Rental Market Discrimination in the Housing Choice Voucher Program

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A dissertation
submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington

2017

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Abstract

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It is generally accepted that households in the Housing Choice Voucher program (HCV) encounter discrimination when searching for private market units. Observational research suggests that households and program administrators perceive discrimination. Research and enforcement audits, typically carried out in a single metro area, suggest that landlords discriminate against HCV households. However, the extent of HCV discrimination is unknown. This study adds to this research by empirically demonstrating discrimination against HCV households in multiple metro areas. Using an email audit design, over 6,000 landlords were contacted by testers over 60 days during summer 2016 in 14 different metro areas selected to vary in vacancy rates and Source of Income (SOI) law coverage. Testers randomly varied in racial affiliation, conveyed through name, and HCV status, conveyed through email text. Landlord response behavior was recorded and classified to measure discrimination. Findings show that after controlling for tester, unit, neighborhood, and SOI law characteristics, 33.6% of HCV households receive any response from landlords, compared to 48.2% of non-HCV households, a difference of 14.6 percentage points. Only 10.3% of HCV households receive a positive response compared to 46.5% of non-HCV households, a difference of fully 36.2 percentage-points. SOI law coverage is not associated with response behavior. HCV status does not have different effects by racial affiliation. Due to the randomization of tester attributes, it is likely that these effects are causal: HCV households experience discrimina-

tion when contacting landlords advertising rental units online. Given the severity of this discrimination, HCV program administrators and advocates should focus on rental search assistance for households and reducing the time it takes to complete pre-leasing approvals.

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ACKNOWLEDGMENTS

I thank Robert Plotnick. Somehow, you always manage to be patient and supportive while still being critical in a useful way. Your guidance got me through PhD school even when things got rough and my path seemed uncertain. Thank you, Bob. Thanks for hanging in there with me.

I thank all the Evans School doctoral students, both past and present. I benefitted from your support throughout my time at Evans. I am extremely proud to be associated with you all.

DEDICATION

For MEK & CRK.

Chapter 1

INTRODUCTION

Over several decades, research has demonstrated the presence of racial discrimination in the US housing market: black and Hispanic/Latino households are less likely to be shown units and receive responses from inquiries to landlords and property managers compared to white households (Yinger, 1986; Page, 1995; Ondrich et al., 1999; Carpusor and Loges, 2006; Hanson and Hawley, 2011; Ewens et al., 2014). The population of Housing Choice Voucher program (HCV)[1] heads of households are majority minority: nearly 7 in 10 heads of household are minority (HUD, 2016b).

In addition to racial discrimination, HCV holders may experience discrimination based on Source of Income (SOI). Voucher holder status may be negatively perceived by landlords as signaling that households are low-income and could have poor rental or credit history. Stigmas around the HCV program may lead landlords to consider voucher households to be troublesome tenants (Marr, 2005). The rules and requirements to participate in the HCV program may be considered too burdensome by landlords (Varady et al., 2013; Greenlee, 2014). Landlords may object to participating in a government program (Greenlee, 2014). Any or all of these factors could play into a landlord's preference for unsubsidized households.

Past research indicates voucher households perceived discrimination during rental searches, particularly when landlords were aware they have a voucher, when children were present in the household, and the head of household was a minority (Popkin and Cunningham, 1999; Popkin et al., 2000a; Basolo and Nguyen, 2005; Teater, 2009). The extent of this discrimina-

[1]The HCV program is also referred to as Section 8. In 1998, the Section 8 voucher and Section 8 certificate programs were merged and renamed the Housing Choice Voucher program. Even though this change occurred over 15 years ago, PHAs, clients, and the general public still use and recognize the name Section 8.

tion is not known (Turner et al., 2000; Galvez, 2011; Freeman and Li, 2013). Any estimates based on self-reported discrimination or claim filings potentially under- or over-estimate discrimination rates (Pager and Shepherd, 2008).

This study examines discrimination rates for Housing Choice Voucher holders searching for private-market rental units. The analysis focuses on the behavior of landlords responding to email audit tester inquiries about apartments advertised online in fourteen metro areas that differ in the types of local and state Source of Income (SOI) protections in place. Tester emails vary in the race of sender (conveyed through name) and whether the sender discloses HCV status.

This study contributes to the existing research by providing further insight into rental search barriers by examining the relationship of SOI and racial discrimination for HCV households in an experimental setting. Findings have implications for the design of the HCV program and ongoing efforts to assist HCV households in accessing high-quality neighborhoods.

The remainder of this document is organized as follows. Chapter 2 reviews the structure of the HCV program, the past research on HCV discrimination, and the broader rental discrimination literature. Chapter 3 explains the structure and operation of the email audit. Chapter 4 presents a description of the data and variables used in modeling. Chapter 5 presents the results. Chapter 6 discusses the policy implications of this study.

Chapter 2

LITERATURE REVIEW

This chapter brings together several areas of research that provide the context and motivation for this study. First, I will provide a summary of what the HCV program is and how it operates. Then, I will discuss previous housing discrimination research, with a particular focus on email audit designs examining racial discrimination in rental market searches. Then, I will discuss research on HCV discrimination. Finally, I will discuss this study's contributions and relationship to the existing literature.

2.1 HCV background

Over 2.4 million US households use Housing Choice Voucher (HCV) subsidies (HUD, 2016b).[1] The HCV program is funded by the US Department of Housing and Urban Development (HUD) and is administered at the local level by over 2,000 local Public Housing Authorities (PHA). PHAs issue vouchers to provide a partial subsidy for a private-market rental unit for households that are very low income.

Based on 2016 national data (see table 2.1), the average HCV household headcount is over two individuals. Nearly half of HCV households contain at least one child under the age of 18 and 89% of those households are headed by a single parent. Households are majority minority with 69% of households classified as minority. Of those minority households, over 70% are black. Incomes in these households are very low: 38% of all households have an income below $10,000; household incomes average 23% of local area median income.

[1]The HCV program is also referred to as Section 8. In 1998, the Section 8 voucher and Section 8 certificate programs were merged and renamed the Housing Choice Voucher program. Even though this change occurred over 15 years ago, PHAs, clients, and the general public still use and recognize the name Section 8.

In the national publicly available data, the details on the types of units HCV households lease are limited to size and cost of units. Seven out of ten subsidized apartment units have two or more bedrooms. HCV households pay an average of $364 per month with the subsidy providing an average payment of $760 per month towards rent.

To receive subsidy benefits, households issued a voucher must identify a unit that: meets rental cost criteria (called payment standards, set by the PHA within HUD guidelines), meets housing quality and safety standards, and the landlord is willing to participate in the voucher program (Schwartz, 2010).[2] Research indicates not all households that receive a voucher end up receiving benefits, meaning that not all households rent an HCV-supported unit (lease-up). In 2000, only 69% of US voucher households leased-up and lease-up rates were even lower in tight rental markets (Finkel and Buron, 2001). This suggests that the rental search process is unsuccessful for some households.

The HCV leasing process involves a series of consecutive events that must be accomplished to successfully lease-up: search rental listings, contact landlords, view units, submit a unit for rent reasonableness evaluation and housing quality and safety inspection, and so on (see Figure 2.1). If a single search event is unsuccessful, the household must begin the overall search process again. Further, an HCV household has time limits on how long they may search for a voucher unit. At minimum, HCV is issued with 60 days to search.[3] An HCV household's search can be more complicated than typical, unsubsidized searches.

Identifying a willing landlord can be a particularly difficult point in the HCV search process. Accepting HCV increases the administrative burden for landlord. For an unsub-

[2]In some cases the voucher's benefits are subject to geographical constraints. Technically, HCV vouchers are good for any qualifying unit in the US. For example, if a household is issued a voucher by a PHA in New Jersey, federal rules allow for its use in California. However, it is common for PHAs to require that the first year of leasing on a voucher occur within their jurisdiction.

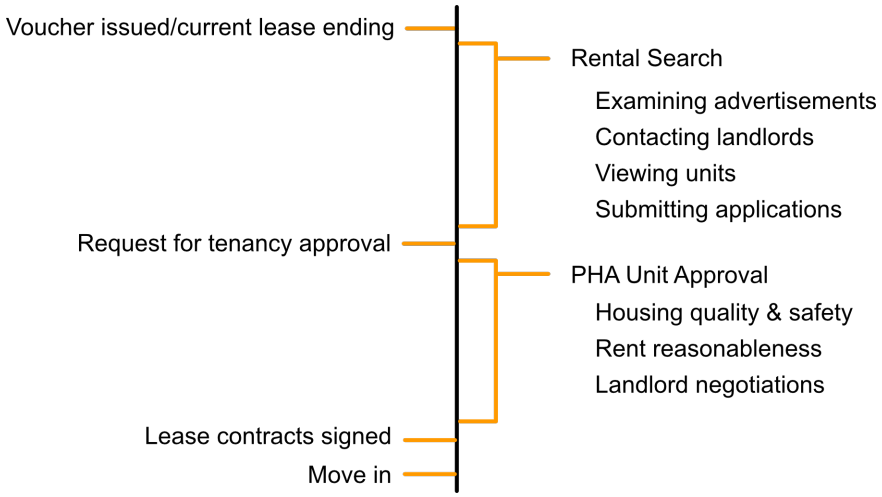
[3]PHAs have different rules around time limits and the extension of search periods (24 CFR §982.30). Originally, PHAs were required to issue vouchers for no more than 120 days. In 1999, PHAs were permitted to issue vouchers for over 120 days (Finkel and Buron, 2001, 2-5). PHAs are allowed discretion to re-issue the voucher after expiration. Once the voucher expires the PHA can do one of two things: they can either instruct the household to reapply to the HCV program or put the family back on the waiting list (HUD, 2001, 8-13).

Table 2.1: US HCV Leased-up Household Characteristics in 2016 (HUD, 2016b)

	2016
Total units[1]	2,474,400
% occupied	93%
Household characteristics	
Average household head count	2.4
Households with children	45%
Single parent households as % of households with children	89%
Female headed households	79%
Minority headed households	69%
Black headed households	48%
Native American headed households	1%
Asian or Pacific Islander headed households	3%
Hispanic headed households	17%
Average household yearly income	$14,122
Households with yearly income below $10,000	38%
Household income as a percent of local AMI	23%
Rental unit characteristics	
0 - 1 bedrooms	30%
2 bedrooms	35%
3+ bedrooms	35%
Tenant paid monthly rent	$364
Subsidy paid monthly rent	$760
Average utility allowance	$130
% with utility allowance	88%

[1]This number is total units of subsidy. The number of households reported is 2,265,478.

Figure 2.1: HCV search & leasing processes



sidized household, the landlord executes a single contract with the household and receives a single monthly payment from the household. For an HCV household, the landlord has a relationship with both the household and the PHA. Separate contracts are executed with both the household and the PHA. The total rent arrives in two separate payments: one from the household and the remainder from the PHA.

The differences do not stop there, because federal HCV program rules impose additional requirements and restrictions that a landlord would not experience dealing with an unsubsidized household. Program rules require that HCV rents must be reasonable in the sense that they are comparable to similar units being offered in the area and that they are also in line with any rents being asked within the same site (HUD, 2001, 9-1). Landlords must also provide the amount of rent obligation of the previous tenant and if there is a large difference between the previous and current rent, the landlord must justify the difference (HUD, 2001, 8-15). If the PHA determines that rent is too high, it may try to negotiate to reduce the asking rent. If the landlord does not want to reduce the rent, she can decline to lease to the voucher household.

Landlords must allow HCV leased units to undergo an initial housing quality and safety

inspection prior to lease signing and then undergo inspections every two years going forward.[4] If an inspection finds any aspect of the unit that is out of compliance with program standards, the landlord is made aware of the findings and is given an opportunity to bring the unit back into compliance. If a landlord does not want to make the necessary repairs or modifications to the unit, she can cancel the leasing agreement with both the tenant and the PHA. Landlords have little incentive to address findings when an alternative unsubsidized tenant is available.

These pre-leasing steps take time - time in which the landlord is not receiving rental income. In qualitative interviews, Ohio-based HCV landlords expressed frustration with participating in HCV. One landlord estimated that all the requirements to execute a lease slowed down the process by a month compared to an unsubsidized tenant (Varady et al., 2013, 123). If there are numerous unsubsidized rental searchers in the market, there is little financial incentive for the landlord to complete the HCV pre-leasing process.

If the unit makes it through all reviews, the landlord must agree to separate contracts with the tenant and the PHA. During occupancy, rental payments come from both the tenant and the PHA. If the tenant's income is changing, the PHA may change the size of the tenant-paid portion of the rent, resulting in the landlord receiving different amounts for both payers. While the landlord would still be getting full rent, this accounts-receivable complexity may bother some landlords.

Once under lease, units are subject to physical inspections, usually every two years. Any rent increases have to be approved through the PHA. As with pre-leasing, if the landlord does not wish to remedy the PHA's review findings, the landlord can end her HCV participation.

There is stigma, above and beyond racial stereotypes, attached to HCV renters. Landlords may think they are going to be troublesome, under-qualified tenants with little experience in maintaining good tenancy (Marr, 2005, 92). Additionally, some landlords may object to participating in government programs (Greenlee, 2014, 514).

Viewed in a different light, HCV can also be attractive to landlords. The PHA-paid

[4]Biennial inspections were allowed across all PHAs starting in FY 2014 (GPO, 2014). Prior to that, inspections were required yearly.

portion of the rent is guaranteed. An Ohio landlord explained the benefit:

> "But if I have a tenant who is Section 8 and they get laid off, Section 8 picks up the rest of the rent... If they're a market rate tenant and they get laid off, they're pretty well done." (Varady et al., 2013, 123).

Further, while HCV cannot be used in units that are too dilapidated to meet inspection criteria, HCV clients may be more willing to pursue units that are not attractive to either wealthier unsubsidized tenants or those looking for homeownership. Both landlords and housing authority administrators in the Varady et al. (2013) study described the situation where declining property values in neighborhoods with housing stock that had become objectionable on the grounds of aesthetics (e.g., older homes without "charm", homes without basements) made those neighborhoods particularly accessible to voucher households. Qualitative work in Baltimore found that some landlords make acquisition, renovation, and marketing decisions specifically to attract HCV households into renting less desirable units in lower quality neighborhoods Rosen (2014). HCV participation would be attractive to a landlord with properties such as these in his portfolio.

2.2 Previous housing discrimination research

Discrimination is the differential treatment of groups of persons based on attributes (Pager and Shepherd, 2008). In the housing search context, most research has focused on discrimination on the basis of race. There are two dominant theories of racial discrimination in the housing search literature: taste-based (Becker, 1971; Yinger, 1986) and statistical discrimination (Aigner and Cain, 1977). Taste-based discrimination arises from the preferences that individuals either hold themselves or that they believe others hold. For example, taste-based discrimination occurs when a landlord chooses to ignore all inquiries from prospective tenants in a particular racial group either because he prefers not to have tenants of that race or he believes his tenants prefer not to reside near tenants of that race. Taste-based discrimination is motivated by deeply held beliefs that are likely resistant to change. Statistical

discrimination occurs when decision makers have low or incorrect information about minority groups. Because they have little experience with group members, they base decisions on more familiar, observable characteristics. For example, a landlord may have never rented to an Hispanic household, but he has heard that these households are problem tenants. The landlord would select a white household as a tenant.

It is likely that both types of discrimination lead to similar end results for minority groups: differential access to opportunities on the basis of racial affiliation. However, the type of discriminatory mechanism at work has implication for policy design. Statistical discrimination is a form of information asymmetry, and as such, theory suggests that providing decision makers with more information on applicants can eliminate the disparities in racial outcomes. Policy could aim at preparing minority searchers with tips on approaching prospective landlords and strategically revealing information about the positive attributes of their households' financial and social status. Taste-based discrimination is impervious to additional information and simply providing more information is unlikely to eliminate disparities. This suggests that policies may need to be more aggressive and perhaps more punitive to address discrimination. In practice, it has been difficult for researchers to identify or separate the effects of taste-based and statistical discrimination.

Pager and Shepherd (2008) outline some ways to measure discrimination: perceptions of discrimination, potential discriminators, statistical analyses, and experiments. Measuring perceptions of discrimination requires surveying individuals in at-risk groups to measure the existence or frequency of feeling discriminated against. Sometimes majority group members are included in the survey to provide a comparison to discrimination rates observed in the minority group. Since measures are self-reported, it remains unclear how these perceived events related to the incidence of discrimination. It is possible that an individual was discriminated against, yet was unaware of it in which case the estimates of discrimination would be biased downwards. Alternatively, the individual could have perceived a discriminatory act when none took place in which case the bias would be upwards.

Other researchers have estimated discrimination for the other side of the interaction by

focusing on decision makers. Through surveys or interviews, researchers try to elicit the racial preferences of potential discriminators. Pager and Shepherd (2008) point out that individuals do not always behave in a manner that is congruous with their racial beliefs: preferences may not equate to behavior. Similar to perceived discrimination, this method is open to bias as well.

Statistical analyses of discrimination look for racial disparities in outcomes. After controlling for observed characteristics, any gaps in achievement or access across racial groups are assumed to be the result of discrimination. Generally, there are two approaches to the functional form: main effects and interaction effects. Main effects test whether racial affiliation has a direct effect on the outcome. Interaction effects test whether the interaction between race and other characteristics (e.g., human capital, geography) leads to differential outcomes meaning that similar levels of a characteristic have differing effects on outcomes by race.

The assumption that disparities are solely attributable to discrimination leaves these methods open to bias from omitted variables that also could be the causes of measured disparities. Further, statistical methods are subject to the criticism that control variables used to isolate racial effects could be endogenous to the underlying process. Pager and Shepherd (2008) give the example of estimating credit discrimination while controlling for asset level yet the ability to accumulate assets may itself be affected by discrimination.

Experimental designs have been used to estimate the causal effects attributable to discrimination. Some studies have been carried out in a controlled lab environment. While design such as these have high internal validity, they have low external validity and findings do not generalize well to the contexts in which discrimination occurs.

Other experimental designs have been carried out in real-world contexts. Field experiments have used personal (in-person, telephone) and correspondence interaction with decision makers (real-estate agents, rental brokers, landlords, property managers, etc.) to test for discrimination. These types of designs are sometimes referred to as audit designs. Common to these field experiments, a set of faux identities is developed to be similar in all attributes

save for the attributes that the researcher hypothesizes are related to discrimination.

For personal methods, individuals are trained to hew to these identities during interactions with decision makers. For correspondence methods, text is used to communicate these identities. Since these studies involve dissembling, they are only able to test discrimination that occurs in outcomes connected to housing search, such as invitations to viewings, rather than ultimate housing market outcomes, such as purchase or leasing, which typically require actual physical presence.

In the US, in-person and telephone audit findings consistently show minority auditors are more likely to be discriminated against in housing search settings (Yinger, 1986; Page, 1995; Ondrich et al., 1999, 2003; Zhao, 2005; Zhao et al., 2006). In the early 1980s, a Boston in-person audit found that black testers were less likely to see available housing units in both rental and owner-occupied scenarios. Similar results were found using data from a multi-city in-person audit in the 1989 Housing Discrimination Study (HDS): both black and Hispanic testers were less likely to view units than white testers in both rental and owner-occupied scenarios Page (1995); Ondrich et al. (1999). Real estate agents were more likely to direct black testers to more integrated neighborhoods and to conform less to black testers' stated preference in housing location (Ondrich et al., 2003). Looking at more recent iterations of the HDS, researchers found that racial disparities still persist in housing search outcomes, yet they are not as large as were observed with the 1989 HDS (Zhao et al., 2006; HUD, 2013).

The in-person and telephone audit methods have some logistical and methodological disadvantages (Heckman and Siegelman, 1993; Heckman, 1998). These studies require human individuals to be testers. For causal comparability across tester outcomes, testers need to be equivalent in all aspects save racial affiliation. It is virtually impossible to control for all personal attributes. There will naturally be some human variation between testers apart from racial appearance. Further, implementing in-person audits require money and time to cast, train, and field testers. They are very expensive designs.

Over the past two decades, the majority of advertisement for apartment listings has

migrated from print publications to internet listings. This has created an opportunity for researchers to implement correspondence audit studies through email communication. This method addresses some of the limitations of personal audits such as comparability of testers and study costs.

Email audits are subject to weakness as well. In the rental search context, units can still be identified through other channels: personal connections, print listings, site-specific signage. Email audits will not characterize interactions searchers would have with landlords identified through these sources. As will be discussed later in the section, if correspondence content does not conform to normal search behavior, the estimates may not reveal discrimination so much as the novelty of the content. Additionally, timing of communication can impact outcomes in ways that are independent of the correspondence content.

Three email audit studies have tested for racial differences rental search outcomes in the US. Their designs and results are summarized in Table 2.2. The first email audit to test rental market discrimination was carried out in the Los Angeles County area in 2003 (Carpusor and Loges, 2006). The researchers were interested in testing differential landlord response rates based on racial affiliation conveyed through names. Using names to signal racial status was a method that had been used successfully in previous labor market discrimination work (Bertrand and Mullainathan, 2004). The study focused on one-bedroom private-market rental units that were advertised on two popular listing sites.[5] Apartment advertisements were included in the study if interest in the apartment could be expressed via email inquiries. Over 1,000 listings were randomly assigned to a single response type that varied in the name used in the email: [1] Patrick McDougall to signal white race; [2] Tyrell Jackson to signal black race; [3] Said Al-Rahman to signal Arab/Muslim race. Researchers recorded available information from apartment listings: location, asking rent, private or corporate ownership. The absence or presence of response activity was recorded. Received responses were categorized as positive (apartment still available, invitation to view, further

[5]The sites were www.craigslist.com and www.recycler.com.

information) or negative (apartment no longer available or no response).

Overall, 73% of inquiries received a reply and only 4% of those replies indicated no vacancy (Carpusor and Loges, 2006, 943). Positive response rates differed by race with the black sounding name experiencing the lowest rates. McDougall inquiries were the most likely to receive response: 89% of these inquires received a reply while the response was only 66% for the Al-Rahman inquiries and 56% for the Jackson inquiries. Compared to the white applicant, the Muslim/Arab applicant was three time more likely and the black applicant was four times more likely to receive a negative response from apartment inquiries (Carpusor and Loges, 2006, 947).[6] Ownership type did not have a significant association with positive response rates overall or by race (Carpusor and Loges, 2006, 945). Amount of asking rent was not associated with positive response rates except in one instance: the black sounding name was significantly less likely to receive a positive response when the asking rent was between $1,000-$1,500. These findings suggest that black searchers are at a disadvantage in rental market regardless of unit characteristics.

Two studies expanded analyses of discrimination to multiple US rental markets in 2009 (Hanson and Hawley, 2011; Ewens et al., 2014). Hanson and Hawley (2011, 2014) investigated discrimination against blacks in ten different major metropolitan areas using craigslist.[7] Like Carpusor and Loges (2006), race was signaled through names used in emails to listings for apartments on craigslist. Emails also varied in content with text varying in the quality of grammar and spelling used and statements signaling different levels of financial and social stability. These variations tested the impact of signaling low- versus high-class background. High-class email text contained good grammar and spelling while offering to send *good* references and *recent* credit information. Low-class emails contained bad grammar and spelling and offered to send references and credit information. Each listing received a matched pair

[6]For analysis, negative responses (overt) and non-responses (covert) were combined into a single category as negative response.

[7]These areas were Atlanta GA, Boston MA, Chicago IL, Dallas TX, Washington DC, Houston TX, Los Angeles CA, New York City NY, Seattle WA, and San Francisco CA.

Table 2.2: Past US racial discrimination in rental housing email audit studies

Study	**Carpusor & Loges (2006)**	**Hanson & Hawley (2011, 2014)**	**Ewens et al. (2014)**
Type	Random response	Matched-pairs, 2 or 4 comparisons	Random response
Tester race	White, Black, Arab/Muslim	White, Black	White, Black
Tester gender	Female, male	Male	Female, male
Site(s)	Los Angeles County CA	10 metro areas	34 metro areas
Time	Feb.-April 2003	July-Oct. 2009	Sept.-Oct. 2009
Unit size	1 bedroom	No restrictions	Studios & 1 bedroom
Cost	All	All	20-90th percentile
N	1,115	4,728	14,237
Response rate	73%	64%	65%
Positive	70%	[a]	46%
Negative	3%	[a]	18%
Black/white diff in any response	-33%	-6%	-9%

[a]This study did not classify responses received.

of emails that varied by race, class, or jointly race and class.[8] This is different than the approach utilized in Carpusor and Loges (2006) where each listing received only a single inquiry email. The timing and order of emails was varied and staggered to make the response seem realistic and to control for the effect of order of receipt.[9] The research team tried to make sure that a single landlord was not contacted for more than one listing.

The study sent paired correspondence to 4,728 listings in the selected cities (Hanson and Hawley, 2011, 104). The average bedroom count was just over 2. Nearly half the listings were for apartment units (as opposed to duplexes, single-family units, etc.). Only 45% of the units exceeded their area's median rent. The average asking rent was $1,492.

Around 64% of the pairs received a response to at least one of the inquiries (Hanson and Hawley, 2011, 102). Overall, response rates were significantly lower for black applicants (51%) compared to white applicants (57%) and this trend held at the metropolitan level. This 6 percentage point differential represents the lowest estimate of black discrimination disparities in the US studies. Some race differentials still exist when considering rates by class. Varying class did not lead to differences among white inquiries but it did lead to significant differences among black inquiries: black high-class applicants received responses in 53% of inquiries while low-class black emails received responses for 49%. Holding class constant, white inquiries are significantly more likely to receive response than black inquiries by 4% points within high-class and nearly 9% points within low-class. Interacting race and class, the white advantage persisted. When a high-class white inquiry is paired with a low-class black inquiry, the white inquiry fares better by 8% points. Yet, when a low-class white inquiry is paired with a high-class black inquiry, the white inquiry still fares better by 5% points.

When taking the nature of the response received, the researchers did not find any significant difference between white or black names for being invited to view an apartment.

[8]The possible pairings were high-class white/high-class black, low-class white/low-class black, high-class white/low-class white, high-class black/low-class black, high-class white/low-class black, high-class black/low-class white.

[9]Emails to listings went out the day after the posting was listed.

This mostly held at the city level.[10] Findings from Hanson and Hawley (2011) agrees with previous work in that black searchers experience discrimination, though they find a smaller black-white disparity than other studies. Providing information can lessen, but not eliminate the disparity.

Ewens et al. (2014) also studied rental market discrimination in thirty-four US cities[11], and like the previous studies, they used apartment listings from craigslist. Researchers put more conditions on the types of units that would be included. Only studio and one-bedroom unit listings received inquiries. Unlike the previous studies, listings from large corporate property managers were excluded. Listings were only included if the asking rent was within the 20-90th percentile of the local area.

Each landlord was randomly assigned a single inquiry that varied in race, gender, and information. Race and gender was conveyed through names: Allison Bauer, Ebony Washington, Matthew Klein, and Darnell Booker.[12] Inquiries varied in the type of information included beyond the inquiry into the apartment: positive, negative, and no information. Positive information communicated that the applicant was a non-smoker with a respectable job while the negative information communicated that the applicant had a below-average credit rating and smokes. Emails were also sent without any additional information.[13]

The study contacted over 14,000 landlords and 65% responded to inquiries (Ewens et al., 2014, 24). Less than half of the responses were positive. Black applicants were 16% less likely to receive responses. Revealing positive information was the most advantageous, with revealing no information being a better strategy than revealing negative information. Re-

[10]Seattle was the only city where there was a significant differences with black inquiries being more likely to be invited to a showing.

[11]These cities were Atlanta GA, Austin TX, Baltimore MD, Boston MA, Charlotte NC, Chicago IL, Cleveland OH, Dallas TX, Denver CO, Detroit MI, Washington DC, Houston TX, Indianapolis IN, Jacksonville FL, Kansas City KS, Los Angeles CA, Louisville, KY, Memphis TN, Milwaukee WI, Minneapolis MN, Nashville TN, Oklahoma City OK, Philadelphia PA, Phoenix AZ, Portland OR, Raleigh NC, San Diego CA, San Francisco CA, San Antonio TX, San Jose CA, Santa Barbara CA, Seattle WA, Tampa FL, & Tucson AZ.

[12]Though names also conveyed gender, differences across genders were not significant.

[13]Emails to listings went out 48 hours after the posting was listed.

vealing information lessened racial gaps, but the gaps remained significant. This study's findings are consistent with those of Carpusor and Loges (2006) and Hanson and Hawley (2011).

Similar rental email audit studies testing for racial discrimination have been carried out in international contexts: Toronto (Hogan and Berry, 2011); Sweden (Ahmed and Hammarstedt, 2008; Ahmed et al., 2008, 2010); Spain (Bosch et al., 2010); Italy (Baldini and Federici, 2011).

Common across all email audit studies has been the technique of conveying race through name choice. A few studies have tested gender effects (Ahmed and Hammarstedt, 2008; Baldini and Federici, 2011; Ewens et al., 2014). Most studies focus almost exclusively on areas with tight rental housing markets (vacancy rates less than 8%). Many of the studies focus on available units, regardless of size or cost.

Some have signaled class through email information (Ahmed et al., 2010; Bosch et al., 2010; Baldini and Federici, 2011; Hanson and Hawley, 2011; Ewens et al., 2014). In some of the studies that test discrimination in the presence of information, it is unclear if included information is something a renter is likely to disclose in initial communications. The type of information revealed may constitute a threat to internal validity if it represents an unrealistic search strategy.

The most questionable is the negative information. Ewens et al. (2014) included that an applicant has both poor credit and smokes. Suppose that an individual in want of a rental unit had both poor credit and a smoking habit. These two things are usually looked upon unfavorably by landlords. Poor credit history casts doubt upon whether a tenant will be able to reliably meet their monthly rental obligation. Being a smoker may mean that smoke damage will need to be attended to once the tenant leaves, or nearby-tenants may complain to the landlord of the smell of smoke around the apartment unit. A prospective tenant could decide to reveal this information to a landlord as soon as possible or later in the process. Revealing this information as soon as possible could benefit the searching individual by weeding out the landlords that do not wish to rent to them on the basis of

credit and habits. It could be considered a time saving strategy. However, if most landlords have strong preferences for individuals with good credit and non-smokers, revealing this negative information immediately may mean the overall search process will be unsuccessful. If the searching individual decides not to lead with this information, and instead attempts to establish rapport with the landlord first, disclosing it later may mean it will be more palatable to the landlord because she knows more about the individual's other attributes. If the information that is revealed to landlords in an email audit is atypical of initial disclosures made by searchers, then estimates may reflect landlords' reactions to novel inquiries rather than discriminatory behavior.

2.3 HCV discrimination

Research on housing vouchers has provided multiple examples of assisted households perceiving discrimination in rental market searches. Summarizing across this work, some households experienced discrimination connected to source of income (SOI), racial affiliation, and family status. Households using vouchers connected to racial desegregation consent decrees believed they would experience discrimination in new, lower-poverty, and less-minority neighborhoods and that landlords in those neighborhoods would not want voucher households (Popkin et al., 2000a). Overall, 40% of HCV households surveyed in Orange County, CA, cited their voucher status as a barrier during search; black and Hispanic/Latino households were more likely to cite this type of discrimination compared to white households (Basolo and Nguyen, 2005). Chicago voucher households perceived resistance in renting to families with teenage children or a lot of children (Popkin and Cunningham, 1999). While these findings suggest that discrimination plays a large role in determining HCV search outcomes, the overall extent of the discrimination HCV households encounter during search is unknown (Turner et al., 2000; Galvez, 2011; Freeman and Li, 2013). Further, it is unclear how discrimination towards SOI, racial affiliation, and family status interact to impact rental search experiences and outcomes for HCV households.

There have been four main approaches to addressing discrimination HCV households may

face in the rental market:

1. **Mobility counseling**: Some PHAs have implemented programming to help prepare searching HCV households to have positive interactions with landlords.

2. **Landlord outreach**: PHAs have also engaged in landlord outreach activities to make more landlords aware of the HCV program.

3. **Landlord incentives**: PHAs have provided financial incentives to attract and retain landlords.

4. **SOI laws**: Finally, some jurisdictions have passed local laws to make discriminating against HCV households illegal.

2.3.1 Mobility counseling

Mobility counseling is a broad term for programming intended to help HCV households successfully lease-up. Programs vary in the methods used and their stated goals. Some PHAs have provided mobility counseling that addresses landlord relations, though the intensity of activities varies (Cunningham et al., 2010). It is not uncommon for landlord relation programming to be delivered in a workshop format (Cunningham et al., 2010). Typically, these activities emphasized teaching households how to positively present themselves and their family members to landlords.

In the Moving to Opportunity voucher demonstration program during the 1990s[14], some voucher holders participated in counseling activities that prepared clients to interact with potential landlords. Program staff coached households on how to make a good impression when meeting landlords for the first time; this usually involved role-paying the tenant-landlord

[14]The Moving to Opportunity (MTO) demonstration was implemented as a multi-site randomized study to examine the effects of housing vouchers, voucher-use constraints and mobility counseling on public housing residents' outcomes in a number of domains: neighborhood quality, health, education, safety, and employment. Five sites were selected for the MTO demonstration: Baltimore MD, Boston MA, Chicago IL, Los Angeles CA, and New York City NY.

interaction. Households were also advised to put together a portfolio to give directly to landlords. "These portfolios [could] include pictures of family members, a list of the client's goals, a positive credit report, and references from prior landlords" (Feins et al., 1997, 2-22).

2.3.2 Landlord outreach

Because the participation of landlords is crucial to the functioning of HCV program, administrative effort has been spent on landlord outreach. An early landlord outreach program was developed under a voucher program connected to a consent decree. The Gautreaux program was implemented during the 1970s and 1980s in response to a collection of court rulings that required HUD and the Chicago Housing Authority (CHA) to remediate long-standing segregation in the siting and tenant assignments of public housing developments by providing CHA clients housing opportunities in predominately white or more racially mixed neighborhoods. For the voucher program, real estate staff actively recruited landlords into the program. Identifying landlords was cited as one of the most difficult aspects of program implementation (Rubinowitz and Rosenbaum, 2000, 51). The initial strategy was to focus engagement efforts on property management firms which had a large number of rental units in their portfolio. However, engaging with these firms did not lead to significant placement activity. The approach changed to targeting smaller landlords, which was a more time-consuming process (Rubinowitz and Rosenbaum, 2000, 52). Staff made contacts with landlords, disseminated information to real estate organizations, and enlisted the assistance of fair housing advocacy organizations all in an effort to identify voucher housing units.

Beginning in 1998, HCV PHAs are required to engage in efforts to recruit landlords (Varady and Jaroscak, 2013). There is discretion in structuring and carrying out recruitment activities. PHAs use a variety of methods including informational orientations and open-houses, brochures and flyers, websites and videos. PHAs indicating that they engaged in landlord outreach were significantly associated with higher lease-up rates in 2000 (Finkel and Buron, 2001, 5).

Though many voucher programs include some type of landlord outreach, little is known

about the effectiveness of these activities (Cunningham et al., 2010; Varady and Jaroscak, 2013). Additionally, voucher holders, as opposed to PHAs, might be more likely to be the first point of contact landlords have with the HCV program. In a qualitative study of HCV landlords from Illinois, "most landlords described being unfamiliar with housing authority activities prior to exposure to the program through voucher-assisted tenants" (Greenlee, 2014, 9).

Some HCV recipients have found briefing packet landlord lists unhelpful in identifying vacant apartment units (Popkin and Cunningham, 1999; Teater, 2009). This has also been mentioned by consent decree voucher holders (Popkin et al., 2000b, 3-42). Assuming that these lists are the byproduct of outreach activities, it could suggest that outreach does not necessarily lead to leasing opportunities. However, the lack of leasing could be because it is likely apartment vacancy information is difficult to keep up-to-date.

2.3.3 Landlord incentives

Some voucher programs have provided financial benefits directly to landlords for renting to voucher households. A few PHAs have offered financial incentives to landlords such as a bonus or property tax credit for leasing to an HCV household, grants for repairs to address unit inspection findings, or a bonus for leasing a unit vacated by an HCV household for another HCV household (Popkin et al., 2000b; Cunningham et al., 2010; HACC, 2012; CHA, 2012). The impacts of these incentive programs have not been formally evaluated.

2.3.4 Source of income laws & ordinances

Lastly, laws have been passed to discourage discrimination against voucher holders. In the US, there are federal fair housing laws that aim to discourage discrimination in rental and owner-occupied housing market transactions. The federally protected fair housing classes are race, color, religion, national origin, gender, disability, and familial status (GAO, 2004, 6). Legally, housing market decision-makers, such as landlords, realtors, and lenders, may

not refuse to rent, sell, or lend to individuals just because they are associated with protected classes.[15]

Some states and localities have augmented federal fair housing protections by passing laws that make discrimination on the basis of source of income (SOI) illegal. These SOI laws add protection from discrimination for individuals who receive cash transfers or benefits from sources other than earned or investment income. For example, a landlord considering a potential renter who receives Social Security Disability Insurance (SSDI) must consider any SSDI payments as viable income when determining the tenant's ongoing ability to pay rent.

The states, counties, and cities with active SOI laws that protect HCV are mapped in figure 2.2 (PRRAC, 2016). Just over fifty jurisdictions have SOI laws. There is variation in the definition of income sources that are covered by these laws. For example, three states, California, Minnesota and Wisconsin, have SOI laws that exclude HCV as a protected income source class.[16]

In general, SOI laws make discrimination on the basis of source of income from mainstream benefit programs illegal in most housing market transactions. For example, in Connecticut, protected income sources are any type of Social Security payments, child support, alimony, state and federal housing assistance, and any public assistance income.[17] If a household in a covered jurisdiction believes it received differential treatment in a housing market transaction due to its source of income, it starts the complaint process at a fair housing agency.[18]

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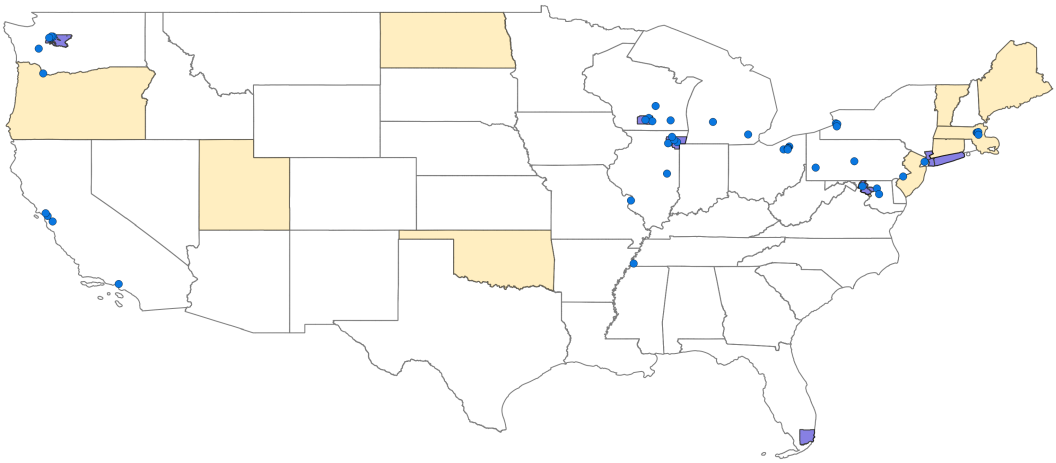
[15]Some properties are excluded from the federal anti-discrimination laws: owner-occupied buildings with less than five units; single-family units owned by a landlord with no more than three single-family properties with the additional requirement that professional advertising or broker services are not utilized during tenant recruitment; religious organizations and private clubs can require membership or affiliation as a condition of occupancy for some types of property; senior housing may set age restrictions (42 USC §3603 & §3607).

[16]Minnesota's SOI law originally included HCV protection, but it was judicially undermined in 2008; Wisconsin's law has been judicially interpreted as excluding HCV (PRRAC, 2016).

[17]General Statutes of Connecticut §46a-63: http://www.cga.ct.gov/2013/pub/chap_814c.htm#sec_46a-63.

[18]At the federal level, HUD's Office of Fair Housing and Equal Opportunity (FHEO) administers the federal fair housing enforcement program. In SOI covered jurisdictions, complaints of discrimination are

Figure 2.2: SOI laws that include HCV, Summer 2016



SOI laws exist only when local or state stakeholders have shepherded proposals through the entire local legislative approval processes. "SOI laws seem to have been passed in an ad hoc manner" (Freeman and Li, 2013, 90). As a result, geographic coverage of these laws is hardly uniform. Some of the jurisdictions are geographically nested. For example, Cook County in Illinois has an SOI law as well as its county seat, Chicago. In California, some cities have enacted laws that include HCV protection even though state law does not. Wide swaths of the US do not have any SOI laws: most of the Southwest, except for California; virtually all of the Midwest; all of the South save Miami-Dade County in Florida.

No jurisdiction has triple coverage, meaning that a municipality has coverage at the state, county, and municipal level. Coverage in a particular municipality is either provided by a single level or two levels of government. Twenty-two municipalities are covered by municipal laws only. Municipalities within five counties are singly covered by their counties' SOI laws. Single coverage is provided at the state level for municipalities in eight states and the District of Columbia. Double coverage occurs in two ways: either a coupling of laws at the state and municipal levels or at the county and municipal levels. State-municipal coverage occurs only in Massachusetts; Boston, Cambridge, Quincy, and Revere maintain their own SOI ordinances. County-city coverage occurs in three different regions: Cook County IL has three cities with their own SOI laws (Chicago, Harwood Heights and Wheeling); King County WA has four cities (Bellevue, Kirkland, Redmond, and Seattle)[19]; Dane County WI has three cities (Madison, Sun Prairie, Wauwatosa).

In theory, SOI laws have the potential to improve Housing Choice Voucher (HCV) households' leasing outcomes. HCV recipients receive a monthly rental subsidy that covers the majority of their rent obligations. HCV targets extremely low-income households, typically those below 50% of area median income. If a landlord evaluates an HCV household's income without considering the voucher as an asset of the household, the household will appear to

filed with state and local Fair Housing Assistance Programs (FHAP) (GAO, 2005, 1).

[19]King County WA's ordinance is unique because it only covers unincorporated parts of the county. After the study's data collection period, the municipalities of Renton and Tukwila passed an SOI ordinance including HCV protection.

have an extremely low ability to pay rent obligations. In most jurisdictions covered by these laws, landlords are supposed to treat vouchers as part of the tenant's income when evaluating ability to pay.

SOI effectiveness

Some studies have approached SOI effectiveness by looking at HCV households' locational outcomes within and outside of SOI-covered jurisdictions. These studies test hypotheses that if SOI laws reduce rental market discrimination, HCV households will have an easier time using their vouchers to lease-up and to access lower-poverty neighborhoods with less racial segregation. So far, three studies have taken this approach (Finkel and Buron (2001), Galvez (2011), and Freeman (2011); Freeman and Li (2013)).

In 2000, Finkel and Buron (2001) conducted a study that sampled PHAs and within each sampled PHA, sampled newly issued voucher households. The study examined the lease-up rate, whether a household issued a voucher ultimately leases a unit with their voucher. The lease-up rate was significantly higher in SOI-covered jurisdictions by 12 percentage points (Finkel and Buron, 2001, 3-17). This study was observational and focused on voucher household lease-up rates. Logically, it did not include a non-voucher comparison group. However, one cannot compare the leasing outcomes of unassisted households with the voucher household within the same jurisdiction. This difference is of interest in discovering the effectiveness of SOI.

Another study looked at how SOI laws were related to average locational outcomes of HCV households (Galvez, 2011). Using cross-sectional data aggregated to the metropolitan statistical area (MSA)[20] level, the researcher examined the association between having an SOI law in effect within the MSA and average locational outcomes for HCV households within the MSA. The locational outcomes were the average tract-level racial segregation and

[20] An MSA consists of a core urban center with a population of at least 50,000; each MSA contains at least one county and any other adjacent counties that are related either socially or economically to the core urban center: https://www.census.gov/population/metro/.

the average tract-level poverty rate. The presence of SOI laws within an MSA did not have a significant association with average racial segregation (Galvez, 2011, 87). However, SOI laws did have a significant association with the average poverty rate: just under a 1% reduction in the average poverty rate (Galvez, 2011, 90).

The results in Galvez (2011) suggest that SOI laws have a positive impact on HCV households' neighborhood poverty rates. However, the unit of analysis in this study was the MSA. MSA boundaries are not relevant to SOI laws because the coverage of laws is necessarily tied to the political boundaries of the jurisdiction that enacts the laws. MSAs are Census-defined jurisdictions that often encompass multiple political jurisdictions. For example, consider an MSA where a single city within the MSA enacted an SOI law. In this modeling approach, all HCV holders within the MSA are represented as having SOI protection when in reality only HCV holders within the covered city enjoy this protection. This approach overstated SOI coverage. Further, the study used cross-sectional data: locational outcomes of HCV households were measured at a single point in time. This type of data does not allow us to determine whether SOI coverage causes residence in lower poverty rate neighborhoods or if SOI laws are simply associated with lower poverty rate neighborhoods for HCV households.

The last study hypothesized that a lack of SOI anti-discrimination protection would result in both lower utilization rates[21] at PHAs and that HCV households will reside in more disadvantaged neighborhoods as measured by tract-level characteristics (Freeman, 2011; Freeman and Li, 2013). The researchers used a difference-in-difference approach to compare outcomes over time in adjacent jurisdictions with and without SOI laws. Jurisdictions with SOI laws demonstrated a significant increase in utilization rates comparing rates from before the law was enacted to when the law was enacted–from 4 to 11 percentage points (Freeman, 2011, viii). Additionally, SOI-covered jurisdictions had voucher holders in slightly less disadvantaged neighborhoods, but the differences were small (Freeman, 2011, vii).

The difference-in-difference design used in this study allows one to attribute differences

[21]The utilization rate is a ratio of the number of vouchers that are currently being used by households divided by the number of vouchers allotted to the PHA.

in outcomes to the absence or presence of an SOI law. This allows for the examination of SOI laws over time within political jurisdictions—SOI coverage is not overstated. This study suggests that SOI has a small effect on neighborhood quality and larger effects on voucher utilization at the PHA level.

However, I believe the utilization rate is not the best outcome measure in this study. This measure has the potential to over-state an HCV population's ability to lease. As mentioned before, the utilization rate has the number of successfully leased households in the numerator. This number is comprised of a mix of recent and long-term households. The denominator is the number of vouchers the PHA is contracted to provide. The residual between the numerator and denominator represents the vouchers not in use–not leased up. However, this residual captures subsidy-level usage, but that does not necessarily equate to households' ability to lease. Therefore, the amount of bias associated with the utilization rate (if it is used to measure ability to lease) will be related to the number of households that did not successfully lease on a given voucher. Consider a toy-data example: two PHA's with ten vouchers each. The first PHA offered vouchers to ten different households, and each household was successful in leasing a unit. This PHA's utilization rate is 100%: 10 leases on 10 vouchers. Now for the second PHA. This PHA also offered vouchers to 10 different households, however, only nine of the households were able to lease. At this time, PHA's utilization rate would be below that of the first PHA: 90%; 9 leases on 10 vouchers. Next, the unused voucher was issued to another household and that household was able to lease. Now, the second PHA's utilization rate would be equivalent to the first PHA: 100%; 10 leases on 10 vouchers.

