Discrimination Against Housing Vouchers: Evidence from Online Rental Listings*

Hector Blanco[†]
Rutgers University

Jaehee Song[‡]
University of Colorado Boulder

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Abstract

The Housing Choice Voucher program offers generous subsidies to low-income households for renting housing in the private market in the United States. However, only a fraction of program recipients successfully lease up a housing unit, often staying in high-poverty areas. This paper examines an important contributor to low lease-up rates especially in low-poverty areas: landlord discrimination against voucher holders. Using the universe of Craigslist rental listings, we identify listings containing voucher-related keywords and analyze their attitude toward voucher holders. Among these listings, we find that many landlords seek out voucher holders in high-poverty, high-minority areas, but discriminatory listings are more frequent in low-poverty, low-minority areas. Using a difference-in-differences design, we provide evidence that statewide legislation prohibiting source-of-income discrimination can significantly reduce discriminatory rental listings, particularly in low-poverty, low-minority areas.

*†Department of Economics, Rutgers University. Contact: hector.blanco@rutgers.edu.
‡Leeds School of Business, University of Colorado Boulder. Contact: jaehee.song@colorado.edu.

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 low take-up rates, particularly in low-poverty areas, can be partially attributed to discrimination against voucher holders by landlords (Garboden et al., 2018; Aliprantis et al., 2022) and that interventions increasing landlord engagement can boost take-up rates in those areas (Bergman et al., 2024). In practice, landlords may reject voucher holders due to concerns about program bureaucracy or property damage, among other reasons. Since voucher holders must secure housing in the private market within a specified time frame to maintain their subsidy, landlord discrimination directly affects the take-up of the program.

In this paper, we study landlord discrimination against voucher holders in online rental markets as a mechanism contributing to low lease-up rates and the concentration of voucher holders in low-social-mobility areas. We focus on two research questions. First, how prevalent is discriminatory language against voucher holders in online rental listings, and does this prevalence vary by neighborhood characteristics? Second, can legislation prohibiting discrimination mitigate these

[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 Fair Market Rents (FMR).

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

discriminatory practices?

To examine these questions, we collect data on the universe of rental listings posted on Craigslist — one of the United States' largest online rental platforms — between August 2022 and August 2023. Prior studies using rental listing data often only include basic details such as price and housing unit characteristics. In addition to these basic listing details, our dataset includes actual listing descriptions from over ten million rental listings during this period. By analyzing the texts, we identify listings referencing vouchers and then classify them as either 'positive' (encouraging the use of vouchers) or 'negative' (rejecting or discouraging the use of vouchers). We combine a dictionary-based approach with commonly-used phrases related to voucher holders (e.g., 'accept vouchers' as positive, 'no Section 8' as negative) and ChatGPT to classify listings. In our dataset, 1.9 percent of all listings and 2.4 percent of the voucher-eligible listings contain voucher-related words.[4] Among these listings, 71 percent of the listings are positive towards vouchers, while 24 percent are negative against vouchers.[5]

We first provide descriptive evidence that the prevalence of explicit discriminatory language on rental listings varies substantially across metropolitan areas and by neighborhood characteristics. In metropolitan areas such as North Port-Sarasota-Brandenton, FL, Portland, ME, and Tulsa, OK, over 10 percent of voucher-eligible listings discriminate against voucher holders, whereas such occurrences are negligible for a large subset of metropolitan areas. We also find that, within a county, discrimination against voucher holders is more frequent in lower-poverty, lower-minority neighborhoods, hindering voucher holders' ability to secure housing in these areas. Conversely, we observe that landlords in higher-poverty, higher-minority neighborhoods are more likely to welcome voucher holders explicitly. This is consistent with qualitative evidence from the existing literature that some landlords in lower-income, higher-poverty neighborhoods specialize in voucher holders due to their guaranteed government income stream (Rosen, 2014; Garboden et al., 2018).

We then study the impact of legislation prohibiting discrimination by the Source of Income (SOI) of the prospective tenant on discriminatory practices. These laws, which have been widely adopted in recent years by state and local jurisdictions, include voucher holders as a protected class against discrimination by landlords. We exploit the implementation of a statewide SOI law in

[4]We define voucher-eligible listings as listings with a price that is below 110 percent of the Fair Market Rent, which determines the maximum rent that is covered by the government's subsidy.

[5]The remaining 5 percent are unclassified.

Hawaii during our sample period to estimate its causal effect. We apply a difference-in-differences (DID) design that compares the evolution of discriminatory wording in Urban Honolulu, which had high discrimination rates of 6.6 percent prior to the SOI adoption, to that of other metropolitan areas that had not adopted an SOI law by August 2023. We find that Hawaii's SOI law led to a 68 percent (or 4.5 percentage points) reduction in the presence of discriminatory wording against voucher holders in rental listings. We show that the results are robust to using synthetic DID (Arkhangelsky et al., 2021) as an alternative identification strategy. Our results also indicate that this reduction in discriminatory language on rental listings is larger in low-poverty, low-minority neighborhoods where the baseline discrimination rate was high.

Taken together, our findings suggest that SOI laws can be an effective measure to reduce explicit discrimination against voucher holders in online rental markets, particularly in low-poverty, low-minority neighborhoods where the HCV program intends to expand housing options for low-income households. We acknowledge two limitations of our analysis. First, the results only speak to the first layer of discrimination faced by voucher holders during their housing search process: the advertisement of rental units. We cannot reject the hypothesis that SOI laws have no impact on landlord discrimination at later stages. For example, explicit discriminatory phrases do not appear on rental listings, but landlords may simply reject their applications. Second, Hawaii's SOI law is more stringent than SOI laws in other municipalities. Hawaii's SOI explicitly mentions voucher holders as a protected class and contemplates penalties for landlords failing to comply with the law. Hence, less stringent SOI laws may not be as effective in mitigating discrimination against voucher holders.

This paper is related to several strands of literature. First, we contribute to the literature examining discrimination in housing markets. Existing studies employ correspondence experiments and audit studies to identify discriminatory behavior from landlords toward specific demographic groups. These studies consistently show that landlords and real estate agents are more likely to discriminate against racial minorities across a variety of 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), with some evidence that such behavior partly reflects statistical discrimination (Ewens et al., 2014). Additional research points to increased discrimination against mothers with younger children (Faber and Mercier, 2022) and racial discrimination in neighborhoods with more economic opportunity and lower pollution exposure (Christensen and Timmins, 2022; Christensen et al., 2022). We add to this literature by focusing on discrimination in online rental markets, which occurs before landlords have any information about the prospective tenant and further narrows the housing options available to voucher holders. Moreover, most existing studies focus on a few geographic areas, while our work analyzes online rental markets all across the U.S.

More narrowly, this paper is related to prior research on discrimination against voucher holders. Most papers in this space find evidence of discriminatory behavior by landlords also using correspondence experiments in either one or a subset of metropolitan areas (Phillips, 2017; Cunningham et al., 2018; Aliprantis et al., 2022; Faber and Mercier, 2022). Notably, Aliprantis et al. (2022) show that a policy that induces moves of voucher holders to low-poverty areas does not change the screening behavior of landlords in those areas. We complement this literature by providing a comprehensive picture of discrimination against voucher holders across U.S. online rental markets. This exercise can help us further understand why voucher holders are more likely to live in high-poverty areas than other low-income households (Galvez, 2010; Lens, 2013; Horn et al., 2014).

Relatedly, the literature also examines the relationship between SOI laws explicitly prohibiting such discrimination and voucher holders' outcomes. SOI laws are associated with a higher probability of leasing up a unit with the voucher (Finkel and Burron, 2001; Freeman, 2012; Ellen et al., 2024) and moving to lower-poverty areas among voucher holders (Freeman and Li, 2014; Ellen et al., 2023). A closely related paper is Hangen and O'Brien (2023), who provide descriptive evidence of discrimination against voucher holders and its relationship with SOI laws using Craigslist data for a sample of 77 U.S. mid-size cities. We build upon this literature by covering the universe of Craigslist listings and providing the first causal estimates of the effect of implementing SOI laws on discriminatory behavior in online rental markets.

Finally, this paper speaks to the public finance literature on the take-up of welfare programs. Most prior work centers on the informational barriers and transaction costs as a way to explain low take-up in these programs (Bettinger et al., 2012; Bhargava and Manoli, 2015; Alatas et al., 2016; Deshpande and Li, 2019; Finkelstein and Notowidigdo, 2019). However, a differential feature of vouchers is that the ultimate use of voucher benefits depends on the private market. While this feature is also present in other programs such as food vouchers (Banerjee et al., 2023), discriminatory behavior by landlords is pervasive in housing markets, which can lead to even lower take-up rates in the housing market context. In this paper, we provide evidence of such discriminatory behavior and assess the extent to which legislation can effectively address this issue.

2 Descriptive Evidence of Landlord Discrimination Against Voucher Holders

We document the prevalence of discriminatory language used by landlords against voucher holders in Craigslist rental listings. We find that landlords are more likely to seek out voucher holders in high-poverty, high-minority neighborhoods. Conversely, discriminatory listings are relatively more likely to appear in low-poverty, white-dominant neighborhoods.

2.1 Data Sources

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. Finally, we link this dataset to tract-level data on the HCV program and neighborhood characteristics.

Online Rental Listings

We collect the universe of Craigslist rental listings between August 2022 and August 2023. We scrape all listings in the 'apartments/housing for rent' section on each of Craigslist's 504 regional websites across the U.S. on a weekly basis. This front-page scraping allows us to gather basic information on the listing identifier, asking rent, title, number of bedrooms, square footage, and the date when it was posted. While most prior research using Craigslist data only gathers information available on this front-page scraping, we take it further and also scrape listing-specific detailed pages. Listing-specific pages include additional information on the listing description, number of bathrooms, street address, and approximate geographic coordinates.

