Landlords and Access to Opportunity

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Abstract: A family can use a housing voucher to move to opportunity only if a landlord in an opportunity neighborhood accepts the voucher. Most landlords in opportunity neighborhoods, though, avoid voucher tenants. We examine a policy change that increases voucher rental payment limits only in high-rent neighborhoods. While the policy induces some new voucher holders to move into high-rent neighborhoods, most landlords do not change their screening behavior in response to the policy. Those landlords who do respond are few and operate at a surprisingly small scale. A sustainable policy of moving to opportunity requires more direct engagement with landlords.

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1 Introduction

Access to neighborhoods can provide or deny access to economic opportunity. The future economic success of otherwise similar children varies widely among neighborhoods in the same city (Chetty et al., 2018). Such neighborhood effects, combined with residential segregation, can drive persistent racial inequity in economic opportunity (Wilson, 1987; Massey and Denton, 1993). Opportunity neighborhoods, i.e. places with positive neighborhood effects, improve the later-in-life economic outcomes of children (Chetty et al., 2016; Chyn, 2018) and adults (Aliprantis and Richter, 2020). Housing vouchers, which subsidize a share of private-market rent, can facilitate moves to such neighborhoods. Housing vouchers' potential for generating moves to opportunity is typically unrealized, however, as most families with federally-subsidized rental vouchers do not live in opportunity neighborhoods. The average voucher holder lives in a neighborhood with a high poverty rate and limited access to good schools (Galvez, 2010; Horn et al., 2014).

Two prominent policies, attaching voucher payments to neighborhood rent levels and housing mobility programs, have shown promise in helping voucher tenants move to opportunity. First, 'Small Area Fair Market Rents' (SAFMRs) set voucher payment limits according to neighborhood, rather than city or metro, rent levels. For early adopting cities, paying more in high-rent neighborhoods affected lease-up locations for tenants with newly-issued vouchers (Collinson and Ganong, 2018; Dastrup et al., 2019; Reina et al., 2019). In 2018 the US Department of Housing and Urban Development (HUD) required SAFMRs in 23 cities and made them available to all other housing authorities. Second, housing mobility programs require or encourage tenants to move to opportunity neighborhoods and provide supports for such moves. The Moving to Opportunity experiment showed that restricting vouchers to low-poverty neighborhoods, alongside limited mobility counseling, affects lease-up locations and increases future earnings for children (Chetty et al., 2016) but also reduces the likelihood the household successfully leases any unit with the voucher (Shroder, 2002; Galiani et al., 2015). More intensive mobility programs that add higher payment limits, intensive counseling for tenants, flexible support for landlords, and short-term financial assistance have shown greater success, dramatically changing lease-up locations without reducing lease-up rates (DeLuca and Rosenblatt, 2017; Bergman et al., 2019).

Understanding how landlords respond to such policies may shed light on why these interventions show early success and whether that success can be sustained. Both SAFMRs and mobility programs work at least in part by making vouchers more attractive to landlords. However, the literature on SAFMRs and mobility programs focuses almost entirely on how they affect tenants. Qualitative evidence on landlord response to vouchers in general finds that many landlords avoid vouchers but others specialize in vouchers to increase stability of rent payments or to capture differences between voucher payments and private market rents, often doing so in high-poverty neighborhoods (Garboden et al., 2018). Yet quantitative evidence on whether and how landlords respond to policies designed to increase access to opportunity is scarce.

This paper investigates how landlords respond to a policy designed to move voucher holders to opportunity. In 2017, Washington, DC moved closer to a SAFMR policy. DC sets voucher payment

limits by neighborhood and number of bedrooms. Before 2017, these limits moved with local market conditions in low-rent neighborhoods but were capped in high-rent neighborhoods at 130% of city-wide rent. After 2017, the limit could increase to 175% of city-wide rent. As a result, the gap in the average monthly payment limit between high- and low-rent neighborhoods doubled to about $1,000, and the fraction of online rental listings in high-rent neighborhoods that fall within payment limits increased from 28% to 71%. We focus on how *opportunity landlords*, defined as landlords in high-rent neighborhoods, respond to this possibility of greater rent payments.[1] We conducted a correspondence experiment in two waves just before and just after the policy change. In these experiments, we sent e-mails from fictional prospective tenants to inquire about real listings for rental housing and varied whether they signal a desire to pay by voucher. Our analysis unpacks how landlords respond to the DC SAFMR policy and why. We begin by using the spatial variation in the policy to implement both difference-in-differences and border discontinuity research designs to study how the policy affects landlord responses. We then provide evidence on what drives landlord behavior by augmenting landlord response data with outcomes from rental listings, property tax records, and equilibrium lease-up locations.