A more appropriate measure would be the lease-up rate.[22] As mentioned before, the lease-up rate is the ratio of the number of lease-ups divided by the number of *vouchers issued*. A single voucher can be issued to a sequence of different households until a household is finally successful in leasing-up. If households are systematically encountering difficulty in

[22]Lease-up rate is a measure that exists in the HCV literature (c.f. Finkel and Buron (2001); Wood et al. (2008); Edin et al. (2012)).

successfully leasing, it is likely that there are many voucher issues made relative to the one successful lease. If households are having an easy time leasing up, it is likely that there would be a single issue relative to a successful lease. Turning back to the two housing authorities, for the first, the lease-up rate is equivalent to the utilization rate: the number of issues is the same as the number of leases. For the second PHA, the lease-up rate is lower than the utilization rate: the number of issues exceeds the number of leases (91% versus 100%). This means that the utilization rate has the potential to mask the impact of failed searches–to bias results upward. This fact casts doubt as to whether the increase utilization rates is a sign of an increased ability to lease for households in SOI jurisdictions.

Taken together, these studies suggest that SOI laws may have an effect on leasing-up and overall utilization and modest effects on HCV locational outcomes. An alternative approach to determining whether SOI laws were effective would be to determine if SOI laws are associated with lower rates of discrimination for voucher holders. This study will take this approach.

2.3.5 HCV audits

A handful of studies have adopted audit designs to examine HCV discrimination in a variety of communities. In June 2001 and February 2002, a Chicago-based law firm specializing in housing law conducted a telephone audit to examine housing voucher discrimination (LCBH, 2002). There were SOI laws protecting HCV at the municipal and county level during the audit. In 207 phone tests, a tester classified as white, called sampled Chicago-area print rental listings and asked if housing vouchers were accepted for the advertised unit. Of the 207 advertisements, 83 (43%) received a positive response. Those 83 advertisements were then contacted by a black tester. Only 35 of these advertisements (42%) received a positive response for the back tester, though they had all previously responded positively to the white tester.

This study did not focus on comparing outcomes between having and not having a voucher. That on its own does not matter however, the design of this study makes it

difficult to make causal inferences about racial affiliation from its findings. It is uncertain how landlords that said no to white testers would respond to black testers. While the results strongly suggest that black voucher households are at a search disadvantage compared to white households in similar circumstances, the absence of matched-comparisons for each case is a problem. Further, the black voucher holder always contacts the landlord last. It would have been helpful to randomly assign the order of contact for testers. As it stands, the possibility of the order of contact effecting results cannot be ruled out.

It is unclear from the study report if there were any size and cost criteria imposed in the selection of listings. If not, given the constraints of HCV, it is not known if all these units are close to the payment standards.

Over the summer of 2009, a non-profit civil rights organization conducted a telephone audit of two-bedroom units for rent with rents of $1,250 or less in the greater New Orleans, LA area (GNOFHAC, 2009). These size and cost criteria restricted the sample to units a two-bedroom voucher could afford at the time. Postings that explicitly mentioned housing vouchers either positively or negatively were excluded. Postings were randomly sampled from a mix of print and online-only sources (including craigslist.org). No jurisdiction within the study area had SOI laws.

One hundred tests were carried out over a four-month period. Each selected advertisement received three calls: white tester without a voucher; white tester with a voucher; black tester with a voucher. There was not a call from a black tester without a voucher. Results were that 82% of the landlords contacted refused vouchers or included "insurmountable barriers" to utilizing the voucher (GNOFHAC, 2009, 10). A formal definition of "insurmountable barriers" is not given, nor the percentage of refusals only. In nine tests, landlords responded positively to the white voucher holder and negatively to black voucher holder–evidence of the racial discrimination across voucher holders.

Like LCBH (2002), this study is missing the black non-voucher holder tester. The strongest evidence is only available for comparisons between the HCV testers. The report does not mention the ordering of contact with respect to the three tester groups.

In August of 2014, an Indiana non-profit focusing on fair housing, conducted a telephone audit of rental properties in Marion County, IN (FHCCI, 2014). Postings were randomly sampled from a mix of print and online-only sources (including craigslist.org). It is unclear whether sampled units met payment standards because no sampling criteria were applied with regards to size and cost. No jurisdiction within the study area had SOI laws. Testers made 51 calls. Testers did not vary their attributes–they all had HCV. An overwhelming majority of landlords refused HCV (82%). This study has a small sample size and no comparison groups. It suggests that most landlords do not accept HCV, but the differential for unsubsidized households and any racial effects are not discoverable from this design.

Another audit study in Chicago investigated HCV discrimination when cold-calling landlords either by phone or in-person (CLC, 2014). Audit activities took place in November 2010 through December 2011. The study included two components that tested for HCV discrimination. The first component included 29 tests with landlords already participating in HCV. These landlords were identified through the Chicago Housing Authority (CHA). Testers were given size and cost criteria, but were free to select any unit with the CHA-identified landlord. For 59% of the tests, HCV testers were discriminated against (CLC, 2014, 18).

The second component tested landlords without HCV that "advertised rental units in Chicago opportunity areas, defined by the CHA as areas with less than 23.49% of individuals having income below the poverty level and with no more than 30% of the resident families being African American" (CLC, 2014, 6). First, a white voucher tester would contact the landlord (123 tests), then only if the white voucher tester was received positively, a black voucher tester would contact the same advertisement (55 tests). White testers experienced HCV discrimination 55% of the time (CLC, 2014, 27). Of the landlords that responded positively to white testers, black testers received positive responses 53% of the time (CLC, 2014, 28).

The first email audit study to examine HCV discrimination was conducted in the DC area in the summer of 2015 (Phillips, 2017). DC has had an SOI ordinance that includes HCV

since 1977. Using randomly selected online apartment listings, the study emailed landlords inquiries that varied in terms of the tester's race (conveyed through names from Bertrand and Mullainathan (2004)), HCV status (conveyed through a declarative statement), and other attributes. A single tester email had a 25% chance of having HCV. A single listing could receive 1, 2, or 4 tester emails. Over 1,300 listings received at least one study inquiry.

Phillips selected studio, one- and, two-bedroom apartments with advertised rents at or below $1,500.[23] During this time, the DC-area FMRs were $1,167, $1,230, and $1,458 for the selected unit sizes (Phillips, 2017, 49). Putting the $1,500 threshold in terms of FMR percentage leads to studios up to 129%, one-bedrooms up to 122%, and three-bedrooms up to 103% of FMR. While imposing a single cost threshold for all bedroom types simplifies audit operations, it may lead to the selection of different quality units between unit sizes. I advocate for tailoring cost criteria to each unit-size category.

Further complicating setting a cost threshold is that at the start of the study period DC's payment standard was at 110% of FMR, where it had been since 2009.[24] A few weeks into the study, the payment standard was increased to 130% FMR.[25] Particularly for two-bedroom units, it is possible that likely eligible units were excluded from the study.

Phillips (2017) finds that HCV households are 26 percentage-points less likely to receive a positive response from landlords and black households are 6 percentage points less likely when apartment characteristics are controlled for.

The HCV audit work discussed here varies in geographic scope, integrity of experimental design, and sample size. But taken together, it is likely that HCV households experience rental market discrimination.

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[23] It is a little unclear to me whether or not he included three-bedroom units in his study (c.f., categories in Table 1.)

[24] http://www.dcregs.dc.gov/Gateway/FinalAdoptionHome.aspx?RuleVersionID=3486294

[25] http://www.dcregs.dc.gov/Gateway/FinalAdoptionHome.aspx?RuleVersionID=4417203

2.4 Study's contributions to literature

This study builds on the previously discussed rental audits focused on racial discrimination and HCV discrimination. This study's approach shares many design attributes with these past studies. Like others, I will use online rental listings to email landlords while conveying the race of the tester through proper names. This study departs from previous work is in a focus on rental listings that are likely eligible for HCV participation and examining landlord behavior in multiple cities with different SOI law coverage.

As previously discussed, the Phillips (2017) study used rental cost selection criteria that does not relate to size-specific FMRs or payment standards. As I will explain in the next chapter, in addition to size and cost constraints, other criteria, that were informed by HCV guidelines and rules, were used to isolate rental postings that would be eligible for HCV participation.

SOI coverage has been studied in multiple cities before (Finkel and Buron, 2001; Galvez, 2011; Freeman, 2011; Freeman and Li, 2013) but with a focus on leasing or locational attainment outcomes. This is the first study to look at SOI coverage's association with landlord response behavior.

This study's primary contribution is to provide empirical estimates of HCV discrimination. Mobility is an explicit feature of the HCV program. Success in rental searches are required to begin and continue receiving HCV support. There is much anecdotal and observational data that supports the idea that HCV discrimination is something all voucher holders contend with. Empirically verifying that belief and ascertaining the scale of the discrimination is important.

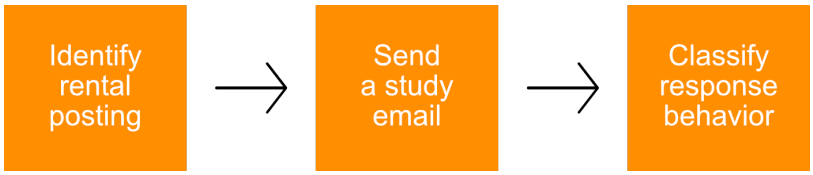
Chapter 3

AUDIT METHODS

3.1 Overview

This study drew heavily on the previously discussed email audit research designs to structure a study framework to align more closely with the rental search parameters relevant to voucher households. It tests for differential treatment on the basis of HCV while accounting for race. This chapter details the specifics of the design and operation of the experiment. A simplified flowchart of the audit process is presented in Figure 3.1. The first step in the process was to find rental postings. The study sites and online rental listing source that were used will be described. The specific attributes a rental posting had to have to be included in the study will also be described and justified. Then, each selected posting was sent a study email. The content of these emails will be described. Finally, I classified the response behavior of posters to study emails. The rationale and process behind the classification will be explained.

Figure 3.1: Audit process

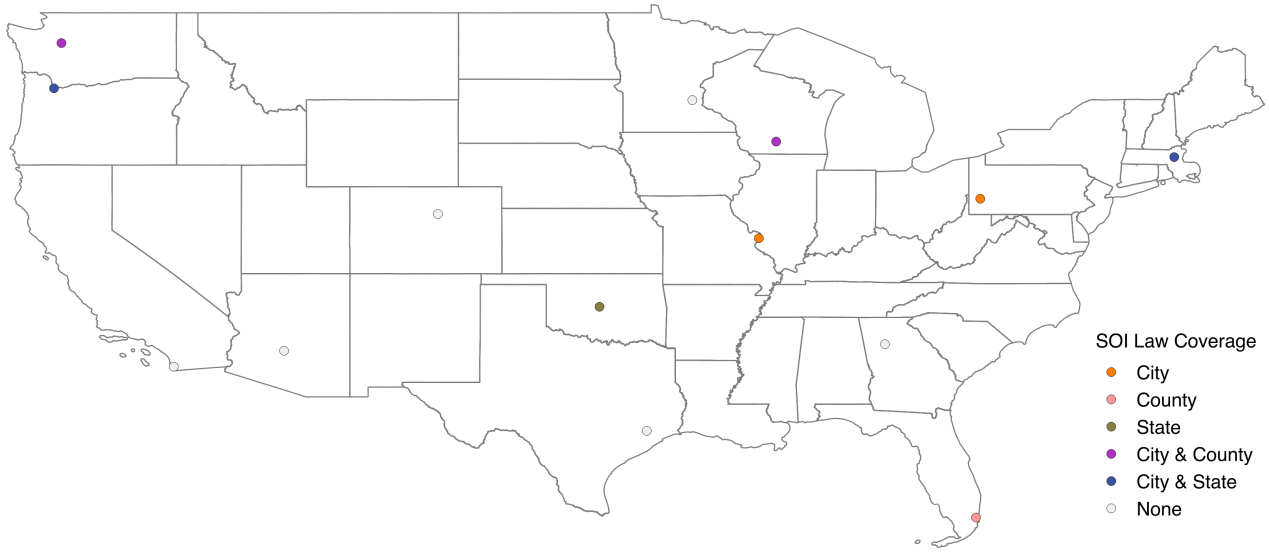


3.2 Identifying rental postings

3.2.1 Sites

Fourteen different cities were purposively chosen for this study (see Figure 3.2): Atlanta GA, Boston MA, Denver CO, Houston TX, Miami FL, Minneapolis MN, Oklahoma City OK, Portland OR, St. Louis MO, San Diego CA, Seattle WA, Madison WI, Pittsburgh PA, and Phoenix AZ. Sites were selected to vary in the SOI coverage and rental market vacancy rates. Sites also had to have a sizeable voucher population.

Figure 3.2: Study sites by SOI law coverage



The sites' SOI coverage is summarized in Table 3.1. Six sites have no SOI laws protecting HCV: Atlanta, Denver, Houston, Minneapolis, San Diego, and Phoenix. The remaining sites

Table 3.1: Study sites by SOI law coverage levels

Site	**None**	**City**	**County**	**State**
Atlanta GA	✓			
Boston MA		✓		✓
Denver CO	✓			
Houston TX	✓			
Madison WI		✓	✓	
Miami FL			✓	
Minneapolis MN	✓			
Oklahoma City OK				✓
Phoenix AZ	✓			
Pittsburgh PA		✓		
Portland OR		✓		✓
San Diego CA	✓			
Seattle WA		✓[1]	✓	
St. Louis MO		✓		

[1]King County WA's SOI law only covers unincorporated areas of the county.

have SOI laws protecting HCV at one or two political levels. Oklahoma City has coverage at the state level. Miami has protection at the county level. St. Louis and Pittsburgh have coverage at the city level. Boston and Portland have coverage at the city and state level. Lastly, Seattle and Madison have coverage at the city and county level. At the time of this study, no jurisdiction in the US had SOI coverage at the city, county, and state level.

Study sites had to have an active craigslist site with rental listings for units in and around the city. Craigslist was the only rental listing source used for this study. In each jurisdiction, there are multiple online venues for apartment listings. Beyond craigslist, Trulia, Zillow,

RadPad, PadMapper and other sites are significant sources of rental listings in most, if not all of these cities. This study focused solely on craigslist because of its size, ubiquity, and its interface. craigslist has operated for over two decades. Currently, there are over 400 US craigslist sites. Virtually all major metro areas have a craigslist site with many smaller metro areas also represented in craigslist. Monthly average usage characteristics begin to give some idea of the overall craigslist usage: 50 billion page views per month; 60 million US users each month; 80 million classifieds posted each month (craigslist, 2014).

The structure underlying craigslist sites is straightforward. The html structure of the listing pages make them amendable to simple web scraping schemes to collect information on each listing. As long as a scraping scheme does not make too many or too frequent requests of craigslist servers, it can operate unobstructed. Simply structured search result pages and RSS feeds make getting timely information on the URLs of new listings easy as well. Other newer rental listing sites typically employ more complicated page structures that are not as simple to scrape and some sites actively discourage systematic scraping. For these technical reasons, craigslist was a desirable source for rental listings.

There are sites that provide rental listings that target HCV households directly, with the largest being GoSection8.com and Socialserve.com. These sites were not included in this study. Listing with these sites is voluntary. These dedicated marketplaces may not provide rental seekers diverse housing options that include high quality neighborhoods. Researchers examined GoSection8.com and Socialserve.com listings in six jurisdictions and found that most listings were for units located in high poverty neighborhoods (PRRAC, 2015).[1]

Each study site had to have an active craigslist site that included rental listings for the core city and surrounding area. For the most part, craigslist does not place specific geographic bounds on postings and the functional geographic bounds are ultimately shaped by the aggregate geography of users' postings. For example, Boston's craigslist postings

[1]It is possible that within these dedicated marketplaces, landlords and property managers that advertise as accepting housing vouchers may racially discriminate among subsidized households. This study does not address this question, but it would be great if someone did!

include Boston, Cambridge, Quincy, Revere and more; Miami's craigslist includes postings from Miami-Dade, Broward, and Palm Beach Counties. This study accepted the geographic spread of craiglist sites and did not constrain posting selection to a single municipality for the most part.[2] Because of this, study sites could have a patchwork of SOI coverage and non-coverage for their postings. In the six sites without any SOI coverage, none of the postings had coverage. For all the Oklahoma City postings, which were all for municipalities within the state of Oklahoma, all postings had coverage.

For the remaining sites, there was a mixture of coverage and no coverage. This was the case for Boston, Madison, Miami, Seattle, Pittsburgh, Portland, and St. Louis. In Boston's craiglist there are multiple cities that have SOI (Boston, Cambridge, Quincy, Revere) in addition to Massachusetts' SOI and some listings are in nearby cities in Rhode Island and New Hampshire–both states without any SOI laws. In Madsion's craigslist site, Dane County and the cities of Cambridge, Madison, and Sun Prairie all had SOI laws. In Miami's craigslist site, any postings outside of Miami-Dade County did not have protection. In Seattle's craiglist site, unincorporated King County and the cities of Bellevue, Kirkland, Redmond, Seattle, and Tumwater had SOI. In Pittsburgh's craiglist site, any posting outside of the city of Pittsburgh was unprotected. In Portland's craigslist site, any posting in Oregon State or in Vancouver WA was covered. In St. Louis' craiglist site, any posting outside of the city of St. Louis was not covered.

Sites were also selected to vary in rental market tightness. Market tightness tries to describe how hard it is to find rental housing within a market. Market tightness is often measured through vacancy rates: the percentage of all rental units that are vacant. Higher vacancy rates mean more vacant units and searching for a rental unit will likely be easier.

Using Finkel & Buron's (2001, 1-13) classification of rental markets[3], the study sites are

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[2]On a few occasions, postings were excluded because they were outliers–outside of the functional bounds of the craigslist site. For example, a posting from the Madison WI craigslist site was for an apartment complex in Madison AL; a posting from the San Diego CA craigslist site was for a unit in Los Angeles CA. This type of mis-posting was extremely rare.

[3]Finkel and Buron (2001) studied success rates for newly issued vouchers in many metro areas. They

Table 3.2: Study sites' 2015 ACS five-year vacancy rates

Study Site	**Vacancy Rate**	**Tightness**	**SOI Coverage**
Houston TX	8.7	Loose	No coverage
Atlanta GA	8.6	Loose	No coverage
Phoenix AZ	8.6	Loose	No coverage
Miami FL	7.4	Loose	County
Oklahoma City OK	7.4	Loose	State-wide
St. Louis MO	7.1	Loose	City
Pittsburgh PA	4.7	Moderate	City
Denver CO	4.2	Moderate	No coverage
San Diego CA	4.1	Moderate	No coverage
Seattle WA	3.9	Tight	County & City
Boston MA	3.6	Tight	State-wide & City
Minneapolis MN	3.5	Tight	No Coverage
Portland OR	3.2	Tight	State-wide & City
Madison WI	2.8	Tight	County & City

classified by rental market tightness as measured by ACS rental vacancy rates in Table 3.2. Six sites are loose with vacancy rates from 7.1% up to 8.7%. Three sites are classified as moderate with vacancy rates of 4.1% to 4.7%. The remaining five are classified as tight with vacancy rates of 2.8% up to 3.9%.

Selected sites also needed a sizable voucher population. If there are too few vouchers utilized within a jurisdiction, landlords might become suspicious of inquiries from HCV households and it would have undermined the audit. Table 3.3 contains 2016 data summariz-

classified rental markets by vacancy rate: 2% or lower is extremely tight; above 2% and up to 4% is tight; above 4% and up to 7% is moderate (between 4 and 7 percent vacancy rate); above 7% and up to 10% is loose (between 7 and 10 percent); above 10% is extremely loose.

ing voucher counts at the metropolitan statistical area or metropolitan division (MSA/MD) level (HUD, 2016b).[4] This data is reported in geographical divisions that do not exactly match the geographic bounds of the craigslist site for reasons described above. For the most part, the craigslist geography is larger than the MSA/MD geography therefore these voucher counts can be considered as a lower bound to the true voucher count for the corresponding craigslist site.

Looking at the table, all but Madison WI have at least 12,000 vouchers. Across sites, anywhere from 5-14% of the voucher inventory experienced a new move-in in 2016. This does not include the households that have been on the voucher program for more than a year and moved into a different unit with the same voucher (HUD, 2016a). Therefore, this fact combined with the MSA/MD-craiglist geography mismatch, means that the total count of voucher households that are shopping in the private market with their voucher in each craigslist site in 2016 is likely higher. For the smallest site, it is estimated that at least 296 households could be shopping during the year–an average of 25 households per month. For the largest site, at least 3,597 households could be shopping–an average of 300 households per month. These voucher counts and move-in rates were deemed sufficient to avoid audit detection.

3.2.2 Posting content

craigslist rental advertisement postings have a standard structure. Posters on craigslist vary in how much information they disclose in a post. Figure 3.3 is an example of a craigslist posting. I will explain the important components of the general posting structure by referring to the specific posting in this Figure. I will start at the top of the posting, working left to

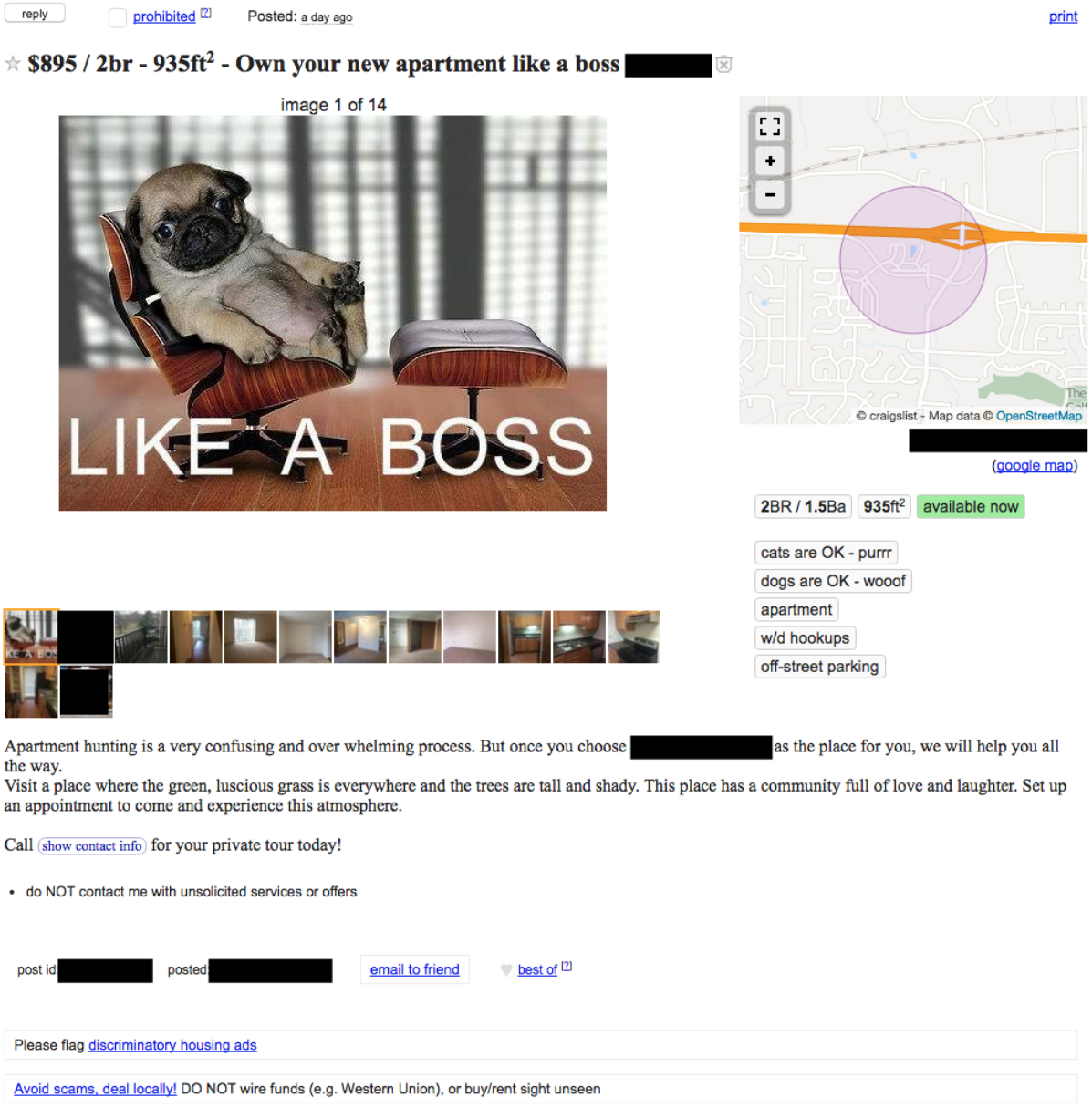
[4]The Picture of Subsidized Housing (POSH) provides yearly snap shots of characteristics of HUD-subsidized households aggregate at different geographic and administrative levels: census tract, public housing authority, city, county, state, US total, and core based statistical areas. The 2015 POSH core based statistical areas are reported either for metropolitan statistical areas, micropolitan statistical areas, or metropolitan divisions. For example, POSH provides data for the Boston metropolitan division, but no data is available for the Boston-Cambridge-Newton, MA-NH metropolitan statistical area. POSH data is not publicly available at the household level, so one must adapt to the available aggregations.

Table 3.3: Study sites' 2016 voucher counts & move-in rates (HUD, 2016b)

Study Site	**# of Vouchers**	**% moved in past year**	**# moved in past year**
Nationally	2,474,400	11%	272,184
Atlanta GA	39,969	9%	3,597
Boston MA	30,584	5%	1,529
Denver CO	17,803	9%	1,602
Houston TX	28,546	11%	3,140
Madison WI	3,291	9%	296
Miami FL	25,114	7%	1,758
Minneapolis MN	23,851	9%	2,147
Oklahoma City OK	12,158	12%	1,459
Phoenix AZ	13,894	11%	1,528
Pittsburgh PA	19,982	10%	1,998
Portland OR	18,336	11%	2,017
San Diego CA	30,254	7%	2,118
Seattle WA	26,837	10%	2,684
St. Louis MO	20,955	14%	2,934

right.

Figure 3.3: Example of craigslist posting



In the upper left-hand corner, there is a box containing the word 'reply'. This is the primary source for the email contact information necessary to contact posters with tester

emails and for telephone numbers which were utilized in the de-duplication process. This element is a button, that when pressed reveals a box with contact information for the poster. Most postings have this button. Posters can opt to provide any of the following pieces of information: contact name, telephone number, texting number, email address. If posters decide to use the craigslist relay, the relay address will appear in this box. The craiglist relay provides a way for posters and potential tenants to communicate without either party disclosing their actual email address–it is a way to anonymize communications for all participants. Of postings that received a study email, over 87% of the posters used the craiglist relay.

The next important posting component is the title. In the example figure the title is the text, "$895 / 2br - 935ft2 - Own your new apartment like a boss (XXXXXXXXX)". The first three elements of the title provide the price, bedroom size, and square-footage for the apartment. Listings varying in whether they include any of these data elements. This cost and size information is necessary to assess the unit for HCV eligibility. The fourth element is text that ranges from attention-grabbing statements to short descriptions of the unit or unit's geographic location. During the study, some titles provided more geographic detail for unit location when other post components intended to be explicit about geography were missing or incomplete. Additionally, some posters put a signature-like pattern in the posting title. For example, one poster put the name of his management company followed by the pound sign in all of his postings. Habits such as these helped de-duplication. The final component in the parentheses–which is blacked out in the figure–is usually a word or phrase about the geographic location of the unit. Not all postings have this component. If the post does have this component, there is no requirement for what the contents should be. Posters tend to provide a city name, neighborhood name, cross streets, intersection, address, or apartment complex name in this space. Like the title text, this component might offer more information to clarify the geography of the unit.

Below the posting title is the image space (the large image bordered by the rows of thumbnail images). Most postings have at least one image. Most often these images are of

the advertised unit and surrounding area. For apartment complexes, posters might include a complex sign image that can provide additional geographic and contact information. Images also aided in assessing the authenticity of a post: is the posting fraudulent? For example, a common trend among fraudulent postings was to have photos that carry a watermark from a large, professional property management company, yet visiting the company's website would indicate that the unit at the address advertised was either not in their holdings or not available. Also, fraudulent postings tend to have a pastiche of photos that seem to come from many different units and when considered in tandem do not make sense. Images also aided in de-duplication because frequent posters might use the same images over and over.

Posters have the option to provide a location for a Google Map–the map image in the righthand corner. Posters can be specific or vague about the location of the unit. Some posters provide precise addresses for units, others provide the nearest intersection, and others an approximate location in a neighborhood. Depending on the type of geography the poster provides, there may be text beneath the Google Map image corresponding to the address or intersection presented in the image.

Below the Google Map image, there are a collection of text boxes that contain attributes of the unit. Like other elements, providing information for these boxes is voluntary. These boxes can contain information about the unit specifications, amenities, and rental contract terms. Information in these boxes helped assessing units for HCV eligibility.

Below the apartment images is a space reserved for text. Again, this component is voluntary for posters. The extent of the content and information provided here varies considerably across posters. Some posters provide lots of information on the unit including terms, location, and the application process. Other posters just include basic details of the unit. This text can help identify geography, de-duplicate posters, and assess HCV eligibility.

Within the text space, there can be contact information. This information is either new or duplicative of the reply box information at the top of the posting. The rounded box with the phrase 'show contact info' can be clicked to reveal contact information–usually a telephone number, sometimes an email address. This information was collected and helped

with de-duplication.

Below the text space is the post ID. This numeric value is unique to each posting across all craigslist sites. This de-duplicates a posting instance. A poster can update a single post overtime and these updates will continue to be associated with the original post ID. The post ID does not effectively de-duplicate units though. Some posters create numerous posts for the same unit or building. This posting behavior cannot be de-duplicated by post ID alone.

Next to post ID is the posted date. This information was used to measure the response time–the time between the posted date and when a study email was sent.

3.2.3 Posting volume

Each day[5], I examined postings from the previous 24 hours of craigslist activity in the study sites. The average number of postings in 24 hours was 11,142 across the sites. Table 3.4 presents the average and median posting counts by jurisdiction. Miami was the highest volume site with an average of 1,237 listings per period, followed by Atlanta with an average of 1,027 listings per period. The smallest volume site was Madison with just 394 listings per period.[6] The largest posting period was Tuesday morning to Wednesday morning, averaging 12,437 postings; the smallest posting period was Saturday morning through Sunday morning, averaging 9,906. This trend held at the site level as well (see Figures 3.4 and 3.5 for weekday means and medians by site).

It is important to note that these posting volumes are not de-duplicated. Some postings can be de-duplicated by post ID. The post ID is a craigslist-generated value that unique identifies listings across all craigslist sites. However, many craigslist posters submit multiple ads for the same unit daily: the same unit is associated with multiple post IDs. Multiple

[5]I was actively selecting and emailing postings for 60 consecutive days: June 15, 2016 through August 13, 2016.

[6]Initially, Memphis TN was included as a study site. Its daily posting volume averaged 288. After day 11, Memphis was excluded as a site due to concerns with experiment detection due to low volume of postings.

Table 3.4: Mean & median of daily posting volume during study period

Area	**Mean**	**Median**
All study sites	11141.7	11141
Atlanta GA	1026.7	1042
Boston MA	900.8	915.5
Denver CO	796.5	798.5
Houston TX	921.8	914.5
Madison WI	393.7	401
Miami FL	1236.7	1233.5
Minneapolis MN	654.5	657
Oklahoma City OK	666.7	679
Phoenix AZ	850.8	847.5
Pittsburgh PA	803.3	849.5
Portland OR	569.6	572
San Diego CA	870.2	890.5
Seattle WA	854.5	872
St. Louis MO	596.2	605.5

Figure 3.4: Mean of posting volume by day of week by site during study period

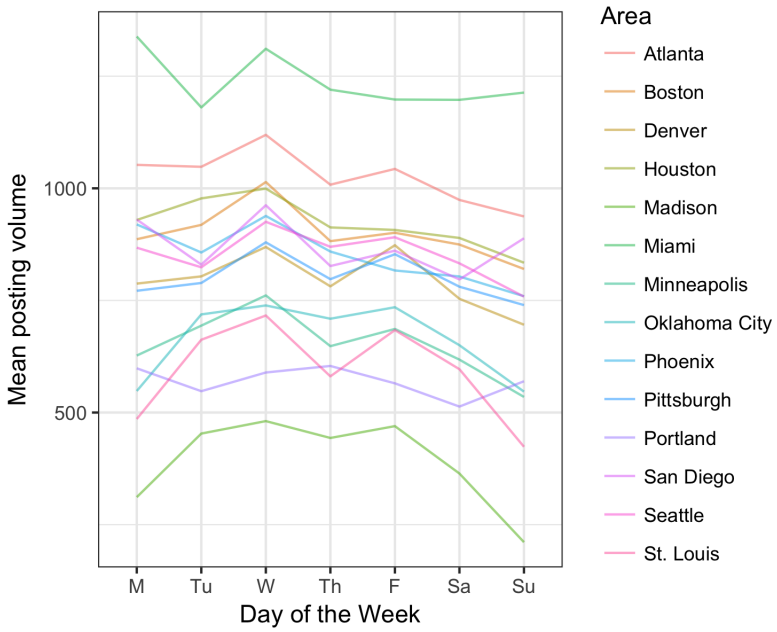
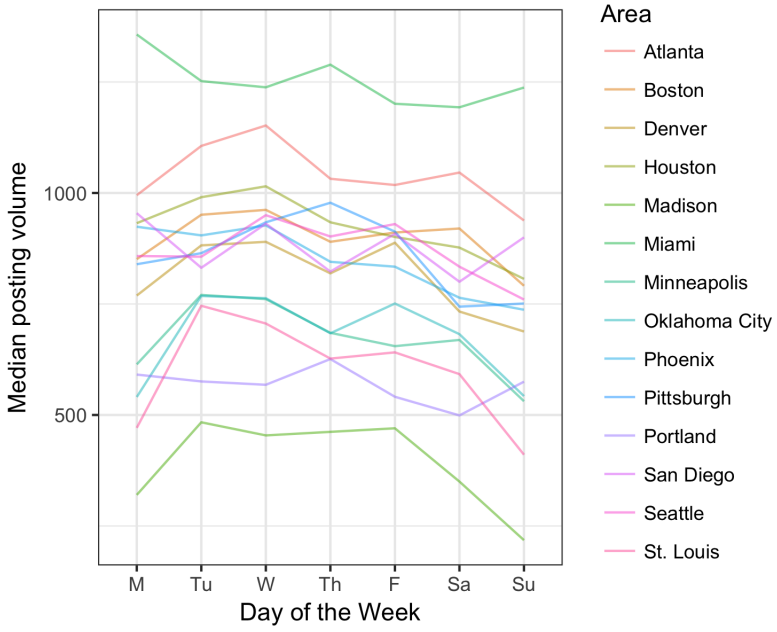


Figure 3.5: Median of posting volume by day of week by site during study period



postings cannot be de-duplicated by post ID alone. Further steps are needed to de-duplicate–I will discuss these steps in more detail in subsequent sections.

3.2.4 Eligible postings

I examined all postings to identify units that were likely eligible for HCV participation. One cannot know for certain from a posting whether a unit will meet all the criteria of the HCV program. For example, postings do not always provide enough information to assess the gross rent (utilities and asking rent) of the advertised unit making it difficult to definitively say whether the unit meets cost and size requirements. Photos and descriptions of a unit do not provide enough information to assess whether the unit will pass the safety and quality inspection required by the program. Additionally, unmentioned rental terms, such as short-term leases, could render a unit ineligible.

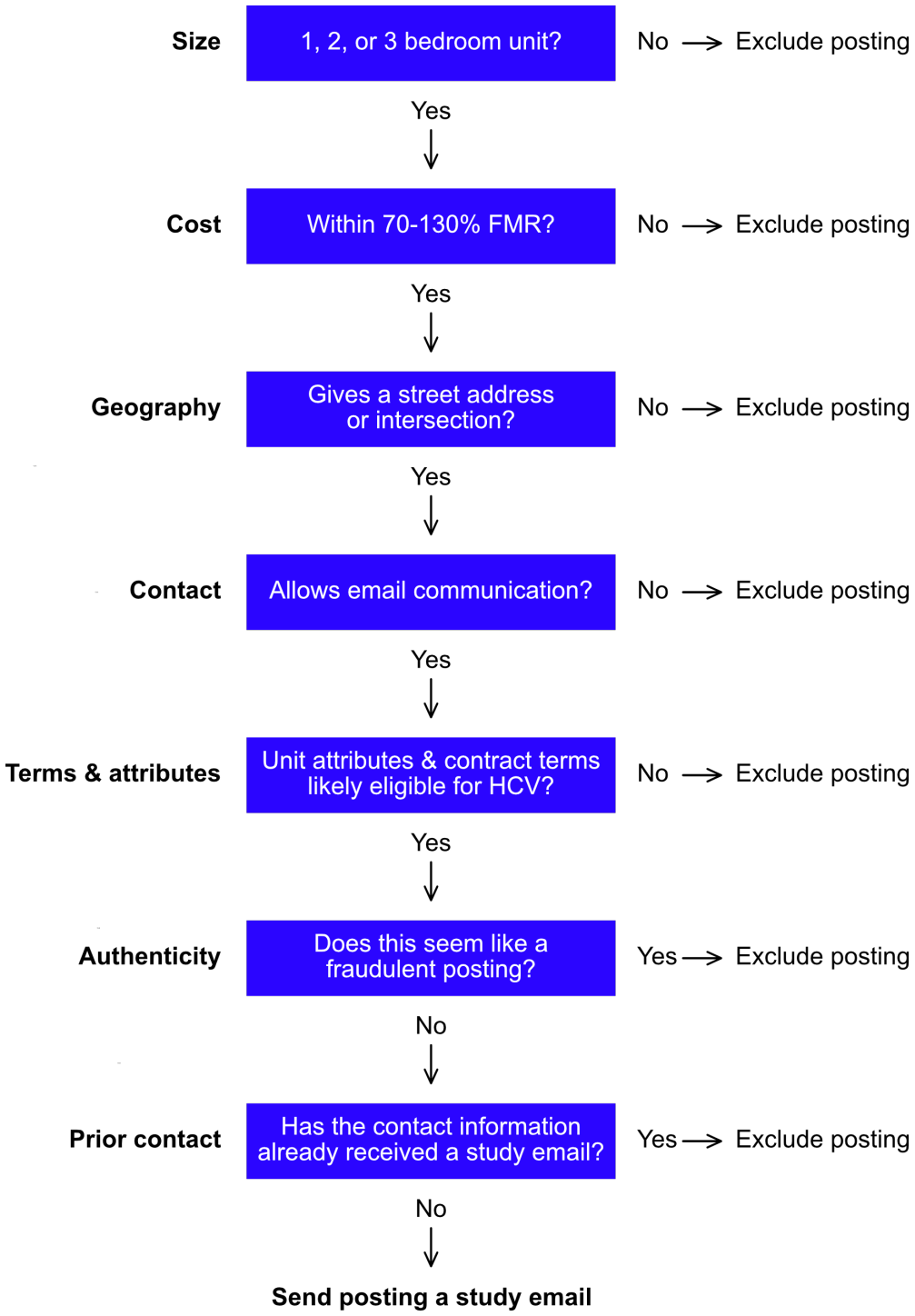
It is impossible to definitively assess the HCV eligibility of a unit based only on the information provided in a craiglist posting. However, I imposed several criteria on postings to help increase the likelihood that selected postings would be eligible. I imposed other criteria to make sure the format of the study emails to posters would not violate instructions in the posting text or be sent to repeat posters. These criteria–cost and size, geographic specificity, mode of contact, response specificity, rental unit terms and attributes, authenticity, and prior study contact (de-duplication)–are explained below. The criteria are summarized in Figure 3.6.

Cost & size

PHAs set their voucher payment standards–the maximum purchasing power of the voucher–based on the Fair Market Rents (FMRs). FMRs are gross rent[7] estimates that are published by HUD for each federal fiscal year for metropolitan and nonmetropolitian county HUD-defined FMR areas (HUD, 2007, 1). The intent behind the FMRs is to estimate the price

[7]Gross rent "include[s] the shelter rent plus the cost of all tenant-paid utilities, except telephones, cable or satellite television service, and internet service" (HUD, 2007, 1).

Figure 3.6: Eligibility criteria for each posting



of a standard mid-market unit by bedroom count. Most areas' FMRs are calculated using data on recent movers in the American Community Survey (ACS) and rent and utility data from the Consumer Price Index (CPI) data. Most FMRs are set at the 40th percentile of gross rents. A handful of areas' FMRs are set at the 50th percentile; these areas are identified by HUD as communities with a lack of units throughout the area that are at or below the 40th percentile FMR (24 CFR §888.111). Some areas' FMRs are set by local surveys. To set FMRs by local survey data, a PHA must get HUD's approval to do so (24 CFR §888.111). Lastly, a few areas have FMRs set at the zipcode-level, as opposed to metro area or county-wide standards.

The study sites' FMRs are presented in Table 3.5. A majority of the sites have 40th percentile FMRs. Denver is the only site with a 50th percentile FMR. Two sites, Portland and Seattle, have their FMRs determined by a local survey.

Most PHAs are required to set their payment standards[8] within 90-110% of the HUD FMR–known as the 'basic range' (24 CFR §982.503). For example, in Oklahoma City the FMR for a one bedroom apartment is $614. This means the Oklahoma City Housing Authority is permitted to set their one-bedroom payment standard anywhere between $553 and $675. If PHAs wish to set payment standards above or below the 90-110% FMR range, they must obtain permission from HUD.

For this study, I only include units that advertised a rent value within 70 to 130% of the HUD-published FMR of the core city. I decided not to adhere to the exact payment standards for each PHA in the study areas, meaning I did not collect each PHA's payment standards and then apply that standard if a selected unit fell into the PHA's jurisdiction.

I chose not to for several reasons. First, in some cases, HCV households may rent a unit with a gross rent above the payment standard if they are willing to pay more than 30% of their income towards rent. In most cases, tenant payments are capped at 40% of their income (24 CFR §982.508). Including units priced above the payment standard allows for

[8]Payment standards determine the overall the purchasing power of the voucher–the maximum gross rent of the unit for which the voucher can be used.

Table 3.5: Study sites' FY 2016 Fair Market Rents (FMRs)

HUD Metro FMR Area Name	**Area Type**	**FMR Type**	**1 BR**	**2 BR**	**3 BR**
Atlanta-Sandy Springs-Marietta, GA	non-CBSA	40th	$820	$949	$1,253
Boston-Cambridge-Quincy, MA-NH	non-CBSA	40th	$1,261	$1,567	$1,945
Denver-Aurora-Broomfield, CO MSA	MSA	50th	$965	$1,227	$1,788
Houston-Baytown-Sugar Land, TX	non-CBSA	40th	$773	$948	$1,291
Madison, WI	non-CBSA	40th	$780	$936	$1,294
Miami-Miami Beach-Kendall, FL	non-CBSA	40th	$975	$1,250	$1,671
Minneapolis-St. Paul-Bloomington, MN-WI	non-CBSA	40th	$813	$1,027	$1,444
Oklahoma City, OK	non-CBSA	40th	$614	$791	$1,087
Phoenix-Mesa-Glendale, AZ	MSA	40th	$735	$914	$1,332
Pittsburgh, PA	non-CBSA	40th	$657	$827	$1,026
Portland-Vancouver-Hillsboro, OR-WA	MSA	Local survey	$1,021	$1,208	$1,757
San Diego-Carlsbad-San Marcos, CA	MSA	40th	$1,153	$1,499	$2,167
Seattle-Bellevue, WA	non-CBSA	Local survey	$1,225	$1,523	$2,220
St. Louis, MO-IL	non-CBSA	40th	$645	$840	$1,109

this. Second, as mentioned before, there is not always enough information to determine the gross rent for a unit on craigslist. Strictly adhering to a local payment standard is more problematic when rent data is imprecise. It can lead to the inclusion of non-viable units with asking rents near the payment standard, yet when true utility costs are accounted for, the unit would be above the payment standard. Third, just because a unit is within the payment standard does not mean it will pass the required rent reasonableness assessment. This assessment tries to ensure that the HCV program is not paying a higher price than tenants living in similar units. Determining rent reasonableness would be difficult to do: it requires data on comparable units within the market. Fourth, I felt I would not be able to administer a study that necessitated determining each posting's accurate gross rent and precise PHA jurisdiction. There are over 130 different PHA jurisdictions represented in the study sites' craigslist data. And this study did not have additional staff to support the vetting of postings. Given the time constraints and available resources, I believed I would not be able to do this reliably.

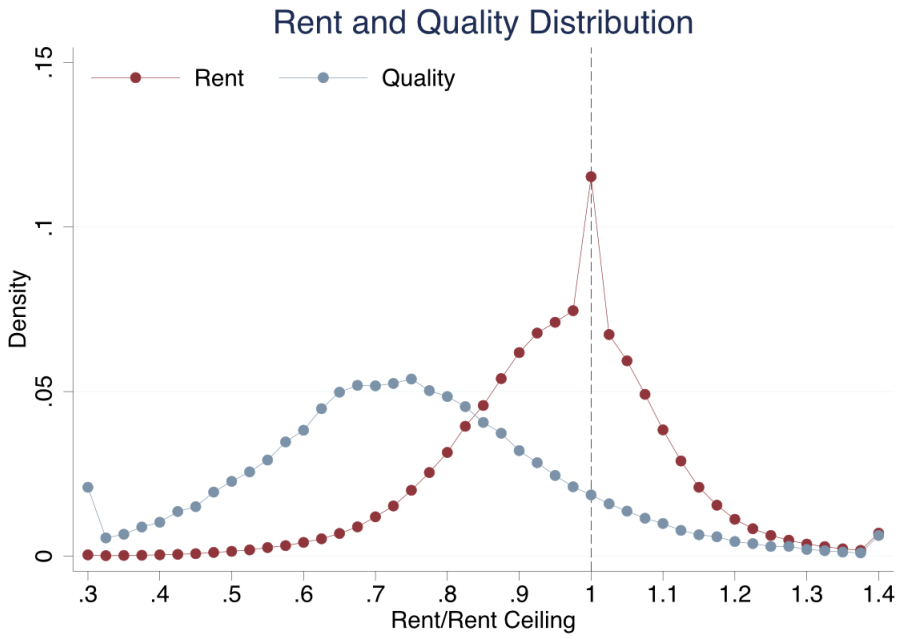
All these reasons led to the decision to focus on units that had advertised rents within a range of the core city's FMR. This means the study has included some units that would never be approved by local PHAs on terms of cost and has excluded some units that would have been approved.

I selected the 70-130% FMR range for several reasons.[9] First, I wanted to exclude units that were low quality and likely to meet the Housing Quality & Safety (HQS) standards without significant repair and renovation. I decided to use price as a proxy for quality. So, I excluded any units below 70% of FMR. This lower bound also helps filter out some fraudulent postings (which tend to have sensationally low prices) and postings for services rather than rentals (locators, home buying, credit repair, etc.). Second, I wanted to provide

[9]Presently, there is no publicly available data to determine the distribution of the actual gross rents as a percentage of FMR for local areas. One could determine area-specific distributions by making a data request to HUD or by accessing restricted-use ACS data. I did not do either of these things. Anecdotally, I had experience at a single PHA where gross rents for units leased through HCV clustered around the payment standard.

for the possibility that households would pay more than 30% of their income for rent. Lastly, I wanted to provide for the possibility that PHAs could set their rents above the 110%. Figure 3.7, taken from Collinson and Ganong (2016), shows that most units have gross rents within 70-130% of the FMR.