We restrict the sample of listings as follows. First, because some listings are posted multiple times with the exact same content, we eliminate duplicated listings and remove outliers in our sample. In particular, we keep listings that are unique at the street address-number of bedrooms-title-description level. Second, we remove listings with zero prices, descriptions of less than 30 words, and listings that changed prices more than five times. These deduplication and outlier removal steps leave us with roughly 5.5 million listings among 10.7 million raw listings. Third, we restrict the analysis to regions with a minimum level of activity on Craigslist rental markets by keeping only those listings located in a Core-Based Statistical Area (CBSA) where at least 10 unique rental listings are posted each day on average (i.e., 3,650 listings a year).

The final sample contains approximately 5.1 million unique rental listings across 152 CBSAs. The sample CBSAs are shown as the shaded areas in Figure 1. Appendix A provides more details about the construction of the dataset and shows supportive evidence that median rental prices on Craigslist are fairly representative of median population rents as measured by the Census.

HCV Program and Neighborhood Characteristics

We complement Craigslist data with two datasets. First, we gather information on several aspects of the Housing Choice Voucher program from the Department of Housing and Community Development (HUD). We merge the Craigslist dataset with Fair Market Rents (FMR), which are computed as the 40th percentile of the area median rent. Public Housing Authorities (PHAs) use FMRs to determine payment standards, which are the maximum amount of rent covered by the HCV program for its beneficiaries. In practice, PHAs can set the payment standard to be between 90 and 110 percent of FMR. In our analysis, we define listings with a rental price equal to or smaller than 110 percent of FMR as (fully) 'voucher-eligible' listings, proxying for low-income housing units particularly vulnerable to discrimination against voucher holders. We also merge the listings dataset with the number of voucher holders leasing a unit in their Census tract in 2022, which we obtain from the Picture of Subsidized Households by HUD.

Second, we collect data on neighborhood characteristics from the 2019 5-year American Community Survey. These data contain information on several demographic, socioeconomic, and housing characteristics, such as racial composition, household median income, poverty rates, housing vacancy rates, median contract rents, renter-occupied units, and median construction year. We compile the 2019 ACS data at the Census tract and CBSA levels and merge it with the listings data.

2.2 Identification and Classification of Discriminatory Language

We identify rental listings with discriminatory phrases against voucher holders in the following way. We first filter listings containing voucher-related keywords in either their title or the description.[6] In the full sample, we observe such keywords in roughly 96,000 listings (1.9%); in the voucher-eligible subset, we observe them in approximately 56,000 listings (2.4%).

Next, we classify listings as either positive or negative towards voucher holders. Positive listings actively seek out voucher holders (e.g., 'accept vouchers', 'Section 8 welcome'), while negative listings explicitly specify that they do not accept vouchers (e.g., 'voucher not allowed' and 'no Section 8'). Our classification process combines a dictionary-based approach with ChatGPT. First, we classify listings using a dictionary of commonly used phrases that we manually build. If a listing that contains voucher-related keywords also includes 'accept', 'approve', 'eligible', or 'welcome', for example, without any negation, then the listing is classified as positive. If such a listing also contains 'not' or 'no' in the same sentence, then we classify it as negative. Second, we use ChatGPT 3.5 for an automated classification of the listings.[7] Using these two alternative methods, we create the final classification into 'positive', 'negative', or 'unclassified'. If the results from ChatGPT and the dictionary-based classification match, we assign either the corresponding positive or negative classification to the listing. If one approach yields an 'unclassified' result, we adopt the classification the other method generates. We designate the listing as unclassified when both approaches fail to provide a clear classification. Appendix A.1 provides statistics from the final classification. To validate this algorithm, we compare its outcomes with a manual examination of 500 listings, achieving a match rate of 93.7%.

Among listings containing voucher-related keywords, 71 percent are positive, 24 percent are negative, and 5 percent are unclassified in the full sample. In the voucher-eligible sample ($\leq$ 110%

[6]We use the following keywords: 'voucher','hcv', 'section 8', 'section-8', 'section8', 'sec 8', 'sec8', 'housing authority', 'housing authorities', 'project-based'.

[7]In particular, we use the following prompt: "For each description I provide, I need you to classify it as positive or negative. The positive listings are those who seek out voucher holders or section 8 (e.g., 'voucher welcome', 'will not refuse voucher for rental housing assistance', 'section 8 welcome') while the negative listings are those who do not accept voucher holders' applications (e.g., 'voucher not accepted', 'no section 8'). I also need to document the 4-5 keywords used to classify each listing."

FMR), 63 percent are positive, 31 percent are negative, and 6 percent are unclassified.

2.3 Mapping Discrimination

Using this dataset, we document the prevalence of landlord discrimination against voucher holders in online rental listings across U.S. metropolitan areas. While we focus on discrimination explicitly expressed in online rental listings, other forms of discrimination may occur during the subsequent application and leasing process that have been documented in the literature. Our research design does not allow us to capture these further discriminatory behaviors throughout the process. Thus, our estimates may underestimate the full extent of discrimination in rental markets.

Figure 2 presents the percentage of listings with positive and negative mentions regarding vouchers in the top 50 metropolitan areas with the highest incidence of negative mentions. Panel (a) uses the full sample, and Panel (b) uses voucher-eligible listings (i.e., those priced below 110 percent of FMR). While the ranking of metropolitan areas remains consistent across both samples, the share of negative mentions is notably higher among voucher-eligible listings and almost doubled in many metropolitan areas. Within the voucher-eligible sample, North Port-Sarasota-Bradenton, FL, stands out with 23 percent of their listings explicitly discriminating against vouchers, followed by Portland, ME, and Tulsa, OK, with roughly 16 and 12 percent of discriminatory listings, respectively. Nine metropolitan areas exhibit discrimination rates between 4 and 8 percent, while the share of negative mentions is below 4 percent for the rest of the sample. Appendix Table C.1 shows a list of the top 25 metropolitan areas with the highest rates of negative and positive mentions of voucher holders.

The presence of Source of Income (SOI) laws does not necessarily correlate with lower rates of discrimination. In Figure 2, we indicate the CBSAs where an SOI law has been enacted at the state level in blue, those with count- or municipality-level SOI laws in orange, and those without any SOI laws in gray. Metropolitan areas in states with SOI laws are equally represented on the right-hand side of the negative mention distribution as jurisdictions without SOI laws. Examples of states with SOI laws and metropolitan areas with high discrimination rates are Maine, Maryland, and Oklahoma. Notably, Cleveland, OH, which traditionally exhibited one of the highest discrimination rates in the country, is absent from the ranking, possibly due to the adoption of an SOI law in 2021.[8]

[8]Hangen and O'Brien (2023) document that about 11 percent of Craigslist listings in Cleveland, OH, discriminated

This case suggests that certain forms of SOI legislation may be more effective at addressing online discriminatory practices than others.[9]

2.4 Prevalence of Discrimination by Neighborhood Characteristics

We examine how the appearance of voucher-related keywords correlates with a range of neighborhood characteristics in Table 1. We study four dependent variables indicating whether the listing contains any voucher-related keywords, a positive voucher mention, and a negative voucher mention and whether the listing contains a negative voucher mention conditional on the listing containing a voucher-related keyword. Columns 1 to 4 show results using the full sample of listings, while columns 5 to 8 focus on voucher-eligible listings. In each column, we estimate a linear probability model that regresses each outcome on various 2019 Census tract characteristics where the listing is located.[10] The regressions control for month and county fixed effects, as well as listing-specific characteristics such as the number of bedrooms, bathrooms, and square footage.

We find that the share of listings with positive voucher mentions is more than double that of negative mentions (see the last row of the table). These positive mentions have a strong positive correlation with the share of voucher holders in a tract, the Black population share, and the median age of a building, especially in the case of voucher-eligible listings (columns 2 and 6). This behavior is consistent with prior literature documenting that landlords in less profitable, low-income areas often specialize in voucher holders because they provide a more certain stream of income — since part of it is paid by the government — than other potentially higher-delinquency rate tenants (Rosen, 2014; Garboden et al., 2018).

In contrast, negative mentions appear more frequently in low-poverty, low-minority neighborhoods. While negative mentions are associated with higher poverty rates and older housing stocks (column 3) in the full sample, this relationship is entirely explained by whether the listing price is below FMR; this relationship disappears in the voucher-eligible sample (column 7). Conditional

against voucher holders in 2019.

[9]Washington-Arlington-Alexandria, DC-VA-MD-WV illustrates another interesting case. 6.4 percent of voucher-eligible listings in this metropolitan area contained negative mentions, and another 6.4 percent contained positive mentions. Washington, DC, has a SOI law, and 0 percent of its listings contain negative mentions, while 34 percent of them contain positive listings. That is, negative mentions are solely driven by listings in Maryland, Virginia, and West Virginia, where 7.3 percent of listings contain negative mentions and only 2.8 percent contain positive mentions — despite SOI laws also being in place in Maryland and Virginia.

[10]An exception is the share of voucher holders in a given tract, which is computed for the year 2022.

on containing any voucher-related keywords, negative mentions are less likely to appear in neighborhoods with more voucher holders, higher Black population shares, and higher poverty rates (columns 4 and 8). Notably, negative mentions are less frequent in neighborhoods with tighter housing markets as measured by vacancy rates. These results are in line with the landlord specialization hypothesis.[11]

Overall, the descriptive analysis implies that discrimination against voucher holders is more prevalent in relatively low-poverty, low-minority neighborhoods. Conversely, positive language towards voucher holders is more frequent in these neighborhoods. This finding emphasizes landlord discrimination as an obstacle voucher holders face when seeking access to low-poverty areas with better economic opportunities.

3 Do Source of Income Laws Mitigate Discrimination?

We investigate whether and to what extent legislation prohibiting discrimination against voucher holders reduces discriminatory rental listings on Craigslist. Using the adoption of a state-level SOI law in Hawaii as a case study, we show that such laws can effectively protect voucher holders from explicit discrimination by landlords, especially in lower-poverty, lower-minority neighborhoods.

