) GPT-4o mini (fine-tuned)	(2) GPT-4o mini	(3) GPT-4	(4) GPT-4o	(5) GPT-3.5 Turbo
Training	0.976				
Validation	0.972	0.909	0.921	0.842	0.818

Panel B. Confusion Matrix of Fine-Tuned GPT-4o mini

$N = 253$	Positive	Negative	Unresolved
Positive	203	1	0
Negative	0	43	0
Unresolved	5	1	0

Note. This table illustrates the performance of the fine-tuned GPT-4o mini in classifying voucher-mention listings into positive and negative. Panel A shows the classification accuracy in the training set (N=250) used in fine-tuning GPT-4o mini and the validation set (N=253), both classified by a human. Column (1) shows our fine-tuned GPT-4o mini and Columns (2)-(5) contains alternative AIs without fine-tuning. Panel B reports the confusion matrix of fine-tuned GPT-4o mini in the validation set.

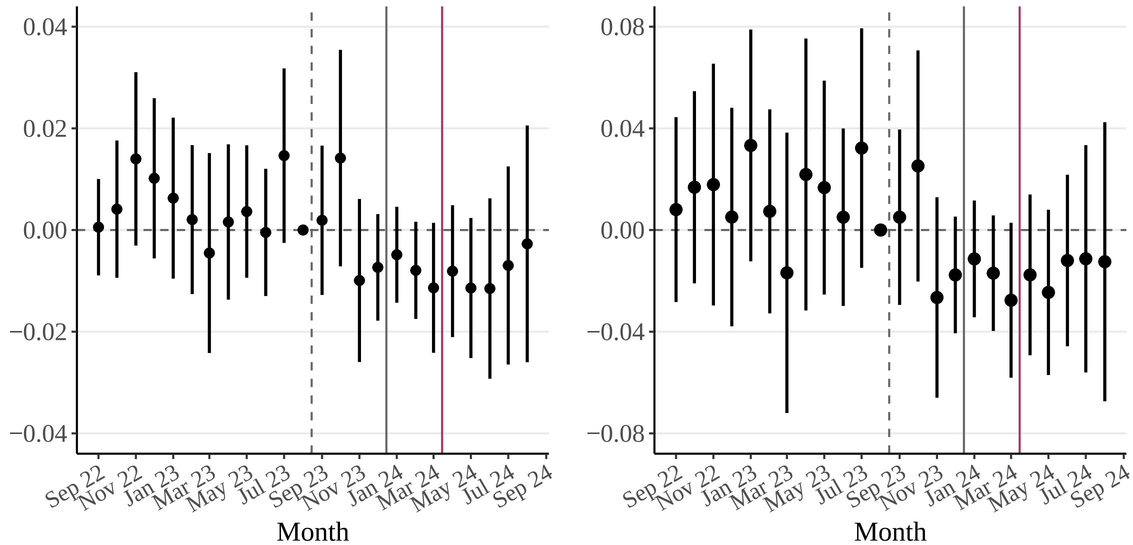
B The Impact of SOI Law in Boise City, ID

During our sample period, Boise City, ID, is another jurisdiction with a sufficient number of online rental listings to analyze as a case study. The city passed the SOI law in September 2023, which became effective on January 1, 2024, but was later repealed on March 27, 2024. This SOI law explicitly included voucher holders as a protected category. However, the legislation did not specify any enforcement agency and did not contemplate any penalties for violations, such as fines. Consequently, Boise City's SOI law represents a less stringent treatment compared to Hawaii's. Before the SOI law was passed, Boise City, ID exhibited a notable share of discriminatory listings: an average of 1.7 percent of all listings contained negative mentions against voucher holders, while this figure was 4.1 percent for listings priced below 110 percent of FMR.

We apply the same difference-in-differences approach described in Section 5.1 to estimate the impact of Boise City's SOI law on discriminatory practices in online listings. As we observe the time period before the SOI law was passed in September 2023, we show event studies and synthetic DID results for post-adoption/pre-enforcement (from Sep 2023 to Dec 2023), post-enforcement/pre-repeal (from Jan 2024 to Mar 2024), and post-repeal (from Apr 2024 to Sep 2024). Figure B.1 reports the event study results of the main specification, which uses non-SOI jurisdictions as a comparison group. Figure B.2 uses the synthetic difference-in-differences methodology in Arkhangelsky et al. (2021). It is important to note that, while the SOI law was at the city level, we run the synthetic method at the metropolitan area level and, thus, we include other adjacent localities in the geographical definition of Boise.