Figure 3.7: Distribution of HCV gross rents as a percentage of FMR from 2013 5-year ACS data: Excerpt from Collinson and Ganong (2016)



The study only included postings for units that had 1, 2, or 3 bedrooms. National data from HUD are aggregated in a manner that does not allow separation by unit size. But looking across data sources can give some sense of the distribution of households by unit size. National HUD data from 2016 HCV-leased households shows that 30% of households are in a studio or one bedroom unit, 35% are in a two bedroom unit, and 35% are in a three bedroom or larger unit (HUD, 2016b). Metro-area level estimates from this same data source

indicate that there is some variation in the exact percentages for each size classification across metro areas, but for the most part, the distribution is similar (see Table 3.6).

Finkel and Buron (2001) conducted a study that sampled PHAs and within each sampled PHA, sampled newly issued voucher households. Their data (see Table 3.7) show that only 4% of sampled households are looking for a 0 bedroom unit and only 7% of households are looking for a 4 bedroom unit. The vast majority of households are looking for 1 to 3 bedroom units.[10]

To be clear, the HUD data and the Finkel and Buron (2001) data are not directly comparable. The HUD data summarizes all leased households while the Finkel and Buron's data represents households that have just received a voucher–not all of these households end up leasing a unit with their voucher. Further, the data sources are separated by 15 years. However, it seems likely that studio units and units larger than three bedrooms play a minor role in the HCV program. Therefore, this study focused only on 1, 2, and 3 bedroom units.

If a posting was missing either price or bedroom size, I excluded it from the study because without this information it is impossible to calculate its FMR percentage.

Geographic specificity

Postings had to be specific about the location of the advertised unit. Location could be a street address, an intersection, or the name of an apartment building or complex. Pragmatically, this is a criterion that one could envision applying during an actual apartment search: it is easier to consider a unit if one knows where it is located. Further, in pre-study testing, it became apparent that postings that were vague about geography more often tended to be fraudulent, ads for services instead of rentals, or ads for apartment locators. Requiring geographic specificity simplified unit selection. This criterion means that some viable units were excluded. However, most of the time, postings excluded for lack of geographic specificity were non-viable.

[10]The data in Finkel and Buron (2001) is published as unweighted. It is unclear how weighted estimates would differ.

Table 3.6: HUD data: HCV households in 2016 by bedroom size of unit (HUD, 2016b)

Area	**% 0-1 BR**	**% 2 BR**	**% 3+ BR**
Nationally	30%	35%	35%
Atlanta GA	22%	32%	45%
Boston MA	30%	33%	38%
Denver CO	33%	35%	32%
Houston TX	25%	34%	40%
Madison WI	28%	37%	35%
Miami FL	37%	31%	32%
Minneapolis MN	33%	33%	35%
Oklahoma City OK	30%	35%	35%
Phoenix AZ	34%	27%	39%
Pittsburgh PA	36%	34%	30%
Portland OR	37%	38%	25%
San Diego CA	34%	39%	27%
Seattle WA	41%	32%	27%
St. Louis MO	23%	36%	41%

Table 3.7: Finkel and Buron (2001) data: Sample of newly-issued voucher holders in 2000

Bedroom size needed	**%**
0 bedrooms	4
1 bedrooms	21
2 bedrooms	40
3 bedrooms	29
4 bedrooms	7

Mode of contact

Testers only contacted posters through email. Posters had to provide an email address or use the craigslist relay for communication. In some cases, the poster would enable the craigslist relay, yet in the text of their posting they would ask not to be contacted by email. These types of postings were excluded when encountered.[11]

Specificity of response

Postings that required specific actions that would not be satisfied by the components of the automated tester email were excluded (the components of the tester email will be discussed in a later section). Some postings ask respondents to include specific components in their responses. For example, a posting's text might say "respond to this posting by including 'Westside duplex' as your email subject". Other postings might include a set of questions that the poster would like potential tenants to answer when responding to the ad. The study emails did not allow for customization of the email subject line or text. These types of postings were excluded when encountered.[12]

Rental unit terms & attributes

Some units were obviously ineligible for HCV when their attributes were considered. Other units had special or unique characteristics that did not unilaterally bar them from eligibility, but would require special approval from the PHA or HUD to participate in HCV. Some units required residents to have certain characteristics to lease. Any units with these terms or attributes were excluded. Further description of these instances follows.

Furnished units are technically eligible for HCV, but PHAs may partition the cost of

[11]There were some postings that prohibited email contact, yet accidentally received emails. If this happened, the posting and any response behavior were excluded from the study.

[12]Here too, some postings requiring a specific response accidentally received emails. If this happened, the posting and any response behavior were excluded from the study.

the furniture rental and require the household to pay for it. Similarly, mobile homes[13] may be eligible for HCV, but requires PHA approval (24 CFR §982.620). Further, the FMR, and consequently the resulting payment standard, that applies to mobile home rental is usually 40% of the FMR for two bedroom units (24 CFR §888.115)–which would be outside of the 70-130% FMR range. Rent-to-own and purchase postings were excluded from the study. HCV subsidy can be used for the costs of home ownership in some instances, but this requires PHA approval (24 CFR §982.625). Further, very few HCV subsidies are utilized for homeownership: in 2012, just 1,514 households closed on a home purchase utilizing HCV (HUD 2012). Due to these complexities, these units were excluded.

Some postings were for units with non-standard lease arrangements. Short-term rentals (defined as less than a year) were excluded: in general, the HCV program requires voucher holders to enter into one-year leases (24 CFR §982.309). Some postings were for sublet units: units that are leased to a person who wishes to lease the unit to another person typically for a short period. Some postings were for lease-takeovers: a unit that is leased to a person who wishes to lease the unit to another person for the remainder of the original lease. HCV requires the voucher holder to enter into their own lease with the unit owner or management. This makes subletting and lease takeovers ineligible for HCV.

Some postings were advertising the opportunity to get on a waiting list for rental units. Though there is nothing stopping an HCV household from getting on such a waitlist, outcomes tied to the admittance or non-admittance to such waitlists were not of interest to this study. These listings were excluded.

I excluded units that required residents to have specific attributes for admittance were excluded from this study. Typically, these units were in complexes operated exclusively for college students or seniors. Additionally, HCV subsidies can be used for roommate renting situations (called 'shared housing'), but this requires PHA approval (24 CFR §982.615). Though HCV can be used in these types of properties, I wished to avoid the complexity that

[13]RVs and trailers were also treated as mobile homes and were excluded from the study.

these additional criteria would impose on the perception of my testers.

Lastly, units that were tied to other sources of subsidy were excluded. Most often these properties were Low Income Housing Tax Credit (LIHTC) projects. I wanted to avoid the complexity of subsidy layering.

Authenticity

Postings that appeared to be fraudulent were excluded. The response behavior of rental scammers towards HCV households was not of interest. Fraudulent postings were identified through several actions. Many fraudulent postings had already been excluded by previous criteria, primarily specificity of geography and unit cost and size. However, some fraudulent postings met those criteria. If fraud was still suspected, I checked the posting against other listing services (e.g. Trulia, Zillow) because sometimes fraudulent postings use properties that are presently for sale. Some fraudulent postings use photos that are from a range of units, and when considered together, they do not make visual sense. Other fraudulent postings borrow pictures from larger, professional management companies, yet the accompanying text is not as professional as the photos would suggest. It was very difficult to avoid all fraudulent postings.[14]

Prior study contact

Great care was taken to avoid sending the same contact or property more than one study email. Study contacts could share membership in the same group or company, but their communications needed to appear separate. For example, one management firm operated units in multiple properties in each study jurisdiction. The study would email a posting made by this firm if the phone number, email address, and property name was new to the

[14]There were three dominant fraud campaigns I came across during the study period. In nearly every study site, these campaigns would respond to tester emails in similar ways (see Appendix FRAUD for examples of fraudulent responses). If a fraudulent posting was emailed by a tester, the response and posting data was excluded from the study.

study. If any of this information matched previously recorded data, the posting would be excluded.

De-duplication was very difficult. As mentioned before, post ID is not enough to de-duplicate posters. De-duplication was aided by recording any identifying information: phone number(s), email address (if not using the relay), company name, property name, and websites. Sometimes lengthy manual web searches were needed to clarify the ownership or management tied to a specific posting. Each post's text was assessed for text similarity with previously emailed postings. If there was a high amount of text similarity, the matching text was brought up and manually assessed to see if it was a duplicate contact or property.

The most difficult postings to de-duplicate were for posters only using the craigslist relay for communication, who did not provide any company name or phone number, the unit address did not connect to further information through manual web searches, and the post's text did not have significant text similarities with any other postings. This study will assume that these postings are generated by separate contacts at separate organizations. However, this is likely not correct for all these cases.

3.2.5 Posting selection process

As mentioned before, each day I examined the postings from the previous 24 hours to identify those eligible for inclusion. The first step in this process was to randomly sort all postings; this was done to achieve variation in response time (the time difference between the ad's posting time and a tester sending a study email). Then examination of specific postings could begin. A script automated the overall process of examining, selecting, and contacting postings. Certain aspects of contact data collection and the overall assessment of posting de-duplication and suitability were manually executed by the researcher working with the script's output.

First, the script would check the post ID to make sure the listing had not received a study email already. If the post ID was already in the study, the posting would be excluded. Next, the script would check to make sure the cost and size of the advertised unit was within

70-130% of the FMR for the jurisdiction. If the posting was still viable, then the script would bring up the web page of the posting for the researcher to inspect. The script would then display any words or phrases that appear in the text that suggest the posting might need to be excluded–like 'rent-to-own', 'over 55', 'senior community', 'mobile home', 'roommate', 'tax credit'.

The presence of any of these phrases was not enough evidence to automatically exclude a posting. Consider the word 'roommate': a posting might include the statement "This unit is great for roommates" meaning the posting is for an entire unit, not just a roommate to fill a vacant bedroom within a larger unit. Because of this type of uncertainty, the researcher ultimately decided whether to exclude the posting.

Then, the script would check for any text similarities in the title and body of the posting with postings that had previously received a study email. If any strong matches were found, the researcher would examine them. If the researcher felt the poster had already received a study email, the posting would be excluded.

Next, the researcher would collect the contact information from the posting manually by clicking required buttons on the posting's webpage and putting any available information into a form generated by the script. craigslist discourages the automatic capture of contact data, primarily by keeping such data behind a reCAPTCHA. Manually obtaining the protected contact information prevented craigslist from blocking the IP the researcher was using.

The script would examine the posting address and the contact information entered by the researcher to check one last time for duplicate contacts. If no duplicates were found, the script asked if the researcher wanted a study email to be sent to this posting. At this point, the researcher made the final determination if the posting should be included in the study. If the posting was included, the script generated a study email and sent it off, then moved onto the next posting. If the posting was excluded, the script simply moved onto the next posting.

Posting data were collected for sixty days from June 15, 2016 through July 13, 2016. At the start of the study, I aimed to contact 30 to 45 postings per day per study site. Vetting

and de-duplicating postings proved labor intensive and became more difficult overtime as more posting contacts were included in the study. I eventually reached a steady state of 6-9 postings per day per study site. A few times throughout the study, technical difficulties made identifying and contacting postings difficult. The main issues encountered were a craigslist bug for about 36 hours where price data were missing from postings, craigslist temporarily blocking my IPs, periodically requiring manual gmail login for tester email accounts, and Firefox changing from Selenium to Marionette as an automation driver.

3.3 Sending study emails

3.3.1 Tester attributes

It may be advantageous to choose the audit tester racial names to correspond to a municipality's HCV population (as represented in the HUD (2016b) data). For example, if a municipality in southern California was selected, it would make sense to include Hispanic/Latina names because PHAs in that area are more likely to serve Hispanic/Latino households. For most of the sites in Table 3.8 black/white comparisons are more salient. However, for Miami, Boston, Denver, and San Diego, black/white/hispanic comparisons would be warranted given the high percentage of Hispanic/Latina HCV households with these jurisdictions.[15]

Selected postings received an email from a tester. This study utilized thirty different tester identities. All testers were women. Women were the sole focus because a majority (79%) of HCV heads of households are women (HUD, 2016b). Gender differences in response behavior cannot be examined.

Audit testers varied in terms of race. Race was be conveyed through names, as in other audit studies.[16] Names were generated through an iterative process. Initially, a first and last name were chosen. Last names came from common surnames that appeared in the 2000

[15]Originally, I intended to make all three comparisons in Phoenix but, due to a coding error, the only testers where white and Hispanic/Latino.

[16]c.f. Bertrand and Mullainathan (2004); Carpusor and Loges (2006); Ahmed and Hammarstedt (2008); Ahmed et al. (2008, 2010); Bosch et al. (2010); Hanson et al. (2011); Hanson and Hawley (2011); Hogan and Berry (2011); Ewens et al. (2014)

Table 3.8: HUD data: HCV households in 2016 by race of household head (HUD, 2016b)

Area	**% Minority**	**%Black Non-Hispanic**	**% Hispanic**	**%White Non-Hispanic**
Nationally	69%	48%	17%	31%
Atlanta GA	96%	93%	2%	4%
Boston MA	66%	40%	22%	34%
Denver CO	65%	33%	28%	35%
Houston TX	93%	83%	9%	7%
Madison WI	59%	53%	4%	41%
Miami FL	98%	42%	56%	2%
Minneapolis MN	68%	61%	3%	32%
Oklahoma City OK	68%	60%	4%	32%
Phoenix AZ	66%	37%	26%	34%
Pittsburgh PA	58%	56%	1%	42%
Portland OR	35%	20%	8%	65%
San Diego CA	68%	22%	35%	32%
Seattle WA	51%	35%	6%	49%
St. Louis MO	80%	79%	1%	20%

Census (Word et al., 2003). First names drew on stereotypes and pop culture. Then, a first and last name pairing's racial perceptions were tested through Amazon Mechanical Turk (AMT).

AMT is an online platform to support the management of and participation in crowd-sourced projects. Individuals can submit small tasks to AMT that willing workers complete for pay. "The basic philosophy of microtasking and AMT is to delegate tasks that are difficult for computers to do to a human workforce" (Martin et al., 2014, 224). For this study, individuals responding to the testers' emails made this assessment. Therefore, it was of interest how humans assess the race of testers' names. AMT was used to pre-test human perceptions of the racial affiliation of names.

I tested names on AMT from May 11, 2016 through June 3, 2016.[17] Workers had to be located in the US and have 'Master' status.[18] Master status is a designation AMT gives to workers that have consistently and accurately carried out tasks (AMT, 2016). Requiring this status is thought to provide better results.

The evaluation of each name was contained in a single task. Workers were allowed to participate in more than one of my tasks. Across all the tasks, 357 unique workers participated. A single task asked 100 workers to select any of the following racial categories they associated with the given name: White, Black, Hispanic or Latina, and Other.[19] Workers could select anywhere from one to four categories.

The workers' results are presented in Tables A.1, A.3, and A.2. The percentages in these tables correspond to the percentage of workers that singly identified the name as being associated with the researcher-assumed racial category. For example, looking at the first row in Table A.1, 99% of workers indicated that they associated the name DeShauna Williams with being Black. First and last name pairings were generated and tested until each racial

[17] All workers were paid $0.05 for each classification. The average time to complete the classification of a name was 20.18 seconds and median time was 6 seconds. Ninety percent of workers finished the task in 29 seconds or less. The average wage was $8.92 per hour and the median wage was $30.00 per hour.

[18] An example of job specifications is presented in Figure A.1.

[19] An example of the classification question is presented in Figure A.2.

Table 3.9: Black tester names, usernames, and races

Full name	**gmail username**	**Race**
Cheranique Tankson	cheraniquetankson	Black
Damisha Edgerson	damishaedgerson	Black
DeShauna Williams	deshaunawilliams24	Black
Keisha Smalls	smallskeisha2310	Black
Lateefah Jefferson	lateefahjefferson	Black
Shardae Washington	washingtonshardae76	Black
Sheniqua Callands	sheniquacallands	Black
Tamika Odum	odumtamika	Black
Tashara Readus	tasharareadus	Black
Tyleesha Harris	tyleeshaharris	Black

category had ten names that more than 90% of workers singly identified with the racial category of interest.

To be clear, these AMT results do not guarantee that these names will always be perceived in this way. Rather, these results merely help to avoid names that are likely to be perceived in numerous ways. If a name was racially ambiguous to most people, it would be difficult to separate out discrimination effects due to race. Additionally, there is no way to assess the comparability of the demographics of the AMT workers and the craigslist posters. AMT workers may perceive the race of names differently than craigslist posters. Further, the context for where these perceptions are being made are very different: the AMT work environment is very different from the work environment for leasing agents, landlords, and property managers. Despite these weaknesses, the AMT results were a helpful aid in selecting tester names. The final names and email usernames are presented in Tables 3.9, 3.10, and 3.11.

Table 3.10: Hispanic/Latina tester names, usernames, and races

Full name	**gmail username**	**Race**
Esmeralda Renderos	esmeraldarenderos44	Hispanic/Latina
Esperanza Garcia	zaperezgarcia	Hispanic/Latina
Estefani Lopez	estefani101lopez	Hispanic/Latina
Fernanda Casarrubias	fernandacasarrubias16	Hispanic/Latina
Frida Fuentas	fridafuentas	Hispanic/Latina
Graciela Contreras	gracielacontreras974	Hispanic/Latina
Isabel Jimnez	jimenezisabel841	Hispanic/Latina
Juanita Cabreja	juanitacabreja	Hispanic/Latina
Rosa Hernandez	rosahernandez7501	Hispanic/Latina
Valentina Rodriguez	rodriguez8valentina	Hispanic/Latina

Table 3.11: White tester names, usernames, and races

Full name	**gmail username**	**Race**
Cailey Schwartz	caileyschwartz	White
Ellie Schnieder	elschnieder	White
Jodi Mueller	jomuellerdi	White
Kacie Olsen	kacieolsen88	White
Lacee Gallagher	gallagherlacee626	White
Linsey Erickson	linseyerickson98	White
Madalyn Fischer	maddiefischer1234	White
Mandi Becker	beckerdimand	White
Nicole Bauer	nicolebauer274	White
Piper Meyer	meyerpip	White

3.3.2 Email content

Previous email audits have used either of the following approaches in responding to advertisements: matched responses or randomized responses. In a matched responses approach, each landlord is sent all permutations of audit responses. This approach gives the benefit of causal comparability because each landlord is exposed to all inquiries and any differences in response behavior of a landlord can be attributed to the variation in tester correspondence. A drawback to this approach is that sending a single landlord numerous inquiries may make him/her suspicious of senders or aware of the experiment. The randomized response approach involves sending landlords a single or small number of all the possible permutations of audit responses that have been randomly selected. Landlords are less likely to become suspicious because they receive fewer study inquiries. However, more statistical controls are necessary. It also requires a larger sample size to ensure all permutations are sent to enough listings.

This study utilized a randomized response due to the two-way comparisons by HCV status and race that were central to this study. Varying across the two statuses' categories leads to six distinct combinations. For example, black-HCV is one combination, white-no HCV is another. For a matched response design, each listing would need to receive six separate inquiries. To get so many inquiries for one posting could have appeared suspicious to landlords, undermining the integrity of the experiment.

For selected postings, an email was sent that had its content randomized to achieve variation in: [1] the racial identity of the sender; [2] the HCV status of the sender; [3] prose components: greeting, closing, request to view unit. I will describe each of these aspects.

The racial identity of the sender was signaled through the signature of the email and, if not using the craigslist relay, the email address. For each selected posting, a script would randomly select the racial affiliation of the tester from available choices for the jurisdiction. Then within the selected racial group, the script would randomly select one of the ten tester names (see Tables 3.9, 3.10, and 3.11).

HCV status was conveyed through the absence or presence of a reference to HCV in the email text. For example, emails will include a sentence about HCV: "I have a housing voucher", "I have Section 8", "Do you accept Section 8?" Qualitative work with Illinois landlords indicated that most HCV households are initially concerned with whether landlords will accept HCV (Greenlee, 2014, 510). Fourteen different statements were used. Half were declarative sentences, the other half were questions. To add further variation, three different phrases were used to reference HCV: "housing voucher", "Section 8 voucher", and "Section 8". These phrases were used because the HCV program's name is not as well recognized as these phrases. In 1998, the Section 8 voucher and Section 8 certificate programs were merged and renamed the Housing Choice Voucher program. Even though this change occurred over 15 years ago, PHAs, clients, and the general public still use and recognize the name Section 8 and the more general term housing voucher.

Overall, there were 72 unique combinations of statements and HCV phrases. They are listed in Appendix B. For each selected posting, a script would randomly select whether the tester would signal HCV status or not. If the tester had been selected for HCV status, the script would randomly select one of the phrases.

The remaining prose components of the email were randomly selected from lists (see Appendix B). Again, the variety in language and punctuation were used to achieve variation in an effort to avoid detection.

Each email included the posting title as the email subject line and included the url to its related posting in the email body. I chose to include these components because it is the default when using craiglist's 'webmail links' option for gmail. This is a feature that craiglist offers that opens up an email composer for a specific email service and auto-populates the recipient email address, subject, and email body fields. From there, the email can be modified by the writer and sent to the poster.

To demonstrate how all these components come together, here is an example of an email message's text:

To: XXXXX-XXXXXXXXXX@hous.craigslist.org

From: XXXXX-XXXXXXXXXX@hous.craigslist.org

Subject: Top Floor 1 Bedroom! 1 Month Free Rent!

Hi-

I am interested in the unit advertised on craigslist. Can I see it sometime this week?

Part of my rent will come from a housing voucher.

Thanks!

Keisha Smalls

http://XXXXXXX.craigslist.org/apa/XXXXXXXXXX.html

If the posting indicated a viable contact name, that name would be utilized in the greeting. For example, it someone named Paul was the contact person, the email would reflect that:

To: XXXXX-XXXXXXXXXX@hous.craigslist.org

From: XXXXX-XXXXXXXXXX@hous.craigslist.org

Subject: Top Floor 1 Bedroom! 1 Month Free Rent!

Paul:

I am interested in the unit advertised on craigslist. Can I see it sometime this week?

Part of my rent will come from a housing voucher.

Thanks!

Keisha Smalls

http://XXXXXXX.craigslist.org/apa/XXXXXXXXXX.html

If the posting did not utilize the craigslist relay, the real email address was visible for both parties:

To: XXXXX@XXXXXXXX.com

From: smallskeisha2310@gmail.com

Subject: Top Floor 1 Bedroom! 1 Month Free Rent!

Paul:

I am interested in the unit advertised on craigslist. Can I see it sometime this week?

Part of my rent will come from a housing voucher.

Thanks!

Keisha Smalls

http://XXXXXXX.craigslist.org/apa/XXXXXXXXXX.html

For all the study emails, my goal was to communicate in basic terms–to send unremarkable emails. I was not interested in analyzing the performance of specific messaging.[20] Here, the intent was to see what kind of reception generic inquiries got.

3.4 Classifying response behavior

The presence or absence of landlord responses was recorded for up to two weeks after the study stopped sending out emails. If no emails were received in response to a tester's specific email, that was recorded as non-response. Overall, half of the tester emails received a response. Table 3.12 presents response rates by study site. Sites' rates varied between a low of 38% in Phoenix and a high of 62% in Pittsburgh.

I personally read all the email content to arrive at classification for the response behavior. Each email was read twice at separate times. Classification of response behavior was based on the first email received for each tester email.[21]

In some studies, researchers have restricted positive responses to only those that included

[20]This would be an interesting area for further research. To anyone who engages in this, I would strongly recommend examining the Gatreaux and MTO literature–particularly the operation manual (Feins et al., 1994)–as well as more modern work on present day mobility counseling programs to learn about the existing in-person strategies to help HCV households positively engage with landlords (Galvez et al., 2017).

[21]A minority of emails received more than one response. In a handful of cases, the second or third email response was used to classify behavior. These were cases where the first response or responses were vacation messages, encoding errors, or user errors (e.g., inadvertently sending a blank email that was closely followed by an email with content).

Table 3.12: Response rate by study site

Jurisdiction	#	%
Overall	2977	49.2%
Atlanta GA	177	45.2%
Boston MA	216	42.7%
Denver CO	301	50.7%
Houston TX	226	46.8%
Madison WI	199	56.9%
Miami FL	196	40.8%
Minneapolis MN	216	56.8%
Oklahoma City OK	211	54.8%
Phoenix AZ	149	38.2%
Pittsburgh PA	220	62.3%
Portland OR	213	54.2%
San Diego CA	293	51.0%
Seattle WA	183	45.8%
St. Louis MO	177	47.3%

an invitation to view the unit or confirmed that the unit is still available while continuing the discussion (Ewens et al., 2014; Phillips, 2017). I depart slightly from this approach by using a broader definition of positive response. Phillips (2017) describes a subset of responses classed as negative:

> Following Ewens et al. (2014), I also do not include disinterested landlords who provide/request more information without answering whether the apartment is available and landlords who simply state that the apartment is available and nothing else. (p. 49)

My approach differs by including these responses as positive. While reviewing the content of landlords' responses, it became clear that landlords have different preferences for the ordering of operations during pre-leasing. Some landlords wish tenants to view units before discussing the application process, detailed lease terms, or taking any personal information from prospective tenants. Other landlords want prospective tenants to communicate their personal and financial situation in an informal method, like over the phone or email, prior to filling out an application or viewing the unit–pre-screening first. It was not uncommon for landlords to request interested tenants to do a 'drive-by' of the unit and surrounding neighborhood prior to engaging with the landlord. Alternatively, some landlords want to see full application forms before making an invitation to view a unit. These preferences seemed to be randomly distributed across landlords–not varying solely by city, unit, or tester attributes.

This behavior suggests that different landlords like to screen and select tenants in different ways. This impacts the classification of response behavior. For example, consider a tester email that includes the question of whether the tester can come view the unit. A landlord responds with the following text: "Thanks for your interest in the apartment. How many people will be living in the apartment with you?" The landlord did not extend an invitation to view the unit, but she did not outright reject the prospective tenant either. She did ask a pre-screening question related to occupancy–a common practice. For Phillips and Ewens et al., this response would be negative. For this study, responses such as these are

classified as positive. Additionally, some landlords write lengthy responses others are very brief. Briefness could be interpreted as disinterest, but it could also be a preference for informal, quick communication. I think there is too little information in the text of emails to ascertain disinterest when the text is nominally positive.

Due to the variation in landlord preferences in tenant selection processes and communication styles, the question I used to guide my classification decision was, "**Is the pre-leasing process for this tester for this unit going to continue based on the content of this response?**". If the process would continue, the response was classified as positive. If the pre-leasing process stopped based on the content of the response, the response was classified as negative. This is an optimistic approach. If responses are nominally positive–if on their face they do not present an insuperable obstacle for the tester–they are considered positive. This approach avoids interpreting the subtext of responses.

To demonstrate how classification worked in application, I will present some examples of actual tester email text and the response text and how they are classified by this study.[22] Examples are shown for testers with and without a voucher.

Example 1 Positive response: setting up time for viewing

> ***Tester***: Hi- I am inquiring about the apartment you advertised on craigslist. May I see this unit? Thanks so much!
>
> ***Landlord***: Certainly. When are you available?
>
> ***Interpretation***: Positive. Clearly intends to show unit to tester–the pre-leasing process would continue.

Example 2 Positive response: continued communication

> ***Tester***: Hi, I am interested in this apartment. Can I see it this week? Thanks for your time,
>
> ***Landlord***: Can you call or text me Thanks!

[22] Any identifying information has been removed from text examples. Original text spacing is not preserved.

Interpretation: Positive. Though the response does not contain an invitation to view the unit, it does contain an invitation to communicate further by phone or text–the pre-leasing process would continue.

Example 3 Positive response: delay in viewing

Tester: Hi, I am inquiring about the apartment advertised on craigslist. Can I see it sometime this week? Thanks,

Landlord: Its not open to view yet as its available sept 1 though u may view the video links in the ad

Interpretation: Positive. Not open to viewing yet, but will be in future–the pre-leasing process would continue.

Example 4 Positive response: short, but positive

Tester: I am writing about the unit you advertised. May I see it this week? Thanks so much!

Landlord: Yes

Interpretation: Positive. This landlord is not providing any additional information, but he responds positively–the pre-leasing process would continue.

Example 5 Negative response: rental activity

Tester: Hi, I am inquiring about this apartment. May I see this apartment? Regards,

Landlord: Thanks for your interest. I just accepted a deposit.

Interpretation: Negative. The landlord says that she has accepted a deposit suggesting that she has a likely tenant already. In related scenarios, if landlords talked about having too many showings booked or applications accepted already, I classified that as negative–the apartment was likely to be unavailable to the tester.

Example 6 Positive response: accepts voucher

Tester: Hello, I am interested in the unit you advertised. Can I see it this week? Can

you accept Section 8? Thank you!

Landlord: Yes do we accept section 8, we were actually going to rent with a section 8 tenant but it fell through. That being said we have already had the inspection done with their office and all paperwork in with them.

Interpretation: Positive. The landlord clearly accepts the voucher–the pre-leasing process would continue.

Example 7 Positive response: accepts voucher

Tester: Hello, I am inquiring about the unit you advertised. May I see this apartment? Part of my rent will come from Section 8. Thank you,

Landlord: Of course, what is your availability over the next few days to tour? Also, how many people would be moving in? The reason I ask is that I need to find out what the maximum occupancy for this unit is per [the city] occupancy permit dept.

Interpretation: Positive. The landlord clearly accepts the voucher–the pre-leasing process would continue.

Example 8 Negative response: rejects voucher

Tester: Hi- I am interested in the unit advertised. Can I see this apartment sometime this week? May I use a housing voucher? Best regards,

Landlord: Hi, It is a house, not an apartment, and I have no vouchers. Thanks for your interest.

Interpretation: Negative. The landlord rejects the voucher– the pre-leasing process stops.

Example 9 Negative response: rejects voucher

Tester: I am inquiring about the unit you advertised. When may I see it? Can I use a Section 8 voucher here? Thanks for your time, Tamika Odum

Landlord: sorry no section 8

Interpretation: Negative. The landlord rejects the voucher– the pre-leasing process

stops.

Example 10 Positive response: short, but positive

Tester: Hi, I am inquiring about the unit you advertised. Is this apartment still vacant? I will use a Section 8 voucher. Thanks for your consideration!

Landlord: Yes

Interpretation: Positive. This landlord is not providing any additional information, but does not outright reject the voucher, and she her response in nominally positive–the pre-leasing process would continue.

Example 11 Negative response: will take you, but not your voucher

Tester: Hi: I am writing about the apartment you advertised. May I see this apartment? Do you accept Section 8? Thank you for your time,

Landlord: we do not take sec 8 any more. But if you do have income that may qualify you with in reaching 2.5 a month you can apply with out it. :-)

Interpretation: Negative. This landlord rejects the voucher.

Example 12 Negative response: steering to different properties

Tester: I am interested in the unit you advertised. Is this apartment still available? Can you accept a Section 8 voucher? Cheers,

Landlord: Good morning, XXX is pleased that you have chosen us for your possible future home. The three bedroom duplex at XXXX is still available. Rent is $1350 plus electric. Any photos we have would be on our website at XXX. If you would like to set up an appointment to view any of the communities, I would be more than happy to set that up for you. We schedule tours every day between 10:00 AM and 6:00 PM. We just need to provide our current residents with a 24 hour notice of entry. We don't accept Section 8 vouchers at this property, but if you are willing to move to XXXXX, you could call our on-site caretaker XXX at XXX-XXX-XXX and ask about the availability at the XXXXXX apartments. She would be able to answer any questions you have an

set up a showing. I am more than happy to assist you with any questions you may have. We look forward to helping you find your new home!

Interpretation: Negative. The voucher is rejected for the unit at the property that the tester emailed about–the pre-leasing process for this particular unit would not continue. The respondent does indicate that the company has a different property that would take a voucher, but that is not the unit the tester emailed about.

Example 13 Positive response: unsure of or unfamiliar with HCV

Tester: Hello - I am writing about the unit you advertised on craigslist. Is this apartment still available? May I use a housing voucher? Look forward to hearing from you,

Landlord: Yes it is. I'm not familiar with a housing voucher, can you explain what this is? Thanks

Interpretation: Positive. The landlord does not know about HCV. The pre-leasing process could continue with the prospective tenant writing back to explain the voucher. At that point, it is absolutely possible that the landlord might reject the voucher, however extended interactions with landlords was not part of this study. So, for this initial interaction, the response is positive.

Response classification by study site is presented in Table 3.13. Like overall response rate, sites vary by response type classification. The negative response rate varies from 6% in Boston up to 23% in Minneapolis. The positive response rate varies from 27.2% in Phoenix up to 47% in Portland.

Table 3.13: Response classification by study site

Jurisdiction	**No response**	**Negative**	**Positive**
Overall	50.8%	13.7%	35.5%
Atlanta GA	54.8%	14.8%	30.4%
Boston MA	57.3%	6.1%	36.6%
Denver CO	49.3%	16.0%	34.7%
Houston TX	53.2%	14.9%	31.9%
Madison WI	43.1%	10.6%	46.3%
Miami FL	59.2%	12.1%	28.8%
Minneapolis MN	43.2%	23.4%	33.4%
Oklahoma City OK	45.2%	19.2%	35.6%
Phoenix AZ	61.8%	11.0%	27.2%
Pittsburgh PA	37.7%	19.3%	43.1%
Portland OR	45.8%	7.6%	46.6%
San Diego CA	49.0%	14.6%	36.4%
Seattle WA	54.3%	9.5%	36.3%
St. Louis MO	52.7%	14.2%	33.2%

Chapter 4

DATA

This chapter provides a description of all the data elements used in the study's analyses. This study includes data about rental unit postings, tester-email attributes, neighborhood characteristics. I will describe each source and any independent variables associated with each source. These variables serve as statistical controls for unit, SOI law, neighborhood, and study site characteristics in regression models in Chapter 5 that isolate the effects of race and HCV status on landlord response behavior. Finally, I will show descriptive statistics to assess the causal comparability of HCV status groups.

4.1 Variables

4.1.1 Posting data

Posting data were collected during the study period. Once posting data were cleaned and any ineligible postings (see Section 3.2.4) were excluded, 6,054 postings are included in the final sample. Variables from the posting data were either scraped from craigslist posts' HTML or gathered manually from web search results. Posting data variables represent rental unit characteristics and control for the study site in regression analyses.

Jurisdiction

The jurisdiction for each posting was recorded. The counts of postings by jurisdiction are presented in Table 4.1. Jurisdictions where three racial comparisons (see Section 3.3.1) were being made were sent more emails than jurisdictions where only two comparisons were made. Jurisdiction fixed effects appear in regressions analyses to control for study site specific variation.

Table 4.1: Study sites by number of tester emails sent

Study site	#
Atlanta GA	392
Boston MA	506
Denver CO	594
Houston TX	483
Madison WI	350
Miami FL	480
Minneapolis MN	380
Oklahoma City OK	385
Phoenix AZ	390
Pittsburgh PA	353
Portland OR	393
San Diego CA	574
Seattle WA	400
St. Louis MO	374

Table 4.2: Study postings' unit size percentages

Study site	**1 Bedroom**	**2 Bedrooms**	**3 Bedrooms**
Overall	29.8%	43.1%	27.1%
Atlanta GA	29.8%	39.5%	30.6%
Boston MA	26.1%	50.6%	23.3%
Denver CO	32.2%	40.1%	27.8%
Houston TX	44.7%	30.4%	24.8%
Madison WI	26.0%	48.9%	25.1%
Miami FL	24.6%	47.7%	27.7%
Minneapolis MN	29.5%	42.4%	28.2%
Oklahoma City OK	23.4%	34.0%	42.6%
Phoenix AZ	29.5%	43.1%	27.4%
Pittsburgh PA	37.7%	42.8%	19.5%
Portland OR	26.2%	43.8%	30.0%
San Diego CA	24.0%	46.7%	29.3%
Seattle WA	32.0%	45.3%	22.8%
St. Louis MO	32.4%	48.9%	18.7%

Bedroom count

The study only contacted postings advertising one to three bedroom units. The percentages of unit size by bedroom count is presented in Table 4.2. Overall, 30% of postings were for one bedroom units, 43% for two bedroom, and 27% for three bedroom. No quotas were placed on the number of postings by unit size leading to different distributions of unit sizes across jurisdictions. This categorical variable represents unit size in regression analyses.

Table 4.3: Distribution of advertised rents for selected units

Study site	**Min**	**25% Q**	**Median**	**75% Q**	**Max**	**Mean**
Overall	$450	$890	$1,185	$1,500	$2,850	$1,240
Atlanta GA	$579	$830	$972	$1,146	$1,615	$997
Boston MA	$675	$1,450	$1,725	$1,950	$2,505	$1,701
Denver CO	$740	$1,100	$1,350	$1,583	$2,320	$1,392
Houston TX	$550	$813	$940	$1,133	$1,678	$1,000
Madison WI	$550	$810	$943	$1,195	$1,660	$1,019
Miami FL	$725	$1,200	$1,375	$1,600	$2,150	$1,408
Minneapolis MN	$600	$900	$1,075	$1,298	$1,875	$1,129
Oklahoma City OK	$450	$650	$810	$1,000	$1,400	$855
Phoenix AZ	$515	$777	$923	$1,130	$1,800	$984
Pittsburgh PA	$475	$650	$775	$900	$1,300	$799
Portland OR	$759	$1,115	$1,299	$1,550	$2,250	$1,372
San Diego CA	$850	$1,400	$1,695	$1,947	$2,805	$1,754
Seattle WA	$860	$1,300	$1,523	$1,838	$2,850	$1,605
St. Louis MO	$465	$650	$775	$900	$1,400	$804

Advertised price

The advertised price from each posting was collected (see Table 4.3). Using the price, bedroom, and study site data, each posting's price as a percentage of FMR was calculated (see Table 4.4). The FMR percentage is a useful measure because it takes all units regardless of size and location into the same scale. This scale has administrative salience because it plays a role in setting the purchasing power of vouchers (see Section 3.2.4). The FMR percentage represents price in regression analyses.

Table 4.4: Distribution of FMR percentages for selected units

Study site	**Min**	**25% Q**	**Median**	**75% Q**	**Max**	**Mean**
Overall	70.0%	92.0%	104.7%	116.9%	130.0%	103.9%
Atlanta GA	70.1%	87.4%	99.6%	111.9%	130.0%	99.8%
Boston MA	70.2%	95.7%	111.7%	121.3%	129.9%	108.0%
Denver CO	71.3%	98.4%	109.1%	119.0%	130.0%	107.6%
Houston TX	71.2%	92.4%	105.2%	116.5%	130.0%	104.7%
Madison WI	70.5%	90.8%	101.8%	115.9%	129.5%	103.0%
Miami FL	70.0%	99.7%	110.3%	120.0%	129.2%	108.7%
Minneapolis MN	70.2%	93.5%	105.2%	116.8%	129.8%	104.6%
Oklahoma City OK	70.8%	83.3%	95.3%	110.4%	129.6%	97.3%
Phoenix AZ	70.0%	88.6%	101.2%	112.6%	129.9%	100.7%
Pittsburgh PA	70.1%	84.6%	98.9%	113.4%	129.4%	99.7%
Portland OR	70.4%	95.2%	103.5%	115.5%	129.8%	104.2%
San Diego CA	71.7%	99.7%	110.8%	120.1%	129.9%	109.3%
Seattle WA	70.2%	89.6%	101.2%	117.1%	130.0%	101.7%
St. Louis MO	70.8%	83.3%	96.5%	108.5%	129.8%	97.1%

Management type

The final unit characteristic represented in analyses pertains to the type of ownership or management connected to the advertised unit. For each posting, I collected any available information on the person or company that was associated with the unit. This information was collecting through manual web searches for most postings. It is not guaranteed that posting information will provide enough detail to ascertain the ownership or management of a particular unit. In general, larger firms with multiple buildings have a more overt, professionalized marketing strategy in both craigslist postings and on the internet. This makes them easy to identify. Landlords with a small number of units are less likely to expend effort in establishing branding and marketing for their rental business. For landlords such as these, the task is to identify an absence of a web presence which is a less certain, more laborious task.

It is difficult to know for certain the extent of the inventory and functional area of service for landlords with no web presence. It is much easier to assess the inventory of large management firms. For example, consider Drucker & Falk Real Estate, a firm that was *not* contacted by the study, but is similar to many of the large firms that were contacted. Drucker & Falk maintains a website[1], that includes a listing of the specific properties in their multi-state inventory. Given the presence of more data on firms such as this, I created a binary variable to distinguish between postings associated with a firm that had properties in more than one state. The distribution of this variable is presented in Table 4.5. There is lots of variation across study sites in this measure. Pittsburgh and Madison have the least with just 2-4% of contacted postings being connected to multi-state firms. Portland, Phoenix, and Atlanta have the largest share of multi-state posters (42-57%).

To be clear, this is a crude measure to classify management or ownership. Ideally, I would have information about the size and geographic extent of the rental business attached to each poster. This information does not exist for all posters. This multi-state measure

[1] http://dfapartments.com/

Table 4.5: Percentage of selected postings associated with company with multi-state inventory

Study site	**Multi-state**
Overall	24.8%
Atlanta GA	56.6%
Boston MA	14.2%
Denver CO	29.0%
Houston TX	35.2%
Madison WI	4.0%
Miami FL	16.7%
Minneapolis MN	12.6%
Oklahoma City OK	20.5%
Phoenix AZ	46.4%
Pittsburgh PA	2.5%
Portland OR	42.2%
San Diego CA	13.6%
Seattle WA	37.5%
St. Louis MO	16.6%

is an attempt to see if there are differences in response behavior between larger firms and smaller firms or individual landlords.

4.1.2 Tester-email attributes

Listing response time

The response time–the time between the posting's date and time and when a study email was sent–was calculated for each posting (see Table 4.6). All time stamps were converted

Table 4.6: Distribution of tester email response time for selected units (in hours, all times converted to PDT)

Study site	**Min**	**25% Q**	**Median**	**75% Q**	**Max**	**Mean**
Overall	0.1	15.4	22.9	27.8	56.4	21.9
Atlanta GA	0.4	12.4	22.7	28.0	47.9	21.0
Boston MA	0.1	14.6	23.2	28.8	51.4	22.4
Denver CO	0.1	14.7	22.3	27.5	49.1	21.2
Houston TX	0.3	17.3	25.7	32.4	56.4	25.4
Madison WI	0.4	18.1	26.0	31.3	53.5	24.7
Miami FL	0.3	15.4	23.9	30.1	50.7	23.6
Minneapolis MN	0.9	13.3	22.4	27.1	48.4	20.3
Oklahoma City OK	0.4	16.0	23.2	27.7	48.0	21.9
Phoenix AZ	0.3	17.6	22.1	26.8	51.1	21.5
Pittsburgh PA	0.6	12.0	21.8	27.0	53.8	20.6
Portland OR	0.3	18.7	23.4	27.0	45.8	22.2
San Diego CA	0.1	17.1	22.7	27.0	51.0	21.7
Seattle WA	0.1	15.2	20.6	24.9	49.0	20.0
St. Louis MO	0.1	11.5	21.5	26.3	48.7	19.9

to Pacific Daylight Time. The overall median response time was 23 hours from posting. An overwhelming majority of emails were sent within 48 hours of the posting time (99.5%). The small number of postings that were sent after 48 hours of posting time occurred during periods were technical difficulties hampered audit operations.

Figure 4.1: Study response time to selected postings

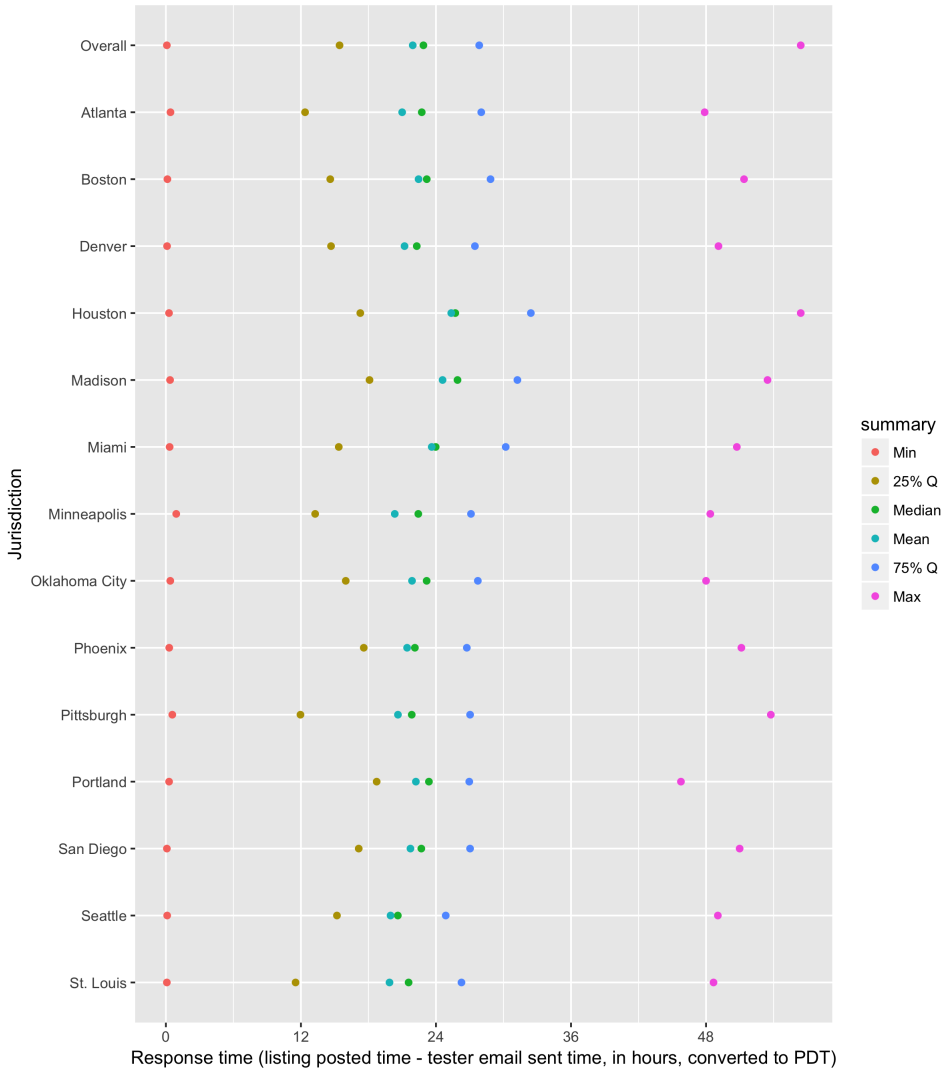


Table 4.7: Percentages of tester race for emails sent to selected units

Study site	**Black**	**Hispanic**	**White**
Overall	39.5%	17.3%	43.2%
Atlanta GA	51.3%		48.7%
Boston MA	35.2%	31.0%	33.8%
Denver CO	33.0%	33.3%	33.7%
Houston TX	33.5%	32.3%	34.2%
Madison WI	50.3%		49.7%
Miami FL	34.2%	32.5%	33.3%
Minneapolis MN	47.6%		52.4%
Oklahoma City OK	54.3%		45.7%
Phoenix AZ		49.0%	51.0%
Pittsburgh PA	51.6%		48.4%
Portland OR	45.8%		54.2%
San Diego CA	33.3%	32.8%	34.0%
Seattle WA	50.5%		49.5%
St. Louis MO	44.9%		55.1%

Race

Tester race was randomly assigned for each study email according to the racial comparisons that were relevant for each study site. The percentages of emails sent for each racial affiliation are presented in Table 4.7.

HCV status

HCV status was randomly assigned to each study email. The percentages of HCV status are presented in Table 4.8.