3.1 Background: Source of Income Law in Hawaii

In recent years, there has been a significant rise in the implementation of Source of Income (SOI) laws by state and local jurisdictions. These laws aim to prohibit discrimination based on the source of income used by tenants to pay rent. The Poverty & Race Research Action Council (PRRAC) maintains an updated record of all federal, state, and local jurisdictions that prohibit discrimination based on SOI, a resource frequently cited in previous research (Ellen et al., 2023; Hangen and O'Brien, 2023). As of December 2018, SOI laws protected 34 percent of the voucher

[11] In Appendix Table C.2, we hone in more tightly on the presence of discriminatory wording across the distribution of two variables: the poverty rate and the Black population share. We estimate the same linear probability models as in Table 1, but replacing the two continuous variables with quartile indicators — one at a time. We omit the first quartile in the regressions; hence, quartile coefficients can be interpreted as differences in discriminatory behavior relative to listings located in the lowest-poverty rate (or lowest-Black share) neighborhoods. While the estimates are less precise, columns 4 and 8 suggest that conditional on the presence of any voucher-related keyword, negative mentions are relatively more frequent in Census tracts in the two lowest quartiles in terms of poverty rates and Black population shares.

holder population (Bell et al., 2018). By September 2022, 57 percent of voucher holders lived in jurisdictions with an SOI in place, according to PRRAC (Knudsen, 2022).

Regarding voucher holders, SOI laws vary widely across jurisdictions in their explicitness about voucher holders and enforcement mechanisms. Some SOI laws provide limited or no protection for voucher holders by excluding them as a protected class, for example, in Delaware and Wisconsin. In others, some explicitly identify voucher holders as a protected class and some do not.[12] Even when voucher holders are explicitly mentioned, their protection against landlord discrimination 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. Regarding enforcement, some jurisdictions impose fines on landlords for violations, while others do not.

Despite the wide adoption of these laws, there is no causal evidence linking the passing of these laws to changes in explicit landlord discriminatory behavior. Prior research primarily focused on the impact of SOI laws on voucher holders' locational outcomes,[13] and only provides suggestive evidence that voucher holders in states with SOI laws have higher success rates in finding suitable housing units (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 but does not establish a causal relationship between the two.

In this paper, we focus on Hawaii as a case study. Hawaii enacted Act 310 into law in July 2022, which became effective in May 2023. This law prohibits landlords from "*discriminating against current and prospective tenants based on participation in Permanent Supportive Housing Programs or the HCV program*" and contemplates fines ranging from $2,000 for the first offense to $2,500 for subsequent violations.

Hawaii provides an ideal empirical setting for two reasons. First, Urban Honolulu ranks among

[12]For instance, Illinois' law HB2775, which amended the Human Rights Act 775 in May 2022 and became effective in January 2023, defines "source of income" as the "*lawful manner by which an individual supports himself or herself and his or her dependents*".

[13]Freeman and Li (2014) and Ellen et al. (2023) find evidence that, after SOI laws are implemented, existing voucher holders who move find housing in neighborhoods with lower poverty rates and lower racial minority shares but no evidence of neighborhood improvements for new voucher holders.

the top metropolitan areas exhibiting discrimination against voucher holders on Craigslist, as depicted in Figure 2. Prior to the enforcement, wording related to voucher holders was present in 9.3 percent of Craigslist's low-income rental listings, 72 percent of which were negative mentions. Second, Hawaii's law is explicit and includes a penalty system, placing it in the range of the 'more enforceable' SOI laws. While our findings do not speak directly to the impacts of less stringent SOI laws, they provide insights into the effectiveness of stringent SOI legislation as a means to combat landlord discrimination.

3.2 Empirical Strategy: Differences-in-Differences

We use a difference-in-differences (DID) design to estimate the impact of Hawaii's SOI law on landlord discrimination. We compare the presence of voucher-related keywords in Urban Honolulu — the only Hawaiian metropolitan area in our analysis sample — before and after the SOI law became effective in May 2023 to that of a comparison group composed of all other local jurisdictions that had not passed any SOI laws by August 2023. The identifying assumption is that had Hawaii not passed the SOI law, landlords' discriminatory behavior on Craigslist in Urban Honolulu would have evolved similarly to that of landlords in comparison jurisdictions.

Throughout the rest of the paper, we present the results using the voucher-eligible sample.[14] To reduce the noise in our estimates, we also restrict the sample to metropolitan areas with an average of at least five daily listings within this subset. Our final sample contains 670 comparison localities across a total of 70 metropolitan areas.

Using the universe of Craigslist listings for the treated and comparison jurisdictions from September 2022 to August 2023, we estimate the following equation at the listing i level:

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

The dependent variable Y_i is an indicator variable for whether listing i contains voucher-related keywords (any words, positive, or negative). β captures the main effect of interest, i.e., the impact of the SOI law on landlord discrimination against voucher holders. More specifically, β is the

[14] We also reproduce the DID estimates and event study plots for the full sample of listings — instead of only voucher-eligible listings — and obtain similar results, as shown in Appendix Table C.3 and Figure B.1 In this case, the comparison group includes 770 localities across a total of 96 comparison metropolitan areas.

coefficient on the interaction of an indicator variable (Post_i) for whether the listing was posted after Hawaii's SOI became effective in May 2023 with an indicator variable (Treated_i) for whether the listing is in Urban Honolulu. We cluster standard errors at the locality level.

We include several control variables to address the concern that treated and non-treated jurisdictions are not fully comparable. We include month fixed effects ($\alpha_{m(i)}$) and Census tract fixed effects ($\phi_{t(i)}$) to control for time-invariant neighborhood-specific characteristics and for time patterns that affect all listings across locations, respectively. We also control for a vector of listing characteristics $\mathbf{X_i}$, including the number of bedrooms, number of bathrooms, and square footage.

There are two caveats to our main results. First, we are unable to control for seasonality trends since we use data for a one-year period. It is possible that landlords are more likely to refer to voucher holders during different times of the year, e.g., depending on seasonal trends in the demand for rental housing. We plan to address this issue in the future: the data collection process is ongoing and we will expand the sample to two years of data. Second, Hawaii may have a unique housing market compared to the mainland U.S., making it challenging to find an adequate comparison group. While we provide event study results to discuss the validity of the parallel trends assumption below, we also use synthetic controls as a robustness check.

3.3 Results

We find substantial reductions in landlords' explicit discrimination against voucher holders after the SOI law takes effect in Hawaii. Panel A of Table 2 shows the estimates of β in Equation (1) for the three primary voucher outcomes: whether the listing contains any voucher-related keyword, any negative mention of voucher holders, or any positive mention of voucher holders. After SOI implementation, the share of listings with voucher-related keywords decreased by 5.5 percentage points in Urban Honolulu, equivalent to a 60 percent reduction from the baseline. Most of this change comes from a 4.5 percentage-point reduction in negative mentions (a decrease of 4.5 p.p., 68%), while there was a smaller reduction in positive mentions (a decrease of 1.1 p.p., 42%).

To assess the parallel trends assumption, we estimate a dynamic version of Equation (1), where we interact the Treated_i variable with indicator variables for each month in our sample instead of the Post_i indicator variable. Figure 3 shows the results of this exercise for three outcomes. Trends are relatively stable across all outcomes in the pre-treatment period, and there is a clear and significant drop in general voucher mentions and negative mentions after May 2023, when the SOI law was adopted. Notably, the number of negative mentions slightly increased in April 2023 in anticipation of the policy. Regarding positive mentions, the event study suggests that we should interpret the negative coefficient in the DID specification cautiously, given that none of the event-year coefficients is statistically significant.

Given the descriptive evidence indicating that negative wording is relatively more frequent in lower-poverty neighborhoods with lower Black population shares, we further investigate the heterogeneous effects of SOI laws along these two Census tract characteristics. In particular, we estimate the following equation:

$$Y_i = \alpha_{m(i)} + \phi_{l(i)} + \sum_{q=1}^{4} \beta_q \, \text{Post}_i \times \text{Treated}_i \times \mathbb{1}(\text{Quartile}_i = q) + \gamma' \mathbf{X_i} + \varepsilon_i \tag{2}$$

That is, we interact the treatment variables with indicator variables denoting the poverty rate or Black share quartile of the Census tract where the listing is located. Quartiles are computed within a county. Panels B and C Table 2 report the corresponding estimates, estimated separately for each Census tract characteristic.

We find that the SOI law was effective in all neighborhood income groups but much more in low-poverty, low-minority Census tracts. Column 6 shows that the SOI law achieved the strongest reductions in negative mentions in the lowest-poverty rate quartile, an 8.8 percentage-point decrease. The magnitude of these reductions goes down to 6 p.p. in the second quartile, and to roughly 4 p.p. in the two highest-poverty rate quartiles. A similar story holds when using Black population shares. Census tracts in the first two quartiles reduce negative mentions by 6.5-7.8 percentage points, while such reductions are less pronounced in tracts with high Black shares (2.4-4.8 p.p.). There is no clear pattern for positive mentions.

Taken together, these results suggest that SOI laws can be an effective tool to tackle landlord explicit discrimination against voucher holders, particularly in areas plausibly offering better opportunities for social mobility. This is especially policy-relevant, given that prior research documents that voucher holders tend to live in high-poverty areas (Galvez, 2010; Horn et al., 2014; Lens, 2013).

Robustness: Synthetic DID. We test the robustness of the results by using an alternative empirical strategy. The main concern of the DID design is that the average locality without a SOI law may not be a plausible comparison group, given that Urban Honolulu is a metropolitan area that differs from others along many observable and unobservable characteristics. Despite the fact that event studies seem to mitigate this concern, we also address this issue by estimating the effect of SOI adoption using the synthetic difference-in-differences methodology proposed by Arkhangelsky et al. (2021).

Synthetic DID is appealing in our setting for two reasons. First, and similar to traditional synthetic controls, 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.[15] Second, it allows for unit-level shifts, such as in the traditional DID, but unlike traditional synthetic controls. This second point is particularly important given that only a few metropolitan areas have negative mention rates as high as Urban Honolulu (see Figure 2). We implement synthetic DID by collapsing the dataset at the metropolitan area-by-month level, where Urban Honolulu is the treated unit and the remaining 70 metropolitan areas constitute the donor pool.