Both figures present a consistent narrative. The share of negative listings decreased after the passage of the SOI law and kept decreasing until it was repealed. Five months after the law was repealed, the share of negative listings went back up to levels comparable to those before the passage of the law. The estimated effects are starker in results from the synthetic control design, which constructs the comparison group to follow the same pre-treatment period trend as Boise. Overall, the Boise case study reinforces our findings from the statewide SOI adoption in Hawaii, demonstrating the effectiveness of SOI laws in reducing voucher-negative listings.

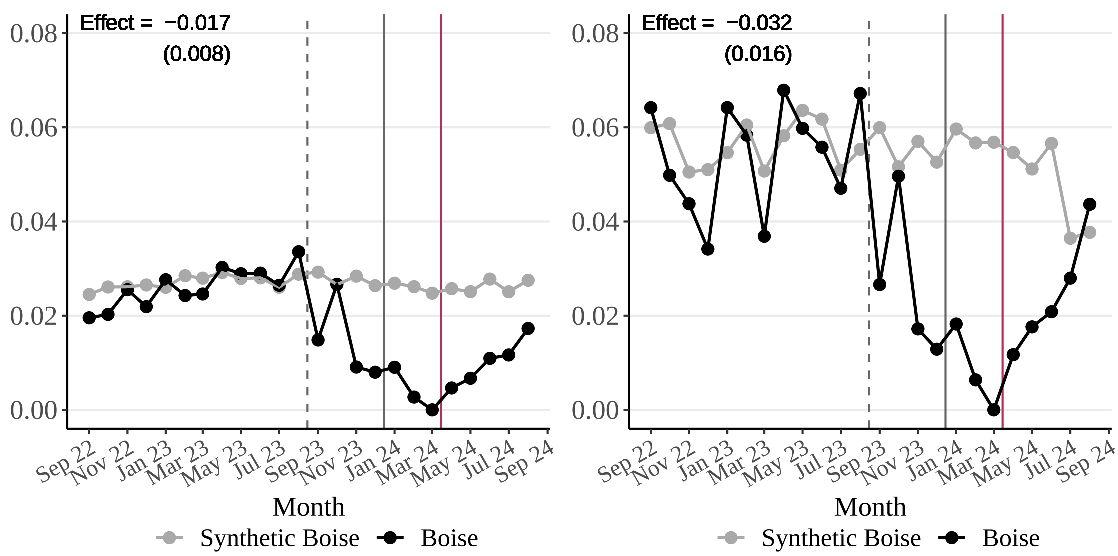
Figure B.1: Event studies: Effect of Boise City's SOI law on voucher-negative listings



(a) All listings **(b)** Below 110% FMR listings

Note. The figures depict coefficient estimates and 95% confidence intervals on the interaction of Treated$_i$ with indicator variables for each month (instead of Post$_i$) in a regression analogous to Equation (1). The outcome variable is an indicator for whether the listing includes negative mentions towards voucher holders. The interaction with September 2023 is omitted. Panel (a) uses all listings, panel (b) uses listings with a price below 110% FMR. Standard errors are clustered at the census tract level. The vertical lines depict, from left to right: when the SOI law was approved, when it took effect, and when it was repealed.

Figure B.2: Synthetic DID: Effect of Boise City's SOI law on voucher-negative listings