Table 4.8: Percentages of tester HCV status for emails sent to selected units

Study site	**Without HCV**	**With HCV**
Overall	49.4%	50.6%
Atlanta GA	52.8%	47.2%
Boston MA	48.0%	52.0%
Denver CO	48.7%	51.3%
Houston TX	46.4%	53.6%
Madison WI	47.1%	52.9%
Miami FL	49.6%	50.4%
Minneapolis MN	50.5%	49.5%
Oklahoma City OK	50.1%	49.9%
Phoenix AZ	49.0%	51.0%
Pittsburgh PA	49.9%	50.1%
Portland OR	51.1%	48.9%
San Diego CA	52.8%	47.2%
Seattle WA	47.5%	52.5%
St. Louis MO	47.9%	52.1%

4.1.3 Neighborhood characteristics

SOI coverage

SOI coverage was determined by the location of the unit. Based on address, each unit was assessed to whether it was located in any type of jurisdiction that had an SOI law in place during the study. Table 4.9 shows the overall and study site specific percentages of units with SOI coverage. Hypothetically, each unit can have no coverage or coverage at one or more political levels: city, county, and state. The 'Any Coverage' column corresponds to the percentage of units that have SOI coverage for at least one of the political levels. The cumulative sum of the 'City', 'County', and 'State' columns will not necessarily sum to the 'Any Coverage' percentage. However, the 'Any Coverage' percentage and 'None' will sum to 100%.

SOI coverage varies considerably by study site. That is expected because sites were selected based on their SOI coverage. Six study sites have no SOI coverage for any units (Atlanta, Denver, Houston, Minneapolis, Phoenix, and San Diego). Oklahoma City is the only site has all units covered–the result of both a state law and the greater municipal area being contained entirely within Oklahoma. Three sites have over 85% of units covered (Boston, Miami, and Portland). The remain four study sites have coverage percentages ranging from 37-56%.

It is likely that SOI coverage is overstated in covered areas. If the SOI laws make exceptions for particular types of ownership configurations (e.g., landlords with a small number of units or mother-in-law units), this measure will incorrectly assign SOI coverage. It was deemed too difficult to positively ascertain the ownership configuration for all postings, particularly for small landlords. While the particular unit may not be subject to SOI protections, what is true is that the unit is located in a political environment where protections for HCV have been passed.

Table 4.9: Percentages of SOI coverage for selected units

Study site	**City**	**County**	**State**	**Any Coverage**	**None**
Overall	15.0%	7.7%	19.8%	37.2%	62.8%
Atlanta GA	0.0%	0.0%	0.0%	0.0%	100.0%
Boston MA	19.8%	0.0%	98.6%	98.6%	1.4%
Denver CO	0.0%	0.0%	0.0%	0.0%	100.0%
Houston TX	0.0%	0.0%	0.0%	0.0%	100.0%
Madison WI	60.6%	87.7%	0.0%	88.0%	12.0%
Miami FL	0.0%	30.2%	0.0%	30.2%	69.8%
Minneapolis MN	0.0%	0.0%	0.0%	0.0%	100.0%
Oklahoma City OK	0.0%	0.0%	100.0%	100.0%	0.0%
Phoenix AZ	0.0%	0.0%	0.0%	0.0%	100.0%
Pittsburgh PA	56.1%	0.0%	0.0%	56.1%	43.9%
Portland OR	16.8%	0.0%	80.7%	97.5%	2.5%
San Diego CA	0.0%	0.0%	0.0%	0.0%	100.0%
Seattle WA	36.8%	3.3%	0.0%	37.5%	62.5%
St. Louis MO	49.2%	0.0%	0.0%	49.2%	50.8%

Table 4.10: Tract-level individual poverty rates for selected units (ACS 2015 5yr estimates)

Study site	**Min**	**25% Q**	**Median**	**75% Q**	**Max**	**Mean**
Overall	0.0%	8.2%	14.0%	22.5%	83.2%	16.7%
Atlanta GA	1.7%	11.7%	19.6%	29.4%	56.0%	20.6%
Boston MA	0.0%	5.5%	9.7%	17.0%	67.3%	12.8%
Denver CO	0.0%	7.3%	13.5%	20.8%	61.2%	15.0%
Houston TX	0.6%	9.1%	15.9%	24.8%	56.0%	17.7%
Madison WI	1.3%	6.7%	13.1%	21.3%	83.2%	16.7%
Miami FL	1.4%	10.7%	16.0%	24.0%	54.3%	18.4%
Minneapolis MN	0.6%	6.8%	11.2%	20.7%	74.2%	16.3%
Oklahoma City OK	0.5%	8.6%	15.7%	24.2%	56.1%	17.5%
Phoenix AZ	1.1%	9.3%	16.9%	29.8%	73.0%	20.8%
Pittsburgh PA	1.0%	8.2%	13.0%	22.4%	76.0%	16.9%
Portland OR	1.0%	8.1%	14.4%	19.7%	45.1%	15.6%
San Diego CA	1.2%	10.0%	14.8%	20.4%	52.6%	17.1%
Seattle WA	0.7%	6.4%	10.4%	16.5%	56.4%	12.9%
St. Louis MO	1.6%	8.7%	13.7%	24.1%	55.9%	17.2%

Poverty rate

The individual poverty rate, measured at the tract-level, is included in models to provide a measure of neighborhood quality.[2] The summary statistics for poverty rate by study site is presented in Table 4.10.

[2]Census 2015 ACS 5-year field name: DP03_0128PE

Table 4.11: Tract-level percentage of white-only residents for selected units (ACS 2015 5yr estimates)

Study site	**Min**	**25% Q**	**Median**	**75% Q**	**Max**	**Mean**
Overall	0.0%	8.2%	14.0%	22.5%	83.2%	16.7%
Atlanta GA	1.7%	11.7%	19.6%	29.4%	56.0%	20.6%
Boston MA	0.0%	5.5%	9.8%	17.0%	67.3%	12.8%
Denver CO	0.0%	7.3%	13.5%	20.8%	61.2%	15.0%
Houston TX	0.6%	9.1%	15.9%	24.8%	56.0%	17.7%
Madison WI	1.3%	6.7%	13.1%	21.3%	83.2%	16.8%
Miami FL	1.4%	10.7%	16.0%	24.0%	54.3%	18.4%
Minneapolis MN	0.6%	6.8%	11.2%	20.7%	74.2%	16.3%
Oklahoma City OK	0.5%	8.6%	15.7%	24.2%	56.1%	17.5%
Phoenix AZ	1.1%	9.3%	16.9%	29.8%	73.0%	20.8%
Pittsburgh PA	1.0%	8.2%	13.0%	22.4%	76.0%	16.9%
Portland OR	1.0%	8.1%	14.4%	19.7%	45.1%	15.6%
San Diego CA	1.2%	10.0%	14.8%	20.4%	52.6%	17.1%
Seattle WA	0.7%	6.4%	10.4%	16.5%	56.4%	12.9%
St. Louis MO	1.6%	8.6%	13.7%	24.1%	55.9%	17.2%

Percent white

The percentage of residents that are white-only and not Hispanic or Latino/a, measured at the tract level, is included in models to provide a measure of neighborhood integration.[3] The summary statistics for percentage of white residents by study site is presented in Table 4.11.

[3]Census 2015 ACS 5-year field name: DP05_0072PE

Vacancy rate

The rental vacancy rate, measured at the tract level, is included in models to provide a measure of rental market tightness.[4] The vacancy rate is the number of vacant, available rental units divided by the number of all rental units, both occupied and vacant. Lower values indicate low numbers indicate tighter rental market conditions, fewer options for searchers, with higher values indicating looser conditions, more options for searchers. The summary statistics for vacancy rate by study site is presented in Table 4.12.

Median rent

The median rent[5] in a selected unit's census tract is included in models to account for different price levels in rental sub-markets. Summary statistics for median rent are presented in Table 4.13.

Voucher count percentage

The concentration of voucher holders, again, measured at the tract-level, was included in models. This measure was calculated by the number of vouchers in use in a given census tract[6] divided by the total number of housing units[7]. Higher percentages mean more of the housing units are rented by voucher holders. Summary statistics on concentrations of voucher holders are presented in Table 4.14.

4.2 Comparability of groups

Study emails were randomized for HCV status. Each email, regardless of study site or any unit or neighborhood characteristics, had a 50% chance being assigned HCV status. Given

[4]Census 2015 ACS 5-year field name: DP04_0005E

[5]Census 2015 ACS 5-year field name: DP04_0134E

[6]From HUD (2016b)

[7]Census 2015 ACS 5-year field name: DP04_0001E

Table 4.12: Tract-level rental vacancy rates for selected units (ACS 2015 5yr estimates)

Study site	**Min**	**25% Q**	**Median**	**75% Q**	**Max**	**Mean**
Overall	0.0%	0.0%	4.4%	8.6%	60.4%	5.6%
Atlanta GA	0.0%	3.6%	8.2%	12.3%	30.1%	8.8%
Boston MA	0.0%	0.0%	3.1%	5.9%	21.4%	3.9%
Denver CO	0.0%	0.0%	3.5%	5.9%	15.7%	3.9%
Houston TX	0.0%	3.7%	7.8%	12.6%	60.4%	8.8%
Madison WI	0.0%	0.0%	0.9%	3.2%	28.9%	2.5%
Miami FL	0.0%	3.8%	7.1%	11.0%	46.4%	7.9%
Minneapolis MN	0.0%	0.0%	2.7%	4.9%	23.0%	3.4%
Oklahoma City OK	0.0%	3.1%	7.4%	11.1%	25.8%	7.7%
Phoenix AZ	0.0%	4.9%	9.2%	13.0%	43.0%	9.6%
Pittsburgh PA	0.0%	0.0%	4.0%	7.1%	18.8%	4.6%
Portland OR	0.0%	0.0%	2.1%	5.2%	17.4%	3.2%
San Diego CA	0.0%	0.0%	3.3%	5.5%	19.7%	3.7%
Seattle WA	0.0%	0.0%	3.1%	6.2%	22.6%	3.8%
St. Louis MO	0.0%	2.6%	7.2%	11.0%	44.9%	7.4%

Table 4.13: Tract-level median rent for selected units in $1000s (ACS 2015 5yr estimates)

Jurisdiction	**Min**	**25% Q**	**Median**	**75% Q**	**Max**	**Mean**
Overall	0.275	0.844	0.995	1.1945	2.668	1.049
Atlanta GA	0.588	0.873	0.957	1.074	2.154	0.980
Boston MA	0.358	1.054	1.209	1.392	2.231	1.229
Denver CO	0.353	0.865	1.002	1.191	2.065	1.060
Houston TX	0.584	0.825	0.937	1.113	2.071	0.999
Madison WI	0.586	0.819	0.870	0.957	1.598	0.899
Miami FL	0.275	1.005	1.142	1.345	2.574	1.201
Minneapolis MN	0.415	0.813	0.920	1.046	1.873	0.949
Oklahoma City OK	0.482	0.711	0.818	0.944	1.718	0.858
Phoenix AZ	0.556	0.779	0.928	1.095	2.668	0.973
Pittsburgh PA	0.345	0.659	0.757	0.885	1.459	0.776
Portland OR	0.709	0.916	1.018	1.111	2.005	1.043
San Diego CA	0.849	1.135	1.311	1.510	2.371	1.366
Seattle WA	0.691	1.045	1.175	1.371	2.311	1.219
St. Louis MO	0.314	0.737	0.820	0.957	1.678	0.848

Table 4.14: Tract-level percentage of voucher units for selected units (HUD (2016b) & ACS 2015 5yr estimates)

Study site	**Min**	**25% Q**	**Median**	**75% Q**	**Max**	**Mean**
Overall	0.0%	0.3%	1.3%	3.2%	34.8%	2.4%
Atlanta GA	0.0%	0.2%	0.8%	2.4%	34.8%	2.1%
Boston MA	0.0%	1.2%	2.6%	5.1%	23.2%	3.9%
Denver CO	0.0%	0.4%	1.2%	3.0%	11.5%	2.1%
Houston TX	0.0%	0.0%	0.3%	1.9%	14.5%	1.3%
Madison WI	0.0%	0.4%	1.1%	2.6%	9.0%	1.8%
Miami FL	0.0%	0.2%	0.8%	2.7%	21.7%	1.9%
Minneapolis MN	0.0%	0.6%	1.4%	3.5%	22.3%	2.6%
Oklahoma City OK	0.0%	0.2%	1.2%	4.5%	26.0%	2.9%
Phoenix AZ	0.0%	0.2%	0.7%	1.7%	13.8%	1.1%
Pittsburgh PA	0.0%	0.5%	1.2%	2.8%	25.3%	2.4%
Portland OR	0.0%	0.6%	1.5%	3.4%	13.6%	2.2%
San Diego CA	0.0%	0.7%	2.0%	5.1%	17.1%	3.4%
Seattle WA	0.0%	0.6%	1.7%	3.9%	23.8%	2.8%
St. Louis MO	0.0%	0.2%	1.0%	3.7%	17.4%	2.5%

this fact, it is important to verify the comparability of the independent variables between emails with and without HCV status. Any dissimilarity between the two groups would be a cause for concern. It would suggest that randomization process was flawed and would undermine the ability to make causal claims based on HCV status because the groups would vary not just in HCV status, but other attributes as well. To assess comparability, Table 4.15 presents descriptive statistics by each group. Both groups are statistically similar on each independent variable suggesting the randomization process worked as intended and causal claims can be made.

Recall that racial affiliation was randomized, but the groups available for assignment varied by study site. For example, in Atlanta each posting had a 50% chance of being assigned to one of two racial categories (black and white), while in Boston, posters had a 33% chance of being assigned to one of three racial categories (black, Hispanic/Latina, and white). To assess the integrity of the racial affiliation randomization, I examine the comparability within study site. Each of the site-specific summary statistics are presented in Appendix E. In some sites, there are one or two significant differences at baseline. This is to be expected when making multiple comparisons. On the whole, randomization appears to have produced comparable subgroups.

Table 4.15: Comparability of groups: Unsubsidized (no HCV) and with HCV

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	6054		2991		3063		
Race:							No
Black	2390	39.5%	1165	39.0%	1225	40.0%	
Hispanic/Latina	1046	17.3%	524	17.5%	522	17.0%	
White	2618	43.2%	1302	43.5%	1316	43.0%	
Bedrooms:							No
1	1805	29.8%	884	29.6%	921	30.1%	
2	2611	43.1%	1303	43.6%	1308	42.7%	
3	1638	27.1%	804	26.9%	834	27.2%	
FMR % (mean)	1.04		1.04		1.04		No
Response time	21.94		21.94		21.93		No
SOI coverage:							
City	901	14.9%	447	14.9%	460	15.0%	No
County	465	7.7%	226	7.6%	239	7.8%	No
State	1201	19.8%	590	19.7%	611	19.9%	No
Any	2252	37.2%	1108	37.0%	1144	37.3%	No
Individual poverty rate (mean)	0.167		0.168		0.166		No
% White (mean)	0.579		0.576		0.581		No
Vacancy rate (mean)	0.056		0.056		0.056		No
Median rent (mean, in $1000s)	1.049		1.051		1.047		No
Voucher units % (mean)	0.024		0.024		0.024		No
Multi-state management	1503	24.8%	750	25.1%	753	24.6%	No

Chapter 5

REGRESSION RESULTS

This chapter discusses the results from the audit experiment.

In the previous studies which are the most like this study (Ewens et al., 2014; Phillips, 2017), authors used linear probability models to analyze response behavior. Linear probability models (LPM) treat a binary outcome (1,0) as linear; predictor's coefficient describes the change in the probability of taking 1 as an outcome given a change in that predictor. I take the same approach here.

There are disadvantages to using linear regression to analyze a binary response. Binary dependent variables violate the homoscedasticity requirement of the linear model. It follows that standard errors and related tests of significance can be incorrect. The model may produce impossible predicted probabilities because linear regression does not constrain predictions to only fall between 0 and 1. However, in certain cases, logistic and the linear probability model produce similar results (Hellevik, 2009): if there is a large enough sample size and the modeled probabilities are not extreme values (near zero or one). If most of the predicted probabilities from the LPM lie on the unit interval–few impossible predictions–the concern over biased and inconsistent estimates is reduced (Horrace and Oaxaca, 2006). This is the case here, as I will demonstrate. Further, the LPM bias is less of a concern when estimating binary treatment effects (Deke, 2014). The main policy relevant variable in all analyses is a binary outcome, HCV status.

There are problems with using the LPM to analyze binary outcomes. However, in this case, the LPM and logit models produce very similar average marginal effects (AMEs). The similarity in results and the simple interpretation of linear regression coefficients lead to the decision to focus on these results in this chapter. Throughout the chapter, I will reference

any related logistic regression results which are contained in the appendices.

The rest of this chapter will focus on two sets of regression models. First, I will present models predicting the probability of receiving a response to a tester's email: how likely is a tester to get any response? Next, I will present models predicting the probability of positive, negative, or non-response from a landlord or property manager. These models will address the primary research questions of this study:

1. Do HCV households experience discrimination in rental market searches?

2. Do state and local laws making discrimination based on source of income illegal reduce discrimination for HCV households?

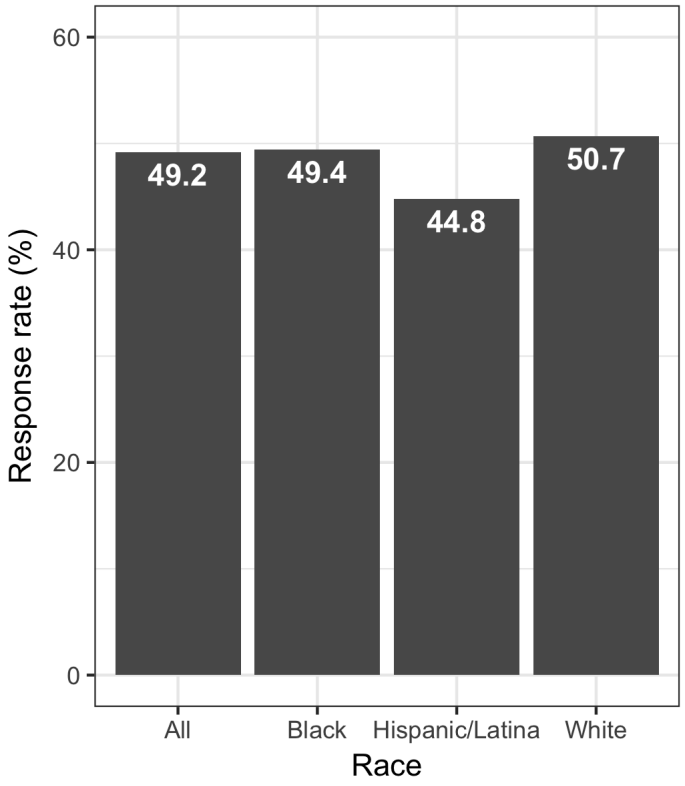
5.1 Any response

The first set of models look at the likelihood of receiving a response, regardless of the type of response. I include this outcome variable to allow the reader to see how the results play out for an objective outcome (presence of response) versus a more subjective outcome (presence of a positive response) in later models.

About half of the testers' emails received a response (49%, see Figure 5.1). White testers' rate was 1.5 percentage points more than the overall rate. Black testers' is slightly above the overall rate by two-tenths of a percentage point. Hispanic/Latina testers' had the lowest response rate: 4.4 percentage points below.

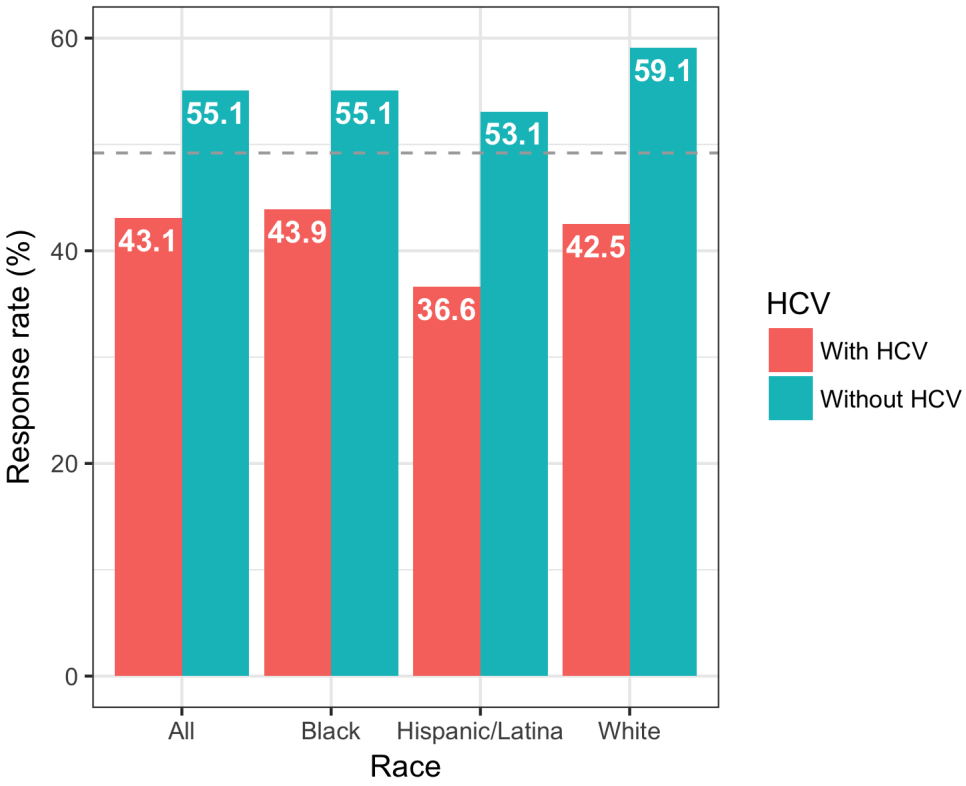
The percentage of testers that received any response is broken down further by HCV status in Figure 5.2. In the figure, the dashed line references the overall response rate. Looking at percentages for all respondents, it is clear that HCV testers received fewer emails: 12 percentage points less than unsubsidized testers with unsubsidized testers' rate being 5.9 points higher than the base rate. The gap between HCV and unsubsidized holds for every racial category, while differing in magnitude. For black testers, HCV testers were 11.2 percentage points below; for Hispanic/Latina testers, 16.5 points below; for white testers, 16.6 points below. Hispanic/Latina households fare the worst with regards to response rate

Figure 5.1: Response rate by race



outcomes, followed by blacks, with white testers doing the best. The penalty, in terms of response rate, for HCV is high for all testers.

Figure 5.2: Response rate by race & HCV status



Linear probability models are estimated to predict the likelihood of receiving a response. Models are built up by starting with a single predictor of tester's race (1), then adding HCV status (2), SOI coverage (3), unit characteristics (4), neighborhood characteristics (5), and study site fixed effects (6). Models' estimates and fit statistics are presented in Tables 5.1-5.6.[1] Every model performs better than naive guessing. As more explanatory variables are included the explanatory power increases though, the models only explain a small portion of the variation: the best model explains just over 5% of the total observed variation (Model 6).

[1] An alternative layout of the model output is in Appendix F.

Red coefficient estimates indicate significant effects[2] that reduce the likelihood of receiving a response and green estimates indicate significant effects that increase the likelihood. I will now discuss each model in succession, emphasizing the significant estimates and any changes in magnitude and significance across the models.

Table 5.1: **Any** response LPM models; Tester characteristics

	Model	1	2	3	4	5	6
Tester characteristics	**Tester race: Hispanic/Latina**	**-0.045**	**-0.047**	**-0.044**	**-0.047**	-0.031	0.005
	se	0.019	0.018	0.019	0.018	0.019	0.020
	p	0.015	0.010	0.018	0.012	0.098	0.801
	Tester race: White	0.014	0.012	0.012	0.017	0.016	0.024
	se	0.014	0.014	0.014	0.014	0.014	0.014
	p	0.339	0.387	0.376	0.224	0.239	0.090
	HCV status: Has HCV		**-0.144**	**-0.144**	**-0.145**	**-0.147**	**-0.146**
	se		0.013	0.013	0.013	0.013	0.013
	p		0.000	0.000	0.000	0.000	0.000

5.1.1 Model 1: just race

This model has tester's race as the only variable. Black is the omitted category–being black has a marginal effect of zero relative to the other categories. The coefficient for Hispanic/Latina is negative and significant. Changing from black to Hispanic/Latina reduces the chance of getting a response by 4.5 percentage points. The coefficient for white is positive, yet not significant. Changing from black to white increases the chance by 1.4 percentage points.

[2]Threshold for significance level is set at the 0.05 level.

Table 5.2: **Any** response LPM models; SOI coverage & unit characteristics

	Model	1	2	3	4	5	6
SOI coverage	**SOI coverage: City**			0.011	-0.007	-0.024	-0.038
	se			0.019	0.019	0.019	0.024
	p			0.541	0.713	0.214	0.113
	SOI coverage: County			0.018	-0.014	-0.022	-0.031
	se			0.025	0.025	0.025	0.041
	p			0.476	0.586	0.376	0.457
	SOI coverage: State			0.010	0.001	-0.012	0.019
	se			0.016	0.016	0.017	0.062
	p			0.518	0.935	0.458	0.756
Unit characteristics	**Unit size: 2 bedroom**				-0.005	0.004	0.004
	se				0.015	0.015	0.015
	p				0.730	0.805	0.810
	Unit size: 3 bedroom				0.025	**0.050**	**0.043**
	se				0.017	0.018	0.018
	p				0.144	0.006	0.018
	FMR %				**0.103**	**0.172**	**0.178**
	se				0.041	0.045	0.046
	p				0.012	0.000	0.000
	Listing response time (in hrs)				0.001	0.001	0.001
	se				0.001	0.001	0.001
	p				0.453	0.351	0.352
	Management: Multi-state				**-0.147**	**-0.137**	**-0.138**
	se				0.015	0.015	0.016
	p				0.000	0.000	0.000

Table 5.3: **Any** response LPM models; Neighborhood characteristics

	Model	1	2	3	4	5	6
Neighborhood characteristics	**Individual poverty rate (%)**					-0.029	-0.041
	se					0.073	0.075
	p					0.689	0.586
	White residents (%)					**0.082**	0.030
	se					0.032	0.040
	p					0.013	0.451
	Vacancy rate (%)					-0.222	-0.052
	se					0.118	0.125
	p					0.061	0.677
	Median rent (in $1000s)					**-0.138**	**-0.101**
	se					0.027	0.033
	p					0.000	0.003
	Voucher concentration (%)					0.150	0.056
	se					0.236	0.252
	p					0.526	0.823

Table 5.4: **Any** response LPM models; Study site fixed effects

	Model	1	2	3	4	5	6
Study site fixed effects	**Boston**						-0.091
	se						0.074
	p						0.220
	Denver						0.007
	se						0.035
	p						0.842
	Houston						-0.012
	se						0.034
	p						0.725
	Madison						0.068
	se						0.058
	p						0.238
	Miami						**-0.080**
	se						0.037
	p						0.033
	Minneapolis						0.034
	se						0.039
	p						0.380
	Oklahoma City						0.006
	se						0.073
	p						0.932

Table 5.5: **Any** response LPM models; Study site fixed effects

	Model	1	2	3	4	5	6
Study site fixed effects	**Phoenix**						**-0.088**
	se						0.037
	p						0.019
	Pittsburgh						**0.088**
	se						0.044
	p						0.045
	Portland						0.044
	se						0.065
	p						0.499
	San Diego						0.014
	se						0.037
	p						0.696
	Seattle						0.012
	se						0.039
	p						0.762
	St. Louis						-0.024
	se						0.040
	p						0.557

Table 5.6: **Any** response LPM models; Intercept & model information

Model		1	2	3	4	5	6
	Constant	**0.494**	**0.568**	**0.562**	**0.482**	**0.510**	**0.482**
	se	0.010	0.012	0.013	0.047	0.062	0.067
	p	0.000	0.000	0.000	0.000	0.000	0.000
	N	6054	6054	6054	6054	6043	6043
	R^2	0.002	0.023	0.023	0.040	0.047	0.055
	Adjusted R^2	0.001	0.022	0.022	0.039	0.045	0.050
	Residual Std. Error	0.500	0.494	0.494	0.490	0.489	0.487
	F statistic	5.222	46.545	23.500	23.049	18.694	12.013
	AIC	8784	8658	8663	8563	8513	8492
	Predictions outside [0,1]	0	0	0	0	0	0

5.1.2 Model 2: adding HCV status

This model adds the other randomized attribute to the model: HCV status. The racial categories maintain similar patterns of magnitude and significance as seen in Model 1. Having HCV has a large, negative, and significant coefficient estimate. Having HCV is predicted to reduce the chance of response by 14.4 percentage points.

5.1.3 Model 3: adding SOI coverage

This model includes a set of dummies for having SOI law coverage for HCV at the city, county, and/or state level. Coverage at any level increases the chance of getting a response by 1 to 2 percentage points, however, none of these increases are statistically significant. Tester race and HCV status estimates keep a similar pattern of size and significance as seen in Model 2.

5.1.4 Model 4: adding unit characteristics

Now unit characteristics are added to the model: unit size, unit price as FMR percentage, listing response time, and management type.

For unit size, the comparison category is one bedroom. Going from a one to a two bedroom unit decrease the chance of response by just half a percentage point and going from one to three bedrooms increases the chances by 2.5 percentage points. Neither of the unit size coefficients are significant.

FMR percentage has a positive significant coefficient. For a one percentage point increase in the FMR (0.01), the chance of response increases by one-tenth of a percentage point. While this increase is significant, it is not sizeable for small changes in the FMR. Consider the most extreme change in FMR possible given the FMR conditions imposed on selected postings: going from 70% to 130% of FMR. That change would increase the response chance by 6.2 percentage points.

Listing response time's effect is small and not statistically significant. Adding one hour to the response time only increases the chance of response by one-tenth of a percentage point.

For posting associated with a multi-state management company the effect on response is large and significant: a decrease of 14.7 percentage points–near equivalent to the impact of HCV status on prediction.

Again, tester race and HCV status estimates keep a similar pattern of size and significance as seen in previous models.

5.1.5 Model 5: adding neighborhood characteristics

Here, neighborhood characteristics are added to the response model: individual poverty rate, percentage of white-only residents, vacancy rate, median rent, and voucher household concentration. Note that this model, and subsequent models, lose 11 observations due to list-wise deletion because of missing ACS data on rental units, specifically median rent and rental vacancy rate.

An increase in the poverty rate is associated with a decrease in the chance of response, yet the difference is not large or significant. For a ten percentage point change in the poverty rate (0.10), the response probability decreases by two-tenths of a percentage point.

An increase in the percentage of residents that are white-only is associated with an increase in the chance of response. The difference is significant. For a ten percentage point change in the percentage of whites (0.10), the response probability increases by eight-tenths of a percentage point. For the most extreme change possible, going from no whites to exclusively white, the response probability increases by 8.2 percentage points.

Looser markets are associated with a decrease in the chance of response, yet the difference is small and not significant. A one percentage point change in the vacancy rate (0.01), decreases the chance of response by two-tenths of a percentage point.

Increases in the median rent are associated with a decrease in the likelihood of response, and the difference is significant. A $100 increase in the median rent (0.1) reduces the response chance by 1.4 percentage points.

Increasing voucher concentration is associated with an increase in the probability of response, yet this difference is not significant. For a one percentage point increase in the voucher concentration (0.01), the probability of response increases by just two-tenths of a percentage point.

The SOI variables remain insignificant. The HCV variable remains large, negative, and significant. However, the Hispanic/Latina variable maintains its magnitude, yet loses its significance once neighborhood attributes are added. The white coefficient remains positive and insignificant. The estimate for three bedroom units also becomes significant and larger: changing from a one to three bedroom unit increases the chance of response by 5 percentage points.

5.1.6 Model 6: adding study site fixed effects

This last model adds in fixed effects for each study site. Atlanta is the comparison category. The sites' coefficients vary in their size and sign. Only three sites have significant estimates

and all are large. Miami is associated with an 8.0 percentage point decrease in response, Phoenix with an 8.8 percentage point decrease, and Pittsburgh with an 8.8 percentage point increase. The remaining sites are not statistically different from the comparison site.

Compared to Model 5, many variables remain insignificant: race, SOI coverage, listing response time, poverty rate, vacancy rate, and voucher concentration. The percentage of white-only residents loses its significance. The remaining variables retain significance and similar magnitudes as the previous model.

In summary, race effects fall out of significance once neighborhood and study site fixed effects are included. Holding all things constant, the **race of a tester is not predictive of receiving a response**. This is surprising given other rental audit work that has shown racial disparities in rental market search outcomes (Hanson and Hawley, 2011; Ewens et al., 2014), even when HCV status is considered (Phillips, 2017).

HCV status consistently remains a significant predictor: changing from no HCV to having HCV, while accounting for control variables, results in a **15 percentage point drop in the response probability**. This effect is strong and consistent across all models. This is not surprising given the stigma and administrative complexity associated with HCV that has been documented in previous survey and qualitative research. HCV testers experienced discrimination in receiving a response from posters.

Having SOI coverage laws at any political level is not predictive. This is not entirely expected given previous work that showed SOI laws as positively associated with other leasing and locational outcomes (Finkel and Buron, 2001; Galvez, 2011; Freeman, 2011; Freeman and Li, 2013).

Another **important control variable was management type**. In fact, management type's magnitude is close in size to having HCV. Sending an email to a unit with a multi-state management firm was **associated with a 14 percentage point drop in response probability**. This effect is expected given qualitative and observational work in the past that discussed the difficulty of getting larger management firms to participate in the HCV program (Rubinowitz and Rosenbaum, 2000). However, this effect applies to unsubsidized

renters as well, suggesting difficulty for everyone in contacting large firms through email in response to advertisements on craiglist.

Unit size was significant in predicting response. **Three bedroom unit inquiries were 5 percentage points more likely to receive a response**. Interpreting these effects is difficult. Part of the difficulty stems from occupancy. Testers' emails did not include any details about who, either than the sender, would live in the rental unit. Households with more people are more likely to target larger units. It is unclear how landlords are interpreting unmentioned occupancy: in other words, this study was not designed to isolate family status effects. It is not unreasonable to think that the unit size coefficients are picking up some family status effects, but how much and in what direction is unclear.

FMR percentage, or price, was predictive. For a one percentage point increase in the FMR (0.01), the chance of response **increases by two-tenths of a percentage point**. So, as the advertised rent of the unit increases, testers are more likely to receive a response.

The **median rent in the unit's census tract was predictive**. For every one-hundred dollar increase in median rent, the **probability of response drops by 1 percentage point**. Landlords with units in more expensive tracts are less likely to respond to testers.

5.1.7 Predicted probabilities

It is simple to picture the impact of categorical variables. Their estimates relate to shifting the y-intercept of predictions without changing the slope of the prediction line. This is the case for the significant categorical variables in models 6: HCV and multi-state management reduce the intercept for predictions, while writing to a 3 bedroom unit increases the intercept. It is a little more complicated to picture the impact of continuous variables, especially when their underlying scale is conceptually transformed: measurement in FMR percentage and median rent in \$1,000s.

Out-of-sample predicted probabilities were calculated to investigate the relationships for the significant continuous variables from the regression modeling. In each graph, visual comparisons are made for the different levels of the experimental variables (HCV status and

race), while varying either FMR % or median rent. In all graphs, the other explanatory variables are held at either their means or modes.[3]

Figure 5.3 shows the effect of changing FMR % on the response rate. As FMR % increases, testers are more likely to get a response. Landlords with more expensive units are more likely to be responsive.

Figure 5.3: Predicted probabilities varying FMR %; LPM **any** response

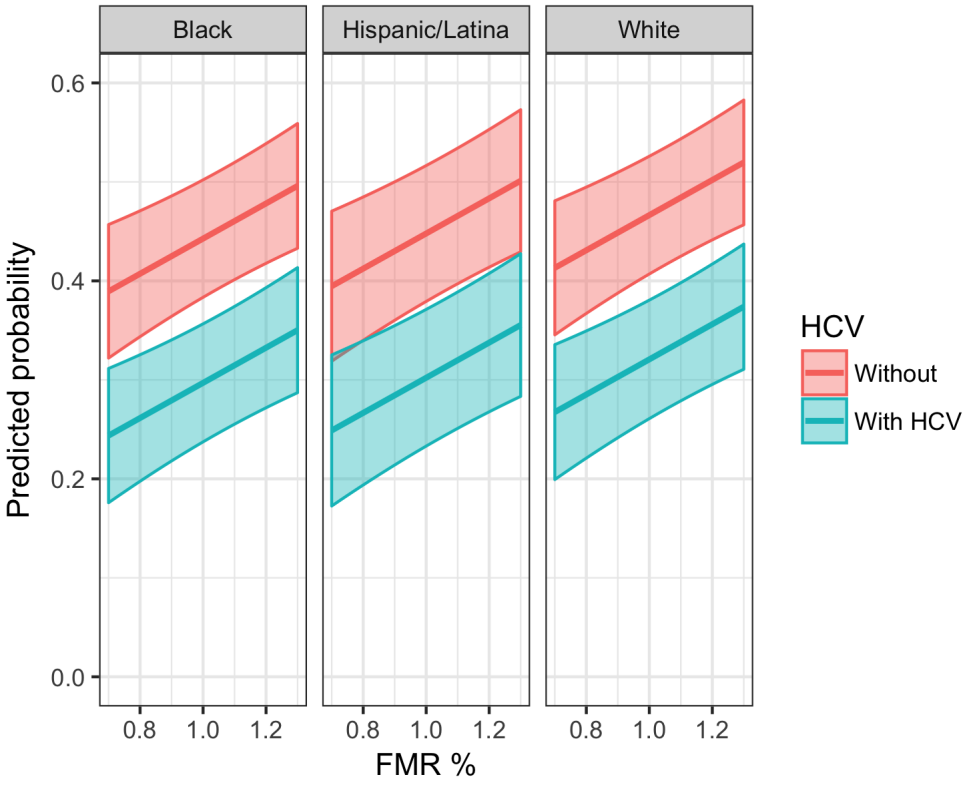
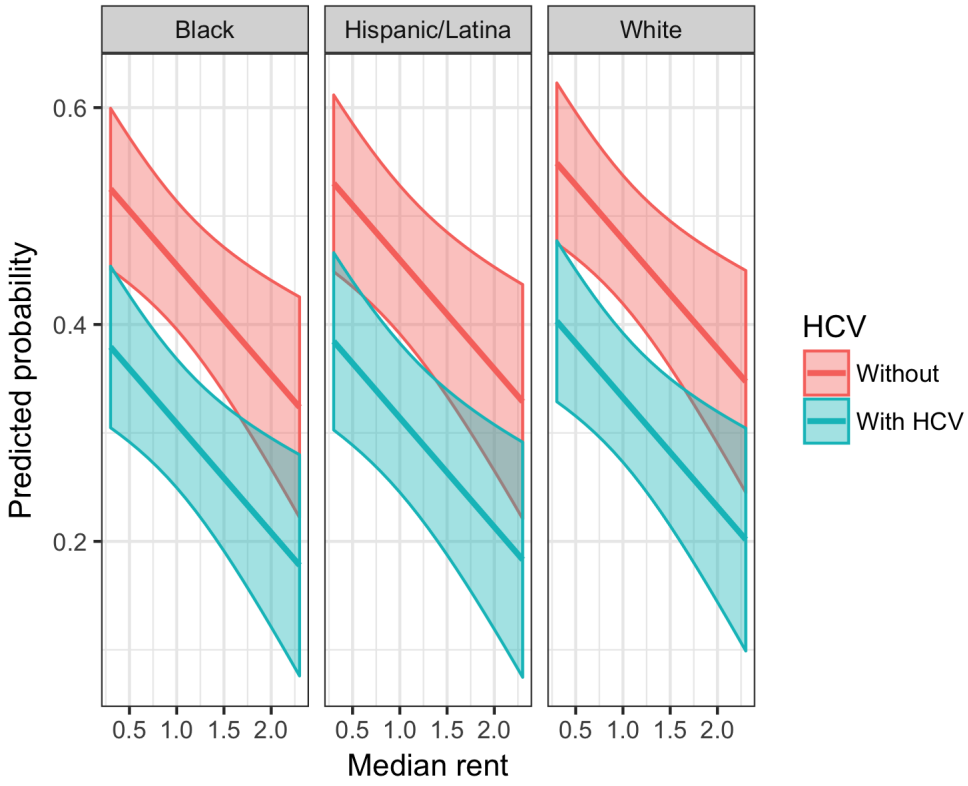


Figure 5.4 shows the effect of changing median rent on the response rate. As median rent increases, landlords are less likely to respond. This increase is about the tendency of rents near the selected unit and not about the particular unit's price. So, landlords in expensive neighborhoods are less likely to respond to any tester.

[3]Modes were no SOI coverage at any level, 2 bedroom unit, non-multi-state management. All predictions used Atlanta, the comparison category site.

Figure 5.4: Predicted probabilities varying median rent; LPM **any** response



5.1.8 Comparing LPM & Logit

Table 5.7 presents the average marginal effects for the variables in the any response model that includes tester, unit, SOI law, and neighborhood characteristics and study site fixed effects (Model 6: LPM in Tables 5.1-5.6 and logit in Appendix G Tables G.1-G.2). The AMEs are similar between the two models: all differences are 0.01 or less. I consider this to be strong evidence of the ability to emphasize LPM results without worrying about biased estimates.

5.1.9 Interactions

Interactions are investigated to assess whether there were differential effects for testers' race or HCV status in receiving responses. All interaction models build on Model 6. For simplicity in tabling, non-interacted terms are omitted from output within the chapter, but are available in Appendix H.

The first interaction tested is tester's race and HCV status (Table 5.8). The intuition behind this interaction is that the effects of HCV status might be different for each racial group. Perhaps white HCV holds are still penalized for HCV, but the magnitude could be less than for other racial groups. Looking at the model estimates, we see that the interaction overall does not help us predict the response any better than the base model. Therefore, HCV does not produce different effects for different racial groups.

The second set of interactions looks at differential effects for unit size (Table 5.9). It could be the case that landlords might exclude particular racial groups or HCV households from certain unit sizes. For example, a landlord might be okay with renting a one-bedroom unit to an HCV household, but prefers to rent larger units to unsubsidized households. An alternative explanation could be that landlords assume minority household heads that are interested in larger units are single-parent families, and the landlord might prefer to find a household without children. The interpretation around unit size continues to be muddied because I did not send landlords clear signals of family status. Looking at the interactions,

Table 5.7: Comparison of Average Marginal Effects for LPM & logistic regression predicting receiving **any** response

Variable	**LPM**	**Logit**	**Variable**	**LPM**	**Logit**
Tester race: Hispanic/Latina	0.005	0.005	Boston	-0.091	-0.091
Tester race: White	0.024	0.024	Denver	0.007	0.006
HCV status: Has HCV	**-0.146**	**-0.146**	Houston	-0.012	-0.013
SOI coverage: City	-0.038	-0.038	Madison	0.058	0.067
SOI coverage: County	-0.031	-0.030	Miami	**-0.080**	**-0.080**
SOI coverage: State	0.019	0.020	Minneapolis	0.034	0.033
Unit size: 2 bedroom	0.004	0.004	Oklahoma City	0.006	0.005
Unit size: 3 bedroom	**0.043**	**0.043**	Phoenix	**-0.088**	**-0.089**
FMR percentage	**0.178**	**0.177**	Pittsburgh	**0.088**	**0.088**
Listing response time (in hrs)	0.001	0.001	Portland	0.044	0.043
Management: Multi-state	**-0.138**	**-0.138**	San Diego	0.014	0.014
Individual poverty rate (%)	-0.041	-0.041	Seattle	0.012	0.012
White residents (%)	0.030	0.030	St. Louis	-0.024	-0.024
Vacancy rate (%)	-0.052	-0.053			
Median rent (in $1000s)	**-0.101**	**-0.101**			
Voucher concentration (%)	0.056	0.055			

Table 5.8: Interaction of tester race × HCV status; **Any** response LPM models

Variable	Model 6	Tester race × HCV
Tester race: Hispanic/Latina	0.005	0.028
se	0.020	0.027
p	0.801	0.310
Tester race: White	0.024	**0.050**
se	0.014	0.020
p	0.090	0.013
HCV status: Has HCV	**-0.146**	**-0.116**
se	0.013	0.020
p	0.000	0.000
Tester race: Hispanic/Latina X Has HCV		-0.045
se		0.036
p		0.217
Tester race: White X Has HCV		-0.051
se		0.028
p		0.065
N	6043	6043
R^2	0.055	0.055
Adjusted R^2	0.050	0.050
Residual Std. Error	0.487	0.487
F Statistic	12.013	11.361
AIC	8492	8492
Predictions outside [0,1]	0	0

it is clear that none of the interactions are significant or useful. There do not appear to be different effects by unit size.

Table 5.9: Interaction of tester attributes × unit size; **Any** response LPM models

Variable	Model 6	Tester race × unit size	HCV × unit size
Tester race: Hispanic/Latina	0.005	-0.004	0.006
se	0.020	0.035	0.020
p	0.801	0.897	0.786
Tester race: White	0.024	0.006	0.024
se	0.014	0.025	0.014
p	0.090	0.821	0.089
HCV status: Has HCV	**-0.146**	**-0.146**	**-0.156**
se	0.013	0.013	0.023
p	0.000	0.000	0.000
Unit size: 2 bedroom	0.004	-0.022	-0.013
se	0.015	0.024	0.021
p	0.810	0.364	0.542
Unit size: 3 bedroom	**0.043**	0.049	**0.050**
se	0.018	0.027	0.025
p	0.018	0.077	0.043
Tester race: Hispanic/Latina × 2 Bedroom		0.035	
se		0.043	
p		0.413	
Tester race: White × 2 bedroom		0.044	
se		0.033	
p		0.177	
Tester race: Hispanic/Latina × 3 bedroom		-0.022	
se		0.048	
p		0.648	
Tester race: White × 3 bedroom		-0.005	
se		0.037	
p		0.900	
Has HCV × 2 bedroom			0.033
se			0.030
p			0.266
Has HCV × 3 bedroom			-0.014
se			0.033
p			0.673
N	6043	6043	6043
R^2	0.055	0.055	0.055
Adjusted R^2	0.050	0.050	0.050
Residual Std. Error	0.487	0.487	0.487
F Statistic	12.013	10.659	11.325
AIC	8492	8496	8493
Predictions outside [0,1]	0	0	0

Next, interactions will focus on the percentage or white-only residents (Table 5.10). In the base model, the white-only term was not significant, yet there might be a racial segregation

effect or landlords advertising in whiter neighborhoods may respond differently to HCV testers. Both interactions have significant interaction terms suggesting differing slopes for predictions either race or HCV categories as the white-only percentage increases. Figures 5.5 & 5.6 plot these interactions effects as the white-only percentage changes. I believe neither of these interactions are useful given the constrains on the range of the % white-only variable. Though the regression models have no problem making predictions for tracts with less than 0% or more than 100% white-only residents, we know this explanatory variable is constrained to 0% to 100%–0 to 1 in terms of proportion. Looking at the predicted probabilities in Figure 5.5, the confidence bounds for the race interaction are large enough to allow for a line with the same slope and intercept to be drawn through all three racial categories simultaneously–meaning it is possible that all three lines could be the same and the interaction is not statistically meaningful. For this visualization, the slope and intercept must be the same, because in the base model tester race was not significant. If % white-only could take on impossible values, the predictions would no longer allow for the same line to be drawn through each racial category's confidence region.