Appendix Figure B.2 plots the dependent variable series for Urban Honolulu and its synthetic control and reports the coefficient estimates and standard errors.[16] The estimates are very similar to the DID specification. Negative mentions decreased by 4.6 percentage points, which is statistically significant at the 5 percent significance level. The effect on positive mentions is not statistically significant, which is consistent with the event study plot in Figure 3, where none of the event-year estimates is statistically significant.

4 Conclusion

The Housing Choice Voucher program is the largest federal rental assistance program in the United States. However, despite long wait lists for receiving the subsidies, lease-up rates in the

[15] Importantly, synthetic DID places more weight on both donor units and pre-treatment periods that are more similar to the treated unit. Such a feature is appealing in this context, given that voucher-related wording may also vary in frequency and type not only across metropolitan areas but also across pre-treatment periods.

[16] Since there is only one treated unit — Urban Honolulu —, the synthetic DID methodology constructs standard errors by estimating several placebo tests on units in the donor pool and comparing the distribution of these placebo effects with the actual treatment effect on the treated unit.

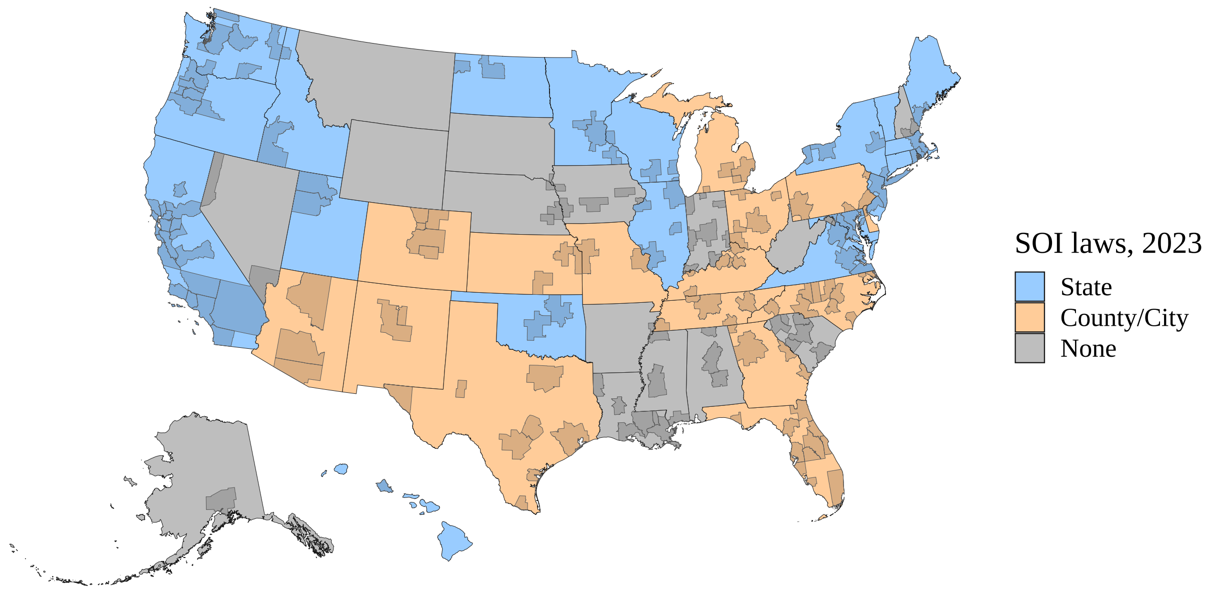
program are surprisingly low. One explanation for low lease-up rates is the discrimination voucher holders face from private landlords.

In this paper, we use a novel dataset of the universe of online rental listings on Craigslist to measure discrimination faced by voucher holders in private rental markets. We find that such discrimination is frequent, especially in low-poverty, low-minority neighborhoods. Relative to prior literature, we also document that a significant share of landlords positively advertise to voucher holders, possibly indicating that some landlords specialize in these demographics due to the stable stream of income provided by the government. We also find that the newly adopted state-level Source of Income law in Hawaii substantially reduced discrimination against voucher holders, particularly in low-poverty, low-minority neighborhoods.

While our findings highlight the potential efficacy of legislation prohibiting source of income discrimination in reducing discrimination, we acknowledge that our results specifically speak to a more stringent subset of SOI laws. Hawaii's law explicitly protects voucher holders and contemplates penalties for landlords who engage in discriminatory practices. Legislation lacking similar explicitness or enforcement mechanisms may not yield comparable outcomes.

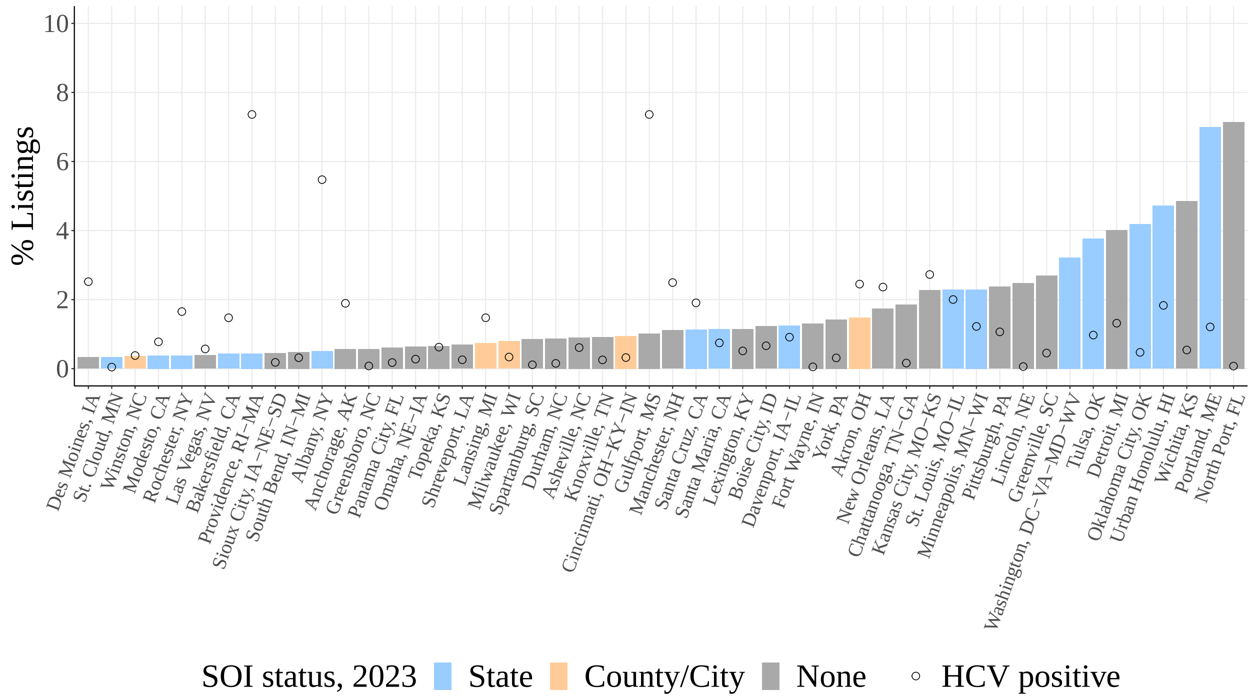
Figures

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

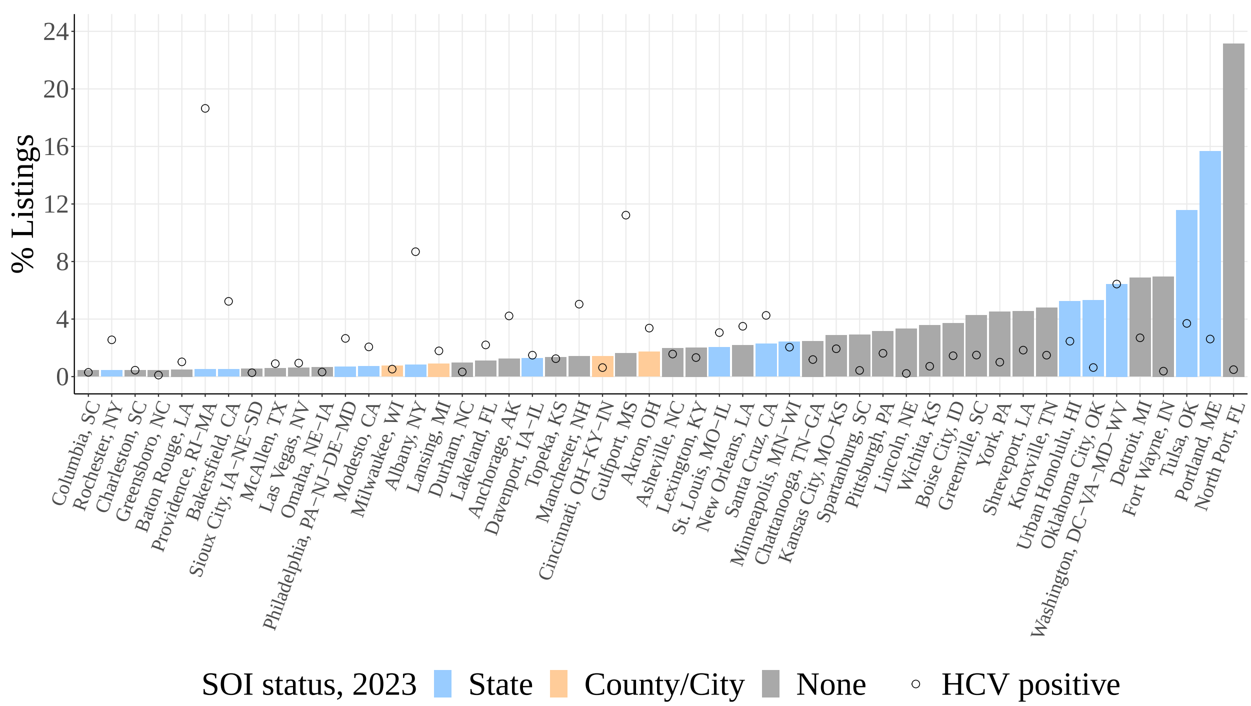


Note. Shaded areas represent the 152 Core-Based Statistical Areas (CBSAs) included in the analysis sample. Colors represent the status regarding Source of Income (SOI) laws in each state: statewide SOI law (blue), at least one SOI law at the county or locality level (orange), and no SOI laws.