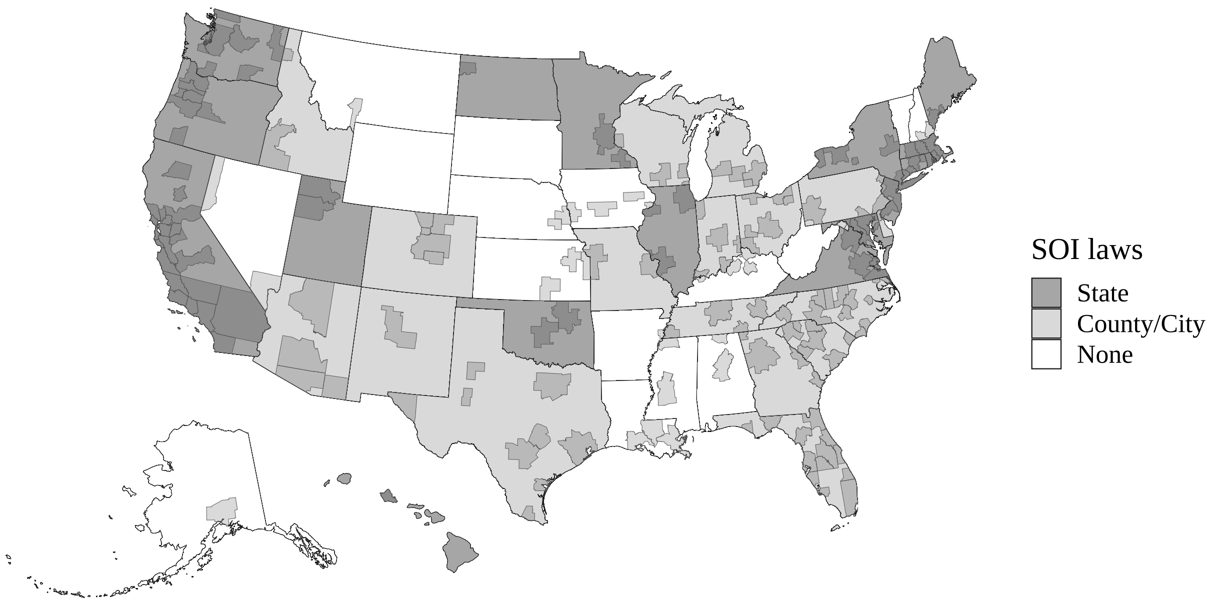


(a) All listings **(b)** Below 110% FMR listings

Note. The figures show the negative share of listings towards voucher holders for Boise and synthetic Boise. Panel (a) uses all listings and panel (b) uses listings with a price below 110% FMR. The vertical lines depict, from left to right: when the SOI law was approved, when it took effect, and when it was repealed. The pooled post-treatment effect is on the top-left corner with its standard error, obtained using the placebo methodology in Arkhangelsky et al. (2021).

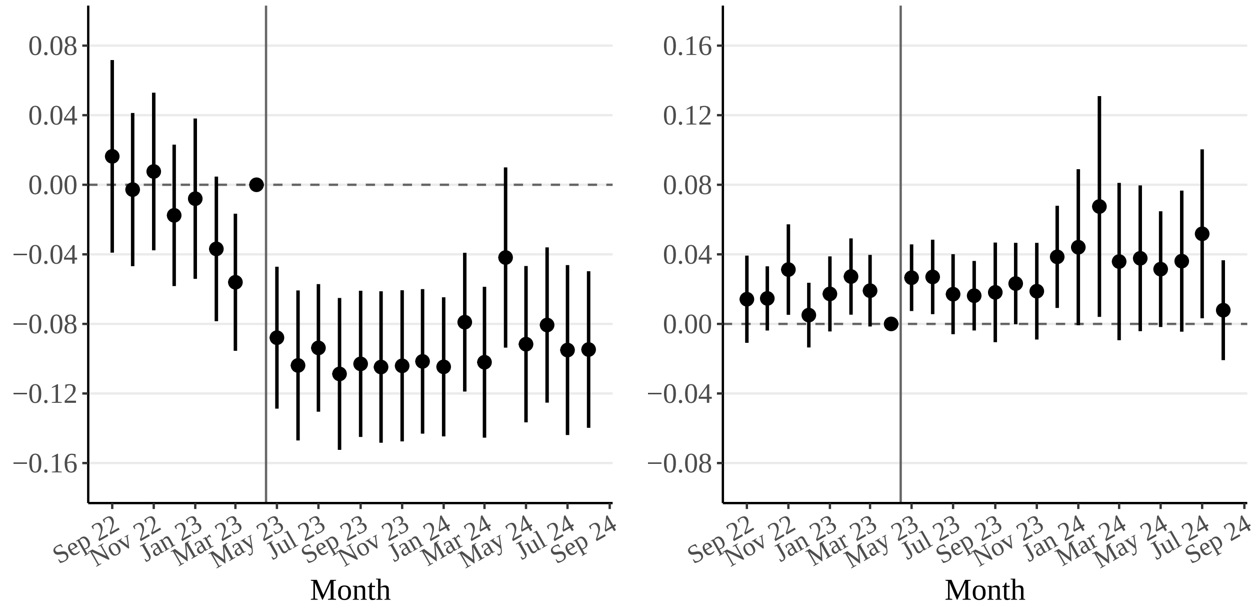
C Appendix Figures and Tables

Figure C.1: Metropolitan areas in the analysis sample and states by SOI law status



Note. Shaded areas represent the 155 Core-Based Statistical Areas (CBSAs) included in the analysis sample. Colors represent the status regarding Source of Income (SOI) laws in each state: statewide SOI law (dark gray), at least one SOI law at the county or locality level (light gray), and no SOI laws (white).