For HCV status, we want to think about whether the two prediction lines could be parallel over the range of possible % white-only values. Only the slope of the line is of interest because HCV status was significant in the base model: we do not expect HCV and non-HCV prediction lines to have the same intercept. The confidence regions in Figure 5.6 are large enough to allow for lines of the same slope to be possible in both confidence regions. Again, if % white-only could take extreme values, this would no longer hold. Given the results of these visual examinations, these interactions do not add predictive power.

The next set of interactions examines unit and neighborhood rental costs (Table 5.11). Perhaps landlords with more expensive units or units in more expensive neighborhoods treat prospective tenants differently based on race or HCV status. However, none of the cost interaction terms are significant and the models are not fitting better than the base model.

The last interaction examines HCV status and SOI law coverage (Table 5.12). Perhaps landlords with units in SOI-covered jurisdictions treat prospective tenants differently based

Table 5.10: Interaction of tester attributes × % white-only; **Any** response LPM models

Variable	Model 6	Tester race × % white-only	HCV × % white-only
Tester race: Hispanic/Latina	0.005	-0.081	0.005
se	0.020	0.044	0.020
p	0.801	0.065	0.811
Tester race: White	0.024	-0.042	0.024
se	0.014	0.035	0.014
p	0.090	0.241	0.089
HCV status: Has HCV	**-0.146**	**-0.146**	**-0.073**
se	0.013	0.013	0.031
p	0.000	0.000	0.019
% white-only	0.030	-0.051	**0.091**
se	0.040	0.052	0.046
p	0.451	0.323	0.050
Tester race: Hispanic/Latina × % white-only		**0.160**	
se		0.075	
p		0.032	
Tester race: White × % white-only		**0.110**	
se		0.055	
p		0.046	
Has HCV × % white-only			**-0.125**
se			0.049
p			0.011
N	6043	6043	6043
R^2	0.055	0.056	0.056
Adjusted R^2	0.050	0.051	0.051
Residual Std. Error	0.487	0.487	0.487
F Statistic	12.013	11.446	11.838
AIC	8492	8490	8487
Predictions outside [0,1]	0	0	0

Figure 5.5: Predicted probabilities varying % white-only; LPM **any** response with % white-only × race

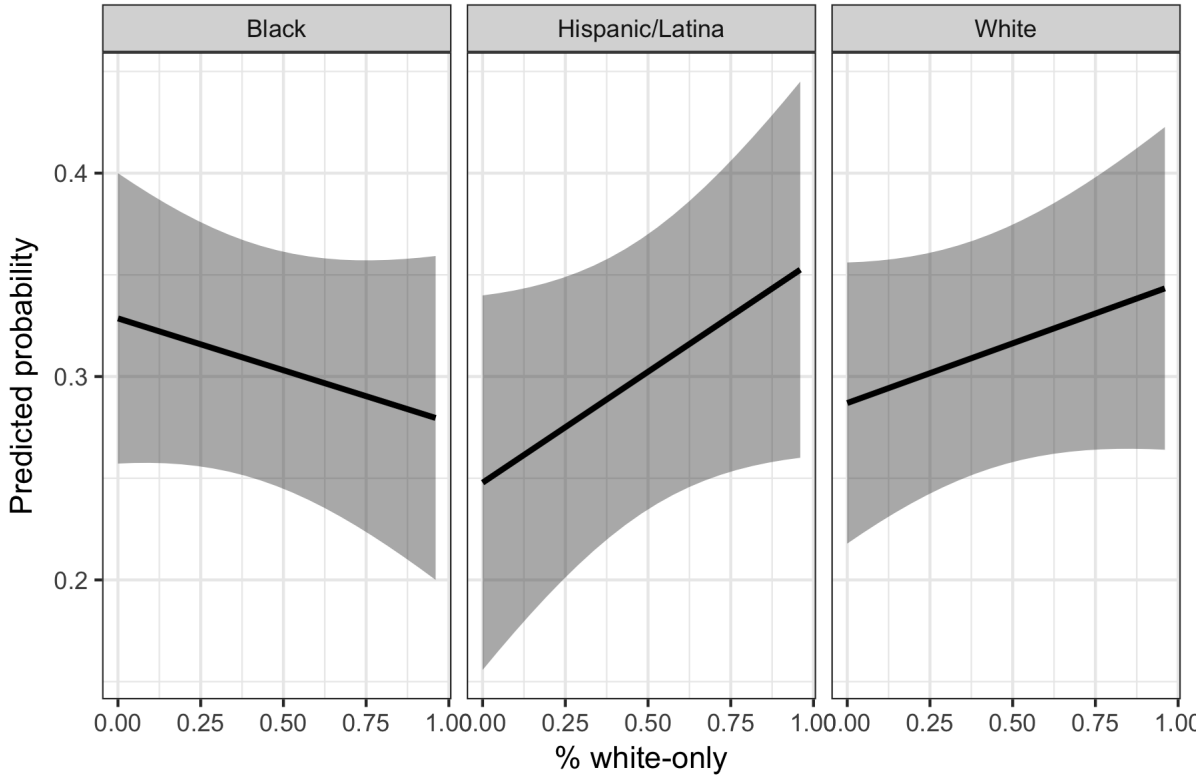


Figure 5.6: Predicted probabilities varying % white-only; LPM **any** response with % white-only × HCV

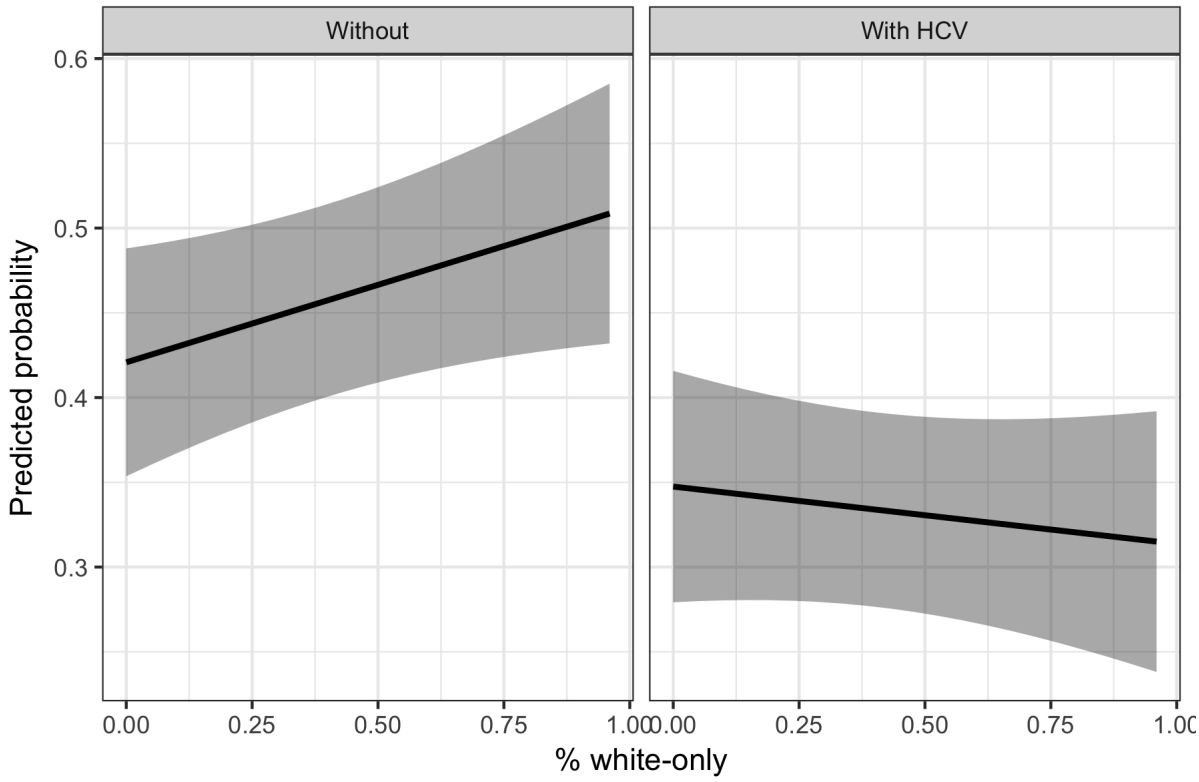


Table 5.11: Interaction of tester attributes × costs; **Any** response LPM models

Variable	Model 6	Tester race × FMR %	Tester race × Median rent	HCV × FMR %	HCV × Median rent
Tester race: Hispanic/Latina	0.005	-0.010	-0.065	0.005	0.005
se	0.020	0.130	0.073	0.020	0.020
p	0.801	0.942	0.375	0.806	0.798
Tester race: White	0.024	-0.015	0.004	0.024	0.024
se	0.014	0.092	0.052	0.014	0.014
p	0.090	0.871	0.946	0.089	0.089
HCV status: Has HCV	**-0.146**	**-0.146**	**-0.146**	-0.087	**-0.132**
se	0.013	0.013	0.013	0.084	0.047
p	0.000	0.000	0.000	0.304	0.005
FMR %	**0.178**	**0.159**	**0.179**	**0.207**	**0.177**
se	0.046	0.068	0.046	0.062	0.046
p	0.000	0.020	0.000	0.001	0.000
Median rent (in $1000s)	**-0.101**	**-0.100**	**-0.123**	**-0.101**	**-0.094**
se	0.033	0.033	0.043	0.033	0.039
p	0.003	0.003	0.005	0.003	0.017
Tester race: Hispanic/Latina × FMR %		0.014			
se		0.121			
p		0.906			
Tester race: White × FMR %		0.037			
se		0.088			
p		0.671			
Tester race: Hispanic/Latina × Median rent			0.062		
se			0.062		
p			0.318		
Tester race: White × Median rent			0.019		
se			0.048		
p			0.694		
Has HCV × FMR %				-0.057	
se				0.080	
p				0.481	
Has HCV × Median rent					-0.013
se					0.043
p					0.763
N	6043	6043	6043	6043	6043
R^2	0.055	0.055	0.055	0.055	0.055
Adjusted R^2	0.050	0.050	0.050	0.050	0.050
Residual Std. Error	0.487	0.487	0.487	0.487	0.487
F Statistic	12.013	11.240	11.268	11.628	11.613
AIC	8492	8496	8495	8493	8494
Predictions outside [0,1]	0	0	0	0	0

on HCV status. Of all the interaction terms, the HCV status and state-level SOI interaction is significant. However, an F test indicates that including the interactions do not result in a better fit over model 6[4].

Table 5.12: Interaction of HCV status × SOI; **Any** response LPM models

Variable	Model 6	HCV × SOI
HCV: Has HCV	**-0.146**	**-0.121**
se	0.013	0.016
p	0.000	0.000
SOI coverage: City	-0.038	-0.013
se	0.024	0.031
p	0.113	0.678
SOI coverage: County	-0.031	-0.003
se	0.041	0.048
p	0.457	0.955
SOI coverage: State	0.019	0.055
se	0.062	0.064
p	0.756	0.398
SOI coverage: City × Has HCV		-0.049
se		0.037
p		0.178
SOI coverage: County × Has HCV		-0.054
se		0.049
p		0.270
SOI coverage: State × Has HCV		**-0.064**
se		0.032
p		0.044
N	6043	6043
R^2	0.055	0.056
Adjusted R^2	0.050	0.051
Residual Std. Error	0.487	0.487
F Statistic	12.013	11.116
AIC	8491	8490
Predictions outside [0,1]	0	0

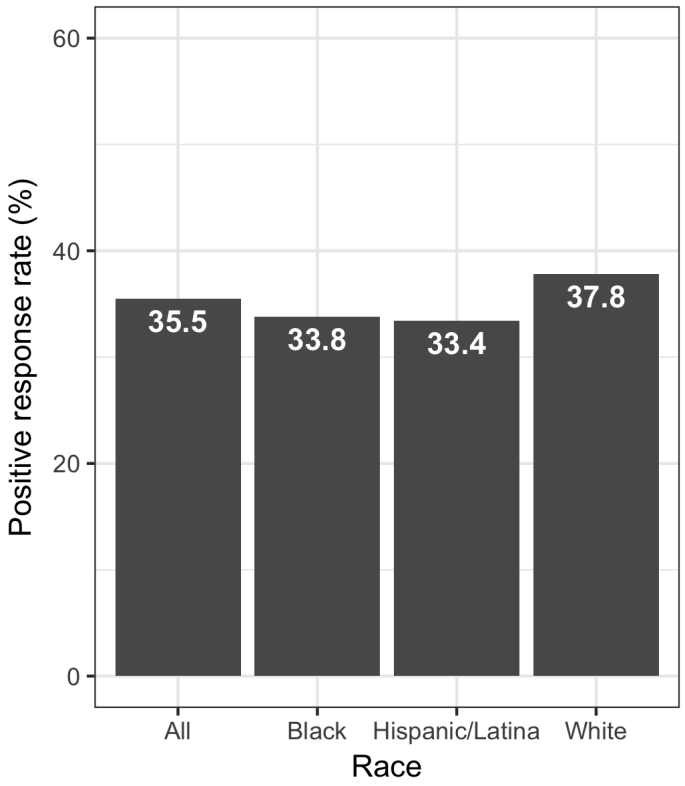
5.2 Positive response

The second set of models look at the likelihood of receiving a *positive* response. A positive response means a landlord contacted with a tester in such a way that the pre-leasing process could continue (see Section 3.4 for more explanation of the classification of responses). About a third of the testers' emails received a positive response (35%, see Figure 5.7). The opposite

[4] $F = 2.373$, $p = 0.068$

of receiving a positive outcome here is receiving either no response (51%) or a negative response (14%). Concatenating these two categories is an approach other researchers have used (Ewens et al., 2014; Phillips, 2017).

Figure 5.7: Positive response rate by race

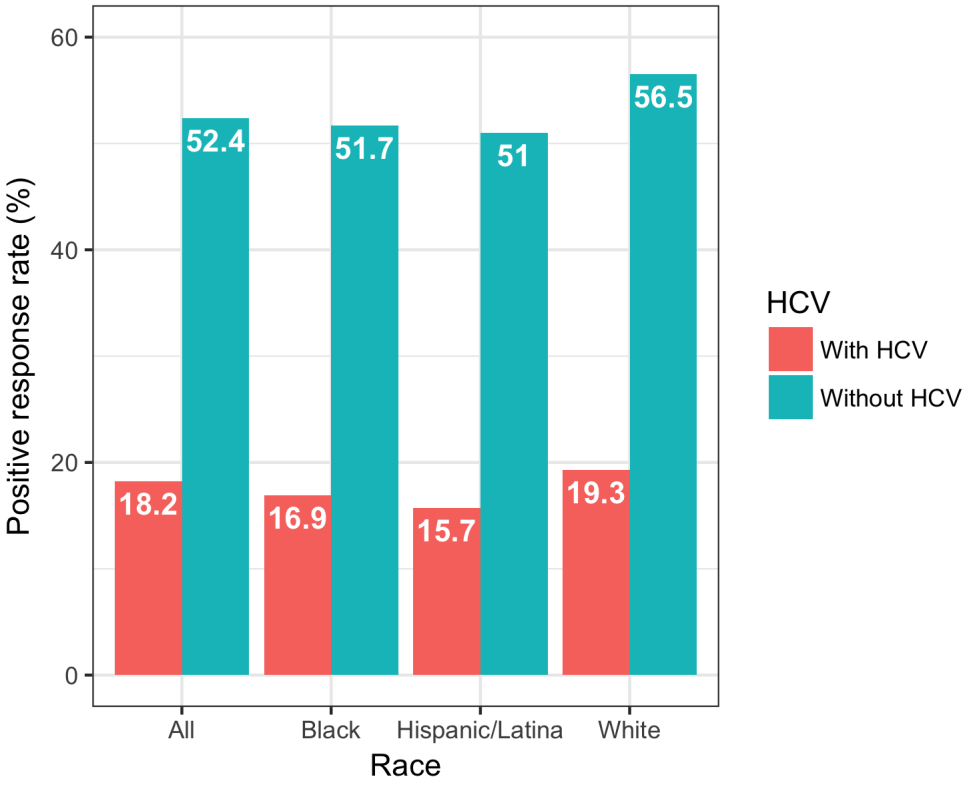


The percentage of testers that received a positive response is broken down further by HCV status in Figure 5.8.

Linear probability models are estimated to predict the likelihood of receiving a positive response. Again, models are built up by adding variables. Models' estimates and fit statistics are presented in Tables 5.13-5.18.[5] Every model performs better than guessing. As more explanatory variables are included the explanatory power increases–though overall the models

[5] An alternative layout of the model output is in Appendix F.

Figure 5.8: Positive response rate by race & HCV status



only explain a small portion of the variation: the best model explains 17% of the total observed variation (Model 6)–an improvement in explanatory power compared to the any response models.

Table 5.13: **Positive** response LPM models; Tester characteristics

	Model	1	2	3	4	5	6
Tester characteristics	**Tester race: Hispanic/Latina**	-0.005	-0.010	0.005	0.004	0.013	0.030
	se	0.018	0.016	0.017	0.017	0.017	0.018
	p	0.785	0.556	0.773	0.803	0.440	0.101
	Tester race: White	**0.039**	**0.036**	**0.037**	**0.041**	**0.040**	**0.043**
	se	0.014	0.013	0.013	0.012	0.012	0.013
	p	0.004	0.005	0.003	0.002	0.002	0.001
	HCV status: Has HCV		**-0.359**	**-0.359**	**-0.360**	**-0.361**	**-0.362**
	se		0.011	0.011	0.011	0.011	0.011
	p		0.000	0.000	0.000	0.000	0.000

5.2.1 Model 1: just race

This first model looks at tester's race only. Black is the omitted category–being black has a marginal effect of zero relative to the other categories. The coefficient for Hispanic/Latina is near-zero and insignificant. Changing from black to Hispanic/Latina reduces the chance of getting a response by half a percentage point. The coefficient for white is positive and significant. Changing from black to white increases the chance by 3.9 percentage points.

5.2.2 Model 2: adding HCV status

This model adds in HCV status. Having HCV has a large, negative, and significant coefficient estimate. Having HCV is predicted to reduce the chance of a positive response by

Table 5.14: **Positive** response LPM models; SOI coverage & unit characteristics

	Model	1	2	3	4	5	6
SOI coverage	**SOI coverage: City**			**0.055**	**0.041**	0.027	0.002
	se			0.017	0.017	0.017	0.022
	p			0.002	0.016	0.115	0.924
	SOI coverage: County			**0.049**	0.028	0.023	-0.034
	se			0.022	0.022	0.023	0.037
	p			0.027	0.208	0.308	0.356
	SOI coverage: State			**0.060**	**0.054**	**0.043**	0.092
	se			0.014	0.014	0.015	0.056
	p			0.000	0.000	0.005	0.101
Unit characteristics	**Unit size: 2 bedroom**				-0.007	-0.001	-0.002
	se				0.014	0.014	0.014
	p				0.599	0.944	0.912
	Unit size: 3 bedroom				0.009	0.028	**0.033**
	se				0.015	0.016	0.016
	p				0.553	0.074	0.040
	FMR %				0.049	**0.111**	**0.133**
	se				0.037	0.040	0.042
	p				0.184	0.006	0.002
	Listing response time (in hrs)				0.000	0.000	0.000
	se				0.001	0.001	0.001
	p				0.741	0.886	0.749
	Management: Multi-state				**-0.112**	**-0.105**	**-0.114**
	se				0.014	0.014	0.015
	p				0.000	0.000	0.000

Table 5.15: **Positive** response LPM models; Neighborhood characteristics

	Model	1	2	3	4	5	6
Neighborhood characteristics	**Individual poverty rate (%)**					0.023	0.002
	se					0.066	0.067
	p					0.732	0.980
	White residents (%)					**0.067**	0.022
	se					0.029	0.036
	p					0.022	0.542
	Vacancy rate (%)					-0.059	0.117
	se					0.106	0.112
	p					0.577	0.296
	Median rent (in $1000s)					**-0.089**	**-0.110**
	se					0.024	0.029
	p					0.000	0.000
	Voucher concentration (%)					0.324	0.177
	se					0.212	0.226
	p					0.126	0.434

Table 5.16: **Positive** response LPM models; Study site fixed effects

	Model	1	2	3	4	5	6
Study site fixed effects	**Boston**						-0.048
	se						0.066
	p						0.469
	Denver						0.022
	se						0.031
	p						0.480
	Houston						0.010
	se						0.031
	p						0.753
	Madison						**0.134**
	se						0.052
	p						0.011
	Miami						-0.028
	se						0.033
	p						0.396
	Minneapolis						-0.023
	se						0.035
	p						0.512
	Oklahoma City						-0.089
	se						0.066
	p						0.177

Table 5.17: **Positive** response LPM models; Study site fixed effects

	Model	1	2	3	4	5	6
Study site fixed effects	**Phoenix**						-0.050
	se						0.033
	p						0.136
	Pittsburgh						0.050
	se						0.039
	p						0.208
	Portland						0.075
	se						0.058
	p						0.199
	San Diego						0.040
	se						0.033
	p						0.226
	Seattle						**0.081**
	se						0.035
	p						0.020
	St. Louis						-0.016
	se						0.036
	p						0.657

Table 5.18: **Positive** response LPM models; Intercept & model information

Model		1	2	3	4	5	6
	Constant	**0.338**	**0.522**	**0.495**	**0.482**	**0.455**	**0.465**
	se	0.010	0.011	0.012	0.042	0.056	0.060
	p	0.000	0.000	0.000	0.000	0.000	0.000
	N	6054	6054	6054	6054	6043	6043
	R^2	0.002	0.142	0.147	0.158	0.162	0.170
	Adjusted R^2	0.001	0.142	0.146	0.156	0.160	0.166
	Residual Std. Error	0.478	0.443	0.442	0.440	0.439	0.437
	F statistic	5.435	334.889	173.725	102.756	72.771	42.554
	AIC	8250	7333	7307	7241	7205	7171
	Predictions outside [0,1]	0	0	0	0	11	22

35.9 percentage points. The racial categories maintain similar patterns of magnitude and significance as seen in Model 1.

5.2.3 Model 3: adding SOI coverage

This model includes the SOI law coverage. Coverage at any level increases the chance of getting a response by 5 to 6 percentage points and all of these increases are statistically significant. Tester race and HCV status estimates keep a similar pattern of size and significance as seen in Model 2.

5.2.4 Model 4: adding unit characteristics

Now unit characteristics are added to the model. Unit size coefficients are both near-zero and insignificant. FMR percentage has a positive, yet insignificant coefficient. For a one percentage point increase in the FMR (0.01), the chance of response increases by four-

hundredths of a percentage point. Like the any response models, listing response time's effect is small and not statistically significant.

For posting associated with a multi-state management company the effect on response is large and significant: a decrease of 11.2 percentage points.

Again, tester race and HCV status estimates keep a similar pattern of size and significance as seen in previous models. SOI coverage at the city and state level retain similar patterns, while county-level coverage is no longer significant.

5.2.5 Model 5: adding neighborhood characteristics

Now, neighborhood characteristics are added to the response model. Again, this and subsequent models, lose 11 observations due to missing ACS data on rental units.

An increase in the poverty rate is associated with an increase in the chance of response, yet the difference is not large or significant.

An increase in the percentage of residents that are white-only is associated with an increase in the chance of response. The difference is significant. For a ten-percentage point change in the percentage of whites (0.10), the response probability increases by seven-tenths of a percentage point. For the most extreme change possible, going from no whites to exclusively white, the response probability increases by 6.7 percentage points.

Looser markets are associated with a decrease in the chance of response, yet the difference is small and not significant.

Increases in the median rent are associated with a decrease in the likelihood of response, and the difference is significant. A $100 increase in the median rent (0.1) reduces the response chance by nine-tenths of a percentage point.

Increasing voucher concentration is associated with an increase in the probability of response, yet this difference is not significant.

Tester race and HCV status remain like previous models. SOI coverage at the state-level remains positive and significant, while city-level coverage becomes insignificant like county-level coverage. All unit characteristics remain similar, except for FMR % becoming

significant and increasing in size. A one-point increase in FMR, increases the probability by one-tenth of a percentage point and going from lowest to highest FMR increases the probability by 6.7 percentage points.

5.2.6 Model 6: adding study site fixed effects

This last model adds in fixed effects for each study site. Atlanta is the comparison category. The coefficients vary in their size and sign. Only two sites have significant estimates and both are large. Seattle is associated with an 8.1 percentage point decrease in response and Madison with a 13.4 percentage point increase. The remaining sites are not statistically different from the comparison site.

Compared to the previous models, race and HCV status remain similar. SOI is no longer significant at any level. Unit size becomes significant, with three bedroom units 3.3 percentage points more likely to receive a response. FMR percentage remains significant with a change from lowest to highest FMR associated with an 8 point increase in the probability of response. Response time was insignificant. Management types remains the same. All neighborhood characteristics are the same, except that the percentage of white-only residents is no longer significant.

In summary, race effects hold their size and significance even when other characteristics and study site fixed effects are included. Holding all things constant, **being white is predictive of receiving a positive response**. This is like other rental audit work that has shown racial disparities in rental market search outcomes (Ewens et al., 2014), including when HCV status is considered (Phillips, 2017).

HCV status remains a significant predictor: changing from no HCV to having HCV, while accounting for control variables, **results in a 36.2 percentage point drop in the positive response probability**. Like the any response model, it remains clear that HCV testers experienced discrimination in receiving a positive response from posters. However, for a positive response, HCV status' impact on the prediction is even greater.

Having **SOI coverage laws at any political level is not predictive**.

Another **important control variable was management type**. Sending an email to a unit associated with a multi-state management firm was **associated with a 11 percentage point drop in positive response probability**. As mentioned before, this effect applies to unsubsidized renters as well, suggesting difficulty for everyone in contacting large firms through email in response to advertisements on craiglist.

Unit size was significant in predicting response. Three bedroom unit inquiries were **3 percentage points more likely to receive a response**.

FMR percentage, or price, was predictive. For a one percentage point increase in the FMR (0.01), the chance of response **increases by one-tenth of a percentage point**. So, as the advertised rent of the unit increases, testers are more likely to receive a response.

The **median rent in the unit's census tract was predictive**. For every one hundred dollar increase in median rent, the **probability of response drops by one-tenth of a percentage point**. Landlords with units in more expensive tracts are less likely to respond to testers.

5.2.7 Predicted probabilities

Again, out-of-sample predicted probabilities were calculated to investigate the relationships for the significant continuous variables from the regression modeling. These graphs look very similar to the previous graphs, however the differences between HCV statuses are larger, and overall the predictions are slightly tighter, more certain.

Figure 5.9 shows the effect of changing FMR % on the positive response probability. As FMR % increases, testers are more likely to get a response. Landlords with more expensive units are more likely to be respond positively.

Figure 5.10 shows the effect of changing median rent on the response rate. As median rent increases, landlords are less likely to respond positively. This increase is about the tendency of rents near the selected unit and not about the particular unit's price. So, landlords in expensive neighborhoods are less likely to respond positively to any tester.

Figure 5.9: Predicted probabilities varying FMR %; LPM **positive** response

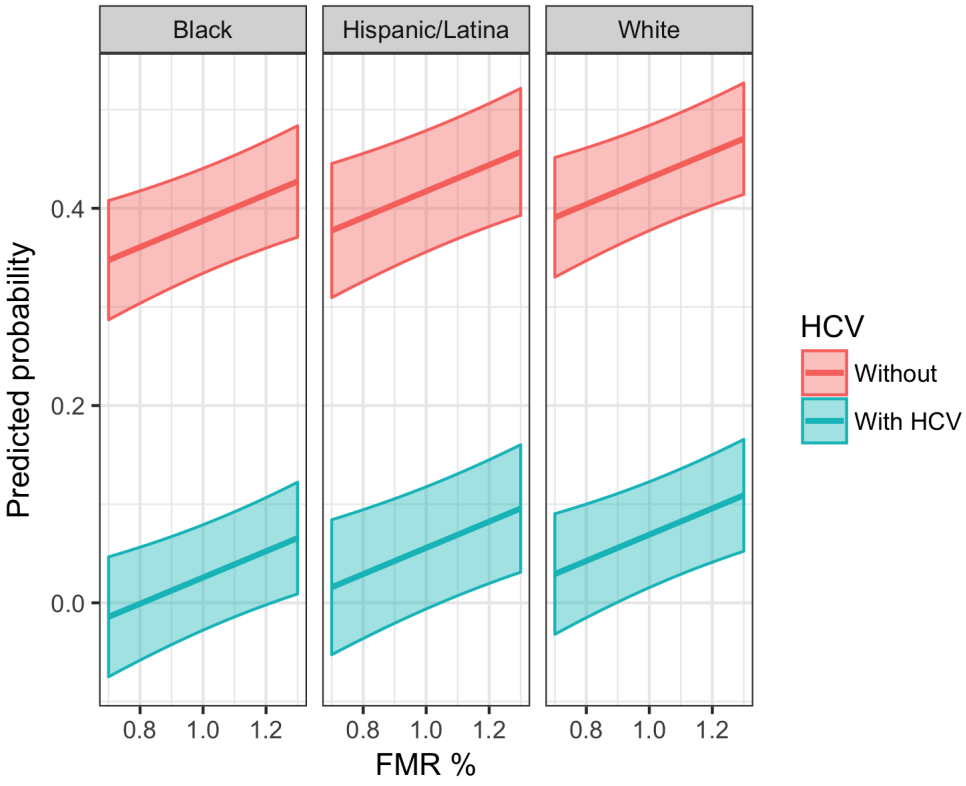
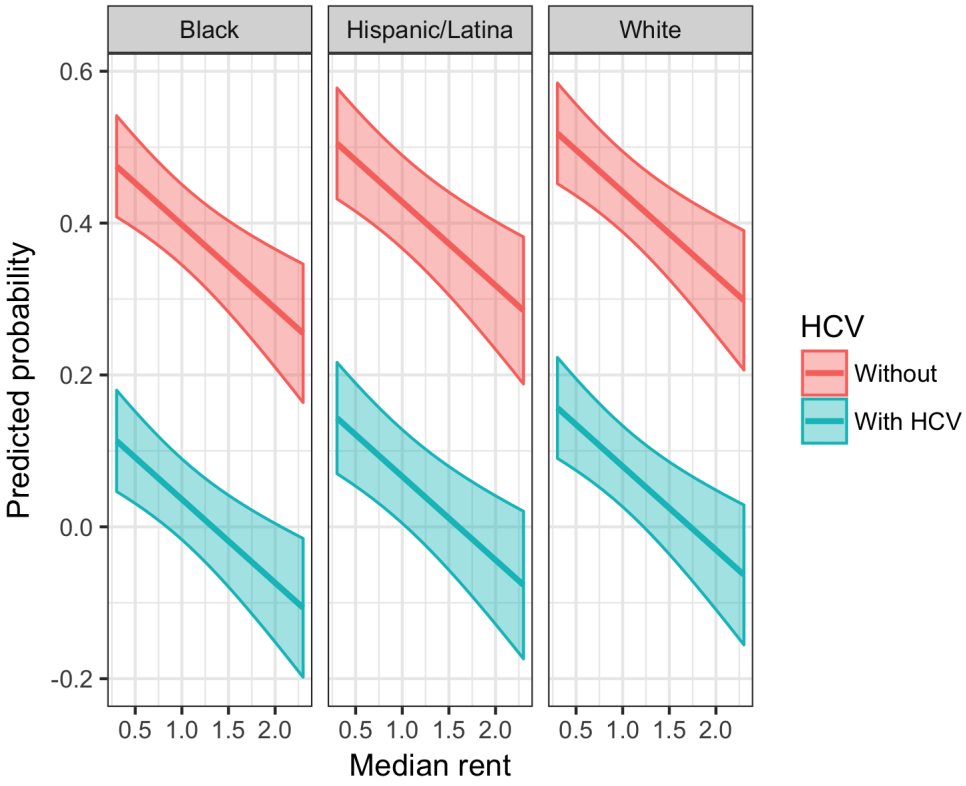


Figure 5.10: Predicted probabilities varying median rent; LPM **positive** response



5.2.8 Comparing LPM & Logit

Table presents the average marginal effects for the variables in the any response model that includes tester, unit, SOI law, and neighborhood characteristics and study site fixed effects (Model 6: LPM in Tables 5.13-5.18 & logit in Appendix G). Again, the AMEs are similar between the two models. The biggest difference between AMEs is 0.015 for vacancy rate, though this variable was not significant in either specification. Otherwise, most differ by less than .01. I consider this to be strong evidence of the ability to emphasize LPM results for positive response without worrying about biased estimates.

5.2.9 Interactions

The same interaction specifications for the any response outcome were run for the positive response outcome. Similar patterns of significance and practical importance were observed (see Tables 5.20 through 5.24 for estimates and Figures 5.11 and 5.12 for the % white-only predicted probabilities). There were no relevant interactions discovered.

5.2.10 Regression results summary

Table 5.25 summarizes the significant AMEs for the two outcomes' full models. Regardless of the outcome variable, functional form of the model, or the set of predictor variables, the HCV status variable has very large, negative and significant coefficient estimates. Across all specifications, HCV status remains the strongest predictor and is associated with extremely negative rental search outcomes for HCV households. These results suggest that HCV discrimination is real and a large disadvantage for searchers making initial email inquiries to craigslist rental postings. Race effects are not present for the probability of receiving a response. However, white testers have an advantage in receiving a positive response. SOI laws did not play a significant role in predictions for any outcome.

Table 5.19: Comparison of Average Marginal Effects for LPM & logistic regression predicting receiving **positive** response

Variable	**LPM**	**Logit**	**Variable**	**LPM**	**Logit**
Tester race: Hispanic/Latina	0.030	0.030	Boston	-0.048	-0.047
Tester race: White	**0.043**	**.043**	Denver	0.022	0.021
HCV status: Has HCV	**-0.362**	**-0.362**	Houston	0.010	0.009
SOI coverage: City	0.002	0.001	Madison	**0.134**	**0.133**
SOI coverage: County	-0.034	-0.034	Miami	-0.028	-0.030
SOI coverage: State	0.092	0.092	Minneapolis	-0.023	-0.024
Unit size: 2 bedroom	-0.002	-0.001	Oklahoma City	-0.089	-0.083
Unit size: 3 bedroom	**0.033**	**0.034**	Phoenix	-0.050	-0.051
FMR percentage	**0.133**	**0.130**	Pittsburgh	0.050	0.045
Listing response time (in hrs)	0.000	0.000	Portland	0.075	0.071
Management: Multi-state	**-0.114**	**-0.113**	San Diego	0.040	0.038
Individual poverty rate (%)	0.002	0.009	Seattle	**0.081**	**0.081**
White residents (%)	0.022	0.023	St. Louis	-0.016	-0.017
Vacancy rate (%)	0.117	0.102			
Median rent (in $1000s)	**-0.110**	**-0.109**			
Voucher concentration (%)	0.177	0.177			

Table 5.20: Interaction of tester race × HCV status; **Positive** response LPM models

Variable	Model 6	Tester race × HCV
Tester race: Hispanic/Latina	0.030	0.031
se	0.018	0.025
p	0.101	0.212
Tester race: White	**0.043**	**0.056**
se	0.013	0.018
p	0.001	0.002
HCV status: Has HCV	**-0.362**	**-0.351**
se	0.011	0.018
p	0.000	0.000
Tester race: Hispanic/Latina × Has HCV		-0.001
se		0.032
p		0.970
Tester race: White × Has HCV		-0.024
se		0.025
p		0.326
N	6043	6043
R^2	0.170	0.170
Adjusted R^2	0.166	0.166
Residual Std. Error	0.437	0.437
F statistic	42.554	39.839
AIC	7171	7174
Predictions outside [0,1]	22	14

Table 5.21: Interaction of tester attributes × unit size; **Positive** response LPM models

Variable	Model 6	Tester race × unit size	HCV × unit size
Tester race: Hispanic/Latina	0.030	0.014	0.031
se	0.018	0.031	0.018
p	0.101	0.648	0.093
Tester race: White	**0.043**	0.032	**0.044**
se	0.013	0.023	0.013
p	0.001	0.165	0.001
HCV status: Has HCV	**-0.362**	**-0.362**	**-0.351**
se	0.011	0.011	0.021
p	0.000	0.000	0.000
Unit size: 2 bedroom	-0.002	-0.018	-0.008
se	0.014	0.022	0.019
p	0.912	0.412	0.674
Unit size: 3 bedroom	**0.033**	0.030	**0.063**
se	0.016	0.025	0.022
p	0.040	0.222	0.005
Tester race: Hispanic/Latina × 2 Bedroom		0.036	
se		0.039	
p		0.359	
Tester race: White × 2 bedroom		0.023	
se		0.030	
p		0.436	
Tester race: Hispanic/Latina × 3 bedroom		0.001	
se		0.043	
p		0.979	
Tester race: White × 3 bedroom		0.006	
se		0.033	
p		0.845	
Has HCV × 2 bedroom			0.013
se			0.027
p			0.617
Has HCV × 3 bedroom			-0.059
se			0.030
p			0.049
N	6043	6043	6043
R^2	0.170	0.170	0.171
Adjusted R^2	0.166	0.166	0.167
Residual Std. Error	0.437	0.437	0.437
F statistic	42.554	37.420	40.076
AIC	7171	7177	7168
Predictions outside [0,1]	22	22	20

Table 5.22: Interaction of tester attributes × % white-only; **Positive** response LPM models

Variable	Model 6	Tester race × % white-only	HCV × % white-only
Tester race: Hispanic/Latina	0.030	-0.046	0.030
se	0.018	0.039	0.018
p	0.101	0.243	0.105
Tester race: White	**0.043**	-0.014	**0.044**
se	0.013	0.032	0.013
p	0.001	0.663	0.001
HCV status: Has HCV	**-0.362**	**-0.362**	**-0.278**
se	0.011	0.011	0.028
p	0.000	0.000	0.000
% white-only	0.022	-0.049	**0.092**
se	0.036	0.046	0.042
p	0.542	0.285	0.027
Tester race: Hispanic/Latina × % white-only		0.141	
se		0.067	
p		0.035	
Tester race: White × % white-only		0.096	
se		0.049	
p		0.050	
Has HCV × % white-only			**-0.144**
se			0.044
p			0.002
N	6043	6043	6043
R^2	0.170	0.171	0.172
Adjusted R^2	0.166	0.167	0.168
Residual Std. Error	0.437	0.437	0.436
F statistic	42.554	40.028	41.556
AIC	7171	7169	7162
Predictions outside [0,1]	22	26	21

Table 5.23: Interaction of tester attributes × costs; **Positive** response LPM models

Variable	Model 6	Tester race × FMR %	Tester race × Median rent	HCV × FMR %	HCV × Median rent
Tester race: Hispanic/Latina	0.030	-0.032	-0.016	0.030	0.030
se	0.018	0.116	0.065	0.018	0.018
p	0.101	0.780	0.806	0.105	0.105
Tester race: White	**0.043**	0.081	0.082	**0.044**	**0.043**
se	0.013	0.083	0.047	0.013	0.013
p	0.001	0.324	0.081	0.001	0.001
HCV status: Has HCV	**-0.362**	**-0.361**	**-0.361**	**-0.253**	**-0.407**
se	0.011	0.011	0.011	0.076	0.042
p	0.000	0.000	0.000	0.001	0.000
FMR %	**0.133**	**0.140**	**0.134**	**0.186**	**0.133**
se	0.042	0.061	0.042	0.055	0.042
p	0.002	0.022	0.002	0.001	0.002
Median rent (in $1000s)	**-0.110**	**-0.111**	**-0.104**	**-0.110**	**-0.132**
se	0.029	0.029	0.039	0.029	0.035
p	0.000	0.000	0.008	0.000	0.000
Tester race: Hispanic/Latina × FMR %		0.058			
se		0.108			
p		0.591			
Tester race: White × FMR %		-0.037			
se		0.079			
p		0.640			
Tester race: Hispanic/Latina × Median rent			0.039		
se			0.056		
p			0.488		
Tester race: White × Median rent			-0.037		
se			0.043		
p			0.389		
Has HCV × FMR %				-0.104	
se				0.072	
p				0.148	
Has HCV × Median rent					0.044
se					0.039
p					0.257
N	6043	6043	6043	6043	6043
R^2	0.170	0.170	0.171	0.171	0.170
Adjusted R^2	0.166	0.166	0.166	0.166	0.166
Residual Std. Error	0.437	0.437	0.437	0.437	0.437
F statistic	42.554	39.827	39.875	41.213	41.180
AIC	7171	7174	7173	7171	7172
Predictions outside [0,1]	22	23	21	24	16

Table 5.24: Interaction of HCV status × SOI; **Positive** response LPM models

Variable	Model 6	HCV × SOI
HCV: Has HCV	**-0.362**	**-0.379**
se	0.011	0.014
p	0.000	0.000
SOI coverage: City	0.002	-0.024
se	0.022	0.027
p	0.924	0.390
SOI coverage: County	-0.034	-0.051
se	0.037	0.043
p	0.356	0.238
SOI coverage: State	0.092	0.069
se	0.056	0.058
p	0.101	0.232
SOI coverage: City × Has HCV		0.050
se		0.033
p		0.129
SOI coverage: County × Has HCV		0.033
se		0.044
p		0.452
SOI coverage: State × Has HCV		0.039
se		0.029
p		0.171
N	6043	6043
R^2	0.170	0.171
Adjusted R^2	0.166	0.167
Residual Std. Error	0.437	0.437
F Statistic	42.554	38.732
AIC	7171	7172
Predictions outside [0,1]	22	35

Figure 5.11: Predicted probabilities varying % white-only; LPM **positive** response with % white-only × race

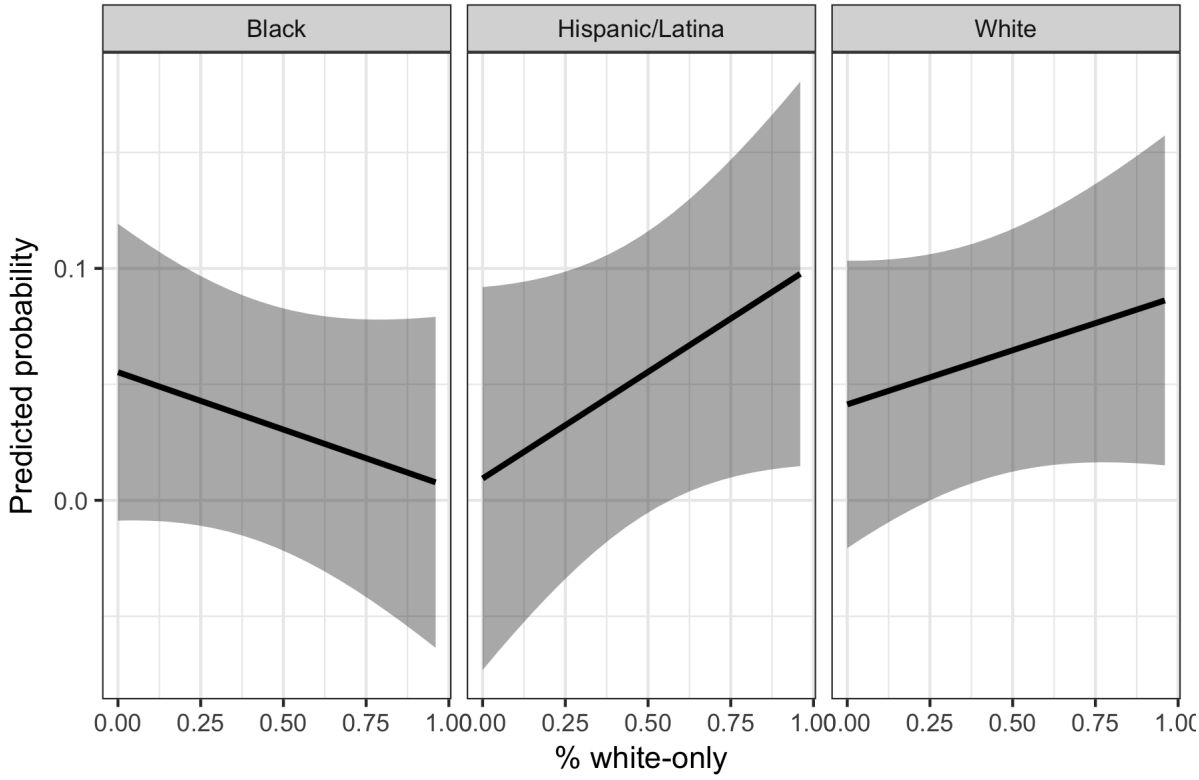


Figure 5.12: Predicted probabilities varying % white-only; LPM **positive** response with % white-only × HCV

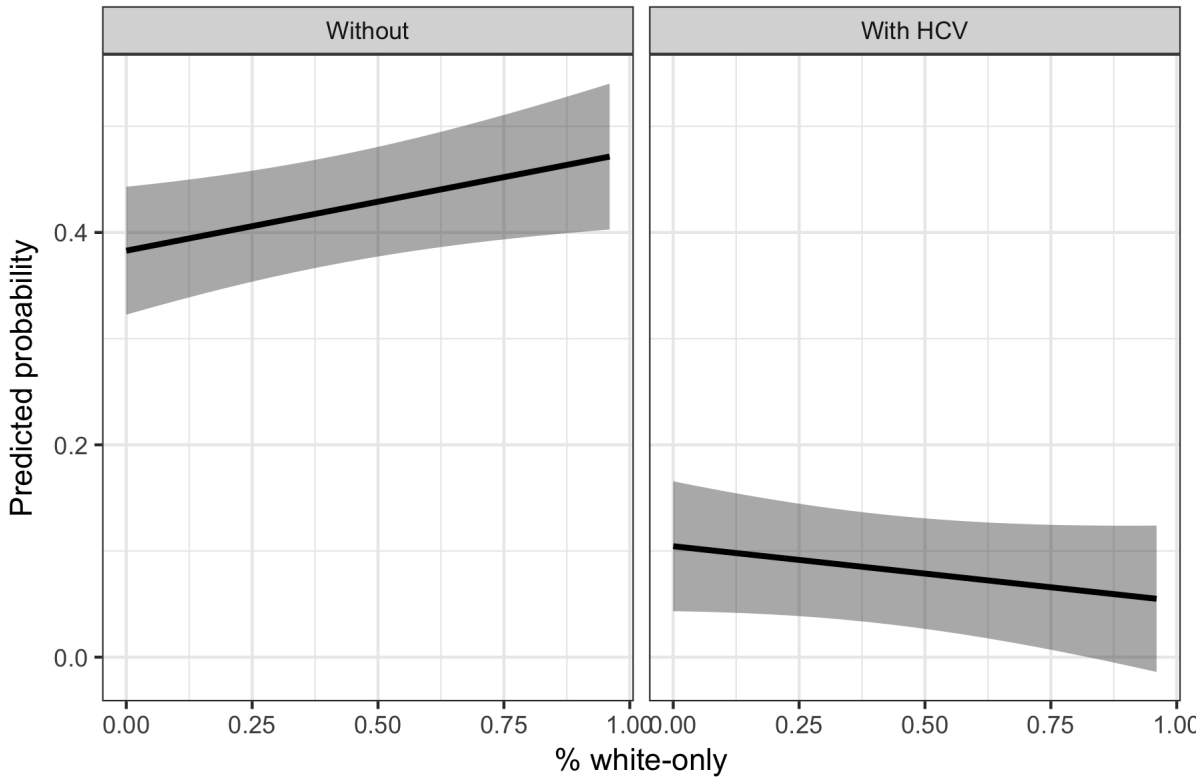


Table 5.25: Significant variables from LPM models

Variable	Any Response		Positive Response	
Tester race: White			**4.3%**	↑
HCV Status	**-14.6%**	↓	**-36.2%**	↓
Unit Size: 3 bedroom	**4.3%**	↑	**3.3%**	↑
1-point FMR % increase	**0.2%**	↑	**0.1%**	↑
Multi-state management	**-13.8%**	↓	**-11.4%**	↓
$100 increase in median rent	**-1.0%**	↓	**-1.1%**	↓
Madison			**13.4%**	↑
Miami	**-8.0%**	↓		
Phoenix	**-8.8%**	↓		
Pittsburgh	**8.8%**	↑		
Seattle			**8.1%**	↑

5.3 Discussion

I will compare these results to similar studies. Then, I will discuss the limitations of this study.