Figure 2: % Negative and positive HCV mentions for top negative CBSAs



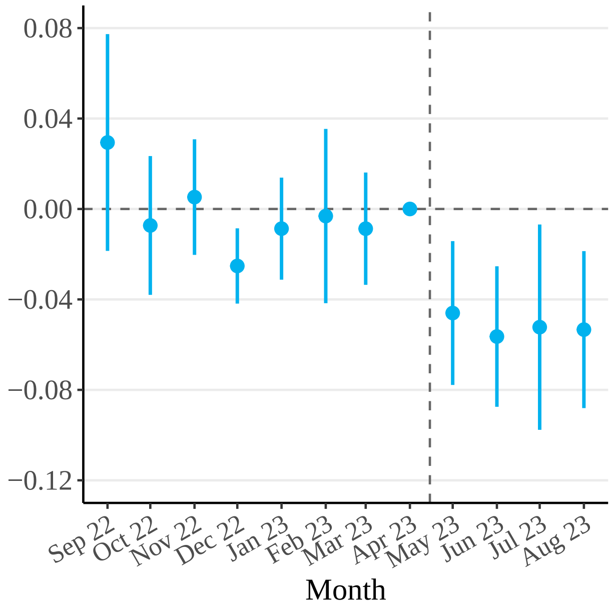
(a) All listings



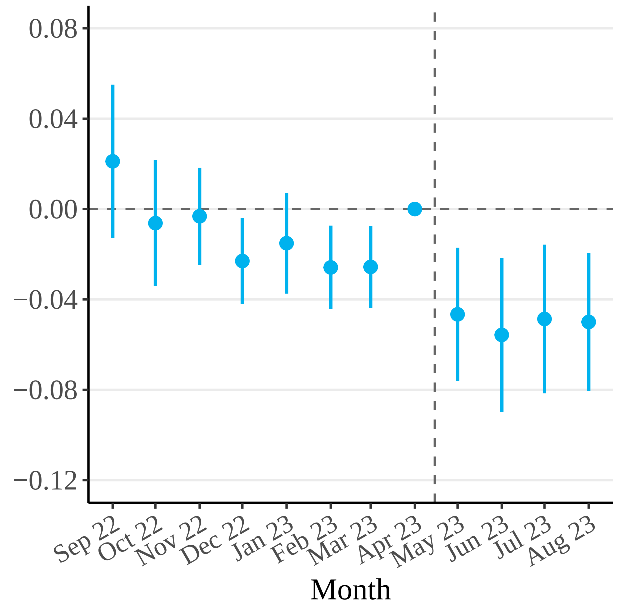
(b) Voucher-eligible listings (below 110% FMR)

Note. The figure depicts the proportion of listings with positive and negative mentions of Housing Choice Vouchers by CBSA. Only the 50 CBSAs with the highest share of negative mentions are included. The bars indicate % negative listings and the dots indicate % positive listings. Colors indicate whether a state SOI law (blue) or a county/city SOI law (orange) apply to *any* locality within the CBSA.

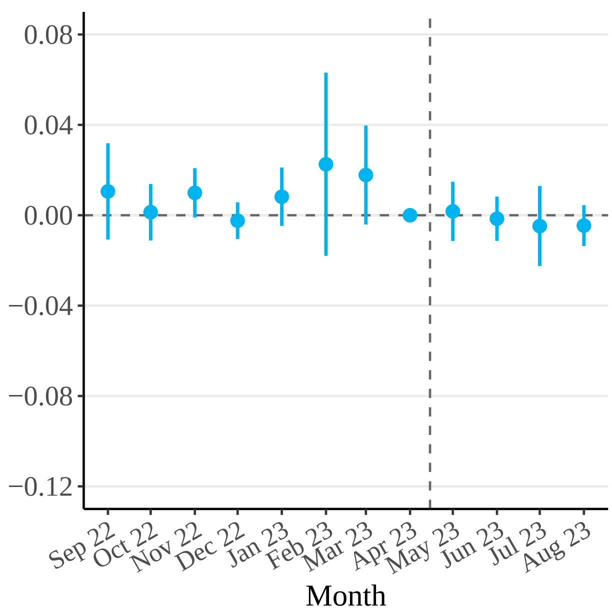
Figure 3: Effect of Hawaii's SOI law (effective May 23) on landlord discrimination



(a) Any HCV



(b) HCV negative



(c) HCV 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 a different indicator variables as an outcome, based on whether the listing includes (a) any voucher-related keywords, (b) negative mentions towards voucher holders, and (c) positive mentions towards voucher holders. The plot uses the sample of voucher-eligible listings (i.e., with a price below 110% of FMR). Standard errors are clustered at the locality level. The vertical dashed lines depict when the SOI law took effect.

Tables

Table 1: Correlation of voucher-related keywords with Census tract characteristics

	All listings				Voucher-eligible (below 110% FMR)			
	Any HCV	Positive	Negative	Neg|Any	Any HCV	Positive	Negative	Neg|Any
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Voucher holders in tract, share	0.020*	0.022**	-0.005	-0.254***	0.065***	0.066***	-0.008	-0.229***
	(0.011)	(0.011)	(0.003)	(0.073)	(0.021)	(0.019)	(0.006)	(0.070)
Black, share	0.006	0.009	-0.005	-0.117***	0.029**	0.035***	-0.007	-0.210***
	(0.011)	(0.010)	(0.004)	(0.040)	(0.012)	(0.010)	(0.005)	(0.052)
Hispanic, share	-0.005	-0.002	-0.004	-0.023	-0.006	-0.001	-0.006	-0.031
	(0.006)	(0.005)	(0.003)	(0.039)	(0.009)	(0.007)	(0.005)	(0.050)
Poverty rate	0.018*	0.011	0.006*	-0.196***	0.008	0.002	0.004	-0.201***
	(0.009)	(0.008)	(0.004)	(0.066)	(0.011)	(0.009)	(0.006)	(0.074)
Vacancy rate	0.000	0.009	-0.010	-0.137	0.004	0.018	-0.015	-0.246*
	(0.013)	(0.010)	(0.008)	(0.089)	(0.020)	(0.016)	(0.013)	(0.135)
Above median building age	0.003	0.002	0.001***	-0.010	0.003	0.004*	0.001	-0.009
	(0.002)	(0.002)	(0.001)	(0.010)	(0.003)	(0.002)	(0.001)	(0.015)
Observations	5,108,996	5,108,996	5,108,996	95,774	2,353,808	2,353,808	2,353,808	56,197
R^2	0.174	0.175	0.203	0.710	0.161	0.093	0.324	0.686
Y mean	0.019	0.013	0.005	0.243	0.024	0.015	0.007	0.307

Note. This table reports the regression results of linear probability models. The outcome variable in columns (1) and (5) is whether the listing mentions voucher-related keywords; in columns (2) and (6), whether the listing contains positive mentions of vouchers; in columns (3)-(4) and (7)-(8), whether the listing contains negative mentions of vouchers. Columns (1)-(4) use the full sample, while columns (5)-(8) use the sample of listings with a rental price at or below 110% of the Fair Market Rent (FMR). Columns (4) and (8) 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 variable 'above median building age' is defined as an indicator variable denoting whether the Census tract's median building age is above the median within the county. All regressions include county and month fixed effects, and control for 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 neighborhood type

	Any HCV		Positive		Negative	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total effect						
Post × Treated	-0.055***		-0.011*		-0.045***	
	(0.014)		(0.007)		(0.010)	
Panel B: Poverty rate quartiles						
Post × Treated × Quartile 1		-0.090***		-0.003		-0.088***
		(0.029)		(0.007)		(0.024)
Post × Treated × Quartile 2		-0.051***		0.004		-0.060***
		(0.020)		(0.005)		(0.011)
Post × Treated × Quartile 3		-0.062**		-0.022*		-0.041**
		(0.025)		(0.012)		(0.017)
Post × Treated × Quartile 4		-0.041***		-0.005		-0.037***
		(0.009)		(0.008)		(0.004)
Panel C: Black share quartiles						
Post × Treated × Quartile 1		-0.068***		-0.005		-0.065***
		(0.018)		(0.011)		(0.011)
Post × Treated × Quartile 2		-0.100***		-0.021*		-0.078***
		(0.020)		(0.011)		(0.016)
Post × Treated × Quartile 3		-0.044***		0.001		-0.048***
		(0.015)		(0.003)		(0.015)
Post × Treated × Quartile 4		-0.043***		-0.020*		-0.024***
		(0.013)		(0.011)		(0.007)
Observations	757,750	757,750	757,750	757,750	757,750	757,750
Y mean (Treated)	0.093	0.093	0.026	0.026	0.066	0.066

Note. This table reports regression estimates of β (odd columns) and β_q (even columns) in Equations (1) and (2), respectively. The outcome variable in columns (1) and (2) is whether the listing mentions any voucher-related keywords; in columns (3) and (4), whether the listing contains positive mentions of vouchers; in columns (5)-(6), whether the listing contains negative mentions of vouchers. All regressions include Census tract- and month-fixed effects, as well as controls for the number of bedrooms, bathrooms, and square footage. The table uses the sample of voucher-eligible listings. Standard errors are clustered at the locality level and are reported in parentheses.
Significance codes: ***: 0.01, **: 0.05, *: 0.1

References

Ahmed, A. M. and Hammarstedt, M. (2008). Discrimination in the rental housing market: A field experiment on the Internet. *Journal of Urban Economics*, 64(2):362–372.