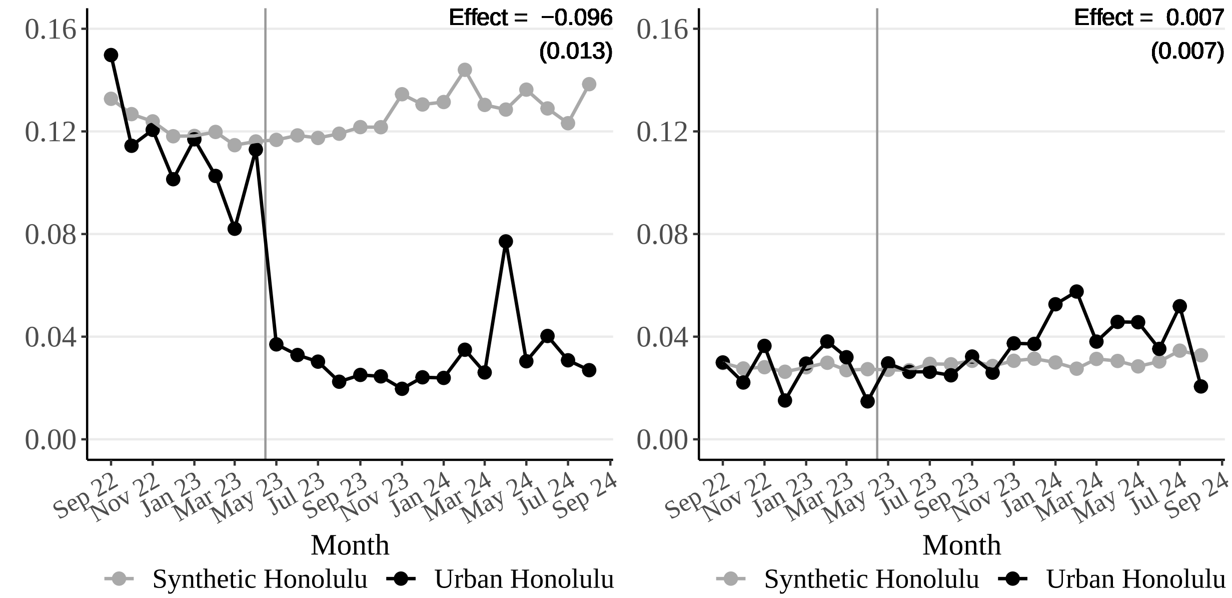
Figure C.2: Event study of the impact of Hawaii's SOI law on landlord discrimination, listings below 110% FMR



(a) Voucher-negative **(b)** Voucher-positive

Note. The figures depict coefficient estimates and 95% confidence intervals on the interaction of Treated_i with indicator variables for each month (instead of Post_i) in a regression analogous to Equation (1). The interaction with April 2023 is omitted from the regression. Each panel uses one of the following indicator variables as the outcome variables: whether the listing includes (a) negative mentions of vouchers and (b) positive mentions of vouchers. The plot uses the sample of listings with a price below 110% of FMR. Standard errors are clustered at the locality level. The vertical lines depict when the SOI law took effect.

Figure C.3: Synthetic DID: The impact of Hawaii's SOI law on landlord discrimination



(a) Voucher-negative

(b) Voucher-positive

Note. The figures depict the evolution of the dependent variable for Urban Honolulu and synthetic Urban Honolulu. Each panel uses one of the following indicator variables as the outcome variables: whether the listing includes (a) negative mentions of vouchers and (b) positive mentions of vouchers. The vertical line depicts when the SOI law took effect (May 2023). The pooled post-treatment effect is reported on the top-right corner along with its standard error, obtained using the placebo methodology in Arkhangelsky et al. (2021).

Table C.1: Top 25 CBSAs by negative mentions

CBSA	All listings	Below 110% FMR
North Port-Sarasota-Bradenton, FL	0.281	0.374
Lincoln, NE	0.095	0.157
Tulsa, OK	0.068	0.103
Cleveland-Elyria, OH	0.062	0.085
Urban Honolulu, HI	0.062	0.072
Oklahoma City, OK	0.050	0.058
Greenville-Anderson, SC	0.048	0.081
Wichita, KS	0.044	0.038
St. Louis, MO-IL	0.044	0.039
Kansas City, MO-KS	0.044	0.049
Omaha-Council Bluffs, NE-IA	0.038	0.042
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	0.037	0.078
Detroit-Warren-Dearborn, MI	0.037	0.057
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.036	0.058
Cincinnati, OH-KY-IN	0.033	0.045
Topeka, KS	0.030	0.037
Minneapolis-St. Paul-Bloomington, MN-WI	0.026	0.028
Pittsburgh, PA	0.024	0.037
Chattanooga, TN-GA	0.023	0.030
Akron, OH	0.022	0.030
Knoxville, TN	0.022	0.030
Spartanburg, SC	0.019	0.019
Boise City, ID	0.018	0.037
Davenport-Moline-Rock Island, IA-IL	0.016	0.015
Durham-Chapel Hill, NC	0.015	0.017