As our first contribution, we show that increasing the maximum voucher payment does not affect the decision to accept a voucher tenant for most landlords. In our correspondence experiment, as in prior studies (Phillips, 2017; Moore, 2018; Cunningham et al., 2018), most opportunity landlords avoid voucher tenants. As our contribution, we show that opportunity landlords do not adjust screening behavior in response to large increases in voucher payment limits. In a difference-in-differences design, landlord positive response rates to voucher inquiries increase by only a statistically insignificant 2.4 percentage points more in high-rent neighborhoods than in low-rent neighborhoods. Differential trends across neighborhoods for inquiries without the voucher signal indicate even this difference is an overestimate. Thus, we prefer a triple-difference specification that uses variation over time, neighborhood, and whether the inquiry includes the voucher signal. This model produces a negative, statistically insignificant point estimate. Similarly, a spatial discontinuity model detects no statistical difference in landlord response rates across the treatment boundary. We also find no evidence for effects among units with posted rent between the old and new payment limits, where theory predicts the largest effects.

While each of these 'zeros' has a confidence interval, they are precisely estimated when compared to the magnitude of either the response penalty toward voucher holders or the intervention. In our experiment, landlords respond positively to voucher tenants 29 percentage points less frequently than to cash tenants. At the most optimistic end of the 95% confidence interval, the policy effect as measured by difference-in-differences, triple difference, and border discontinuity models is 12, 5, and 10 percentage points, respectively. Thus, all specifications reject the hypothesis that most discriminating landlords change their screening behavior in response to the policy. We obtain this result despite the large magnitude of the intervention. The largest change observed in one of our

[1] We refer to neighborhoods with high rent and high opportunity interchangeably. In our sample, rent is highly correlated with poverty rates, children's future earnings from Chetty et al. (2018), and indices of neighborhood characteristics from Aliprantis and Richter (2020) and Noelke et al. (2020). See Section 2 for more details.

identification strategies is across the treatment boundary, where monthly voucher payment limits jump by $1,028. In other specifications looking across all geographies, payment limits increase by $455 more in high-rent neighborhoods than in low-rent neighborhoods. If we average across the three empirical strategies and assume a constant elasticity of the voucher penalty with respect to the voucher payment limit, eliminating the voucher penalty would require more than doubling payment limits, that is, increasing them by at least $2,240.

One potential explanation for why most landlords continue to avoid the voucher program is that it pays market rates but imposes additional costs. The limited number of detailed landlord responses to our inquiries often focus on inspection requirements. Similarly, the qualitative literature argues that landlords wish to avoid the bureaucratic costs of the program, such as inspections, unless they can charge above-market rent to voucher tenants (Garboden et al., 2018). We find evidence that landlords take this strategy with voucher tenants in some neighborhoods in DC, listing presumably low-quality units at exactly the payment limit; however, this rent premium disappears in high-rent neighborhoods. Thus, opportunity landlords may avoid voucher tenants even when payment limits increase if the program imposes additional costs but does not allow for a rent premium.

As our second contribution, we find that paying more in high-rent neighborhoods does indeed expand tenant choice, shifting voucher lease-up locations to high-rent neighborhoods. This effect is large enough to equalize the flow of voucher tenants into high and low-rent neighborhoods, which contrasts with the status quo of many years of voucher tenants disproportionately entering low-rent neighborhoods. However, since most voucher tenants do not move in our two year time frame, the stock of vouchers remains concentrated in low-rent neighborhoods. These results are qualitatively similar to those from Dallas (Collinson and Ganong, 2018) and Seattle (Bergman et al., 2019).

Our third contribution reconciles our two prior results by identifying a small number of idiosyncratic landlords who *do* respond to greater payment limits. We gather rental listings from a website that specializes in marketing to tenants receiving subsidies. After the policy change, rental listings on this site increase in high rent neighborhoods, especially for units with rent between the old and new payment limits. Landlords who respond to higher payment limits are rare and idiosyncratic: they tend to operate at a small scale, have exposure in many types of neighborhoods, and be new to voucher specialization but not to owning property. Financial incentives appear to expand tenants' neighborhood choice sets by engaging these new landlords.