Alatas, V., Banerjee, A., Hanna, R., Olken, B. A., Purnamasari, R., and Wai-Poi, M. (2016). Self-Targeting: Evidence from a Field Experiment in Indonesia. *Journal of Political Economy*, 124(2):371–427. Publisher: The University of Chicago Press.

Aliprantis, D., Martin, H., and Phillips, D. (2022). Landlords and access to opportunity. *Journal of Urban Economics*, 129:103420.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., and Wager, S. (2021). Synthetic Difference-in-Differences. *American Economic Review*, 111(12):4088–4118.

Banerjee, A., Hanna, R., Olken, B. A., Satriawan, E., and Sumarto, S. (2023). Electronic Food Vouchers: Evidence from an At-Scale Experiment in Indonesia. *American Economic Review*, 113(2):514–547.

Bell, A., Sard, B., and Koepnick, B. (2018). Prohibiting Discrimination Against Renters Using Housing Vouchers Improves Results. Technical report, Center on Budget and Policy Priorities.

Bergman, P., Chetty, R., DeLuca, S., Hendren, N., Katz, L. F., and Palmer, C. (2024). Creating Moves to Opportunity: Experimental Evidence on Barriers to Neighborhood Choice. *American Economic Review*, 114(5):1281–1337.

Bettinger, E. P., Long, B. T., Oreopoulos, P., and Sanbonmatsu, L. (2012). The Role of Application Assistance and Information in College Decisions: Results from the H&R Block Fafsa Experiment*. *The Quarterly Journal of Economics*, 127(3):1205–1242.

Bhargava, S. and Manoli, D. (2015). Psychological Frictions and the Incomplete Take-Up of Social Benefits: Evidence from an IRS Field Experiment. *American Economic Review*, 105(11):3489–3529.

Boeing, G. and Waddell, P. (2017). New Insights into Rental Housing Markets across the United States: Web Scraping and Analyzing Craigslist Rental Listings. *Journal of Planning Education and Research*, 37(4):457–476. Publisher: SAGE Publications Inc.

Chan, E. W. and Fan, Y. (2023). Housing discrimination in the low-income context: Evidence from a correspondence experiment. *Journal of Housing Economics*, 59:101889.

Chetty, R. and Hendren, N. (2018a). The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects*. *The Quarterly Journal of Economics*, 133(3):1107–1162.

Chetty, R. and Hendren, N. (2018b). The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates*. *The Quarterly Journal of Economics*, 133(3):1163–1228.

Christensen, P., Sarmiento-Barbieri, I., and Timmins, C. (2021). Racial Discrimination and Housing Outcomes in the United States Rental Market.

Christensen, P., Sarmiento-Barbieri, I., and Timmins, C. (2022). Housing Discrimination and the Toxics Exposure Gap in the United States: Evidence from the Rental Market. *The Review of Economics and Statistics*, 104(4):807–818.

Christensen, P. and Timmins, C. (2022). Sorting or Steering: The Effects of Housing Discrimination on Neighborhood Choice. *Journal of Political Economy*, 130(8):2110–2163. Publisher: The University of Chicago Press.

Chyn, E. (2018). Moved to Opportunity: The Long-Run Effects of Public Housing Demolition on Children. *American Economic Review*, 108(10):3028–3056.

Collinson, R., Ellen, I. G., and Ludwig, J. (2019). Reforming Housing Assistance. *The ANNALS of the American Academy of Political and Social Science*, 686(1):250–285. Publisher: SAGE Publications Inc.

Cunningham, M. K., Galvez, M. M., Aranda, C., Santos, R., Wissoker, D. A., Oneto, A. D., Pitingolo, R., and Crawford, J. (2018). A Pilot Study of Landlord Acceptance of Housing Choice Vouchers.

Deshpande, M. and Li, Y. (2019). Who Is Screened Out? Application Costs and the Targeting of Disability Programs. *American Economic Journal: Economic Policy*, 11(4):213–248.

Ellen, I. G., O'Regan, K., and Strochak, S. (2024). Race, Space, and Take Up: Explaining housing voucher lease-up rates. *Journal of Housing Economics*, 63:101980.

Ellen, I. G., O'Regan, K. M., and Harwood, K. W. H. (2023). Advancing Choice in the Housing Choice Voucher Program: Source of Income Protections and Locational Outcomes. *Housing Policy Debate*, 33(4):941–962. Publisher: Routledge _eprint: https://doi.org/10.1080/10511482.2022.2089196.

Ewens, M., Tomlin, B., and Wang, L. C. (2014). Statistical Discrimination or Prejudice? A Large Sample Field Experiment. *The Review of Economics and Statistics*, 96(1):119–134.

Faber, J. W. and Mercier, M.-D. (2022). Multidimensional Discrimination in the Online Rental Housing Market: Implications for Families With Young Children. *Housing Policy Debate*, 0(0):1–24. Publisher: Routledge _eprint: https://doi.org/10.1080/10511482.2021.2010118.

Finkel, M. and Burron, L. (2001). Study on Section 8 Voucher Success Rates: Volume I Quantitative Study of Success Rates In Metropolitan Areas. Technical report, Abt Associates, Cambridge, MA.

Finkelstein, A. and Notowidigdo, M. J. (2019). Take-Up and Targeting: Experimental Evidence from SNAP*. *The Quarterly Journal of Economics*, 134(3):1505–1556.

Freeman, L. (2012). The impact of source of income laws on voucher utilization. *Housing Policy Debate*, 22(2):297–318. Publisher: Routledge _eprint: https://doi.org/10.1080/10511482.2011.648210.

Freeman, L. and Li, Y. (2014). Do Source of Income Anti-discrimination Laws Facilitate Access to Less Disadvantaged Neighborhoods? *Housing Studies*, 29(1):88–107. Publisher: Routledge _eprint: https://doi.org/10.1080/02673037.2013.824559.

Galvez, M. (2010). What Do We Know About Housing Choice Voucher Program Location Outcomes? A Review of Recent Literature. Technical report, Urban Institute.

Garboden, P. M. E., Rosen, E., DeLuca, S., and Edin, K. (2018). Taking Stock: What Drives Landlord Participation in the Housing Choice Voucher Program. *Housing Policy Debate*, 28(6):979–1003. Publisher: Routledge _eprint: https://doi.org/10.1080/10511482.2018.1502202.

Hangen, F. and O'Brien, D. T. (2023). The Choice to Discriminate: How Source of Income Discrimination Constrains Opportunity for Housing Choice Voucher Holders. *Urban Affairs Review*, 59(5):1601–1625. Publisher: SAGE Publications Inc.

Hanson, A., Hawley, Z., and Taylor, A. (2011). Subtle discrimination in the rental housing market: Evidence from e-mail correspondence with landlords. *Journal of Housing Economics*, 20(4):276–284.

Horn, K. M., Ellen, I. G., and Schwartz, A. E. (2014). Do Housing Choice Voucher holders live near good schools? *Journal of Housing Economics*, 23:28–40.

Katz, L. F., Kling, J. R., and Liebman, J. B. (2001). Moving to Opportunity in Boston: Early Results of a Randomized Mobility Experiment. *The Quarterly Journal of Economics*, 116(2):607–654. Publisher: Oxford University Press.

Kling, J. R., Liebman, J. B., and Katz, L. F. (2007). Experimental Analysis of Neighborhood Effects. *Econometrica*, 75(1):83–119. Publisher: [Wiley, Econometric Society].

Knudsen, B. (2022). Expanded protections for families with Housing Choice Vouchers. Technical report, Poverty & Race Research Action Council.

Lens, M. C. (2013). Safe, but Could Be Safer: Why Do HCVP Households Live in Higher Crime Neighborhoods? *Cityscape*, 15(3):131–152. Publisher: US Department of Housing and Urban Development.

Ondrich, J., Ross, S., and Yinger, J. (2003). Now You See It, Now You Don't: Why Do Real Estate Agents Withhold Available Houses from Black Customers? *The Review of Economics and Statistics*, 85(4):854–873.

Ondrich, J., Ross, S. L., and Yinger, J. (2000). How Common is Housing Discrimination? Improving on Traditional Measures. *Journal of Urban Economics*, 47(3):470–500.

Page, M. (1995). Racial and Ethnic Discrimination in Urban Housing Markets: Evidence from a Recent Audit Study. *Journal of Urban Economics*, 38(2):183–206.

Phillips, D. C. (2017). Landlords avoid tenants who pay with vouchers. *Economics Letters*, 151:48–52.

Rosen, E. (2014). Rigging the Rules of the Game: How Landlords Geographically Sort Low–Income Renters. *City & Community*, 13(4):310–340. Publisher: SAGE Publications.

Yinger, J. (1986). Measuring Racial Discrimination with Fair Housing Audits: Caught in the Act. *The American Economic Review*, 76(5):881–893. Publisher: American Economic Association.

Zhao, B. (2005). Does the number of houses a broker shows depend on a homeseeker's race? *Journal of Urban Economics*, 57(1):128–147.

Zhao, B., Ondrich, J., and Yinger, J. (2006). Why do real estate brokers continue to discriminate? Evidence from the 2000 Housing Discrimination Study. *Journal of Urban Economics*, 59(3):394–419.

Supplementary Appendix

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

Hector Blanco (Rutgers University) and Jaehee Song (University of Colorado - Boulder)

A Data Appendix

A.1 Final classification

Table A.1: Dictionary-based vs. Chat GPT classification

	Chat GPT		
Dictionary-based	positive	negative	unclassified
positive	51258	822	21297
negative	135	18336	7975
unclassified	6309	1319	3967

51,258 listings, classified as positive by the dictionary-based approach and ChatGPT approach, and 27,606 listings, classified as positive by one of the approaches but remained unresolved by the other, are considered positive listings. Similarly, 18,336 listings, classified as negative by both approaches, and 9,294 listings, classified as negative by one but unresolved by the other, are considered negative. The rest 4,924 listings remain unresolved.