The response rate differences by race are significant like previous racial discrimination email audit studies, however the size of the difference is smallest in this study. Direct comparisons with these studies are complicated by that fact that they all focused on one bedroom and/or studio units and included a broader portion of the distribution of asking rents.

In the only other email audit study examining HCV status (Phillips, 2017), the impact of having HCV on getting any response is significant and nearly equivalent to this study's estimate (15%) and the impact on getting a positive response is significant yet smaller than this study's estimate (27% versus 36%). Phillips finds a white advantage for both receiving any response and a positive response: respectively, black testers were -9 and -6 percentage points less likely to receive those responses than white testers. Though I did not find racial differences for receiving any response, the black/white difference for receiving a positive response (-4%) is close to Phillips' estimate. Like Phillips, I did not find a significant interaction between race and HCV status for predicting a positive response. Comparing results on receiving a positive response is difficult because I chose a broader definition of positive response (as explained in Chapter 4). Further, comparing any results is problematic because the criteria for selecting postings to participate in Phillips' study are not similar to this study.

Finally, this study has limitations. This study cannot distinguish between taste-based and statistical discrimination in landlords. Previous studies have included specific text in emails to signal differences in tenant desirability (e.g., smoker, credit status, quality of grammar) with the intent to uncover the type of discrimination that is occurring. It is useful for policy to determine the discrimination type: statistical discrimination is thought to be addressed by providing landlords with more information or better incentives, while taste-based

discrimination is impervious to additional information suggesting inducements may have little effect and stricter enforcement may be required.

I chose not to attempt to separate these effects. I felt that some of the tenant desirability statements used in tester emails sounded weird, or seemed inauthentic. For credit status, I did not think it was advisable to send out many tester emails from HCV households saying they had good credit. There is no national data on the trends of HCV households' credit status–including those who lease and do not lease. Observational work suggests that many HCV households have no or bad credit. Including statements on credit quality might not be valid for HCV households. In other words, I avoided going after these distinctions because I did not think I could do it well.

As discussed previously, craigslist is not the only source for rental unit advertisements. Units can still be identified through other channels: personal connections, print listings, site-specific signage. This study does not characterize interactions searchers would have with landlords identified through these sources. craigslist does not capture the entire market; it is just a market place. Email audits could be designed to incorporate more sources. They would require more resources than I had and some careful thinking on depulication strategies across all sources.

The empirical estimates associated with SOI laws are observational at best–definitely not causal effects. To get at SOI causal effects, one would likely rely on quasi-experiments that exploit geographic variation in the timing of adoption of SOI laws (c.f. Freeman (2011); Freeman and Li (2013)).

It is also difficult to interpret the SOI estimates because they are likely explaining some of the variation that the study site fixed effects are trying to account for as well–it is possible that adding the fixed effects in Model 6 is overcontrolling. Further, we have no information about the variations in the awareness or strength and ease of enforcement of SOI protections at specific sites. Explaining this variation remains a gap in the research literature.

Previous research suggests that HCV households are subject to discrimination on the basis of family status, yet this study cannot isolate the effect of family status. It is likely

that landlords might assume multiple occupancy, especially for correspondence about larger unit sizes. This is an area for further research, especially for in-person methods that offer more organic ways to specify the nature of occupancy.

This study does not address seasonality. It characterizes search experiences during 60 summer days. If there is reason to think the market would treat HCV households differently at another time in the year, a study would need to occur throughout the year. My sense is that HCV discrimination is not subject to seasonal trends, but I have no empirical evidence to support that.

Another drawback, that applies to all email audit studies, is that one never knows the true status of sent and received emails. Some tester emails did not make it to landlords' inboxes and some landlord responses did not make it to testers' inboxes. In other words, technical malfunction, such as server nonresponse or blocking, could be driving some of the non-response. This has likely happened to some correspondence in this study. The hope is that the likelihood of this happening is distributed evenly in subgroups due to randomization.

Despite these limitations, this study provides the first multi-city empirical evidence of HCV discrimination rates. It finds that HCV households are substantially less likely to receive any response from landlords, and are even less likely to receive a positive response for landlords compared to similar unsubsidized renters. The policy implications of these findings will be discussed in the final chapter.

Chapter 6
POLICY IMPLICATIONS

This study examines discrimination rates for Housing Choice Voucher holders searching for private-market rental units. The analysis focuses on the behavior of landlords responding to email audit tester inquiries about apartments advertised online in fourteen metro areas that differ in the types of local and state Source of Income (SOI) protections in place. Tester emails vary in the race of sender (conveyed through name) and whether the sender discloses HCV status. Results indicate that HCV households are substantially less likely to receive any response form landlords (-15%), and are even less likely to receive a positive response for landlords (36%). Race of sender does matter, with white households having a four percentage point advantage in receiving a positive response. There are not differences in the effects of HCV by race. Due to the randomization of assignment by HCV status and race, these effects are very likely causal.

SOI laws were not significantly associated with response behavior. As mentioned before, this study was not designed to uncover the causal impact of SOI laws. What is estimated here are associations. SOI did not have a significant effect in regression modeling however, SOI laws may still be important even if they do not directly reduce discrimination for searching HCV households for two reasons. First, overtime SOI laws may lead to instances of self-policing, and possibly peer-pressure, from landlords. In a handful of interactions, landlords made testers aware of SOI protections. For example:

> "Acceptance of Section 8 is a requirement of most landlords so I hope you aren't hearing no from people on that."

> "Also, in Oregon it is the law that all apartment management companies have to accept section 8."

> "Yes, we accepting housing vouchers (friendly heads up that it is actually is not legal to refuse them)."

The motivation behind these statements is unknown. It could be coming from feelings of altruism or more 'If I have to do it, everyone has to do it'. Regardless of the motivation, these small actions benefit HCV households and are directly associated with SOI laws.

Second, SOI laws protect households that are currently under lease from no-fault evictions due to HCV status. In most unprotected areas, landlords may decide to evict households or decline to renew leases if they wish to no longer participate in the HCV program. Even if HCV households have maintained good tenancy, landlords can still evict them. For households participating in the Baltimore Housing Mobility Project that were leasing in unprotected jurisdictions, there were over 200 of these types of evictions and non-renewals (DeLuca and Rosenblatt, 2017, footnote 9).

Finally, I have some recommendations for the composition of SOI laws. All SOI laws should include protections for HCV as a source of income, both during search and tenancy. In addition to these protections, laws should make the steering of HCV households illegal. This means that when there is an HCV-eligible vacancy that an HCV household expresses interest in, the landlord cannot direct HCV households to other units either held by different landlords, different properties within his or her own portfolio, or other location services. About 5% of the negative responses sent to HCV testers including steering statements. The most common form of steering was within the respondent's own portfolio. Steering constrains the choices available to HCV households and can prolong their search efforts.

Additionally, SOI laws should require that any tenant screening criteria regarding household income should be evaluated in terms of the size of the *tenant-paid* portion of rent–an income scaling requirement. It is common for landlords to require around 3 times the monthly rent in household monthly income to demonstrate ability to pay rent. For example, say the rent of an advertised vacancy is $1,000 per month, the ability to pay threshold is $3,000 per month, the potential HCV tenant household makes $1,000 per month, the tenant will pay

$300 per month in rent, and the voucher will pay $700 per month in rent. In areas without an SOI law, landlords do not have to consider the purchasing power of the voucher. In this case, the HCV household is not income eligible by the landlord's criteria. In areas with SOI protection, but without an income scaling requirement, the landlord now has to consider the voucher as income therefore, the household has a monthly income of $1,700–again, the HCV household is not income eligible by the landlords criteria. In areas with SOI protection that includes an income scaling requirement, the income threshold would change to 3 times the *tenant-paid* rent: $900. Now, the HCV household's income exceeds this threshold and is deemed able to pay.

Some HCV testers in this study were held to income requirements of unsubsidized renters. For example:

> "Your Gross income, including your Sec. 8 income, needs to be $2,950/month. If you meet this income requirement, we'll schedule an appointment to see the apt."

> "To qualify for this Rental we would like you to have proof of income for a minimum [o]f $35,000 per year and a good rental history."

These examples show that without the income scaling requirement, most HCV households are held to income standards that if they could meet on their own would mean that they are probably not income eligible for HCV participation in the first place. This is an incredibly important requirement that could help HCV households.

Existing SOI laws vary in content and some laws already have some or all of the components I recommend here. Future laws should include all these components when it is politically possible.

The rates of discrimination observed in this study suggest the need to improve support for HCV households or for alternative approach to providing housing assistance to low income households. One possible strategy to help combat discrimination or at least help HCV

households identify a participating landlord sooner is to assist them during their search. Presently, most often when HCV households receive search assistance it is part of a mobility counseling program. Mobility counseling is special programming intended to assist households in getting the most out of their voucher with respect to locational outcomes. In other words, mobility counseling seeks to help households lease in neighborhoods with low poverty rates, good schools, and good job opportunities. Mobility counseling is largely project- or PHA-specific and varies in content, intensity, and quality. The majority of HCV households do not receive mobility counseling (Turner and Briggs, 2008; Cunningham et al., 2010). When mobility counseling does occur it is usually operated under special conditions. It was a part of the Gautreaux (Rubinowitz and Rosenbaum, 2000), MTO (Goering et al., 2003), HOPE VI (Popkin et al., 2004), consent decrees (Popkin et al., 2003; DeLuca and Rosenblatt, 2017), and some vouchering-out programs (Varady and Walker, 2007, Ch. 2). Most Moving to Work (MTW)[1] PHAs include mobility counseling programming (Galvez et al., 2017).

Mobility counseling in the past has varied in cost. Gautreaux counseling and administrative costs averaged $1,430 per household in 1996 (Rubinowitz and Rosenbaum, 2000, 66). The MTO study-wide average was $1,200: with the lowest costs in New York City ($590), and the highest in Baltimore ($1,600) (Briggs et al., 2010, 60). At vouchered-out sites, counseling ranged from $348 to $500 per household (Varady and Walker, 2007, 53). These costs would require the typical PHA to use most, if not all, of the administrative fees associated with one year of voucher subsidy to support mobility counseling. This would leave the PHA

[1]In the mid-1990s, Congress authorized the Moving to Work (MTW) demonstration program with the purpose of discovering and testing novel approaches to operating existing affordable housing programs in PHAs (Public Law 104-134). A handful of PHAs, either through competition or assignment, have received the designation as a Moving to Work (MTW) participant. An MTW PHA has more discretion in carrying out its operations compared to a conventional PHA. Selected PHAs are instructed to develop their own programs and interventions to help address the housing needs in their communities. Additionally, PHAs are expected to assess the efficacy of their efforts. The intent is to identify new, viable strategies for administration that could eventually be brought to a federal scale across all PHAs (GAO, 2012, 4). At the moment, 39 PHAs are authorized to participate in MTW (GAO, 2012, 5). Legislation passed during the Obama administration expands MTW (Public Law 114-113 §239), yet this expansion has yet to be implemented.

with little funding to support the costs of the normal tasks associated with administering the voucher during that first year.

In summary, we often study and evaluate mobility counseling programs that nearly all PHAs cannot afford to operate at scale. Investigating smaller strategies, that could be brought to scale at a conventional PHA, that are directly in support of identifying and inquiring about available, eligible units in good neighborhoods should be a priority for researchers and policy makers.

Another option for the program is to work on reducing the time it takes to complete pre-leasing approvals. Pre-leasing approval requirements, as described in Chapter 2, make leasing the an HCV household very different than an unsubsidized household. In a few instances, landlords responding to tester emails gave their opinions on the pre-leasing process. Most of these mentions were negative. For example:

> "I don't take Sec 8 appl because they demand and do [too] much inspection and have me do unnecessary repairs etc., too much of a hassle."

> "HI I appreciate your interest, but I don't like to work w/ section 8. They always lower my rent by 20%, take [too] long to do inspections, cite me for ridiculous things (such as peeling paint on an exterior that turned out to be bird droppings), and take [too] long to do a re-inspection. I have never had good luck. Sorry"

This suggests that landlords find the HCV pre-leasing process onerous–a finding also in earlier qualitative work with landlords (Varady et al., 2013; Greenlee, 2014; Rosen, 2014).

A national study from 2001 estimated that pre-leasing activities take about a month on average (Finkel and Buron, 2001, 2-6). This is the time from when the tenant submits a unit for approval through to the start of the lease. A month is a long time in the rental market–perhaps too long. PHAs should work to reduce the approval process timeline.

PHAs have a new opportunity to potentially reduce time-to-lease by modifying some aspects of the inspection process. This opportunity is authorized by the Housing Opportunity

Through Modernization Act of 2016 (HOTMA).[2] HOTMA brings changes to many aspects of HUD's housing assistance programs and, in particular, it allows PHAs to enter into an HCV lease for a unit that failed inspection as long as the failure was only due to 'non-life-threatening' findings. After inspection, a tenant could move in and the landlord would have 30 days to address the findings. Consider the quote above that mentioned cosmetic repairs to the exterior of the unit: these types of findings under HOTMA would not have delayed leasing. This leeway could be beneficial for both tenants and landlords. For it to work well, PHAs would have to communicate clearly with landlords about due dates and expectations. Starting this spring, all PHAs have the option to use this discretion. It will be interesting to see how many PHAs do so and if it has an effect on lease-up rates and time-to-lease.

Another alternative is to change the disbursement mechanism of housing assistance–to use other policy tools to make housing affordable. This could occur either through tax credits or cash transfers to make housing affordable for low-income households. Using these methods to disburse assistance would remove some of the processes that make HCV households different from unsubsidized households during the pre-leasing process: no more administrative effort to comply with and verify unit size, cost, and quality. These aspects of alternative disbursement would likely be attractive to landlords. However, what would remain is differences for HCV households during the tenant screening process. Assisted renters would still look different in terms of where their income comes from and their credit status. SOI discrimination would likely still be an issue for assisted households even with credits or transfers.

HCV households need to move–it is an explicit feature of the program's design. Addressing the discrimination HCV households face in the private rental market is a significant barrier to accessing and maintaining subsidy benefits. This is an issue that administrators and policy makers will continue to struggle with.

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[2]Public Law 114-201: https://www.congress.gov/114/plaws/publ201/PLAW-114publ201.pdf

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Appendix A

MECHANICAL TURK

Figure A.1: Example of Amazon Mechanical Turk request specifications

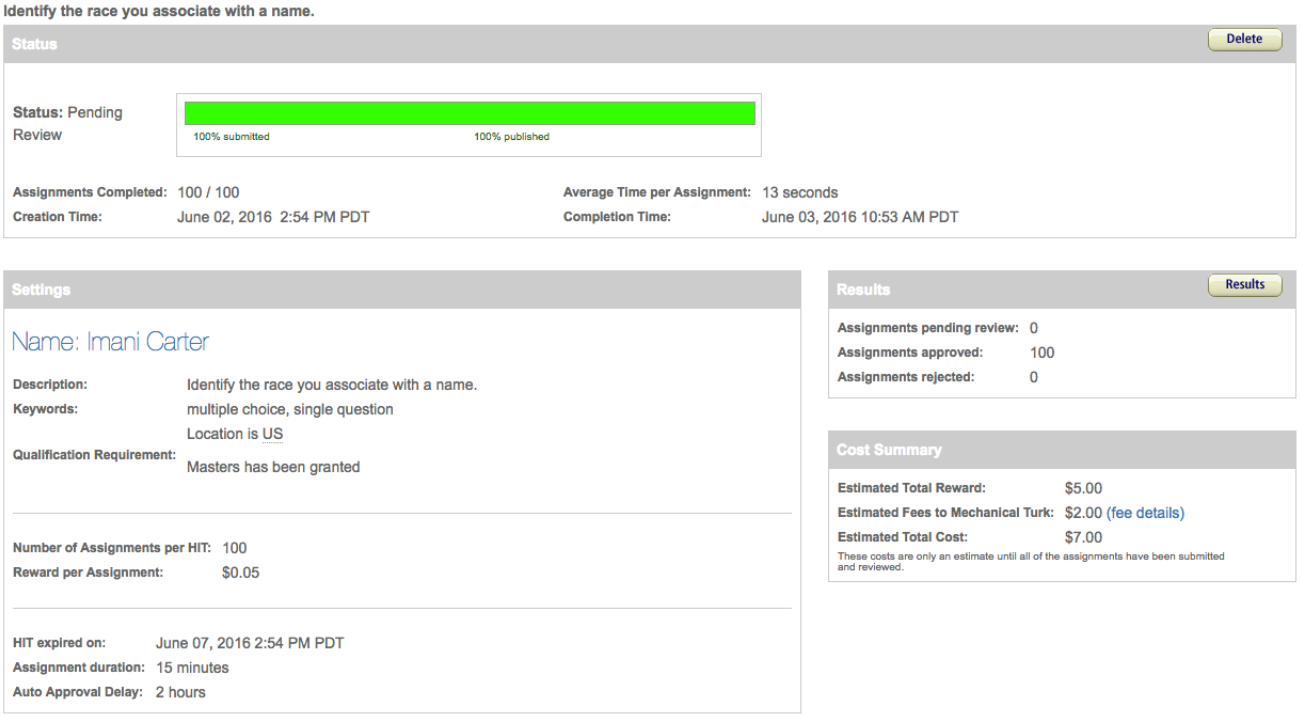


Table A.1: Mechanical Turk results for potential Black tester names

% Workers classifying name as single race	**Race**	**Full name**	**Used as tester**
99%	Black	DeShauna Williams	Yes
98%	Black	Lateefah Jefferson	Yes
98%	Black	Tyleesha Harris	Yes
96%	Black	Sheniqua Callands	Yes
96%	Black	Shardae Washington	Yes
95%	Black	Tamika Odum	Yes
95%	Black	Tashara Readus	Yes
93%	Black	Keisha Smalls	Yes
92%	Black	Damisha Edgerson	Yes
91%	Black	Cheranique Tankson	Yes
88%	Black	Deshauna Batiste	No
86%	Black	Daysha Cooperwood	No
86%	Black	Talisha Rahmings	No
85%	Black	Aaliyah Robinson	No
80%	Black	Mahogany Jiggetts	No
80%	Black	Charnae Vandross	No
79%	Black	Shardae Yelder	No
77%	Black	Laniece Piggee	No
76%	Black	Imani Carter	No
70%	Black	Jaleesa Nwankwo	No
67%	Black	Kamaria Sinkfield	No
60%	Black	Daija Okafor	No
59%	Black	Maliya Gadson	No
58%	Black	Khiana Opoku	No

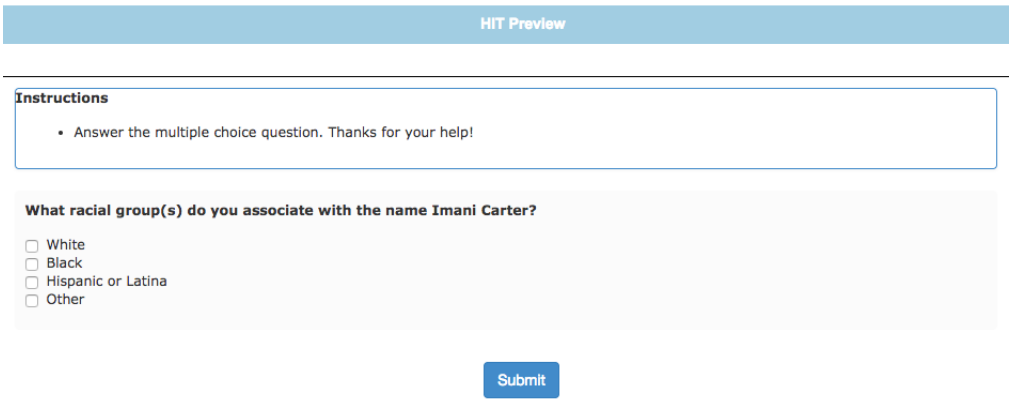
Table A.2: Mechanical Turk results for potential Hispanic & Latina tester names

% Workers classifying name as single race	**Race**	**Full name**	**Used as tester**
100%	Hispanic	Valentina Rodriguez	Yes
99%	Hispanic	Rosa Hernandez	Yes
98%	Hispanic	Esperanza Garcia	Yes
97%	Hispanic	Estefani Lopez	Yes
97%	Hispanic	Juanita Cabreja	Yes
96%	Hispanic	Frida Fuentas	Yes
96%	Hispanic	Graciela Contreras	Yes
96%	Hispanic	Isabel Jiménez	Yes
95%	Hispanic	Esmeralda Renderos	Yes
95%	Hispanic	Fernanda Casarrubias	Yes
90%	Hispanic	Luz Lucatero	No
87%	Hispanic	Perla Conchas	No
86%	Hispanic	Maricela Orejel	No
85%	Hispanic	Josefina Montoya	No
84%	Hispanic	Dulce Escutia	No
83%	Hispanic	Juana Suriel	No
72%	Hispanic	Maribel Zetino	No
71%	Hispanic	Lorena Vences	No
69%	Hispanic	Flor Sicarios	No

Table A.3: Mechanical Turk results for White tester names

% Workers classifying name as single race	**Race**	**Full name**	**Used as tester**
98%	White	Cailey Schwartz	Yes
98%	White	Jodi Mueller	Yes
98%	White	Piper Meyer	Yes
97%	White	Ellie Schnieder	Yes
97%	White	Kacie Olsen	Yes
96%	White	Mandi Becker	Yes
96%	White	Lacee Gallagher	Yes
96%	White	Linsey Erickson	Yes
96%	White	Madalyn Fischer	Yes
96%	White	Nicole Bauer	Yes

Figure A.2: Example of Amazon Mechanical Turk question to classify name by race(s)



Appendix B

EMAIL COMPONENTS

Each study email contained these parts:

1. Subject
2. Landlord's listing email address
3. Email address of prospective tenant
4. Greeting
5. Interest
6. Query
7. HCV status
8. Closing
9. Name of the prospective tenant
10. Listing URL

Except for parts 1[1], 2[2], and 10[3], the parts of the email were determined by random

[1]The subject line was the listing title taken from craigslist listing data. Using the title as the subject line of listing emails is the default when a user allows craigslist to call an email application to generate an email inquiry.

[2]The email address of the Landlord was taken from craigslist listing data.

[3]Including the listing url is a default when a user allows craigslist to call an email application to generate an email inquiry.

assignment[4]. The following describes the parts of the email and their possible values.

Parts 3 & 9 The name and email addresses will be selected by the researcher to convey racial group affiliation. For each email, the computer will randomly assign a name and email pairing. For example, Kenya Washington at `kwash2637@gmail.com`.

Part 3 The greeting was selected from the following list:

1. Hi:
2. Hi,
3. Hi!
4. Hello:
5. Hello,
6. Hello!

Part 4 The interest text was selected from the following list:

1. I am inquiring about the apartment advertised on craigslist.
2. I am inquiring about the apartment advertised.
3. I am inquiring about the apartment you advertised on craigslist.
4. I am inquiring about the apartment you advertised.
5. I am inquiring about the unit advertised on craigslist.
6. I am inquiring about the unit advertised.
7. I am inquiring about the unit you advertised on craigslist.
8. I am inquiring about the unit you advertised.

[4]The `random.choice()` call from the Python module `random` was used to randomly select email parts https://docs.python.org/2/library/random.html.

9. I am interested in the apartment advertised on craigslist.
10. I am interested in the apartment advertised.
11. I am interested in the apartment you advertised on craigslist.
12. I am interested in the apartment you advertised.
13. I am interested in the unit advertised on craigslist.
14. I am interested in the unit advertised.
15. I am interested in the unit you advertised on craigslist.
16. I am interested in the unit you advertised.
17. I am writing about the apartment advertised on craigslist.
18. I am writing about the apartment advertised.
19. I am writing about the apartment you advertised on craigslist.
20. I am writing about the apartment you advertised.
21. I am writing about the unit advertised on craigslist.
22. I am writing about the unit advertised.
23. I am writing about the unit you advertised on craigslist.
24. I am writing about the unit you advertised.

Part 5 The query text was selected from the following list:

1. Is this apartment still available?
2. Is this unit still available?
3. Is it still available?
4. May I see this unit?
5. May I see this apartment?

6. May I see it?
7. Can I see this apartment sometime this week?
8. Can I see this unit sometime this week?
9. Can I see it sometime this week?
10. Can I see this apartment this week?
11. Can I see this unit this week?
12. Can I see it this week?
13. Can I schedule a viewing?
14. Is there a good time to come and see the unit?
15. When may I see this unit?
16. When may I view this unit?
17. When may I see it?

Part 6 First, the computer program randomly assigned whether the email would disclose HCV status or not. If not, this part was excluded. If the email was assigned to disclose HCV status, the statement was selected from the following list:

1. I have a housing voucher.
2. I have a Section 8 voucher.
3. I have Section 8.
4. I will use a housing voucher to pay part of my rent.
5. I will use a Section 8 voucher to pay part of my rent.
6. I will use Section 8 to pay part of my rent.
7. I have received a housing voucher.
8. I have received a Section 8 voucher.

9. I have received Section 8.
10. I have received a housing voucher to help me with rent.
11. I have received a Section 8 voucher to help me with rent.
12. I have received Section 8 to help me with rent.
13. Do you accept housing vouchers?
14. Do you accept Section 8 vouchers?
15. Do you accept Section 8?
16. Will you accept a housing voucher?
17. Will you accept a Section 8 voucher?
18. Will you accept Section 8?
19. I have the documentation for my housing voucher.
20. I have the documentation for my Section 8 voucher.
21. I have the documentation for my Section 8.
22. I have a voucher from the housing authority.
23. I have a Section 8 voucher from the housing authority.
24. I have Section 8 from the housing authority.
25. I will use a housing voucher.
26. I will use a Section 8 voucher.
27. I will use Section 8.
28. Part of my rent will come from a housing voucher.
29. Part of my rent will come from a Section 8 voucher.
30. Part of my rent will come from Section 8.
31. Some of my rent will come from a housing voucher.

32. Some of my rent will come from a Section 8 voucher.
33. Some of my rent will come from Section 8.

Part 7 The closing of the email will be selected from the following list:

1. Best regards,
2. Best regards!
3. Cheers,
4. Cheers!
5. Look forward to hearing from you,
6. Look forward to hearing from you!
7. Many thanks,
8. Many thanks!
9. Regards,
10. Regards!
11. Thank you for your time,
12. Thank you for your time!
13. Thank you,
14. Thank you!
15. Thanks,
16. Thanks!
17. Thank you,
18. Thank you!
19. All the best,

20. All the best!
21. Thanks so much,
22. Thanks so much!
23. Thanks for your consideration,
24. Thanks for your consideration!

Appendix C

ADVERTISED RENTS BY UNIT SIZE

Table C.1: Distribution of advertised rents for selected one bedroom units

Study site	**Min**	**25% Q**	**Median**	**75% Q**	**Max**	**Mean**
Overall	$450	$740	$900	$1,145	$1,600	$944
Atlanta GA	$579	$769	$842	$970	$1,066	$853
Boston MA	$675	$1,200	$1,350	$1,500	$1,600	$1,323
Denver CO	$740	$948	$1,049	$1,150	$1,250	$1,037
Houston TX	$550	$727	$825	$922	$1,000	$818
Madison WI	$550	$723	$800	$883	$1,010	$804
Miami FL	$725	$965	$1,098	$1,200	$1,260	$1,070
Minneapolis MN	$600	$780	$865	$930	$1,050	$859
Oklahoma City OK	$450	$529	$583	$675	$795	$598
Phoenix AZ	$515	$650	$754	$848	$955	$748
Pittsburgh PA	$475	$575	$675	$750	$850	$671
Portland OR	$759	$995	$1,100	$1,236	$1,325	$1,106
San Diego CA	$850	$1,200	$1,320	$1,400	$1,495	$1,292
Seattle WA	$860	$1,103	$1,287	$1,454	$1,592	$1,268
St. Louis MO	$465	$545	$650	$709	$835	$631

Table C.2: Distribution of advertised rents for selected two bedroom units

Study site	**Min**	**25% Q**	**Median**	**75% Q**	**Max**	**Mean**
Overall	$560	$895	$1,175	$1,498	$2,035	$1,208
Atlanta GA	$665	$804	$915	$1,038	$1,233	$935
Boston MA	$1,100	$1,513	$1,800	$1,900	$2,035	$1,719
Denver CO	$950	$1,250	$1,381	$1,484	$1,595	$1,348
Houston TX	$675	$855	$950	$1,088	$1,229	$966
Madison WI	$665	$823	$925	$1,055	$1,205	$942
Miami FL	$875	$1,250	$1,395	$1,500	$1,611	$1,375
Minneapolis MN	$725	$975	$1,095	$1,200	$1,325	$1,078
Oklahoma City OK	$560	$650	$725	$850	$1,025	$749
Phoenix AZ	$640	$808	$905	$1,000	$1,160	$911
Pittsburgh PA	$580	$700	$795	$900	$1,050	$795
Portland OR	$850	$1,128	$1,250	$1,385	$1,560	$1,251
San Diego CA	$1,075	$1,500	$1,675	$1,800	$1,947	$1,646
Seattle WA	$1,075	$1,400	$1,543	$1,789	$1,975	$1,562
St. Louis MO	$595	$700	$800	$895	$1,090	$806

Table C.3: Distribution of advertised rents for selected three bedroom units

Study site	**Min**	**25% Q**	**Median**	**75% Q**	**Max**	**Mean**
Overall	$740	$1,250	$1,550	$1,950	$2,850	$1,616
Atlanta GA	$885	$1,055	$1,203	$1,363	$1,615	$1,218
Boston MA	$1,400	$1,810	$2,100	$2,400	$2,505	$2,087
Denver CO	$1,275	$1,740	$1,895	$2,000	$2,320	$1,866
Houston TX	$950	$1,235	$1,395	$1,550	$1,678	$1,368
Madison WI	$925	$1,263	$1,435	$1,550	$1,660	$1,391
Miami FL	$1,200	$1,600	$1,800	$1,950	$2,150	$1,763
Minneapolis MN	$1,013	$1,333	$1,500	$1,674	$1,875	$1,488
Oklahoma City OK	$775	$900	$1,098	$1,247	$1,400	$1,080
Phoenix AZ	$949	$1,232	$1,350	$1,500	$1,800	$1,353
Pittsburgh PA	$740	$950	$1,075	$1,200	$1,300	$1,057
Portland OR	$1,279	$1,595	$1,795	$1,950	$2,250	$1,781
San Diego CA	$1,675	$2,085	$2,308	$2,525	$2,805	$2,305
Seattle WA	$1,560	$1,803	$2,150	$2,500	$2,850	$2,165
St. Louis MO	$800	$900	$1,096	$1,250	$1,400	$1,101

Appendix D

POSTINGS MENTIONING SUBSIDIES

Table D.1: Percentages of postings mentioning subsidies explicity for selected units

Jurisdiction	**Negative**	**Positive**	**No mention**
Overall	4.5%	1.3%	94.2%
Atlanta GA	2.6%	0.8%	96.7%
Boston MA	1.0%	1.2%	97.8%
Denver CO	6.1%	1.0%	92.9%
Houston TX	1.0%	0.2%	98.8%
Madison WI	0.0%	0.0%	100.0%
Miami FL	1.2%	2.1%	96.7%
Minneapolis MN	15.8%	1.3%	82.9%
Oklahoma City OK	9.6%	2.9%	87.5%
Phoenix AZ	1.0%	0.5%	98.5%
Pittsburgh PA	15.0%	2.8%	82.2%
Portland OR	0.0%	0.5%	99.5%
San Diego CA	6.4%	1.7%	91.8%
Seattle WA	1.3%	0.3%	98.5%
St. Louis MO	4.3%	3.2%	92.5%

Appendix E

COMPARABILITY BY SITE

Table E.1: Comparability of groups: **Atlanta**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	392		207		185		
Race:							No
Black	201	51.3%	104	50.2%	97	52.4%	
White	191	48.7%	103	49.8%	88	47.6%	
Bedrooms:							No
1	117	29.8%	67	32.4%	50	27.0%	
2	155	39.5%	78	37.7%	77	41.6%	
3	120	30.6%	62	30.0%	58	31.4%	
FMR % (mean)	0.998		0.997		0.999		No
Response time	20.995		20.470		21.583		No
SOI coverage:							
City	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	0	0.0%	0	0.0%	0	0.0%	No
Individual poverty rate (mean)	0.206		0.205		0.208		No
% White (mean)	0.328		0.334		0.321		No
Vacancy rate (mean)	0.088		0.085		0.092		No
Median rent (mean, in $1000s)	0.980		0.986		0.973		No
Voucher units % (mean)	0.021		0.023		0.019		No
Multi-state management	222	56.6%	122	58.9%	100	54.1%	No

Table E.2: Comparability of groups: **Atlanta**, race

	All		Black		White		Significant
	#	%	#	%	#	%	difference
Count	392		201		191		
With HCV	185	47.2%	97	46.9%	88	46.1%	No
Bedrooms:							No
1	117	29.8%	57	27.5%	60	31.4%	
2	155	39.5%	84	40.6%	71	37.2%	
3	120	30.6%	60	29.0%	60	31.4%	
FMR % (mean)	0.998		1.013		0.982		No
Response time	20.995		21.591		20.368		No
SOI coverage:							
City	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	0	0.0%	0	0.0%	0	0.0%	No
Individual poverty rate (mean)	0.206		0.204		0.208		No
% White (mean)	0.328		0.360		0.294		**Yes**
Vacancy rate (mean)	0.088		0.082		0.095		No
Median rent (mean, in $1000s)	0.980		0.994		0.965		No
Voucher units % (mean)	0.021		0.017		0.025		No
Multi-state management	222	56.6%	115	55.6%	107	56.0%	No

Table E.3: Comparability of groups: **Boston**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	506		243		263		
Race:							No
Black	178	35.2%	87	35.8%	91	34.6%	
Hispanic/Latina	157	31.0%	74	30.5%	83	31.6%	
White	171	33.8%	82	33.7%	89	33.8%	
Bedrooms:							No
1	132	26.1%	56	23.0%	76	28.9%	
2	256	50.6%	129	53.1%	127	48.3%	
3	118	23.3%	58	23.9%	60	22.8%	
FMR % (mean)	1.080		1.076		1.083		No
Response time	22.424		22.837		22.042		No
SOI coverage:							
City	100	19.8%	46	18.9%	54	20.5%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	499	98.6%	241	99.2%	258	98.1%	No
Any	499	98.6%	241	99.2%	258	98.1%	No
Individual poverty rate (mean)	0.128		0.127		0.129		No
% White (mean)	0.682		0.682		0.681		No
Vacancy rate (mean)	0.039		0.037		0.041		No
Median rent (mean, in $1000s)	1.229		1.241		1.218		No
Voucher units % (mean)	0.039		0.039		0.039		No
Multi-state management	72	14.2%	29	11.9%	43	16.3%	No

Table E.4: Comparability of groups: **Boston**, by race

	All		Black		Hispanic/Latina		White		Significant
	#	%	#	%	#	%	#	%	difference
Count	506		178		157		171		
With HCV	263	52.0%	91	51.1%	83	52.9%	89	52.0%	No
Bedrooms:									No
1	132	26.1%	42	23.6%	42	26.8%	48	28.1%	
2	256	50.6%	95	53.4%	78	49.7%	83	48.5%	
3	118	23.3%	41	23.0%	37	23.6%	40	23.4%	
FMR % (mean)	1.080		1.074		1.075		1.090		No
Response time	22.424		22.673		22.763		21.852		No
SOI coverage:									
City	100	19.8%	31	17.4%	27	17.2%	42	24.6%	No
County	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
State	499	98.6%	175	98.3%	154	98.1%	170	99.4%	No
Any	499	98.6%	175	98.3%	154	98.1%	170	99.4%	No
Individual poverty rate (mean)	0.128		0.125		0.139		0.121		No
% White (mean)	0.682		0.680		0.666		0.698		No
Vacancy rate (mean)	0.039		0.041		0.040		0.035		No
Median rent (mean, in $1000s)	1.229		1.221		1.205		1.260		No
Voucher units % (mean)	0.039		0.037		0.044		0.036		No
Multi-state management	72	14.2%	27	11.1%	25	15.9%	20	11.7%	No

Table E.5: Comparability of groups: **Denver**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	594		289		305		
Race:							No
Black	196	33.0%	87	30.1%	109	35.7%	
Hispanic/Latina	198	33.3%	105	36.3%	93	30.5%	
White	200	33.7%	97	33.6%	103	33.8%	
Bedrooms:							No
1	191	32.2%	86	29.8%	105	34.4%	
2	238	40.1%	125	43.3%	113	37.0%	
3	165	27.8%	78	27.0%	87	28.5%	
FMR % (mean)	1.076		1.075		1.077		No
Response time	21.207		20.574		21.808		No
SOI coverage:							
City	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	0	0.0%	0	0.0%	0	0.0%	No
Individual poverty rate (mean)	0.150		0.152		0.149		No
% White (mean)	0.616		0.604		0.628		No
Vacancy rate (mean)	0.039		0.039		0.040		No
Median rent (mean, in $1000s)	1.060		1.060		1.060		No
Voucher units % (mean)	0.021		0.023		0.020		No
Multi-state management	172	29.0%	86	29.8%	86	28.2%	No

Table E.6: Comparability of groups: **Denver**, by race

	All		Black		Hispanic/Latina		White		Significant
	#	%	#	%	#	%	#	%	difference
Count	594		196		198		200		
With HCV	305	51.3%	109	55.6%	93	47.0%	103	51.5%	No
Bedrooms:									No
1	191	32.2%	66	33.7%	58	29.3%	67	33.5%	
2	238	40.1%	72	36.7%	82	41.4%	84	42.0%	
3	165	27.8%	58	29.6%	58	29.3%	49	24.5%	
FMR % (mean)	1.076		1.062		1.078		1.088		No
Response time	21.207		21.880		21.353		20.405		No
SOI coverage:									
City	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
Any	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
Individual poverty rate (mean)	0.150		0.143		0.161		0.147		No
% White (mean)	0.616		0.621		0.601		0.627		No
Vacancy rate (mean)	0.039		0.039		0.041		0.038		No
Median rent (mean, in $1000s)	1.060		1.086		1.041		1.053		No
Voucher units % (mean)	0.021		0.021		0.024		0.019		No
Multi-state management	172	29.0%	48	16.6%	60	30.3%	64	32.0%	No

Table E.7: Comparability of groups: **Houston**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	483		224		259		
Race:							No
Black	162	33.5%	72	32.1%	90	34.7%	
Hispanic/Latina	156	32.3%	75	33.5%	81	31.3%	
White	165	34.2%	77	34.4%	88	34.0%	
Bedrooms:							No
1	216	44.7%	98	43.8%	118	45.6%	
2	147	30.4%	71	31.7%	76	29.3%	
3	120	24.8%	55	24.6%	65	25.1%	
FMR % (mean)	1.047		1.046		1.048		No
Response time	25.360		26.306		24.541		No
SOI coverage:							
City	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	0	0.0%	0	0.0%	0	0.0%	No
Individual poverty rate (mean)	0.177		0.176		0.177		No
% White (mean)	0.370		0.364		0.375		No
Vacancy rate (mean)	0.088		0.090		0.087		No
Median rent (mean, in $1000s)	0.999		1.023		0.978		No
Voucher units % (mean)	0.013		0.012		0.014		No
Multi-state management	170	35.2%	76	33.9%	94	36.3%	No

Table E.8: Comparability of groups: **Houston**, by race

	All		Black		Hispanic/Latina		White		Significant
	#	%	#	%	#	%	#	%	difference
Count	483		162		156		165		
With HCV	259	53.6%	90	55.6%	81	51.9%	88	53.3%	No
Bedrooms:									No
1	216	44.7%	72	44.4%	72	46.2%	72	43.6%	
2	147	30.4%	49	30.2%	51	32.7%	47	28.5%	
3	120	24.8%	41	25.3%	33	21.2%	46	27.9%	
FMR % (mean)	1.047		1.040		1.047		1.054		No
Response time	25.360		25.698		25.592		24.807		No
SOI coverage:									
City	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
Any	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
Individual poverty rate (mean)	0.177		0.180		0.179		0.172		No
% White (mean)	0.370		0.347		0.365		0.396		No
Vacancy rate (mean)	0.088		0.093		0.080		0.091		No
Median rent (mean, in $1000s)	0.999		0.987		0.996		1.014		No
Voucher units % (mean)	0.013		0.015		0.011		0.013		No
Multi-state management	170	35.2%	53	23.7%	54	34.6%	63	38.2%	No

Table E.9: Comparability of groups: **Madison**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	350		165		185		
Race:							No
Black	176	50.3%	86	52.1%	90	48.6%	
White	174	49.7%	79	47.9%	95	51.4%	
Bedrooms:							No
1	91	26.0%	51	30.9%	40	21.6%	
2	171	48.9%	77	46.7%	94	50.8%	
3	88	25.1%	37	22.4%	51	27.6%	
FMR % (mean)	1.030		1.036		1.025		No
Response time	24.656		24.720		24.599		No
SOI coverage:							
City	212	60.6%	104	63.0%	108	58.4%	No
County	307	87.7%	148	89.7%	159	85.9%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	308	88.0%	148	89.7%	160	86.5%	No
Individual poverty rate (mean)	0.168		0.163		0.172		No
% White (mean)	0.789		0.780		0.797		No
Vacancy rate (mean)	0.025		0.027		0.023		No
Median rent (mean, in $1000s)	0.899		0.895		0.902		No
Voucher units % (mean)	0.018		0.017		0.018		No
Multi-state management	14	4.0%	9	5.5%	5	2.7%	No

Table E.10: Comparability of groups: **Madison**, race

	All		Black		White		Significant
	#	%	#	%	#	%	difference
Count	350		176		174		
With HCV	185	52.9%	90	54.5%	95	54.6%	No
Bedrooms:							No
1	91	26.0%	53	32.1%	38	21.8%	
2	171	48.9%	87	52.7%	84	48.3%	
3	88	25.1%	36	21.8%	52	29.9%	
FMR % (mean)	1.030		1.018		1.043		No
Response time	24.656		24.258		25.058		No
SOI coverage:							
City	212	60.6%	110	66.7%	102	58.6%	No
County	307	87.7%	156	94.5%	151	86.8%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	308	88.0%	156	94.5%	152	87.4%	No
Individual poverty rate (mean)	0.168		0.177		0.159		No
% White (mean)	0.789		0.779		0.799		No
Vacancy rate (mean)	0.025		0.025		0.024		No
Median rent (mean, in $1000s)	0.899		0.896		0.901		No
Voucher units % (mean)	0.018		0.017		0.018		No
Multi-state management	14	4.0%	6	3.6%	8	4.6%	No

Table E.11: Comparability of groups: **Miami**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	480		238		242		
Race:							No
Black	164	34.2%	86	36.1%	78	32.2%	
Hispanic/Latina	156	32.5%	75	31.5%	81	33.5%	
White	160	33.3%	77	32.4%	83	34.3%	
Bedrooms:							No
1	118	24.6%	60	25.2%	58	24.0%	
2	229	47.7%	106	44.5%	123	50.8%	
3	133	27.7%	72	30.3%	61	25.2%	
FMR % (mean)	1.087		1.089		1.085		No
Response time	23.578		23.488		23.667		No
SOI coverage:							
City	0	0.0%	0	0.0%	0	0.0%	No
County	145	30.2%	72	30.3%	73	30.2%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	145	30.2%	72	30.3%	73	30.2%	No
Individual poverty rate (mean)	0.184		0.185		0.183		No
% White (mean)	0.384		0.387		0.380		No
Vacancy rate (mean)	0.079		0.077		0.081		No
Median rent (mean, in $1000s)	1.201		1.199		1.202		No
Voucher units % (mean)	0.019		0.019		0.020		No
Multi-state management	80	16.7%	42	17.6%	38	15.7%	No

Table E.12: Comparability of groups: **Miami**, by race

	All		Black		Hispanic/Latina		White		Significant
	#	%	#	%	#	%	#	%	difference
Count	480		164		156		160		
With HCV	242	50.4%	78	47.6%	81	51.9%	83	51.9%	No
Bedrooms:									No
1	118	24.6%	38	23.2%	41	26.3%	39	24.4%	
2	229	47.7%	82	50.0%	66	42.3%	81	50.6%	
3	133	27.7%	44	26.8%	49	31.4%	40	25.0%	
FMR % (mean)	1.087		1.093		1.073		1.095		No
Response time	23.578		23.221		22.644		24.855		No
SOI coverage:									
City	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
County	145	30.2%	37	22.6%	51	32.7%	57	35.6%	**Yes**
State	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
Any	145	30.2%	37	22.6%	51	32.7%	57	35.6%	**Yes**
Individual poverty rate (mean)	0.184		0.180		0.189		0.182		No
% White (mean)	0.384		0.426		0.361		0.362		**Yes**
Vacancy rate (mean)	0.079		0.081		0.079		0.077		No
Median rent (mean, in $1000s)	1.201		1.214		1.188		1.199		No
Voucher units % (mean)	0.019		0.021		0.020		0.017		No
Multi-state management	80	16.7%	28	11.8%	24	15.4%	28	17.5%	No

Table E.13: Comparability of groups: **Minneapolis**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	380		192		188		
Race:							No
Black	181	47.6%	88	45.8%	93	49.5%	
White	199	52.4%	104	54.2%	95	50.5%	
Bedrooms:							No
1	112	29.5%	55	28.6%	57	30.3%	
2	161	42.4%	86	44.8%	75	39.9%	
3	107	28.2%	51	26.6%	56	29.8%	
FMR % (mean)	1.046		1.038		1.054		No
Response time	20.338		20.525		20.148		No
SOI coverage:							
City	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	0	0.0%	0	0.0%	0	0.0%	No
Individual poverty rate (mean)	0.163		0.172		0.154		No
% White (mean)	0.698		0.708		0.688		No
Vacancy rate (mean)	0.034		0.035		0.034		No
Median rent (mean, in $1000s)	0.949		0.934		0.965		No
Voucher units % (mean)	0.026		0.024		0.027		No
Multi-state management	48	12.6%	24	12.5%	24	12.8%	No

Table E.14: Comparability of groups: **Minneapolis**, race

	All		Black		White		Significant
	#	%	#	%	#	%	difference
Count	380		181		199		
With HCV	188	49.5%	93	48.4%	95	47.7%	No
Bedrooms:							No
1	112	29.5%	56	29.2%	56	28.1%	
2	161	42.4%	69	35.9%	92	46.2%	
3	107	28.2%	56	29.2%	51	25.6%	
FMR % (mean)	1.046		1.036		1.055		No
Response time	20.338		20.165		20.496		No
SOI coverage:							
City	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	0	0.0%	0	0.0%	0	0.0%	No
Individual poverty rate (mean)	0.163		0.155		0.170		No
% White (mean)	0.698		0.698		0.699		No
Vacancy rate (mean)	0.034		0.038		0.031		No
Median rent (mean, in $1000s)	0.034		0.038		0.031		No
Voucher units % (mean)	0.026		0.027		0.024		No
Multi-state management	48	12.6%	20	10.4%	28	14.1%	No