Taken together, our empirical results raise concerns about whether increasing voucher payment limits alone can significantly narrow the gap in equity of opportunity. Neighborhood-specific voucher payment limits are among the leading policies for moving voucher tenants to opportunity at scale, and they do increase the number of households with newly-issued vouchers who flow into opportunity neighborhoods. However, the flow of new voucher tenants over a few years is small; vouchers only use 0.6% of housing units in the median high-rent neighborhood after the policy change, so even a small and idiosyncratic group of landlords can facilitate the changes in lease-up locations we observe. Providing voucher holders with equal access to all neighborhoods would require many more landlords. Our correspondence experiment results suggest, though, that few

landlords are on the margin of accepting a voucher.

The remainder of the paper is organized as follows: Section 2 provides background on the Housing Choice Voucher (HCV) program and its payment rules, a framework for thinking about landlord decision-making, and a description of related policy changes in DC. Section 3 describes our empirical strategy by providing details about the data, the experiment, and the identification strategies we use in our analysis. Section 4 presents our empirical results, and Section 5 interprets them. Section 6 concludes.

2 Background

2.1 Housing Voucher Payment Limits

The Housing Choice Voucher (HCV) program is the United States' largest program for low-income housing assistance. HCV tenants lease rental units found on the private market. Tenants typically pay 30 percent of their income toward rent, with the HCV voucher subsidizing the remainder of the unit's rent. The value of the voucher subsidy is capped, typically near the median of recently leased rents in the tenant's metro.

In principle, voucher recipients can lease-up in any neighborhood. In practice, voucher tenants typically live in low-rent neighborhoods. Washington, DC, provides a clear illustration of where voucher recipients reside when a uniform subsidy is provided in a bimodal rental housing market. As shown in Figure 1a, in the 2012-2016 ACS many tracts in DC have a median rent below $1,000 per month and many others have a median rent above $1,800 per month, with relatively few tracts in between. High-rent neighborhoods tend to cluster to the North and West, while lower-rent neighborhoods cluster to the South and East. Figure 1b shows where in DC households with vouchers lease-up. People with vouchers are concentrated in lower-rent neighborhoods. As shown in Figure 1c, these neighborhoods also tend to have high poverty rates.[2] These patterns match national data. Compared to all low-rent housing units, units leased by HCV tenants tend to be in neighborhoods with similar poverty rates and lower-performing schools (Galvez, 2010; Horn et al., 2014; Davis et al., 2018).

The rules determining the value of a housing voucher could drive high-rent landlords away from accepting voucher tenants. Tenants typically pay 30 percent of their income in rent while the housing authority pays the balance directly to the landlord. With income-based rents tenants have no incentive to economize, so the housing authority typically enforces two procedures to keep voucher payments in check. First, the housing authority analyzes rent reasonableness, comparing a unit to other similar properties to assess if the listed rent is reasonable. Second, the local housing authority will not pay rent that exceeds a cap, known as fair market rent (FMR).[3] Traditionally,

[2] Appendix Table 9 quantifies these differences for a wide range of characteristics. Voucher holders in DC live in neighborhoods with lower rent, income, educational attainment, and employment rates. As a result they rate worse on measures opportunity including poverty ranks, future earnings of children Chetty et al. (2018), and indices of contemporaneous observable characteristics from Aliprantis and Richter (2020) and Noelke et al. (2020).

[3] If a tenant rents a unit above the FMR, the tenant is responsible for the remaining amount of rent. Voucher-

vouchers are capped at a metro-wide FMR, with HUD setting FMR at the 40th percentile of rent for all units with the same number of bedrooms in the entire metro area.[4] Since the FMR limit is constant across the entire metro area, high-rent landlords could have very limited incentives to participate, and the qualitative literature argues that the value of FMR relative to market rents drives much of landlords' responses to vouchers (Garboden et al., 2018).

Attaching the payment limit of a voucher to neighborhood-specific rents could provide voucher holders access to higher opportunity neighborhoods. Small Area Fair Market Rents (SAFMRs) that set payment limits for the voucher by a smaller geography, e.g., ZIP code, would increase the number of high-opportunity units below FMR in many cities (Palm, 2018). Early adoption of SAFMRs in Dallas shifted lease-up locations (Collinson and Ganong, 2018), and a subsequent multi-city HUD demonstration project generated similar results, though with some heterogeneity across sites (Dastrup et al., 2019; Reina et al., 2019). With this possibility in mind, HUD modified FMR rules in early January 2017 to require 23 additional cities to move to SAFMRs and allowed all others to opt-in. After a protracted court battle between conflicting HUD administrations, this rule began implementation on January 1, 2018 (Howell, 2017).