A.2 Summary statistics

Table A.2: Summary Statistics

		Listed monthly rent			Other characteristics		
HCV sentiment	# in sample	Q1	Q2	Q3	avg. # bed	avg. # bath	avg. sq. ft.
No mention	5,475,757	1300	1724	2361	1.393	1.607	938
Positive	82,276	1240	1750	2272	1.252	1.613	872
Negative	26,173	1099	1578	1825	1.390	2.070	1015

A.3 How representative is Craigslist of rental housing markets?

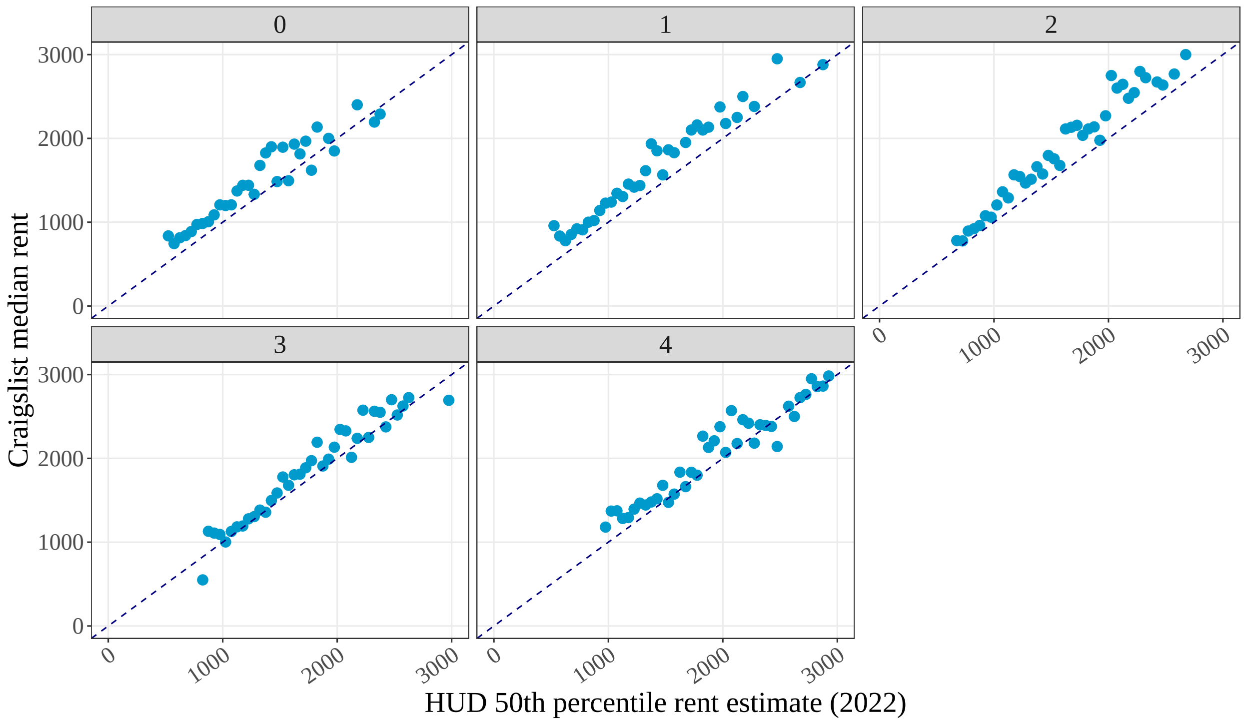
We investigate to what extent rental prices on Craigslist are representative of the distribution of rents of U.S. rental housing markets. In the past, Boeing and Waddell (2017) find a high correlation between median listing prices in Craigslist and median rent estimates reported by the Department of 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 on Craigslist at that level using the number of bedrooms reported in the listing. We can do so for 602 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 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 less bedrooms are slightly above median rents. There are two reasons why Craigslist's median rents may be an overestimate of 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.

Thus, we conclude that Craigslist rents are fairly representative of rental housing markets.

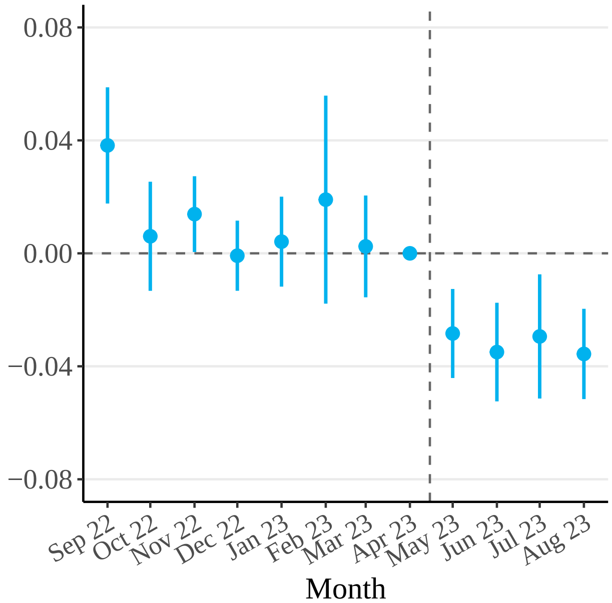
Figure A.1: Representativeness of Craigslist



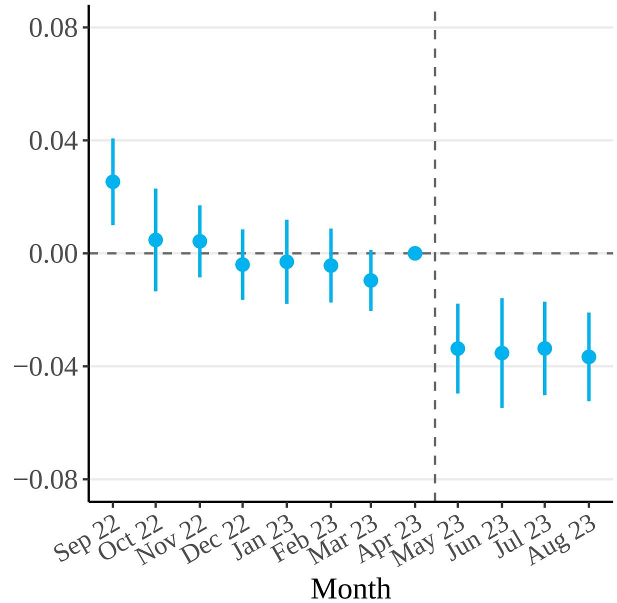
Note. This figure plots the relationship between the median rent in Craigslist between September 2022 and August 2023 at the metropolitan level estimated by the authors, and the 2022 median rent estimates reported by HUD. Each panel reports the results by the number of bedrooms. Dots are combined in 50-dollar bins.

B Appendix Figures

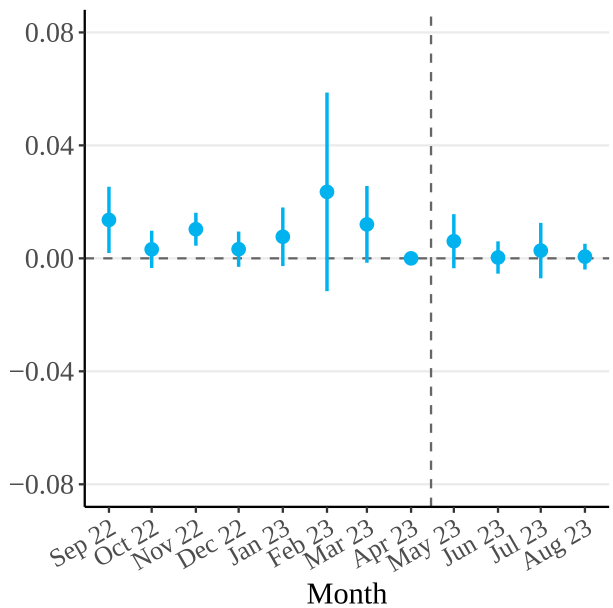
Figure B.1: Effect of Hawaii's SOI law (effective May 23) on landlord discrimination



(a) Any HCV



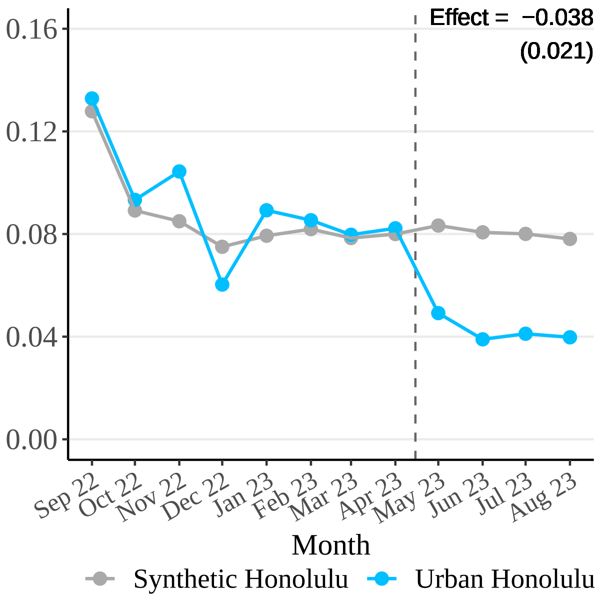
(b) HCV negative



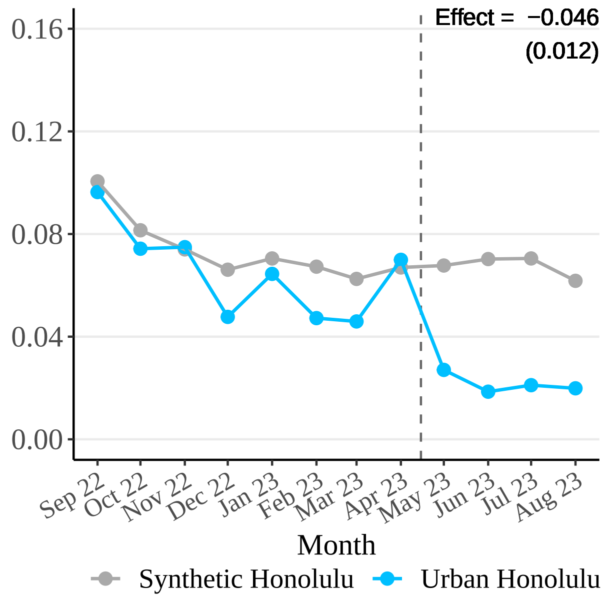
(c) HCV positive

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 a different indicator variables as an outcome, based on whether the listing includes (a) any voucher-related keywords, (b) negative mentions towards voucher holders, and (c) positive mentions towards voucher holders. The plot uses the sample of voucher-eligible listings (i.e., with a price below 110% of FMR). Standard errors are clustered at the locality level. The vertical dashed lines depict when the SOI law took effect.