Note. This table reports the list of 25 CBSAs with the highest share of negative mentions towards voucher holders. The first column reports the share of listings with negative mentions among the full sample of listings, the second column reports the share of listings with negative mentions among the sample of listings with a price below 110% FMR.

Table C.2: Top 25 CBSAs by positive mentions

CBSA	All listings	Below 110% FMR
Springfield, MA	0.180	0.360
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.142	0.086
Akron, OH	0.061	0.092
Rochester, NY	0.057	0.081
Salt Lake City, UT	0.051	0.062
Providence-Warwick, RI-MA	0.050	0.086
St. Louis, MO-IL	0.048	0.057
Corvallis, OR	0.043	0.049
Chicago-Naperville-Elgin, IL-IN-WI	0.036	0.058
Fresno, CA	0.035	0.075
Urban Honolulu, HI	0.033	0.044
Worcester, MA-CT	0.031	0.055
New Haven-Milford, CT	0.030	0.029
Albany-Schenectady-Troy, NY	0.029	0.042
Cleveland-Elyria, OH	0.028	0.044
Detroit-Warren-Dearborn, MI	0.027	0.048
Kansas City, MO-KS	0.027	0.034
Riverside-San Bernardino-Ontario, CA	0.026	0.061
Sierra Vista-Douglas, AZ	0.026	0.193
Chico, CA	0.025	0.034
Ogden-Clearfield, UT	0.024	0.041
Tallahassee, FL	0.024	0.027
El Paso, TX	0.024	0.028
Hartford-East Hartford-Middletown, CT	0.023	0.037
Tulsa, OK	0.022	0.034

Note. This table reports the list of 25 CBSAs with the highest share of positive mentions towards voucher holders. The first column reports the share of listings with positive mentions among the full sample of listings, the second column reports the share of listings with positive mentions among the sample of listings with a price below 110% FMR.

Table C.3: Effect of Hawaii's SOI law on voucher discrimination, total and by neighborhood type, listings below 110% FMR

	Main effect		Heterogeneous effects on negative mentions		
	Positive	Negative	Poverty	Voucher share	Manage
Panel A: Total effect					
Post×Treated	0.014	-0.081***			
	(0.010)	(0.011)			
Panel B: By Census tract quartiles					
Post×Treated×Q1			-0.133***	-0.115***	
			(0.028)	(0.025)	
Post×Treated×Q2			-0.080***	-0.085***	
			(0.021)	(0.020)	
Post×Treated×Q3			-0.087***	-0.065***	
			(0.022)	(0.016)	
Post×Treated×Q4			-0.054***	-0.092***	
			(0.014)	(0.022)	
Panel C: By property management					
Post×Treated×Manage=0					-0.088***
					(0.011)
Post×Treated×Manage=1					-0.027***
					(0.010)
Observations	716,272	716,272			
Manage mean (Treated, Pre-SOI)					0.143
Y mean (Treated, Pre-SOI)	0.036	0.122			
Y mean Q1 (Treated, Pre-SOI)			0.188	0.144	
Y mean Q2 (Treated, Pre-SOI)			0.121	0.137	
Y mean Q3 (Treated, Pre-SOI)			0.125	0.108	
Y mean Q4 (Treated, Pre-SOI)			0.093	0.127	
Y mean, Manage = 0 (Treated, Pre-SOI)					0.138
Y mean, Manage = 1 (Treated, Pre-SOI)					0.029

Note. This table reports regression estimates of β in Equation (1). The outcome variable in column (1) is whether the listing contains positive mentions of vouchers; in the rest of columns, whether the listing contains negative mentions of vouchers. Each cell in this table represents a different regression: the first two columns use the full sample of listings and each heterogeneity result uses the sample of listings of the heterogeneity group. All regressions include census tract- and year-by-month fixed effects, as well as controls for the number of bedrooms, bathrooms, and square footage. The regressions use the sample of listings with a price below 110% FMR. Standard errors are clustered at the census tract level and are reported in parentheses. Significance codes: ***: 0.01, **: 0.05, *: 0.1