2.2 Landlord Decisions

In the workhorse economic model, tenant preferences and rental prices drive neighborhood choice. Tenants can lease any housing unit for which they are willing and able to pay the rent. A competitive market sets rent for each unit, and greater neighborhood opportunity implies greater rent, other things equal. Payment limits define the set of units that are affordable with the voucher, and if a tenant has a voucher that allows her to afford a neighborhood and she moves elsewhere, then she must prefer the other neighborhood. For example, in the context of the Moving to Opportunity experiment, lease-up rates for a voucher restricted to low-poverty neighborhoods are much lower than those for an unrestricted voucher (Shroder, 2002). The model infers that many tenants do not want opportunity moves, and restrictions on locations can be counterproductive Galiani et al. (2015).

However, frictions in the housing market could impose constraints on where voucher tenants locate. For instance, tenants may lack information about neighborhoods (Bergman et al., 2020), or leasing in a different jurisdiction may be administratively difficult (Aliprantis et al., 2020; Garboden, 2021). Mobility programs designed to address such search costs have large effects on lease-up locations, which suggests that frictions are quantitatively important (Bergman et al., 2019).

Landlord behavior appears to represent a key friction facing voucher holders. Correspondence and audit studies find that many landlords screen out prospective tenants who wish to use a voucher

eligible tenants are income constrained and have a strong incentive to rent units below the FMR. Also, exception payment standards require special approval for tenants to lease up in a unit between 110 and 120 percent of FMR, and will typically not allow for vouchers to be used in units that are more than 120 percent of FMR.

[4]The 40th percentile is for the distribution of gross rents paid by recent movers in the private market who are not voucher holders. Note that in 2001 HUD switched from setting FMRs at the 40th percentile to the 50th percentile in 39 metro areas; see Footnote 17 in Collinson and Ganong (2018) for a discussion.

(Phillips, 2017; Moore, 2018; Cunningham et al., 2018). A growing qualitative literature documents that many landlords avoid vouchers due to concerns about property damage and regulatory burden; others specialize in receiving vouchers, steering tenants to units with lower market value or even renovating units to be lower in quality but more durable, e.g., walling off windows (Popkin and Cunningham, 2000; Rosen, 2014; Greenlee, 2014; Desmond, 2016; Garboden et al., 2018). Landlords also may avoid vouchers as a signal of race, since voucher holders are more likely to be black and some landlords screen on race (Hanson and Hawley, 2011; Christensen and Timmins, 2018).

How landlords respond to increasing voucher payment limits depends on their beliefs about voucher tenants and their scope to price voucher units above market rent. In Appendix C, we build a model in which landlords make screening and pricing decisions in a market that includes both cash and voucher tenants. In the model, landlords may experience an additional 'cost' from voucher tenants, which could include hard costs like maintenance and administration as well as subjective costs like the discriminatory preferences of a prejudiced landlord. When the housing authority prevents landlords from charging above-market rent to voucher tenants, only landlords with units below the payment cap who anticipate no additional cost of working with voucher tenants will participate. Increasing the payment cap leads them to make units priced between the old and new payment cap available. On the other hand, if the housing authority is more permissive, some landlords will price units above market rent at exactly the payment limit. When the payment limit increases, some landlords who view participation as costly but are enticed by charging higher rent will change their pricing strategy and specialize in vouchers.

The model in Appendix C does not address entry decisions on the part of landlords into the housing market. Welfare consequences of SAFMR policies depend on not only whether low-income tenants move into high-opportunity areas but also the elasticity of housing supply. With inelastic housing supply, voucher tenants are simply displacing other tenants in high-opportunity areas. While our model and analysis abstract from these issues, we note that the supply of rental housing in DC grew by 14.2 percent between the 2006-2010 and 2015-2019 waves of the ACS. When divided into the top and bottom halves of tracts in DC according to their poverty rate in the 2014-2018 ACS, growth rates were, respectively, 17.1 and 12.2 percent.

2.3 Small Area Fair Market Rents in Washington, DC

Washington, DC, was an early mover in attaching voucher payments to neighborhood market rents, and we investigate the impacts of SAFMRs on landlords and voucher holders in DC. Through a Moving to Work waiver in 2015 (Galvez et al., 2017), DC received permission from HUD to move from city-wide to neighborhood-specific rent limits. Since introducing this policy, the DC Housing Authority (DCHA) conducts a rental analysis that includes referring to existing data and canvassing neighborhoods. It uses these data to compute market rental comparisons by tax neighborhood and number of bedrooms, which are used to compute caps on voucher payments for tax neighborhoods.