Table E.15: Comparability of groups: **Oklahoma City**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	385		193		192		
Race:							No
Black	209	54.3%	101	52.3%	108	56.3%	
White	176	45.7%	92	47.7%	84	43.8%	
Bedrooms:							**Yes**
1	90	23.4%	47	24.4%	43	22.4%	
2	131	34.0%	77	39.9%	54	28.1%	
3	164	42.6%	69	35.8%	95	49.5%	
FMR % (mean)	0.973		0.961		0.986		No
Response time	21.872		21.683		22.063		No
SOI coverage:							
City	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	385	100.0%	193	100.0%	192	100.0%	No
Any	385	100.0%	193	100.0%	192	100.0%	No
Individual poverty rate (mean)	0.175		0.185		0.165		No
% White (mean)	0.629		0.624		0.634		No
Vacancy rate (mean)	0.077		0.076		0.078		No
Median rent (mean, in $1000s)	0.858		0.834		0.881		No
Voucher units % (mean)	0.029		0.031		0.027		No
Multi-state management	79	20.5%	44	22.8%	35	18.2%	No

Table E.16: Comparability of groups: **Oklahoma City**, race

	All		Black		White		Significant
	#	%	#	%	#	%	difference
Count	385		209		176		
With HCV	192	49.9%	108	56.0%	84	47.7%	No
Bedrooms:							No
1	90	23.4%	48	24.9%	42	23.9%	
2	131	34.0%	70	36.3%	61	34.7%	
3	164	42.6%	91	47.2%	73	41.5%	
FMR % (mean)	0.973		0.974		0.972		No
Response time	21.872		21.940		21.793		No
SOI coverage:							
City	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	385	100.0%	209	108.3%	176	100.0%	No
Any	385	100.0%	209	108.3%	176	100.0%	No
Individual poverty rate (mean)	0.175		0.172		0.179		No
% White (mean)	0.629		0.632		0.625		No
Vacancy rate (mean)	0.077		0.077		0.078		No
Median rent (mean, in $1000s)	0.858		0.860		0.855		No
Voucher units % (mean)	0.029		0.030		0.028		No
Multi-state management	79	20.5%	42	21.8%	37	21.0%	No

Table E.17: Comparability of groups: **Phoenix**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	390		191		199		
Race:							No
Black	191	49.0%	98	51.3%	93	46.7%	
White	199	51.0%	93	48.7%	106	53.3%	
Bedrooms:							No
1	115	29.5%	57	29.8%	58	29.1%	
2	168	43.1%	82	42.9%	86	43.2%	
3	107	27.4%	52	27.2%	55	27.6%	
FMR % (mean)	1.007		1.006		1.008		No
Response time	21.500		21.830		21.183		No
SOI coverage:							
City	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	0	0.0%	0	0.0%	0	0.0%	No
Individual poverty rate (mean)	0.208		0.214		0.202		No
% White (mean)	0.544		0.536		0.552		No
Vacancy rate (mean)	0.096		0.094		0.098		No
Median rent (mean, in $1000s)	0.973		0.971		0.976		No
Voucher units % (mean)	0.011		0.011		0.012		No
Multi-state management	181	46.4%	94	49.2%	87	43.7%	No

Table E.18: Comparability of groups: **Phoenix**, race

	All		Hispanic/Latina		White		Significant
	#	%	#	%	#	%	difference
Count	390		191		199		
With HCV	199	51.0%	93	48.7%	106	53.3%	No
Bedrooms:							No
1	115	29.5%	50	26.2%	65	32.7%	
2	168	43.1%	94	49.2%	74	37.2%	
3	107	27.4%	47	24.6%	60	30.2%	
FMR % (mean)	1.007		1.007		1.007		No
Response time	21.500		21.732		21.276		No
SOI coverage:							
City	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	0	0.0%	0	0.0%	0	0.0%	No
Individual poverty rate (mean)	0.208		0.216		0.200		No
% White (mean)	0.544		0.532		0.555		No
Vacancy rate (mean)	0.096		0.098		0.094		No
Median rent (mean, in $1000s)	0.973		0.965		0.981		No
Voucher units % (mean)	0.011		0.011		0.012		No
Multi-state management	181	46.4%	86	45.0%	95	47.7%	No

Table E.19: Comparability of groups: **Pittsburgh**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	353		176		177		
Race:							**Yes**
Black	182	51.6%	81	46.0%	101	57.1%	
White	171	48.4%	95	54.0%	76	42.9%	
Bedrooms:							No
1	133	37.7%	67	38.1%	66	37.3%	
2	151	42.8%	73	41.5%	78	44.1%	
3	69	19.5%	36	20.5%	33	18.6%	
FMR % (mean)	0.997		1.002		0.993		No
Response time	20.622		21.082		20.165		No
SOI coverage:							
City	198	56.1%	100	56.8%	98	55.4%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	198	56.1%	100	56.8%	98	55.4%	No
Individual poverty rate (mean)	0.169		0.155		0.182		**Yes**
% White (mean)	0.794		0.799		0.789		No
Vacancy rate (mean)	0.046		0.047		0.046		No
Median rent (mean, in $1000s)	0.776		0.773		0.779		No
Voucher units % (mean)	0.024		0.024		0.025		No
Multi-state management	9	2.5%	4	2.3%	5	2.8%	No

Table E.20: Comparability of groups: **Pittsburgh**, race

	All		Black		White		Significant
	#	%	#	%	#	%	difference
Count	353		182		171		
With HCV	177	50.1%	101	57.4%	76	44.4%	**Yes**
Bedrooms:							No
1	132	37.4%	58	33.0%	74	43.3%	
2	151	42.8%	86	48.9%	65	38.0%	
3	69	19.5%	37	21.0%	32	18.7%	
FMR % (mean)	0.997		0.988		1.007		No
Response time	20.622		20.399		20.859		No
SOI coverage:							
City	198	56.1%	102	58.0%	96	56.1%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	198	56.1%	102	58.0%	96	56.1%	No
Individual poverty rate (mean)	0.169		0.163		0.175		No
% White (mean)	0.794		0.810		0.777		No
Vacancy rate (mean)	0.046		0.046		0.046		No
Median rent (mean, in $1000s)	0.776		0.786		0.765		No
Voucher units % (mean)	0.024		0.022		0.026		No
Multi-state management	9	2.5%	3	1.7%	6	3.5%	No

Table E.21: Comparability of groups: **Portland**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	393		201		192		
Race:							No
Black	180	45.8%	92	45.8%	88	45.8%	
White	213	54.2%	109	54.2%	104	54.2%	
Bedrooms:							No
1	103	26.2%	54	26.9%	49	25.5%	
2	172	43.8%	86	42.8%	86	44.8%	
3	118	30.0%	61	30.3%	57	29.7%	
FMR % (mean)	1.042		1.028		1.056		No
Response time	22.215		21.233		23.242		**Yes**
SOI coverage:							
City	66	16.8%	39	19.4%	27	14.1%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	307	78.1%	156	77.6%	151	78.6%	No
Any	383	97.5%	195	97.0%	188	97.9%	No
Individual poverty rate (mean)	0.156		0.154		0.157		No
% White (mean)	0.712		0.717		0.706		No
Vacancy rate (mean)	0.032		0.033		0.031		No
Median rent (mean, in $1000s)	1.043		1.040		1.046		No
Voucher units % (mean)	0.022		0.021		0.023		No
Multi-state management	166	42.2%	85	42.3%	81	42.2%	No

Table E.22: Comparability of groups: **Portland**, race

	All		Black		White		Significant
	#	%	#	%	#	%	difference
Count	393		180		213		
With HCV	192	48.9%	88	43.8%	104	48.8%	No
Bedrooms:							No
1	103	26.2%	46	22.9%	57	26.8%	
2	172	43.8%	77	38.3%	95	44.6%	
3	118	30.0%	57	28.4%	61	28.6%	
FMR % (mean)	1.042		1.043		1.041		No
Response time	22.215		22.944		21.598		No
SOI coverage:							
City	66	16.8%	34	16.9%	32	15.0%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	317	80.7%	142	70.6%	175	82.2%	No
Any	383	97.5%	176	87.6%	207	97.2%	No
Individual poverty rate (mean)	0.156		0.162		0.150		No
% White (mean)	0.712		0.703		0.719		No
Vacancy rate (mean)	0.032		0.031		0.032		No
Median rent (mean, in $1000s)	1.043		1.049		1.038		No
Voucher units % (mean)	0.022		0.022		0.022		No
Multi-state management	166	42.2%	71	35.3%	95	44.6%	No

Table E.23: Comparability of groups: **San Diego**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	574		303		271		
Race:							No
Black	191	33.3%	97	32.0%	94	34.7%	
Hispanic/Latina	188	32.8%	97	32.0%	91	33.6%	
White	195	34.0%	109	36.0%	86	31.7%	
Bedrooms:							No
1	138	24.0%	65	21.5%	73	26.9%	
2	268	46.7%	141	46.5%	127	46.9%	
3	168	29.3%	97	32.0%	71	26.2%	
FMR % (mean)	1.093		1.094		1.093		No
Response time	21.732		21.735		21.730		No
SOI coverage:							
City	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	0	0.0%	0	0.0%	0	0.0%	No
Individual poverty rate (mean)	0.171		0.170		0.172		No
% White (mean)	0.458		0.457		0.458		No
Vacancy rate (mean)	0.037		0.037		0.037		No
Median rent (mean, in $1000s)	1.366		1.377		1.354		No
Voucher units % (mean)	0.034		0.031		0.037		No
Multi-state management	78	13.6%	37	12.2%	41	15.1%	No

Table E.24: Comparability of groups: **San Diego**, by race

	All		Black		Hispanic/Latina		White		Significant
	#	%	#	%	#	%	#	%	difference
Count	574		191		188		195		
With HCV	271	47.2%	94	49.2%	91	48.4%	86	44.1%	No
Bedrooms:									No
1	138	24.0%	42	22.0%	46	24.5%	50	25.6%	
2	268	46.7%	100	52.4%	83	44.1%	85	43.6%	
3	168	29.3%	49	25.7%	59	31.4%	60	30.8%	
FMR % (mean)	1.093		1.098		1.082		1.099		No
Response time	21.732		21.565		21.858		21.776		No
SOI coverage:									
City	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
County	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
Any	0	0.0%	0	0.0%	0	0.0%	0	0.0%	No
Individual poverty rate (mean)	0.171		0.175		0.177		0.160		No
% White (mean)	0.458		0.448		0.459		0.465		No
Vacancy rate (mean)	0.037		0.036		0.037		0.036		No
Median rent (mean, in $1000s)	1.366		1.358		1.363		1.376		No
Voucher units % (mean)	0.034		0.037		0.034		0.031		No
Multi-state management	78	13.6%	25	8.3%	26	13.8%	27	13.8%	No

Table E.25: Comparability of groups: **Seattle**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	400		190		210		
Race:							No
Black	202	50.5%	104	54.7%	98	46.7%	
White	198	49.5%	86	45.3%	112	53.3%	
Bedrooms:							No
1	128	32.0%	65	34.2%	63	30.0%	
2	181	45.3%	82	43.2%	99	47.1%	
3	91	22.8%	43	22.6%	48	22.9%	
FMR % (mean)	1.017		1.018		1.016		No
Response time	19.965		19.717		20.190		No
SOI coverage:							
City	147	36.8%	69	36.3%	78	37.1%	No
County	13	3.3%	6	3.2%	7	3.3%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	150	37.5%	70	36.8%	80	38.1%	No
Individual poverty rate (mean)	0.129		0.134		0.124		No
% White (mean)	0.621		0.612		0.628		No
Vacancy rate (mean)	0.038		0.039		0.038		No
Median rent (mean, in $1000s)	1.219		1.217		1.221		No
Voucher units % (mean)	0.028		0.028		0.028		No
Multi-state management	150	37.5%	65	34.2%	85	40.5%	No

Table E.26: Comparability of groups: **Seattle**, race

	All		Black		White		Significant
	#	%	#	%	#	%	difference
Count	400		202		198		
With HCV	210	52.5%	98	51.6%	112	56.6%	No
Bedrooms:							No
1	128	32.0%	66	34.7%	62	31.3%	
2	181	45.3%	93	48.9%	88	44.4%	
3	91	22.8%	43	22.6%	48	24.2%	
FMR % (mean)	1.017		1.025		1.009		No
Response time	19.965		20.583		19.335		No
SOI coverage:							
City	147	36.8%	69	36.3%	78	39.4%	No
County	13	3.3%	5	2.6%	8	4.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	150	37.5%	69	36.3%	81	40.9%	No
Individual poverty rate (mean)	0.129		0.122		0.136		No
% White (mean)	0.621		0.624		0.617		No
Vacancy rate (mean)	0.038		0.042		0.035		No
Median rent (mean, in $1000s)	1.219		1.244		1.194		No
Voucher units % (mean)	0.028		0.027		0.029		No
Multi-state management	150	37.5%	71	37.4%	79	39.9%	No

Table E.27: Comparability of groups: **St. Louis**, HCV status

	All		Unsubsidized		With HCV		Significant
	#	%	#	%	#	%	difference
Count	374		179		195		
Race:							No
Black	168	44.9%	80	44.7%	88	45.1%	
White	206	55.1%	99	55.3%	107	54.9%	
Bedrooms:							No
1	121	32.4%	56	31.3%	65	33.3%	
2	183	48.9%	90	50.3%	93	47.7%	
3	70	18.7%	33	18.4%	37	19.0%	
FMR % (mean)	0.971		0.981		0.963		No
Response time	19.867		20.832		18.980		No
SOI coverage:							
City	184	49.2%	89	49.7%	95	48.7%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	184	49.2%	89	49.7%	95	48.7%	No
Individual poverty rate (mean)	0.172		0.170		0.173		No
% White (mean)	0.628		0.631		0.625		No
Vacancy rate (mean)	0.074		0.078		0.071		No
Median rent (mean, in $1000s)	0.848		0.842		0.854		No
Voucher units % (mean)	0.025		0.024		0.025		No
Multi-state management	62	16.6%	33	18.4%	29	14.9%	No

Table E.28: Comparability of groups: **St. Louis**, race

	All		Black		White		Significant
	#	%	#	%	#	%	difference
Count	374		168		206		
With HCV	195	52.1%	88	49.2%	107	51.9%	No
Bedrooms:							No
1	121	32.4%	59	33.0%	62	30.1%	
2	183	48.9%	80	44.7%	103	50.0%	
3	70	18.7%	29	16.2%	41	19.9%	
FMR % (mean)	0.971		0.983		0.962		No
Response time	19.867		20.207		19.589		No
SOI coverage:							
City	184	49.2%	83	46.4%	101	49.0%	No
County	0	0.0%	0	0.0%	0	0.0%	No
State	0	0.0%	0	0.0%	0	0.0%	No
Any	184	49.2%	83	46.4%	101	49.0%	No
Individual poverty rate (mean)	0.172		0.159		0.182		No
% White (mean)	0.628		0.642		0.617		No
Vacancy rate (mean)	0.074		0.075		0.074		No
Median rent (mean, in $1000s)	0.848		0.868		0.832		**Yes**
Voucher units % (mean)	0.025		0.022		0.027		No
Multi-state management	62	16.6%	35	19.6%	27	13.1%	**Yes**

Appendix F

LINEAR PROBABILITY MODELS

Table F.1: **Any** response LPM models; Part 1

	Model	1	2	3	4	5	6
Tester characteristics	**Tester race: Hispanic/Latina**	**-0.045**	**-0.047**	**-0.044**	**-0.047**	-0.031	0.005
	se	0.019	0.018	0.019	0.018	0.019	0.020
	p	0.015	0.010	0.018	0.012	0.098	0.801
	Tester race: White	0.014	0.012	0.012	0.017	0.016	0.024
	se	0.014	0.014	0.014	0.014	0.014	0.014
	p	0.339	0.387	0.376	0.224	0.239	0.090
	HCV status: Has HCV		**-0.144**	**-0.144**	**-0.145**	**-0.147**	**-0.146**
	se		0.013	0.013	0.013	0.013	0.013
	p		0.000	0.000	0.000	0.000	0.000
SOI coverage	**SOI coverage: City**			0.011	-0.007	-0.024	-0.038
	se			0.019	0.019	0.019	0.024
	p			0.541	0.713	0.214	0.113
	SOI coverage: County			0.018	-0.014	-0.022	-0.031
	se			0.025	0.025	0.025	0.041
	p			0.476	0.586	0.376	0.457
	SOI coverage: State			0.010	0.001	-0.012	0.019
	se			0.016	0.016	0.017	0.062
	p			0.518	0.935	0.458	0.756
Unit characteristics	**Unit size: 2 bedroom**				-0.005	0.004	0.004
	se				0.015	0.015	0.015
	p				0.730	0.805	0.810
	Unit size: 3 bedroom				0.025	**0.050**	**0.043**
	se				0.017	0.018	0.018
	p				0.144	0.006	0.018
	FMR %				**0.103**	**0.172**	**0.178**
	se				0.041	0.045	0.046
	p				0.012	0.000	0.000
	Listing response time (in hrs)				0.001	0.001	0.001
	se				0.001	0.001	0.001
	p				0.453	0.351	0.352
	Management: Multi-state				**-0.147**	**-0.137**	**-0.138**
	se				0.015	0.015	0.016
	p				0.000	0.000	0.000
Neighborhood characteristics	**Individual poverty rate (%)**					-0.029	-0.041
	se					0.073	0.075
	p					0.689	0.586
	White residents (%)					**0.082**	0.030
	se					0.032	0.040
	p					0.013	0.451
	Vacancy rate (%)					-0.222	-0.052
	se					0.118	0.125
	p					0.061	0.677
	Median rent (in $1000s)					**-0.138**	**-0.101**
	se					0.027	0.033
	p					0.000	0.003
	Voucher concentration (%)					0.150	0.056
	se					0.236	0.252
	p					0.526	0.823

Table F.2: **Any** response LPM models; Part 2

	Model	1	2	3	4	5	6
Study site fixed effects	**Boston**						-0.091
	se						0.074
	p						0.220
	Denver						0.007
	se						0.035
	p						0.842
	Houston						-0.012
	se						0.034
	p						0.725
	Madison						0.068
	se						0.058
	p						0.238
	Miami						**-0.080**
	se						0.037
	p						0.033
	Minneapolis						0.034
	se						0.039
	p						0.380
	Oklahoma City						0.006
	se						0.073
	p						0.932
	Phoenix						**-0.088**
	se						0.037
	p						0.019
	Pittsburgh						**0.088**
	se						0.044
	p						0.045
	Portland						0.044
	se						0.065
	p						0.499
	San Diego						0.014
	se						0.037
	p						0.696
	Seattle						0.012
	se						0.039
	p						0.762
	St. Louis						-0.024
	se						0.040
	p						0.557
	Constant	**0.494**	**0.568**	**0.562**	**0.482**	**0.510**	**0.482**
	se	0.010	0.012	0.013	0.047	0.062	0.067
	p	0.000	0.000	0.000	0.000	0.000	0.000
	N	6054	6054	6054	6054	6043	6043
	R^2	0.002	0.023	0.023	0.040	0.047	0.055
	Adjusted R^2	0.001	0.022	0.022	0.039	0.045	0.050
	Residual Std. Error	0.500	0.494	0.494	0.490	0.489	0.487
	F statistic	5.222	46.545	23.500	23.049	18.694	12.013
	AIC	8784	8658	8663	8563	8513	8492
	Predictions outside [0,1]	0	0	0	0	0	0

Table F.3: **Positive** response LPM models; Part 1

Model		1	2	3	4	5	6
Tester characteristics	**Tester race: Hispanic/Latina**	-0.005	-0.010	0.005	0.004	0.013	0.030
	se	0.018	0.016	0.017	0.017	0.017	0.018
	p	0.785	0.556	0.773	0.803	0.440	0.101
	Tester race: White	**0.039**	**0.036**	**0.037**	**0.041**	**0.040**	**0.043**
	se	0.014	0.013	0.013	0.012	0.012	0.013
	p	0.004	0.005	0.003	0.002	0.002	0.001
	HCV status: Has HCV		**-0.359**	**-0.359**	**-0.360**	**-0.361**	**-0.362**
	se		0.011	0.011	0.011	0.011	0.011
	p		0.000	0.000	0.000	0.000	0.000
SOI coverage	**SOI coverage: City**			**0.055**	**0.041**	0.027	0.002
	se			0.017	0.017	0.017	0.022
	p			0.002	0.016	0.115	0.924
	SOI coverage: County			**0.049**	0.028	0.023	-0.034
	se			0.022	0.022	0.023	0.037
	p			0.027	0.208	0.308	0.356
	SOI coverage: State			**0.060**	**0.054**	**0.043**	0.092
	se			0.014	0.014	0.015	0.056
	p			0.000	0.000	0.005	0.101
Unit characteristics	**Unit size: 2 bedroom**				-0.007	-0.001	-0.002
	se				0.014	0.014	0.014
	p				0.599	0.944	0.912
	Unit size: 3 bedroom				0.009	0.028	**0.033**
	se				0.015	0.016	0.016
	p				0.553	0.074	0.040
	FMR %				0.049	**0.111**	**0.133**
	se				0.037	0.040	0.042
	p				0.184	0.006	0.002
	Listing response time (in hrs)				0.000	0.000	0.000
	se				0.001	0.001	0.001
	p				0.741	0.886	0.749
	Management: Multi-state				**-0.112**	**-0.105**	**-0.114**
	se				0.014	0.014	0.015
	p				0.000	0.000	0.000
Neighborhood characteristics	**Individual poverty rate (%)**					0.023	0.002
	se					0.066	0.067
	p					0.732	0.980
	White residents (%)					**0.067**	0.022
	se					0.029	0.036
	p					0.022	0.542
	Vacancy rate (%)					-0.059	0.117
	se					0.106	0.112
	p					0.577	0.296
	Median rent (in $1000s)					**-0.089**	**-0.110**
	se					0.024	0.029
	p					0.000	0.000
	Voucher concentration (%)					0.324	0.177
	se					0.212	0.226
	p					0.126	0.434

Table F.4: **Positive** response LPM models; Part 2

Model		1	2	3	4	5	6
Study site fixed effects	**Boston**						-0.048
	se						0.066
	p						0.469
	Denver						0.022
	se						0.031
	p						0.480
	Houston						0.010
	se						0.031
	p						0.753
	Madison						**0.134**
	se						0.052
	p						0.011
	Miami						-0.028
	se						0.033
	p						0.396
	Minneapolis						-0.023
	se						0.035
	p						0.512
	Oklahoma City						-0.089
	se						0.066
	p						0.177
	Phoenix						-0.050
	se						0.033
	p						0.136
	Pittsburgh						0.050
	se						0.039
	p						0.208
	Portland						0.075
	se						0.058
	p						0.199
	San Diego						0.040
	se						0.033
	p						0.226
	Seattle						**0.081**
	se						0.035
	p						0.020
	St. Louis						-0.016
	se						0.036
	p						0.657
	Constant	**0.338**	**0.522**	**0.495**	**0.482**	**0.455**	**0.465**
	se	0.010	0.011	0.012	0.042	0.056	0.060
	p	0.000	0.000	0.000	0.000	0.000	0.000
	N	6054	6054	6054	6054	6043	6043
	R^2	0.002	0.142	0.147	0.158	0.162	0.170
	Adjusted R^2	0.001	0.142	0.146	0.156	0.160	0.166
	Residual Std. Error	0.478	0.443	0.442	0.440	0.439	0.437
	F statistic	5.435	334.889	173.725	102.756	72.771	42.554
	AIC	8250	7333	7307	7241	7205	7171
	Predictions outside [0,1]	0	0	0	0	11	22

Appendix G

LOGISTIC REGRESSION MODELS

Table G.1: **Any** response logit models; Part 1

	Model	1	2	3	4	5	6
Tester characteristics	**Tester race: Hispanic/Latina**	**-0.182**	**-0.194**	**-0.181**	**-0.195**	-0.129	0.022
	se	0.074	0.075	0.076	0.077	0.078	0.086
	p	0.015	0.010	0.018	0.012	0.100	0.798
	Tester race: White	0.054	0.049	0.051	0.071	0.069	0.101
	se	0.057	0.057	0.057	0.058	0.058	0.059
	p	0.339	0.388	0.376	0.222	0.237	0.088
	HCV status: Has HCV		**-0.583**	**-0.583**	**-0.598**	**-0.609**	**-0.609**
	se		0.052	0.052	0.053	0.053	0.053
	p		0.000	0.000	0.000	0.000	0.000
SOI coverage	**SOI coverage: City**			0.047	-0.029	-0.100	-0.161
	se			0.077	0.078	0.080	0.102
	p			0.541	0.709	0.213	0.115
	SOI coverage: County			0.073	-0.056	-0.093	-0.127
	se			0.102	0.104	0.105	0.174
	p			0.476	0.588	0.376	0.465
	SOI coverage: State			0.043	0.005	-0.052	0.083
	se			0.066	0.067	0.070	0.264
	p			0.518	0.935	0.461	0.752
Unit characteristics	**Unit size: 2 bedroom**				-0.021	0.016	0.016
	se				0.063	0.063	0.064
	p				0.733	0.801	0.809
	Unit size: 3 bedroom				0.104	**0.207**	**0.182**
	se				0.071	0.074	0.076
	p				0.144	0.006	0.018
	FMR %				**0.428**	**0.721**	**0.748**
	se				0.170	0.188	0.196
	p				0.012	0.000	0.000
	Listing response time (in hrs)				0.002	0.003	0.003
	se				0.003	0.003	0.003
	p				0.456	0.353	0.350
	Management: Multi-state				**-0.611**	**-0.573**	**-0.583**
	se				0.064	0.065	0.069
	p				0.000	0.000	0.000
Neighborhood characteristics	**Individual poverty rate (%)**					-0.121	-0.172
	se					0.307	0.315
	p					0.695	0.585
	White residents (%)					**0.341**	0.126
	se					0.136	0.167
	p					0.013	0.453
	Vacancy rate (%)					-0.935	-0.225
	se					0.496	0.527
	p					0.060	0.670
	Median rent (in $1000s)					**-0.577**	**-0.426**
	se					0.113	0.138
	p					0.000	0.003
	Voucher concentration (%)					0.627	0.232
	se					0.988	1.062
	p					0.526	0.827

Table G.2: **Any** response logit models; Part 2

Model		1	2	3	4	5	6
Study site fixed effects	**Boston**						-0.385
	se						0.312
	p						0.218
	Denver						0.026
	se						0.146
	p						0.857
	Houston						-0.053
	se						0.144
	p						0.715
	Madison						0.281
	se						0.245
	p						0.252
	Miami						**-0.337**
	se						0.158
	p						0.034
	Minneapolis						0.138
	se						0.163
	p						0.398
	Oklahoma City						0.020
	se						0.310
	p						0.949
	Phoenix						**-0.376**
	se						0.159
	p						0.018
	Pittsburgh						**0.371**
	se						0.187
	p						0.048
	Portland						0.181
	se						0.273
	p						0.509
	San Diego						0.057
	se						0.154
	p						0.712
	Seattle						0.048
	se						0.164
	p						0.768
	St. Louis						-0.101
	se						0.168
	p						0.548
	Constant	-0.025	0.273	0.249	-0.079	0.038	-0.070
	se	0.041	0.049	0.054	0.194	0.260	0.284
	p	0.540	0.000	0.000	0.685	0.885	0.804
	N	6054	6054	6054	6054	6043	6043
	LL	-4190	-4127	-4126	-4072	-4042	-4018
	AIC	8387	8262	8266	8167	8118	8097

Table G.3: **Positive** response logit models; Part 1

	Model	1	2	3	4	5	6
Tester characteristics	**Tester race: Hispanic/Latina**	-0.022	-0.050	0.025	0.020	0.067	0.157
	se	0.079	0.084	0.086	0.087	0.088	0.097
	p	0.783	0.558	0.768	0.818	0.445	0.106
	Tester race: White	**0.171**	**0.181**	**0.192**	**0.211**	**0.206**	**0.226**
	se	0.059	0.064	0.064	0.065	0.065	0.066
	p	0.004	0.005	0.003	0.002	0.002	0.001
	HCV status: Has HCV		**-1.683**	**-1.694**	**-1.720**	**-1.738**	**-1.757**
	se		0.060	0.060	0.061	0.061	0.062
	p		0.000	0.000	0.000	0.000	0.000
SOI coverage	**SOI coverage: City**			**0.277**	0.202	0.133	0.007
	se			0.084	0.086	0.088	0.112
	p			0.002	0.019	0.133	0.953
	SOI coverage: County			**0.250**	0.147	0.119	-0.181
	se			0.112	0.114	0.115	0.196
	p			0.026	0.195	0.305	0.357
	SOI coverage: State			**0.303**	**0.276**	**0.222**	0.476
	se			0.073	0.074	0.077	0.291
	p			0.000	0.000	0.004	0.103
Unit characteristics	**Unit size: 2 bedroom**				-0.033	-0.003	-0.004
	se				0.070	0.071	0.072
	p				0.636	0.963	0.956
	Unit size: 3 bedroom				0.051	0.151	**0.179**
	se				0.079	0.082	0.085
	p				0.517	0.067	0.035
	FMR %				0.247	**0.573**	**0.687**
	se				0.189	0.210	0.218
	p				0.192	0.007	0.002
	Listing response time (in hrs)				-0.001	-0.001	-0.001
	se				0.003	0.003	0.003
	p				0.732	0.881	0.785
	Management: Multi-state				**-0.600**	**-0.563**	**-0.614**
	se				0.073	0.074	0.079
	p				0.000	0.000	0.000
Neighborhood characteristics	**Individual poverty rate (%)**					0.145	0.048
	se					0.339	0.347
	p					0.670	0.890
	White residents (%)					0.351	0.121
	se					0.152	0.187
	p					0.022	0.518
	Vacancy rate (%)					-0.358	0.538
	se					0.555	0.590
	p					0.519	0.362
	Median rent (in $1000s)					**-0.459**	**-0.576**
	se					0.126	0.156
	p					0.000	0.000
	Voucher concentration (%)					1.666	0.936
	se					1.093	1.171
	p					0.128	0.425

Table G.4: **Positive** response logit models; Part 2

Model		1	2	3	4	5	6
Study site fixed effects	**Boston**						-0.257
	se						0.347
	p						0.460
	Denver						0.109
	se						0.165
	p						0.512
	Houston						0.045
	se						0.165
	p						0.785
	Madison						**0.673**
	se						0.273
	p						0.014
	Miami						-0.164
	se						0.180
	p						0.363
	Minneapolis						-0.130
	se						0.185
	p						0.484
	Oklahoma City						-0.464
	se						0.345
	p						0.179
	Phoenix						-0.277
	se						0.181
	p						0.126
	Pittsburgh						0.236
	se						0.206
	p						0.254
	Portland						0.365
	se						0.304
	p						0.230
	San Diego						0.196
	se						0.173
	p						0.257
	Seattle						**0.416**
	se						0.184
	p						0.024
	St. Louis						-0.090
	se						0.191
	p						0.639
	Constant	**-0.670**	0.076	-0.061	-0.126	-0.269	-0.206
	se	0.043	0.052	0.057	0.216	0.289	0.317
	p	0.000	0.143	0.287	0.559	0.352	0.516
	N	6054	6054	6054	6054	6043	6043
	LL	-3931	-3491	-3474	-3436	-3414	-3384
	AIC	7869	6989	6963	6896	6861	6828

Appendix H

LPM INTERACTIONS

Table H.1: **Any** response LPM models–Race × HCV; Part 1

	Model	Model 6	Race × HCV
Interactions	**Tester race: Hispanic/Latina**	0.005	0.028
	se	0.020	0.027
	p	0.813	0.310
	Tester race: White	0.024	**0.050**
	se	0.014	0.020
	p	0.091	0.013
	HCV status: Has HCV	**-0.146**	**-0.116**
	se	0.013	0.020
	p	0.000	0.000
	Tester race: Hispanic/Latina × Has HCV		-0.045
	se		0.036
	p		0.217
	Tester race: White × Has HCV		-0.051
	se		0.028
	p		0.065
SOI coverage	**SOI coverage: City**	-0.038	-0.038
	se	0.024	0.024
	p	0.113	0.111
	SOI coverage: County	-0.031	-0.030
	se	0.041	0.041
	p	0.457	0.463
	SOI coverage: State	0.019	0.018
	se	0.062	0.062
	p	0.756	0.768
Unit characteristics	**Unit size: 2 bedroom**	0.004	0.004
	se	0.015	0.015
	p	0.810	0.802
	Unit size: 3 bedroom	**0.043**	**0.043**
	se	0.018	0.018
	p	0.018	0.016
	FMR %	**0.178**	**0.178**
	se	0.046	0.046
	p	0.000	0.000
	Listing response time (in hrs)	0.001	0.001
	se	0.001	0.001
	p	0.352	0.364
	Management: Multi-state	**-0.138**	**-0.138**
	se	0.016	0.016
	p	0.000	0.000
Neighborhood characteristics	**Individual poverty rate (%)**	-0.041	-0.042
	se	0.075	0.075
	p	0.586	0.572
	White residents (%)	0.030	0.030
	se	0.040	0.040
	p	0.451	0.456
	Vacancy rate (%)	-0.052	-0.052
	se	0.125	0.125
	p	0.677	0.678
	Median rent (in $1000s)	**-0.101**	**-0.101**
	se	0.033	0.033
	p	0.003	0.003
	Voucher concentration (%)	0.056	0.052
	se	0.252	0.252
	p	0.823	0.838

Table H.2: **Any** response LPM models–Race × HCV; Part 2

Model		Model 6	Race × HCV
Study site fixed effects	**Boston**	-0.091	-0.089
	se	0.074	0.074
	p	0.220	0.227
	Denver	0.007	0.006
	se	0.035	0.035
	p	0.842	0.853
	Houston	-0.012	-0.012
	se	0.034	0.034
	p	0.725	0.723
	Madison	0.068	0.069
	se	0.058	0.058
	p	0.238	0.236
	Miami	**-0.080**	**-0.079**
	se	0.037	0.037
	p	0.033	0.034
	Minneapolis	0.034	0.034
	se	0.039	0.039
	p	0.380	0.384
	Oklahoma City	0.006	0.007
	se	0.073	0.073
	p	0.932	0.925
	Phoenix	**-0.088**	**-0.088**
	se	0.037	0.037
	p	0.019	0.019
	Pittsburgh	**0.088**	**0.087**
	se	0.044	0.044
	p	0.045	0.047
	Portland	0.044	0.045
	se	0.065	0.065
	p	0.499	0.488
	San Diego	0.014	0.014
	se	0.037	0.037
	p	0.696	0.702
	Seattle	0.012	0.013
	se	0.039	0.039
	p	0.762	0.739
	St. Louis	-0.024	-0.023
	se	0.040	0.040
	p	0.557	0.560
	Constant	**0.482**	0.469
	se	0.067	0.068
	p	0.000	0.000
	N	6043	6043
	R^2	0.055	0.055
	Adjusted R^2	0.050	0.050
	Residual Std. Error	0.487	0.487
	F statistic	12.013	11.361
	AIC	8492	8492
	Predictions outside [0,1]	0	0

Table H.3: **Any** response LPM models–× unit size; Part 1

	Model	Model 6	Race × unit size	HCV × unit size
Interactions	**Tester race: Hispanic/Latina**	0.005	-0.004	0.006
	se	0.020	0.035	0.020
	p	0.801	0.897	0.786
	Tester race: White	0.024	0.006	0.024
	se	0.014	0.025	0.014
	p	0.090	0.821	0.089
	HCV status: Has HCV	**-0.146**	**-0.146**	**-0.156**
	se	0.013	0.013	0.023
	p	0.000	0.000	0.000
	Unit size: 2 bedroom	0.004	-0.022	-0.013
	se	0.015	0.024	0.021
	p	0.810	0.364	0.542
	Unit size: 3 bedroom	**0.043**	0.049	**0.050**
	se	0.018	0.027	0.025
	p	0.018	0.077	0.043
	Tester race: Hispanic/Latina × 2 Bedroom		0.035	
	se		0.043	
	p		0.413	
	Tester race: White × 2 bedroom		0.044	
	se		0.033	
	p		0.177	
	Tester race: Hispanic/Latina × 3 bedroom		-0.022	
	se		0.048	
	p		0.648	
	Tester race: White × 3 bedroom		-0.005	
	se		0.037	
	p		0.900	
	Has HCV × 2 bedroom			0.033
	se			0.030
	p			0.266
	Has HCV × 3 bedroom			-0.014
	se			0.033
	p			0.673
SOI coverage	**SOI coverage: City**	-0.038	-0.039	-0.039
	se	0.024	0.024	0.024
	p	0.113	0.109	0.110
	SOI coverage: County	-0.031	-0.030	-0.030
	se	0.041	0.041	0.041
	p	0.457	0.459	0.473
	SOI coverage: State	0.019	0.017	0.018
	se	0.062	0.062	0.062
	p	0.756	0.790	0.773
Unit characteristics	**FMR %**	**0.178**	**0.178**	**0.177**
	se	0.046	0.046	0.046
	p	0.000	0.000	0.000
	Listing response time (in hrs)	0.001	0.001	0.001
	se	0.001	0.001	0.001
	p	0.352	0.391	0.339
	Management: Multi-state	**-0.138**	**-0.138**	**-0.138**
	se	0.016	0.016	0.016
	p	0.000	0.000	0.000

Table H.4: **Any** response LPM models–× unit size; Part 2

	Model	Model 6	Race × unit size	HCV × unit size
Neighborhood characteristics	**Individual poverty rate (%)**	-0.041	-0.043	-0.040
	se	0.075	0.075	0.075
	p	0.586	0.565	0.597
	White residents (%)	0.030	0.029	0.030
	se	0.040	0.040	0.040
	p	0.451	0.470	0.447
	Vacancy rate (%)	-0.052	-0.048	-0.055
	se	0.125	0.125	0.125
	p	0.677	0.698	0.660
	Median rent (in $1000s)	**-0.101**	**-0.099**	**-0.102**
	se	0.033	0.033	0.033
	p	0.003	0.003	0.002
	Voucher concentration (%)	0.056	0.058	0.054
	se	0.252	0.252	0.252
	p	0.823	0.818	0.832
Study site fixed effects	**Boston**	-0.091	-0.088	-0.089
	se	0.074	0.074	0.074
	p	0.220	0.236	0.230
	Denver	0.007	0.007	0.008
	se	0.035	0.035	0.035
	p	0.842	0.846	0.825
	Houston	-0.012	-0.012	-0.012
	se	0.034	0.034	0.034
	p	0.725	0.724	0.736
	Madison	0.068	0.070	0.067
	se	0.058	0.058	0.058
	p	0.238	0.229	0.245
	Miami	**-0.080**	**-0.080**	**-0.080**
	se	0.037	0.037	0.037
	p	0.033	0.033	0.032
	Minneapolis	0.034	0.033	0.035
	se	0.039	0.039	0.039
	p	0.380	0.390	0.371
	Oklahoma City	0.006	0.008	0.009
	se	0.073	0.073	0.073
	p	0.932	0.911	0.900
	Phoenix	**-0.088**	**-0.088**	**-0.088**
	se	0.037	0.037	0.037
	p	0.019	0.019	0.019
	Pittsburgh	**0.088**	**0.091**	**0.088**
	se	0.044	0.044	0.044
	p	0.045	0.040	0.045
	Portland	0.044	0.046	0.045
	se	0.065	0.065	0.065
	p	0.499	0.477	0.488
	San Diego	0.014	0.015	0.015
	se	0.037	0.037	0.037
	p	0.696	0.684	0.691
	Seattle	0.012	0.012	0.012
	se	0.039	0.039	0.039
	p	0.762	0.756	0.758
	St. Louis	-0.024	-0.023	-0.023
	se	0.040	0.040	0.040
	p	0.557	0.566	0.566

Table H.5: **Any** response LPM models–× unit size; Part 3

Model		Model 6	Race × unit size	HCV × unit size
	Constant	**0.483**	**0.493**	**0.489**
		0.067	0.068	0.068
		0.000	0.000	0.000
	N	6043	6043	6043
	R^2	0.055	0.055	0.055
	Adjusted R^2	0.050	0.050	0.050
	Residual Std. Error	0.487	0.487	0.487
	F statistic	12.013	10.659	11.325
	AIC	8492	8496	8493
	Predictions outside [0,1]	0	0	0

Table H.6: **Any** response LPM models–× % white-only; Part 1

	Model	Model 6	Race × % white-only	HCV × % white-only
Interactions	**Tester race: Hispanic/Latina**	0.005	-0.081	0.005
	se	0.020	0.044	0.020
	p	0.801	0.065	0.811
	Tester race: White	0.024	-0.042	0.024
	se	0.014	0.035	0.014
	p	0.090	0.241	0.089
	HCV status: Has HCV	**-0.146**	**-0.146**	**-0.073**
	se	0.013	0.013	0.031
	p	0.000	0.000	0.019
	% white-only	0.030	-0.051	**0.091**
	se	0.040	0.052	0.046
	p	0.451	0.323	0.050
	Tester race: Hispanic/Latina × % white-only		**0.160**	
	se		0.075	
	p		0.032	
	Tester race: White × % white-only		**0.110**	
	se		0.055	
	p		0.046	
	Has HCV × % white-only			**-0.125**
	se			0.049
	p			0.011
SOI coverage	**SOI coverage: City**	-0.038	-0.039	-0.039
	se	0.024	0.024	0.024
	p	0.113	0.106	0.105
	SOI coverage: County	-0.031	-0.026	-0.032
	se	0.041	0.041	0.041
	p	0.457	0.523	0.442
	SOI coverage: State	0.019	0.017	0.021
	se	0.062	0.062	0.062
	p	0.756	0.783	0.736
Unit characteristics	**Unit size: 2 bedroom**	0.004	0.003	0.003
	se	0.015	0.015	0.015
	p	0.810	0.831	0.823
	Unit size: 3 bedroom	**0.043**	**0.043**	**0.043**
	se	0.018	0.018	0.018
	p	0.018	0.018	0.018
	FMR %	**0.178**	**0.175**	**0.175**
	se	0.046	0.046	0.046
	p	0.000	0.000	0.000
	Listing response time (in hrs)	0.001	0.001	0.001
	se	0.001	0.001	0.001
	p	0.352	0.375	0.345
	Management: Multi-state	**-0.138**	**-0.138**	**-0.138**
	se	0.016	0.016	0.016
	p	0.000	0.000	0.000

Table H.7: **Any** response LPM models–× % white-only; Part 2

Model		Model 6	Race × % white-only	HCV × % white-only
Neighborhood characteristics	**Individual poverty rate (%)**	-0.041	-0.042	-0.038
	se	0.075	0.075	0.075
	p	0.586	0.575	0.613
	Vacancy rate (%)	-0.052	-0.049	-0.061
	se	0.125	0.125	0.125
	p	0.677	0.693	0.625
	Median rent (in $1000s)	**-0.101**	**-0.101**	**-0.099**
	se	0.033	0.033	0.033
	p	0.003	0.002	0.003
	Voucher concentration (%)	0.056	0.014	0.050
	se	0.252	0.253	0.252
	p	0.823	0.957	0.844
Study site fixed effects	**Boston**	-0.091	-0.085	-0.092
	se	0.074	0.074	0.074
	p	0.220	0.251	0.212
	Denver	0.007	0.010	0.007
	se	0.035	0.035	0.035
	p	0.842	0.776	0.830
	Houston	-0.012	-0.009	-0.013
	se	0.034	0.034	0.034
	p	0.725	0.802	0.705
	Madison	0.068	0.075	0.071
	se	0.058	0.058	0.058
	p	0.238	0.196	0.223
	Miami	**-0.080**	**-0.075**	**-0.080**
	se	0.037	0.037	0.037
	p	0.033	0.047	0.032
	Minneapolis	0.034	0.042	0.033
	se	0.039	0.039	0.039
	p	0.380	0.279	0.392
	Oklahoma City	0.006	0.015	0.005
	se	0.073	0.074	0.073
	p	0.932	0.834	0.945
	Phoenix	**-0.088**	**-0.084**	**-0.088**
	se	0.037	0.037	0.037
	p	0.019	0.024	0.019
	Pittsburgh	**0.088**	**0.101**	**0.089**
	se	0.044	0.045	0.044
	p	0.045	0.024	0.044
	Portland	0.044	0.054	0.042
	se	0.065	0.065	0.065
	p	0.499	0.410	0.520
	San Diego	0.014	0.019	0.014
	se	0.037	0.037	0.037
	p	0.696	0.611	0.707

Table H.8: **Any** response LPM models–× % white-only; Part 3

Model		Model 6	Race × % white-only	HCV × % white-only
Study site fixed effects	**Seattle**	0.012	0.019	0.012
	se	0.039	0.039	0.039
	p	0.762	0.631	0.757
	St. Louis	-0.024	-0.016	-0.023
	se	0.040	0.040	0.040
	p	0.557	0.687	0.563
	Constant	**0.482**	**0.531**	**0.449**
	se	0.067	0.070	0.068
	p	0.000	0.000	0
	N	6043	6043	6043
	R^2	0.055	0.056	0.056
	Adjusted R^2	0.050	0.051	0.051
	Residual Std. Error	0.487	0.487	0.487
	F statistic	12.013	11.446	11.838
	AIC	8492	8490	8487
	Predictions outside [0,1]	0	0	0

Table H.9: **Any** response LPM models–× % costs; Part 1

	Model 6	Tester race × FMR %	Tester race × Median rent	HCV × FMR %	HCV × Median rent	HCV × Median rent
Interactions	**Tester race: Hispanic/Latina**	0.005	-0.010	-0.065	0.005	0.005
	se	0.020	0.130	0.073	0.020	0.020
	p	0.801	0.942	0.375	0.806	0.798
	Tester race: White	0.024	-0.015	0.004	0.024	0.024
	se	0.014	0.092	0.052	0.014	0.014
	p	0.090	0.871	0.946	0.089	0.089
	HCV status: Has HCV	**-0.146**	**-0.146**	**-0.146**	-0.087	**-0.132**
	se	0.013	0.013	0.013	0.084	0.047
	p	0.000	0.000	0.000	0.304	0.005
	FMR %	**0.178**	**0.159**	**0.179**	**0.207**	**0.177**
	se	0.046	0.068	0.046	0.062	0.046
	p	0.000	0.020	0.000	0.001	0.000
	Median rent (in $1000s)	**-0.101**	**-0.100**	**-0.123**	**-0.101**	**-0.094**
	se	0.033	0.033	0.043	0.033	0.039
	p	0.003	0.003	0.005	0.003	0.017
	Tester race: Hispanic/Latina × FMR %		0.014			
	se		0.121			
	p		0.906			
	Tester race: White × FMR %		0.037			
	se		0.088			
	p		0.671			
	Tester race: Hispanic/Latina × Median rent			0.062		
	se			0.062		
	p			0.318		
	Tester race: White × Median rent			0.019		
	se			0.048		
	p			0.694		
	Has HCV × FMR %				-0.057	
	se				0.080	
	p				0.481	
	Has HCV × Median rent					-0.013
	se					0.043
	p					0.763
SOI coverage	**SOI coverage: City**	-0.038	-0.038	-0.038	-0.038	-0.038
	se	0.024	0.024	0.024	0.024	0.024
	p	0.113	0.113	0.113	0.114	0.114
	SOI coverage: County	-0.031	-0.031	-0.031	-0.030	-0.030
	se	0.041	0.041	0.041	0.041	0.041
	p	0.457	0.456	0.453	0.461	0.461
	SOI coverage: State	0.019	0.019	0.019	0.019	0.019
	se	0.062	0.062	0.062	0.062	0.062
	p	0.756	0.759	0.756	0.758	0.756