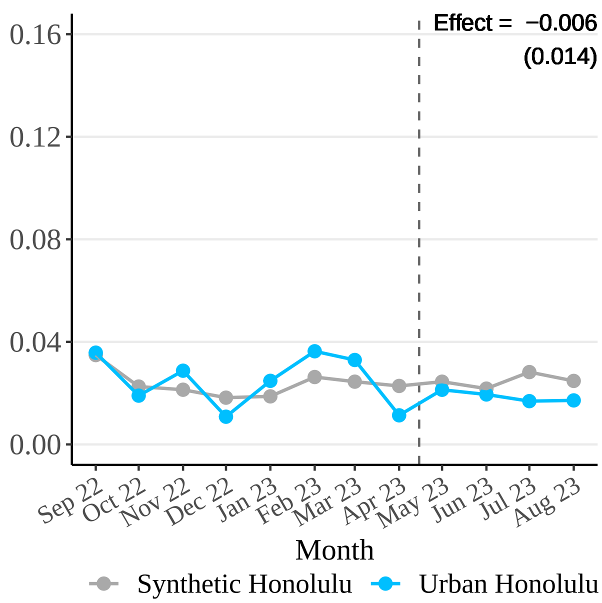
Figure B.2: Effect of Hawaii's SOI law (effective May 23) on landlord discrimination (all listings)



(a) Any HCV



(b) HCV negative



(c) HCV positive

Note. The figures depict the evolution of the dependent variable for Urban Honolulu and synthetic Urban Honolulu. Each panel uses a different indicator variable as an outcome, based on whether the listing includes (a) any voucher-related keywords, (b) negative mentions towards voucher holders, and (c) positive mentions towards voucher holders. The vertical dashed lines depict when the SOI law took effect.

C Appendix Tables

Table C.1: Top 25 CBSAs by negative and positive mentions in voucher-eligible listings

Negative		Positive	
CBSA	Share	CBSA	Share
North Port-Sarasota-Bradenton, FL	0.232	Wenatchee, WA	0.209
Portland-South Portland, ME	0.157	Providence-Warwick, RI-MA	0.183
Tulsa, OK	0.116	Kennewick-Richland, WA	0.146
Fort Wayne, IN	0.070	Gulfport-Biloxi, MS	0.110
Detroit-Warren-Dearborn, MI	0.069	Albany-Schenectady-Troy, NY	0.084
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.064	Virginia Beach-Norfolk-Newport News, VA-NC	0.081
Oklahoma City, OK	0.053	Salt Lake City, UT	0.077
Urban Honolulu, HI	0.052	Chicago-Naperville-Elgin, IL-IN-WI	0.074
Knoxville, TN	0.048	Washington-Arlington-Alexandria, DC-VA-MD-WV	0.064
Shreveport-Bossier City, LA	0.045	Bakersfield, CA	0.052
York-Hanover, PA	0.045	Manchester-Nashua, NH	0.050
Greenville-Anderson, SC	0.043	Santa Cruz-Watsonville, CA	0.042
Boise City, ID	0.037	Wilmington, NC	0.040
Wichita, KS	0.036	Anchorage, AK	0.039
Lincoln, NE	0.033	Ogden-Clearfield, UT	0.038
Pittsburgh, PA	0.031	Fresno, CA	0.038
Spartanburg, SC	0.029	El Paso, TX	0.036
Kansas City, MO-KS	0.029	Denver-Aurora-Lakewood, CO	0.033
Chattanooga, TN-GA	0.025	Akron, OH	0.033
Minneapolis-St. Paul-Bloomington, MN-WI	0.024	Tucson, AZ	0.033
Santa Cruz-Watsonville, CA	0.023	New York-Newark-Jersey City, NY-NJ-PA	0.031
New Orleans-Metairie, LA	0.022	New Orleans-Metairie, LA	0.030
St. Louis, MO-IL	0.021	Des Moines-West Des Moines, IA	0.030
Lexington-Fayette, KY	0.020	St. Louis, MO-IL	0.030
Asheville, NC	0.020	San Jose-Sunnyvale-Santa Clara, CA	0.029

Table C.2: Presence of HCV-related keywords by neighborhood characteristics quartile (all listings)

	All listings				Voucher-eligible (below 110% FMR)			
	Any HCV	Positive	Negative	Neg|Any	Any HCV	Positive	Negative	Neg|Any
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Poverty rate quartiles								
Quartile 2	-0.001	-0.003	0.002	0.003	-0.002	-0.005	0.003	-0.004
	(0.003)	(0.003)	(0.001)	(0.011)	(0.004)	(0.003)	(0.003)	(0.021)
Quartile 3	0.002	0.000	0.001	-0.021	-0.001	-0.004	0.002	-0.045**
	(0.003)	(0.003)	(0.001)	(0.013)	(0.004)	(0.003)	(0.002)	(0.020)
Quartile 4	0.001	-0.001	0.001	-0.040**	-0.002	-0.004	0.002	-0.040*
	(0.003)	(0.003)	(0.001)	(0.015)	(0.004)	(0.003)	(0.002)	(0.023)
Observations	5,117,310	5,117,310	5,117,310	95,723	2,350,296	2,350,296	2,350,296	56,163
R^2	0.174	0.175	0.202	0.710	0.161	0.093	0.324	0.685
Y mean	0.019	0.013	0.005	0.243	0.024	0.015	0.007	0.307
Panel B: Black share quartiles								
Quartile 2	-0.003	-0.008**	0.004**	0.005	0.005	-0.002	0.005	-0.009
	(0.004)	(0.003)	(0.002)	(0.010)	(0.005)	(0.003)	(0.003)	(0.020)
Quartile 3	-0.004	-0.004	0.000	-0.021*	0.002	0.002	-0.001	-0.048**
	(0.003)	(0.003)	(0.001)	(0.012)	(0.003)	(0.003)	(0.001)	(0.019)
Quartile 4	-0.003	-0.002	-0.001	-0.044***	0.000	0.003	-0.002	-0.065***
	(0.003)	(0.003)	(0.002)	(0.017)	(0.004)	(0.003)	(0.002)	(0.023)
Observations	5,117,310	5,117,310	5,117,310	95,723	2,350,296	2,350,296	2,350,296	56,163
R^2	0.174	0.175	0.203	0.710	0.160	0.092	0.325	0.684
Y mean	0.019	0.013	0.005	0.243	0.024	0.015	0.007	0.307

Note. This table reports the regression results of linear probability models. The outcome variable in columns (1) and (5) is whether the listing mentions voucher-related keywords; in columns (2) and (6), whether the listing contains positive mentions of vouchers; in columns (3)-(4) and (7)-(8), whether the listing contains negative mentions of vouchers. Columns (1)-(4) use the full sample, while columns (5)-(8) use the sample of listings with a rental price at or below 110% of the Fair Market Rent (FMR). Columns (4) and (8) is restricted to listings with any voucher-related keywords. Quartiles of Census tract poverty rates (panel A) and Black shares (panel B) are calculated within the counties represented in each sample, and the omitted group is the first quartile (e.g., the lowest Census tract median household income). Standard errors are clustered at the Census tract level and are reported in parentheses. Significance codes: ***: 0.01, **: 0.05, *: 0.1

Table C.3: Effect of Hawaii's SOI law on voucher discrimination, total and by neighborhood type (all listings)

	Any HCV		Positive		Negative	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total effect						
Post × Treated	-0.050***		-0.009*		-0.042***	
	(0.011)		(0.005)		(0.007)	
Panel B: Poverty rate quartiles						
Post × Treated × Quartile 1		-0.090***		-0.004		-0.086***
		(0.017)		(0.003)		(0.015)
Post × Treated × Quartile 2		-0.062***		-0.006**		-0.057***
		(0.009)		(0.003)		(0.006)
Post × Treated × Quartile 3		-0.051**		-0.016		-0.037***
		(0.021)		(0.010)		(0.014)
Post × Treated × Quartile 4		-0.038***		-0.004		-0.033***
		(0.005)		(0.005)		(0.003)
Panel C: Black share quartiles						
Post × Treated × Quartile 1		-0.072***		-0.003		-0.070***
		(0.012)		(0.005)		(0.010)
Post × Treated × Quartile 2		-0.100***		-0.017		-0.082***
		(0.014)		(0.011)		(0.012)
Post × Treated × Quartile 3		-0.043***		-0.002		-0.042***
		(0.012)		(0.002)		(0.013)
Post × Treated × Quartile 4		-0.029**		-0.012		-0.017***
		(0.012)		(0.008)		(0.005)
Observations	1,484,838	1,484,838	1,484,838	1,484,838	1,484,838	1,484,838
Y mean (Treated)	0.081	0.081	0.019	0.019	0.061	0.061

Note. This table reports regression estimates of β (odd columns) and β_q (even columns) in Equations (1) and (2), respectively. The outcome variable in columns (1) and (2) is whether the listing mentions any voucher-related keywords; in columns (3) and (4), whether the listing contains positive mentions of vouchers; in columns (5)-(6), whether the listing contains negative mentions of vouchers. All regressions include Census tract- and month-fixed effects, as well as controls for the number of bedrooms, bathrooms, and square footage. The table uses the entire sample of listings. Standard errors are clustered at the locality level and are reported in parentheses.
Significance codes: ***: 0.01, **: 0.05, *: 0.1