Table H.10: **Any** response LPM models–× % costs; Part 2

	Model 6	Tester race × FMR %	Tester race × Median rent	HCV × FMR %	HCV × Median rent	HCV × Median rent
Unit characteristics	**Unit size: 2 bedroom**	0.004	0.004	0.004	0.004	0.004
	se	0.015	0.015	0.015	0.015	0.015
	p	0.810	0.807	0.799	0.809	0.809
	Unit size: 3 bedroom	**0.043**	**0.043**	**0.043**	**0.043**	**0.043**
	se	0.018	0.018	0.018	0.018	0.018
	p	0.018	0.017	0.018	0.018	0.018
	Listing response time (in hrs)	0.001	0.001	0.001	0.001	0.001
	se	0.001	0.001	0.001	0.001	0.001
	p	0.352	0.357	0.349	0.351	0.352
	Management: Multi-state	**-0.138**	**-0.138**	**-0.138**	**-0.138**	**-0.138**
	se	0.016	0.016	0.016	0.016	0.016
	p	0.000	0.000	0.000	0.000	0.000
Neighborhood characteristics	**Individual poverty rate (%)**	-0.041	-0.040	-0.040	-0.040	-0.041
	se	0.075	0.075	0.075	0.075	0.075
	p	0.586	0.592	0.596	0.590	0.584
	% white-only	0.030	0.030	0.029	0.030	0.030
	se	0.040	0.040	0.040	0.040	0.040
	p	0.451	0.449	0.458	0.451	0.450
	Vacancy rate (%)	-0.052	-0.052	-0.052	-0.054	-0.052
	se	0.125	0.125	0.125	0.125	0.125
	p	0.677	0.678	0.676	0.668	0.679
	Voucher concentration (%)	0.056	0.058	0.047	0.062	0.057
	se	0.252	0.252	0.252	0.252	0.252
	p	0.823	0.819	0.854	0.807	0.823
Study site fixed effects	**Boston**	-0.091	-0.091	-0.089	-0.091	-0.091
	se	0.074	0.074	0.074	0.074	0.074
	p	0.220	0.219	0.230	0.220	0.220
	Denver	0.007	0.007	0.010	0.007	0.007
	se	0.035	0.035	0.035	0.035	0.035
	p	0.842	0.851	0.781	0.844	0.842
	Houston	-0.012	-0.012	-0.010	-0.012	-0.012
	se	0.034	0.034	0.034	0.034	0.034
	p	0.725	0.718	0.778	0.725	0.721
	Madison	0.068	0.068	0.067	0.068	0.068
	se	0.058	0.058	0.058	0.058	0.058
	p	0.238	0.241	0.245	0.242	0.241
	Miami	**-0.080**	**-0.080**	**-0.078**	**-0.080**	**-0.080**
	se	0.037	0.037	0.037	0.037	0.037
	p	0.033	0.033	0.037	0.033	0.033
	Minneapolis	0.034	0.034	0.034	0.034	0.034
	se	0.039	0.039	0.039	0.039	0.039
	p	0.380	0.386	0.383	0.379	0.378

Table H.11: **Any** response LPM models–× % costs; Part 3

	Model 6	Tester race × FMR %	Tester race × Median rent	HCV × FMR %	HCV × Median rent	HCV × Median rent
Study site fixed effects	**Oklahoma City**	0.006	0.006	0.005	0.007	0.007
	se	0.073	0.073	0.073	0.073	0.073
	p	0.932	0.933	0.948	0.926	0.929
	Phoenix	**-0.088**	**-0.088**	**-0.083**	**-0.088**	**-0.088**
	se	0.037	0.037	0.038	0.037	0.037
	p	0.019	0.019	0.027	0.019	0.019
	Pittsburgh	**0.088**	**0.088**	**0.086**	**0.088**	**0.088**
	se	0.044	0.044	0.044	0.044	0.044
	p	0.045	0.046	0.052	0.045	0.045
	Portland	0.044	0.044	0.045	0.044	0.044
	se	0.065	0.065	0.065	0.065	0.065
	p	0.499	0.500	0.490	0.496	0.498
	San Diego	0.014	0.014	0.015	0.014	0.014
	se	0.037	0.037	0.037	0.037	0.037
	p	0.696	0.703	0.682	0.704	0.700
	Seattle	0.012	0.012	0.015	0.011	0.012
	se	0.039	0.039	0.039	0.039	0.039
	p	0.762	0.765	0.699	0.768	0.762
	St. Louis	-0.024	-0.023	-0.025	-0.024	-0.024
	se	0.040	0.040	0.040	0.040	0.040
	p	0.557	0.559	0.537	0.550	0.556
	Constant	**0.482**	**0.502**	**0.505**	**0.453**	**0.476**
	se	0.067	0.085	0.073	0.080	0.071
	p	0.000	0.000	0.000	0.000	0.000
	N	6043	6043	6043	6043	6043
	R^2	0.055	0.055	0.055	0.055	0.055
	Adjusted R^2	0.050	0.050	0.050	0.050	0.050
	Residual Std. Error	0.487	0.487	0.487	0.487	0.487
	F statistic	12.013	11.240	11.268	11.628	11.613
	AIC	8492	8496	8495	8493	8494
	Predictions outside [0,1]	0 0	0	0	0	

Table H.12: Interaction of HCV × SOI; **Any** response LPM models; Part 1

	Model	Model 6	HCV × SOI
Interactions	**HCV: Has HCV**	**-0.146**	**-0.121**
	se	0.013	0.016
	p	0.000	0.000
	SOI coverage: City	-0.038	-0.013
	se	0.024	0.031
	p	0.113	0.678
	SOI coverage: County	-0.031	-0.003
	se	0.041	0.048
	p	0.457	0.955
	SOI coverage: State	0.019	0.055
	se	0.062	0.064
	p	0.756	0.398
	SOI coverage: City × Has HCV		-0.049
	se		0.037
	p		0.178
	SOI coverage: County × Has HCV		-0.054
	se		0.049
	p		0.270
	SOI coverage: State × Has HCV		**-0.064**
	se		0.032
	p		0.044
Race	**Tester race: Hispanic/Latina**	0.005	0.006
	se	0.020	0.020
	p	0.801	0.783
	Tester race: White	0.024	0.024
	se	0.014	0.014
	p	0.090	0.088
Unit characteristics	**Unit size: 2 bedroom**	0.004	0.004
	se	0.015	0.015
	p	0.810	0.785
	Unit size: 3 bedroom	**0.043**	**0.044**
	se	0.018	0.018
	p	0.018	0.015
	FMR %	**0.178**	**0.179**
	se	0.046	0.046
	p	0.000	0.000
	Listing response time (in hrs)	0.001	0.001
	se	0.001	0.001
	p	0.352	0.353
	Management: Multi-state	**-0.138**	**-0.138**
	se	0.016	0.016
	p	0.000	0.000

Table H.13: Interaction of HCV × SOI; **Any** response LPM models; Part 2

	Model	Model 6	HCV × SOI
Neighborhood characteristics	**Individual poverty rate (%)**	-0.041	-0.034
	se	0.075	0.075
	p	0.586	0.648
	White residents (%)	0.030	0.031
	se	0.040	0.040
	p	0.451	0.438
	Vacancy rate (%)	-0.052	-0.053
	se	0.125	0.125
	p	0.677	0.670
	Median rent (in $1000s)	**-0.101**	**-0.099**
	se	0.033	0.033
	p	0.003	0.003
	Voucher concentration (%)	0.056	0.051
	se	0.252	0.252
	p	0.823	0.841

Table H.14: Interaction of HCV × SOI; **Any** response LPM models; Part 3

	Model	Model 6	HCV × SOI
Study site fixed effects	**Boston**	-0.091	-0.093
	se	0.074	0.074
	p	0.220	0.206
	Denver	0.007	0.006
	se	0.035	0.035
	p	0.842	0.868
	Houston	-0.012	-0.014
	se	0.034	0.034
	p	0.725	0.693
	Madison	0.068	0.067
	se	0.058	0.058
	p	0.238	0.247
	Miami	**-0.080**	**-0.081**
	se	0.037	0.037
	p	0.033	0.030
	Minneapolis	0.034	0.034
	se	0.039	0.039
	p	0.380	0.387
	Oklahoma City	0.006	0.003
	se	0.073	0.073
	p	0.932	0.968
	Phoenix	**-0.088**	**-0.089**
	se	0.037	0.037
	p	0.019	0.017
	Pittsburgh	**0.088**	**0.088**
	se	0.044	0.044
	p	0.045	0.047
	Portland	0.044	0.040
	se	0.065	0.065
	p	0.499	0.533
	San Diego	0.014	0.014
	se	0.037	0.037
	p	0.696	0.706
	Seattle	0.012	0.011
	se	0.039	0.039
	p	0.762	0.781
	St. Louis	-0.024	-0.024
	se	0.040	0.040
	p	0.557	0.544
	Constant	**0.483**	**0.467**
	se	0.067	0.067
	p	0.000	0.000
	N	6043	6043
	R^2	0.055	0.056
	Adjusted R^2	0.050	0.051
	Residual Std. Error	0.487	0.487
	F Statistic	12.013	11.116
	AIC	8491	8490
	Predictions outside [0,1]	0	0

Table H.15: **Positive** response LPM models–Race × HCV; Part 1

	Model	Model 6	Race × HCV
Interactions	**Tester race: Hispanic/Latina**	0.030	0.031
	se	0.018	0.025
	p	0.101	0.212
	Tester race: White	**0.043**	**0.056**
	se	0.013	0.018
	p	0.001	0.002
	HCV status: Has HCV	**-0.362**	**-0.351**
	se	0.011	0.018
	p	0.000	0.000
	Tester race: Hispanic/Latina X Has HCV		-0.001
	se		0.032
	p		0.970
	Tester race: White X Has HCV		-0.024
	se		0.025
	p		0.326
SOI coverage	**SOI coverage: City**	0.002	0.002
	se	0.022	0.022
	p	0.924	0.932
	SOI coverage: County	-0.034	-0.034
	se	0.037	0.037
	p	0.356	0.361
	SOI coverage: State	0.092	0.092
	se	0.056	0.056
	p	0.101	0.102
Unit characteristics	**Unit size: 2 bedroom**	-0.002	-0.001
	se	0.014	0.014
	p	0.912	0.926
	Unit size: 3 bedroom	**0.033**	**0.034**
	se	0.016	0.016
	p	0.040	0.039
	FMR %	**0.133**	**0.134**
	se	0.042	0.042
	p	0.002	0.002
	Listing response time (in hrs)	0.000	0.000
	se	0.001	0.001
	p	0.749	0.744
	Management: Multi-state	**-0.114**	**-0.114**
	se	0.015	0.015
	p	0.000	0.000
Neighborhood characteristics	**Individual poverty rate (%)**	0.002	0.002
	se	0.067	0.067
	p	0.980	0.980
	White residents (%)	0.022	0.021
	se	0.036	0.036
	p	0.542	0.547
	Vacancy rate (%)	0.117	0.117
	se	0.112	0.112
	p	0.296	0.297
	Median rent (in $1000s)	**-0.110**	**-0.110**
	se	0.029	0.029
	p	0.000	0.000
	Voucher concentration (%)	0.177	0.172
	se	0.226	0.226
	p	0.434	0.447

Table H.16: **Positive** response LPM models–Race × HCV; Part 2

Model		Model 6	Race × HCV
Study site fixed effects	**Boston**	-0.048	-0.047
	se	0.066	0.066
	p	0.469	0.474
	Denver	0.022	0.022
	se	0.031	0.031
	p	0.480	0.477
	Houston	0.010	0.010
	se	0.031	0.031
	p	0.753	0.752
	Madison	**0.134**	**0.134**
	se	0.052	0.052
	p	0.011	0.010
	Miami	-0.028	-0.028
	se	0.033	0.033
	p	0.396	0.398
	Minneapolis	-0.023	-0.023
	se	0.035	0.035
	p	0.512	0.512
	Oklahoma City	-0.089	-0.089
	se	0.066	0.066
	p	0.177	0.178
	Phoenix	-0.050	-0.049
	se	0.033	0.033
	p	0.136	0.139
	Pittsburgh	0.050	0.049
	se	0.039	0.039
	p	0.208	0.211
	Portland	0.075	0.075
	se	0.058	0.058
	p	0.199	0.197
	San Diego	0.040	0.040
	se	0.033	0.033
	p	0.226	0.227
	Seattle	**0.081**	**0.082**
	se	0.035	0.035
	p	0.020	0.019
	St. Louis	-0.016	-0.016
	se	0.036	0.036
	p	0.657	0.664
	Constant	**0.465**	**0.459**
	se	0.060	0.061
	p	0.000	0.000
	N	6043	6043
	R^2	0.170	0.170
	Adjusted R^2	0.166	0.166
	Residual Std. Error	0.437	0.437
	F statistic	42.554	39.839
	AIC	7171	7174
	Predictions outside [0,1]	22	14

Table H.17: **Positive** response LPM models–× unit size; Part 1

	Model	Model 6	Race × unit size	HCV × unit size
Interactions	**Tester race: Hispanic/Latina**	0.030	0.014	0.031
	se	0.018	0.031	0.018
	p	0.101	0.648	0.093
	Tester race: White	**0.043**	0.032	**0.044**
	se	0.013	0.023	0.013
	p	0.001	0.165	0.001
	HCV status: Has HCV	**-0.362**	**-0.362**	**-0.351**
	se	0.011	0.011	0.021
	p	0.000	0.000	0.000
	Unit size: 2 bedroom	-0.002	-0.018	-0.008
	se	0.014	0.022	0.019
	p	0.912	0.412	0.674
	Unit size: 3 bedroom	**0.033**	0.030	**0.063**
	se	0.016	0.025	0.022
	p	0.040	0.222	0.005
	Tester race: Hispanic/Latina × 2 Bedroom		0.036	
	se		0.039	
	p		0.359	
	Tester race: White × 2 bedroom		0.023	
	se		0.030	
	p		0.436	
	Tester race: Hispanic/Latina × 3 bedroom		0.001	
	se		0.043	
	p		0.979	
	Tester race: White × 3 bedroom		0.006	
	se		0.033	
	p		0.845	
	Has HCV × 2 bedroom			0.013
	se			0.027
	p			0.617
	Has HCV × 3 bedroom			-0.059
	se			0.030
	p			0.049
SOI coverage	**SOI coverage: City**	0.002	0.002	0.002
	se	0.022	0.022	0.022
	p	0.924	0.943	0.927
	SOI coverage: County	-0.034	-0.034	-0.033
	se	0.037	0.037	0.037
	p	0.356	0.350	0.368
	SOI coverage: State	0.092	0.091	0.091
	se	0.056	0.056	0.056
	p	0.101	0.106	0.104
Unit characteristics	**FMR %**	**0.133**	**0.133**	**0.133**
	se	0.042	0.042	0.041
	p	0.002	0.002	0.002
	Listing response time (in hrs)	0.000	0.000	0.000
	se	0.001	0.001	0.001
	p	0.749	0.720	0.758
	Management: Multi-state	**-0.114**	**-0.113**	**-0.114**
	se	0.015	0.015	0.014
	p	0.000	0.000	0.000

Table H.18: **Positive** response LPM models–× unit size; Part 2

	Model	Model 6	Race × unit size	HCV × unit size
Neighborhood characteristics	**Individual poverty rate (%)**	0.002	0.001	0.002
	se	0.067	0.067	0.067
	p	0.980	0.988	0.975
	White residents (%)	0.022	0.021	0.021
	se	0.036	0.036	0.036
	p	0.542	0.553	0.550
	Vacancy rate (%)	0.117	0.118	0.117
	se	0.112	0.112	0.112
	p	0.296	0.295	0.297
	Median rent (in $1000s)	**-0.110**	**-0.109**	**-0.111**
	se	0.029	0.029	0.029
	p	0.000	0.000	0.000
	Voucher concentration (%)	0.177	0.180	0.172
	se	0.226	0.226	0.226
	p	0.434	0.427	0.446
Study site fixed effects	**Boston**	-0.048	-0.046	-0.047
	se	0.066	0.066	0.066
	p	0.469	0.485	0.480
	Denver	0.022	0.022	0.022
	se	0.031	0.031	0.031
	p	0.480	0.480	0.471
	Houston	0.010	0.010	0.010
	se	0.031	0.031	0.031
	p	0.753	0.743	0.753
	Madison	**0.134**	**0.135**	**0.133**
	se	0.052	0.052	0.052
	p	0.011	0.010	0.011
	Miami	-0.028	-0.028	-0.030
	se	0.033	0.033	0.033
	p	0.396	0.404	0.376
	Minneapolis	-0.023	-0.023	-0.022
	se	0.035	0.035	0.035
	p	0.512	0.509	0.524
	Oklahoma City	-0.089	-0.088	-0.086
	se	0.066	0.066	0.066
	p	0.177	0.183	0.194
	Phoenix	-0.050	-0.050	-0.050
	se	0.033	0.033	0.033
	p	0.136	0.134	0.133
	Pittsburgh	0.050	0.051	0.049
	se	0.039	0.039	0.039
	p	0.208	0.197	0.213
	Portland	0.075	0.076	0.075
	se	0.058	0.058	0.058
	p	0.199	0.191	0.194
	San Diego	0.040	0.040	0.039
	se	0.033	0.033	0.033
	p	0.226	0.223	0.233
	Seattle	**0.081**	**0.081**	**0.081**
	se	0.035	0.035	0.035
	p	0.020	0.020	0.020
	St. Louis	-0.016	-0.015	-0.016
	se	0.036	0.036	0.036
	p	0.657	0.668	0.656

Table H.19: **Positive** response LPM models–× unit size; Part 3

	Model	Model 6	Race × unit size	HCV × unit size
	Constant	**0.465**	**0.473**	**0.461**
		0.060	0.061	0.061
		0.000	0.000	0.000
	N	6043	6043	6043
	R^2	0.170	0.170	0.171
	Adjusted R^2	0.166	0.166	0.167
	Residual Std. Error	0.437	0.437	0.437
	F statistic	42.554	37.420	40.076
	AIC	7171	7177	7168
	Predictions outside [0,1]	22	22	20

Table H.20: **Positive** response LPM models–× % white-only; Part 1

Model		Model 6	Race × % white-only	HCV × % white-only
Interactions	**Tester race: Hispanic/Latina**	0.030	-0.046	0.030
	se	0.018	0.039	0.018
	p	0.101	0.243	0.105
	Tester race: White	**0.043**	-0.014	**0.044**
	se	0.013	0.032	0.013
	p	0.001	0.663	0.001
	HCV status: Has HCV	**-0.362**	**-0.362**	**-0.278**
	se	0.011	0.011	0.028
	p	0.000	0.000	0.000
	% white-only	0.022	-0.049	**0.092**
	se	0.036	0.046	0.042
	p	0.542	0.285	0.027
	Tester race: Hispanic/Latina × % white-only		0.141	
	se		0.067	
	p		0.035	
	Tester race: White × % white-only		0.096	
	se		0.049	
	p		0.050	
	Has HCV × % white-only			**-0.144**
	se			0.044
	p			0.002
SOI coverage	**SOI coverage: City**	0.002	0.001	0.001
	se	0.022	0.022	0.022
	p	0.924	0.949	0.959
	SOI coverage: County	-0.034	-0.030	-0.035
	se	0.037	0.037	0.037
	p	0.356	0.413	0.340
	SOI coverage: State	0.092	0.090	0.094
	se	0.056	0.056	0.056
	p	0.101	0.108	0.094
Unit characteristics	**Unit size: 2 bedroom**	-0.002	-0.002	-0.002
	se	0.014	0.014	0.014
	p	0.912	0.892	0.896
	Unit size: 3 bedroom	**0.033**	**0.033**	**0.033**
	se	0.016	0.016	0.016
	p	0.040	0.040	0.043
	FMR %	**0.133**	**0.131**	**0.131**
	se	0.042	0.042	0.041
	p	0.002	0.002	0.002
	Listing response time (in hrs)	0.000	0.000	0.000
	se	0.001	0.001	0.001
	p	0.749	0.718	0.763
	Management: Multi-state	**-0.114**	**-0.114**	**-0.114**
	se	0.015	0.015	0.014
	p	0.000	0.000	0.000

Table H.21: **Positive** response LPM models–× % white-only; Part 2

	Model	Model 6	Race × % white-only	HCV × % white-only
Neighborhood characteristics	**Individual poverty rate (%)**	0.002	0.001	0.005
	se	0.067	0.067	0.067
	p	0.980	0.992	0.939
	Vacancy rate (%)	0.117	0.119	0.107
	se	0.112	0.112	0.112
	p	0.296	0.287	0.341
	Median rent (in $1000s)	**-0.110**	**-0.110**	**-0.108**
	se	0.029	0.029	0.029
	p	0.000	0.000	0.000
	Voucher concentration (%)	0.177	0.139	0.169
	se	0.226	0.227	0.226
	p	0.434	0.539	0.454
Study site fixed effects	**Boston**	-0.048	-0.043	-0.050
	se	0.066	0.066	0.066
	p	0.469	0.519	0.453
	Denver	0.022	0.025	0.023
	se	0.031	0.031	0.031
	p	0.480	0.430	0.467
	Houston	0.010	0.013	0.009
	se	0.031	0.031	0.031
	p	0.753	0.680	0.779
	Madison	**0.134**	**0.140**	**0.136**
	se	0.052	0.052	0.052
	p	0.011	0.008	0.009
	Miami	-0.028	-0.024	-0.029
	se	0.033	0.034	0.033
	p	0.396	0.478	0.384
	Minneapolis	-0.023	-0.015	-0.024
	se	0.035	0.035	0.035
	p	0.512	0.661	0.494
	Oklahoma City	-0.089	-0.081	-0.090
	se	0.066	0.066	0.066
	p	0.177	0.221	0.170
	Phoenix	-0.050	-0.047	-0.049
	se	0.033	0.033	0.033
	p	0.136	0.163	0.139
	Pittsburgh	0.050	0.061	0.050
	se	0.039	0.040	0.039
	p	0.208	0.129	0.204
	Portland	0.075	0.083	0.072
	se	0.058	0.058	0.058
	p	0.199	0.153	0.214
	San Diego	0.040	0.044	0.039
	se	0.033	0.033	0.033
	p	0.226	0.185	0.232

Table H.22: **Positive** response LPM models–× % white-only; Part 3

Model		Model 6	Race × % white-only	HCV × % white-only
Study site fixed effects	**Seattle**	**0.081**	**0.087**	**0.081**
	se	0.035	0.035	0.035
	p	0.020	0.013	0.019
	St. Louis	-0.016	-0.010	-0.016
	se	0.036	0.036	0.036
	p	0.657	0.792	0.665
	Constant	**0.465**	**0.507**	**0.425**
	se	0.060	0.063	0.061
	p	0.000	0.000	0.000
	N	6043	6043	6043
	R^2	0.170	0.171	0.172
	Adjusted R^2	0.166	0.167	0.168
	Residual Std. Error	0.437	0.437	0.436
	F Statistic	42.554	40.028	41.556
	AIC	7171	7169	7162
	Predictions outside [0,1]	22	26	21

Table H.23: **Positive** response LPM models–× % costs; Part 1

	Model	Model 6	Tester race × FMR %	Tester race × Median rent	HCV × FMR %	HCV × Median rent
Interactions	**Tester race: Hispanic/Latina**	0.030	-0.032	-0.016	0.030	0.030
	se	0.018	0.116	0.065	0.018	0.018
	p	0.101	0.780	0.806	0.105	0.105
	Tester race: White	**0.043**	0.081	0.082	**0.044**	**0.043**
	se	0.013	0.083	0.047	0.013	0.013
	p	0.001	0.324	0.081	0.001	0.001
	HCV status: Has HCV	**-0.362**	**-0.361**	**-0.361**	**-0.253**	**-0.407**
	se	0.011	0.011	0.011	0.076	0.042
	p	0.000	0.000	0.000	0.001	0.000
	FMR %	**0.133**	**0.140**	**0.134**	**0.186**	**0.133**
	se	0.042	0.061	0.042	0.055	0.042
	p	0.002	0.022	0.002	0.001	0.002
	Median rent (in $1000s)	**-0.110**	**-0.111**	**-0.104**	**-0.110**	**-0.132**
	se	0.029	0.029	0.039	0.029	0.035
	p	0.000	0.000	0.008	0.000	0.000
	Tester race: Hispanic/Latina × FMR %		0.058			
	se		0.108			
	p		0.591			
	Tester race: White × FMR %		-0.037			
	se		0.079			
	p		0.640			
	Tester race: Hispanic/Latina × Median rent			0.039		
	se			0.056		
	p			0.488		
	Tester race: White × Median rent			-0.037		
	se			0.043		
	p			0.389		
	Has HCV × FMR %				-0.104	
	se				0.072	
	p				0.148	
	Has HCV × Median rent					0.044
	se					0.039
	p					0.257
SOI coverage	**SOI coverage: City**	0.002	0.003	0.002	0.002	0.002
	se	0.022	0.022	0.022	0.022	0.022
	p	0.924	0.902	0.914	0.920	0.931
	SOI coverage: County	-0.034	-0.034	-0.033	-0.033	-0.035
	se	0.037	0.037	0.037	0.037	0.037
	p	0.356	0.354	0.365	0.364	0.342
	SOI coverage: State	0.092	0.093	0.092	0.092	0.092
	se	0.056	0.056	0.056	0.056	0.056
	p	0.101	0.096	0.100	0.102	0.100

Table H.24: **Positive** response LPM models–× % costs; Part 2

	Model	Model 6	Tester race × FMR %	Tester race × Median rent	HCV × FMR %	HCV × Median rent
Unit characteristics	**Unit size: 2 bedroom**	-0.002	-0.002	-0.001	-0.001	-0.002
	se	0.014	0.014	0.014	0.014	0.014
	p	0.912	0.895	0.923	0.916	0.906
	Unit size: 3 bedroom	**0.033**	**0.033**	**0.033**	**0.033**	**0.034**
	se	0.016	0.016	0.016	0.016	0.016
	p	0.040	0.042	0.040	0.042	0.038
	Listing response time (in hrs)	0.000	0.000	0.000	0.000	0.000
	se	0.001	0.001	0.001	0.001	0.001
	p	0.749	0.763	0.772	0.754	0.748
	Management: Multi-state	**-0.114**	**-0.114**	**-0.114**	**-0.113**	**-0.114**
	se	0.015	0.015	0.015	0.015	0.015
	p	0.000	0.000	0.000	0.000	0.000
Neighborhood characteristics	**Individual poverty rate (%)**	0.002	0.001	0.001	0.003	0.002
	se	0.067	0.067	0.067	0.067	0.067
	p	0.980	0.986	0.993	0.970	0.974
	% white-only	0.022	0.021	0.021	0.022	0.022
	se	0.036	0.036	0.036	0.036	0.036
	p	0.542	0.552	0.557	0.542	0.544
	Vacancy rate (%)	0.117	0.116	0.117	0.114	0.116
	se	0.112	0.112	0.112	0.112	0.112
	p	0.296	0.300	0.297	0.308	0.299
	Voucher concentration (%)	0.177	0.171	0.168	0.187	0.176
	se	0.226	0.226	0.226	0.226	0.226
	p	0.434	0.450	0.457	0.409	0.436
Study site fixed effects	**Boston**	-0.048	-0.048	-0.046	-0.048	-0.048
	se	0.066	0.066	0.066	0.066	0.066
	p	0.469	0.467	0.489	0.470	0.470
	Denver	0.022	0.023	0.025	0.022	0.022
	se	0.031	0.031	0.031	0.031	0.031
	p	0.480	0.461	0.426	0.483	0.480
	Houston	0.010	0.011	0.013	0.010	0.010
	se	0.031	0.031	0.031	0.031	0.031
	p	0.753	0.726	0.682	0.751	0.739
	Madison	**0.134**	**0.134**	**0.132**	**0.133**	**0.135**
	se	0.052	0.052	0.052	0.052	0.052
	p	0.011	0.010	0.011	0.011	0.010
	Miami	-0.028	-0.027	-0.027	-0.029	-0.028
	se	0.033	0.033	0.033	0.033	0.033
	p	0.396	0.415	0.422	0.390	0.400
	Minneapolis	-0.023	-0.022	-0.023	-0.023	-0.023
	se	0.035	0.035	0.035	0.035	0.035
	p	0.512	0.530	0.505	0.515	0.505

Table H.25: **Positive** response LPM models–× % costs; Part 3

	Model	Model 6	Tester race × FMR %	Tester race × Median rent	HCV × FMR %	HCV × Median rent
Study site fixed effects	**Oklahoma City**	-0.089	-0.090	-0.090	-0.088	-0.090
	se	0.066	0.066	0.066	0.066	0.066
	p	0.177	0.170	0.171	0.181	0.174
	Phoenix	-0.050	-0.048	-0.045	-0.050	-0.050
	se	0.033	0.034	0.034	0.033	0.033
	p	0.136	0.156	0.179	0.137	0.137
	Pittsburgh	0.050	0.050	0.047	0.049	0.050
	se	0.039	0.039	0.040	0.039	0.039
	p	0.208	0.210	0.233	0.213	0.208
	Portland	0.075	0.074	0.075	0.075	0.075
	se	0.058	0.058	0.058	0.058	0.058
	p	0.199	0.201	0.194	0.195	0.199
	San Diego	0.040	0.041	0.041	0.039	0.040
	se	0.033	0.033	0.033	0.033	0.033
	p	0.226	0.213	0.214	0.233	0.218
	Seattle	**0.081**	**0.081**	**0.084**	**0.081**	**0.081**
	se	0.035	0.035	0.035	0.035	0.035
	p	0.020	0.020	0.017	0.021	0.020
	St. Louis	-0.016	-0.017	-0.018	-0.017	-0.016
	se	0.036	0.036	0.036	0.036	0.036
	p	0.657	0.641	0.613	0.641	0.661
	Constant	**0.465**	**0.459**	**0.458**	**0.409**	**0.488**
	se	0.060	0.076	0.065	0.071	0.064
	p	0.000	0.000	0.000	0.000	0.000
	N	6043	6043	6043	6043	6043
	R^2	0.170	0.170	0.171	0.171	0.170
	Adjusted R^2	0.166	0.166	0.166	0.166	0.166
	Residual Std. Error	0.437	0.437	0.437	0.437	0.437
	F Statistic	42.554	39.827	39.875	41.213	41.180
	AIC	7171	7174	7173	7171	7172
	Predictions outside [0,1]	22	23	21	24	16

Table H.26: Interaction of HCV × SOI; **Positive** response LPM models; Part 1

	Model	Model 6	HCV × SOI
Interactions	**HCV: Has HCV**	**-0.362**	**-0.379**
	se	0.011	0.014
	p	0.000	0.000
	SOI coverage: City	0.002	-0.024
	se	0.022	0.027
	p	0.924	0.390
	SOI coverage: County	-0.034	-0.051
	se	0.037	0.043
	p	0.356	0.238
	SOI coverage: State	0.092	0.069
	se	0.056	0.058
	p	0.101	0.232
	SOI coverage: City × Has HCV		0.050
	se		0.033
	p		0.129
	SOI coverage: County × Has HCV		0.033
	se		0.044
	p		0.452
	SOI coverage: State × Has HCV		0.039
	se		0.029
	p		0.171
Race	**Tester race: Hispanic/Latina**	0.030	0.030
	se	0.018	0.018
	p	0.101	0.105
	Tester race: White	**0.043**	**0.043**
	se	0.013	0.013
	p	0.001	0.001
Unit characteristics	**Unit size: 2 bedroom**	-0.002	-0.002
	se	0.014	0.014
	p	0.912	0.881
	Unit size: 3 bedroom	**0.033**	**0.032**
	se	0.016	0.016
	p	0.040	0.046
	FMR %	**0.133**	**0.132**
	se	0.042	0.042
	p	0.002	0.002
	Listing response time (in hrs)	0.000	0.000
	se	0.001	0.001
	p	0.749	0.753
	Management: Multi-state	**-0.114**	**-0.114**
	se	0.015	0.015
	p	0.000	0.000

Table H.27: Interaction of HCV × SOI; **Positive** response LPM models; Part 2

Model		Model 6	HCV × SOI
Neighborhood characteristics	**Individual poverty rate (%)**	0.002	-0.005
	se	0.067	0.067
	p	0.980	0.945
	White residents (%)	0.022	0.021
	se	0.036	0.036
	p	0.542	0.561
	Vacancy rate (%)	0.117	0.118
	se	0.112	0.112
	p	0.296	0.290
	Median rent (in $1000s)	**-0.110**	**-0.111**
	se	0.029	0.029
	p	0.000	0.000
	Voucher concentration (%)	0.177	0.181
	se	0.226	0.226
	p	0.434	0.423

Table H.28: Interaction of HCV × SOI; **Positive** response LPM models; Part 3

	Model	Model 6	HCV × SOI
Study site fixed effects	**Boston**	-0.048	-0.045
	se	0.066	0.066
	p	0.469	0.499
	Denver	0.022	0.023
	se	0.031	0.031
	p	0.480	0.463
	Houston	0.010	0.011
	se	0.031	0.031
	p	0.753	0.730
	Madison	**0.134**	**0.135**
	se	0.052	0.052
	p	0.011	0.010
	Miami	-0.028	-0.028
	se	0.033	0.033
	p	0.396	0.411
	Minneapolis	-0.023	-0.022
	se	0.035	0.035
	p	0.512	0.519
	Oklahoma City	-0.089	-0.085
	se	0.066	0.066
	p	0.177	0.196
	Phoenix	-0.050	-0.049
	se	0.033	0.033
	p	0.136	0.144
	Pittsburgh	0.050	0.051
	se	0.039	0.039
	p	0.208	0.201
	Portland	0.075	0.078
	se	0.058	0.058
	p	0.199	0.178
	San Diego	0.040	0.040
	se	0.033	0.033
	p	0.226	0.221
	Seattle	**0.081**	**0.082**
	se	0.035	0.035
	p	0.020	0.019
	St. Louis	-0.016	-0.015
	se	0.036	0.036
	p	0.657	0.668
	Constant	**0.465**	**0.478**
	se	0.060	0.060
	p	0.000	0.000
	N	6043	6043
	R^2	0.170	0.171
	Adjusted R^2	0.166	0.167
	Residual Std. Error	0.437	0.437
	F Statistic	42.554	38.732
	AIC	7171	7172
	Predictions outside [0,1]	22	35

Appendix I

TESTER NAME EFFECTS

I test whether an individual tester name has an effect on prediction of either outcome. If a specific name is associated with outcomes, it would suggest that something about the name was being interpreted differently–meaning that the treatment of racial affiliation might be measuring something else, for example, class. Tables I.1-I.5 present regressions for receiving any response and Tables I.6-I.10. For both outcomes, none of the names have significant parameter estimates. However, in the any response model, DeShauna Williams, a black tester's name, is nearly significant (in Table I.1); in the positive response model, Tashara Readus, another black tester's name, is nearly significant too (Table I.6). These estimates suggest that name choice is not influential in results and that racial category is an acceptable stand-in for tester name.

Table I.1: **Any** response LPM models–tester names; Part 1

	Model	Model 6	Names
Tester attributes	**HCV: Has HCV**	**-0.146**	**-0.144**
	se	0.013	0.013
	p	0.000	0.000
	Tester race: Hispanic/Latina	0.005	
	se	0.020	
	p	0.801	
	Tester race: White	0.024	
	se	0.014	
	p	0.090	
Black names	**Tester name: Cheranique Tankson**		-0.014
	se		0.044
	p		0.749
	Tester name: Damisha Edgerson		0.049
	se		0.042
	p		0.249
	Tester name: DeShauna Williams		0.084
	se		0.044
	p		0.054
	Tester name: Keisha Smalls		-0.043
	se		0.044
	p		0.321
	Tester name: Lateefah Jefferson		0.016
	se		0.043
	p		0.703
	Tester name: Shardae Washington		0.020
	se		0.045
	p		0.648
	Tester name: Sheniqua Callands		-0.010
	se		0.044
	p		0.817
	Tester name: Tamika Odum		-0.028
	se		0.043
	p		0.512
	Tester name: Tashara Readus		-0.061
	se		0.045
	p		0.169
	Tester name: Tyleesha Harris		0.011
	se		0.043
	p		0.791

Table I.2: **Any** response LPM models–tester names; Part 2

	Model	Model 6	Names
Hispanic/Latina names	**Tester name: Esmeralda Renderos**		-0.036
	se		0.054
	p		0.506
	Tester name: Esperanza Garcia		0.024
	se		0.058
	p		0.687
	Tester name: Estefani Lopez		-0.013
	se		0.057
	p		0.814
	Tester name: Fernanda Casarrubias		0.020
	se		0.055
	p		0.717
	Tester name: Frida Fuentas		0.084
	se		0.063
	p		0.180
	Tester name: Graciela Contreras		-0.067
	se		0.060
	p		0.268
	Tester name: Isabel Jimenez		0.021
	se		0.056
	p		0.711
	Tester name: Juanita Cabreja		0.004
	se		0.059
	p		0.945
	Tester name: Rosa Hernandez		0.026
	se		0.054
	p		0.627
	Tester name: Valentina Rodriguez		0.029
	se		0.056
	p		0.607

Table I.3: **Any** response LPM models–tester names; Part 3

	Model	Model 6	Names
White names	**Tester name: Ellie Schnieder**		0.038
	se		0.042
	p		0.364
	Tester name: Jodi Mueller		0.027
	se		0.044
	p		0.539
	Tester name: Kacie Olsen		0.060
	se		0.042
	p		0.158
	Tester name: Lacee Gallagher		0.001
	se		0.044
	p		0.992
	Tester name: Linsey Erickson		0.045
	se		0.043
	p		0.297
	Tester name: Madalyn Fischer		0.041
	se		0.042
	p		0.335
	Tester name: Mandi Becker		0.064
	se		0.042
	p		0.125
	Tester name: Nicole Bauer		0.001
	se		0.042
	p		0.986
	Tester name: Piper Meyer		-0.012
	se		0.042
	p		0.774
SOI coverage	**SOI coverage: City**	-0.038	-0.040
	se	0.024	0.024
	p	0.113	0.101
	SOI coverage: County	-0.031	-0.030
	se	0.041	0.041
	p	0.457	0.467
	SOI coverage: State	0.019	0.019
	se	0.062	0.062
	p	0.756	0.767

Table I.4: **Any** response LPM models–tester names; Part 4

	Model	Model 6	Names
Unit characteristics	**Unit size: 2 bedroom**	0.004	0.004
	se	0.015	0.015
	p	0.810	0.813
	Unit size: 3 bedroom	**0.043**	**0.042**
	se	0.018	0.018
	p	0.018	0.020
	FMR %	**0.178**	**0.175**
	se	0.046	0.046
	p	0.000	0.000
	Listing response time (in hrs)	0.001	0.001
	se	0.001	0.001
	p	0.352	0.368
	Management: Multi-state	**-0.138**	**-0.137**
	se	0.016	0.016
	p	0.000	0.000
Neighborhood characteristics	**Individual poverty rate (%)**	-0.041	-0.041
	se	0.075	0.075
	p	0.586	0.583
	White residents (%)	0.030	0.032
	se	0.040	0.040
	p	0.451	0.417
	Vacancy rate (%)	-0.052	-0.047
	se	0.125	0.125
	p	0.677	0.705
	Median rent (in $1000s)	**-0.101**	**-0.100**
	se	0.033	0.033
	p	0.003	0.003
	Voucher concentration (%)	0.056	0.079
	se	0.252	0.253
	p	0.823	0.755

Table I.5: **Any** response LPM models–tester names; Part 5

	Model	Model 6	Names
Study site fixed effects	**Boston**	-0.091	-0.092
	se	0.074	0.074
	p	0.220	0.214
	Denver	0.007	0.005
	se	0.035	0.035
	p	0.842	0.887
	Houston	-0.012	-0.014
	se	0.034	0.034
	p	0.725	0.692
	Madison	0.068	0.066
	se	0.058	0.058
	p	0.238	0.256
	Miami	**-0.080**	**-0.079**
	se	0.037	0.037
	p	0.033	0.034
	Minneapolis	0.034	0.035
	se	0.039	0.039
	p	0.380	0.371
	Oklahoma City	0.006	0.004
	se	0.073	0.074
	p	0.932	0.960
	Phoenix	**-0.088**	**-0.088**
	se	0.037	0.037
	p	0.019	0.019
	Pittsburgh	**0.088**	**0.087**
	se	0.044	0.044
	p	0.045	0.049
	Portland	0.044	0.043
	se	0.065	0.065
	p	0.499	0.511
	San Diego	0.014	0.013
	se	0.037	0.037
	p	0.696	0.716
	Seattle	0.012	0.010
	se	0.039	0.039
	p	0.762	0.802
	St. Louis	-0.024	-0.022
	se	0.040	0.040
	p	0.557	0.590
	Constant	**0.483**	**0.480**
	se	0.067	0.074
	p	0.000	0.000
	N	6043	6043
	R^2	0.055	0.060
	Adjusted R^2	0.050	0.051
	Residual Std. Error	0.487	0.487
	F statistic	12.013	6.766
	AIC	8492	8515
	Predictions outside [0,1]	0	0

Table I.6: **Positive** response LPM models–tester names; Part 1

	Model	Model 6	Names
Tester attributes	**HCV: Has HCV**	**-0.362**	**-0.360**
	se	0.011	0.011
	p	0.000	0.000
	Tester race: Hispanic/Latina	0.030	
	se	0.018	
	p	0.101	
	Tester race: White	**0.043**	
	se	0.013	
	p	0.001	
Black names	**Tester name: Cheranique Tankson**		-0.051
	se		0.040
	p		0.201
	Tester name: Damisha Edgerson		0.043
	se		0.038
	p		0.260
	Tester name: DeShauna Williams		0.017
	se		0.039
	p		0.660
	Tester name: Keisha Smalls		-0.050
	se		0.039
	p		0.203
	Tester name: Lateefah Jefferson		-0.043
	se		0.038
	p		0.258
	Tester name: Shardae Washington		-0.035
	se		0.040
	p		0.385
	Tester name: Sheniqua Callands		-0.052
	se		0.039
	p		0.184
	Tester name: Tamika Odum		-0.038
	se		0.038
	p		0.325
	Tester name: Tashara Readus		-0.077
	se		0.040
	p		0.054
	Tester name: Tyleesha Harris		-0.038
	se		0.039
	p		0.331

Table I.7: **Positive** response LPM models–tester names; Part 2

	Model	Model 6	Names
Hispanic/Latina names	**Tester name: Esmeralda Renderos**		-0.032
	se		0.048
	p		0.505
	Tester name: Esperanza Garcia		-0.042
	se		0.052
	p		0.424
	Tester name: Estefani Lopez		-0.042
	se		0.051
	p		0.416
	Tester name: Fernanda Casarrubias		-0.008
	se		0.049
	p		0.866
	Tester name: Frida Fuentas		0.071
	se		0.056
	p		0.209
	Tester name: Graciela Contreras		-0.065
	se		0.054
	p		0.230
	Tester name: Isabel Jimenez		0.032
	se		0.050
	p		0.517
	Tester name: Juanita Cabreja		0.040
	se		0.053
	p		0.446
	Tester name: Rosa Hernandez		0.036
	se		0.048
	p		0.459
	Tester name: Valentina Rodriguez		0.003
	se		0.050
	p		0.957

Table I.8: **Positive** response LPM models–tester names; Part 3

	Model	Model 6	Names
White names	**Tester name: Ellie Schnieder**		0.018
	se		0.038
	p		0.636
	Tester name: Jodi Mueller		-0.026
	se		0.039
	p		0.504
	Tester name: Kacie Olsen		0.051
	se		0.038
	p		0.176
	Tester name: Lacee Gallagher		-0.009
	se		0.039
	p		0.828
	Tester name: Linsey Erickson		0.038
	se		0.039
	p		0.328
	Tester name: Madalyn Fischer		0.018
	se		0.038
	p		0.626
	Tester name: Mandi Becker		0.046
	se		0.037
	p		0.212
	Tester name: Nicole Bauer		-0.008
	se		0.038
	p		0.838
	Tester name: Piper Meyer		-0.015
	se		0.038
	p		0.693
SOI coverage	**SOI coverage: City**	0.002	-0.001
	se	0.022	0.022
	p	0.924	0.964
	SOI coverage: County	-0.034	-0.034
	se	0.037	0.037
	p	0.356	0.361
	SOI coverage: State	0.092	0.091
	se	0.056	0.056
	p	0.101	0.103

Table I.9: **Positive** response LPM models–tester names; Part 4

	Model	Model 6	Names
Unit characteristics	**Unit size: 2 bedroom**	-0.002	-0.002
	se	0.014	0.014
	p	0.912	0.887
	Unit size: 3 bedroom	**0.033**	**0.032**
	se	0.016	0.016
	p	0.040	0.052
	FMR %	**0.133**	**0.133**
	se	0.042	0.042
	p	0.002	0.002
	Listing response time (in hrs)	0.000	0.000
	se	0.001	0.001
	p	0.749	0.734
	Management: Multi-state	**-0.114**	**-0.114**
	se	0.015	0.015
	p	0.000	0.000
Neighborhood characteristics	**Individual poverty rate (%)**	0.002	-0.002
	se	0.067	0.067
	p	0.980	0.979
	White residents (%)	0.022	0.023
	se	0.036	0.036
	p	0.542	0.523
	Vacancy rate (%)	0.117	0.122
	se	0.112	0.112
	p	0.296	0.279
	Median rent (in $1000s)	**-0.11**	**-0.11**
	se	0.029	0.029
	p	0.000	0.000
	Voucher concentration (%)	0.177	0.195
	se	0.226	0.226
	p	0.434	0.390

Table I.10: **Positive** response LPM models–tester names; Part 5

	Model	Model 6	Names
Study site fixed effects	**Boston**	-0.048	-0.050
	se	0.066	0.066
	p	0.469	0.456
	Denver	0.022	0.019
	se	0.031	0.031
	p	0.480	0.542
	Houston	0.010	0.009
	se	0.031	0.031
	p	0.753	0.761
	Madison	**0.134**	**0.130**
	se	0.052	0.052
	p	0.011	0.013
	Miami	-0.028	-0.029
	se	0.033	0.033
	p	0.396	0.382
	Minneapolis	-0.023	-0.025
	se	0.035	0.035
	p	0.512	0.479
	Oklahoma City	-0.089	-0.092
	se	0.066	0.066
	p	0.177	0.165
	Phoenix	-0.050	-0.050
	se	0.033	0.033
	p	0.136	0.134
	Pittsburgh	0.050	0.049
	se	0.039	0.039
	p	0.208	0.213
	Portland	0.075	0.074
	se	0.058	0.058
	p	0.199	0.206
	San Diego	0.040	0.038
	se	0.033	0.033
	p	0.226	0.252
	Seattle	**0.081**	**0.081**
	se	0.035	0.035
	p	0.020	0.020
	St. Louis	-0.016	-0.014
	se	0.036	0.036
	p	0.657	0.699
	Constant	**0.465**	**0.498**
	se	0.060	0.066
	p	0.000	0.000
	N	6043	6043
	R^2	0.170	0.175
	Adjusted R^2	0.166	0.167
	Residual Std. Error	0.437	0.437
	F statistic	42.554	22.636
	AIC	7171	7192
	Predictions outside [0,1]	22	51