The SAFMR policy rolled out across DC neighborhoods in two stages, as illustrated in the timeline in Figure 2. The first stage occurred in early 2015, prior to the first wave of our experiment.

At that time, HUD allowed DCHA to switch from a common metro-wide limit to neighborhood-specific limits that could be set up to 130 percent of the metro-wide FMR. Since DC exhibits a bimodal rental housing market with high-end rents that are higher on average than those in the remainder of the MSA, the 130 percent cap was binding for a large portion of the city but not all of it. Some low-rent neighborhoods were unrestricted and DCHA set payment limits at the neighborhood median, while other neighborhoods had payments capped at 130 percent of metro-wide FMR during this time. The second stage of the policy occurred in January 2017 when DC obtained a waiver to increase neighborhood rent limits up to 175 percent of the metro-wide FMR. In high-rent neighborhoods, voucher payments that were previously at 130 percent of FMR increased up to 175 percent of FMR. However, in lower-rent neighborhoods voucher payment limits were unchanged. This latter policy change comes between the two waves of our experiment, allowing us to observe how conditions changed over time in neighborhoods that were restricted vs. unrestricted by the earlier cap on voucher payments.

Figure 1d summarizes the geography of the 2017 policy change. It displays 2017 voucher limits, relative to metro-wide FMR, for all neighborhoods. We display values by tax neighborhood, which is the definition of neighborhood used by the DCHA. As is apparent, the limits closely correlate with neighborhood rent levels and poverty rates.[5] The neighborhoods colored in red represent those neighborhoods affected by the policy change. In 2017, red neighborhoods' payment limits are greater than 130 percent of the metro-wide FMR, indicating voucher values would have typically been below market rents in these neighborhoods in the absence of the policy change. Within this group, those neighborhoods in dark red have limits exactly at the 175 percent cap, indicating that the neighborhood payment limit is still constrained to be below the neighborhood median market rent. Finally, those neighborhoods in blue have limits below 130 percent and hence were unaffected by the change. Our analysis will investigate how the policy change in 2017 affected landlord behavior and voucher holders' outcomes in red-shaded neighborhoods where the policy change had bite, relative to the blue-shaded neighborhoods where it did not.

Washington, DC provides a useful context in which voucher rent rules might be particularly likely to affect access to opportunity. In the Appendix, we document several facts about the DC housing market. First, DC's rental market is more bi-modal than most cities (Appendix Figure 9). Second, DC has a large gap in neighborhood opportunity between voucher and non-voucher tenants that is similar to other cities where economic mobility is low (Appendix Figure 10). Third, during our sample period DC experienced progress similar to other places that reformed voucher payment limits (Appendix Figure 10). Fourth, neighborhood conditions correlate more strongly with rent in DC than in most large US cities (Appendix Figure 11). Together, these facts suggest that Washington, DC has the type of segmented housing market where paying landlords more might lead voucher holders to locate in neighborhoods with greater access to economic opportunity.

[5] Appendix Table 9 shows that various measures of economic opportunity differ starkly between treated and untreated neighborhoods.

3 Empirical Strategy

3.1 Data

We use three primary types of data in this paper. We describe them briefly here and in more detail in Appendix A. First, we use Census tract-level statistics from standard government data sources. We use HUD's Picture of Subsidized Households to describe where voucher households locate and the American Community Survey for other neighborhood statistics. Second, we compile rental listings for Washington, DC from two websites. One is a large website, which we refer to as the 'majority market website,' that listed units at a rate of over 80,000 per year during our 2017 sample period. The other site is DCHousingSearch.org, which is a specialist website that focuses on subsidized tenants and income-restricted housing units. As shown in Appendix Table 9, listings on the majority market site tend to come from neighborhoods that score higher on indices of economic opportunity. We link the listings from both sites to property tax records that describe characteristics of the property and owner. Third, we conduct a correspondence experiment, sending inquiries from fictional tenants to rental listings from the majority market website.

The correspondence experiment tests how landlords respond to tenants who state a desire to pay with a subsidized housing voucher. We identified rental listings in Washington, ignoring very high rent apartments unattainable for someone with a voucher. We sent 2,668 e-mail inquiries from fictional tenants to 1,336 real rental listings during 2015 and 4,264 inquiries to 1,810 rental listings in 2017. We randomly varied all components of the inquiry e-mail and focus on comparing e-mails that state a desire to pay by voucher versus not. For example, one such statement is, "I'm looking for a place that takes Section 8." Our main outcome is a measure of whether the landlord responds to the e-mail positively. Most positive responses are an invitation to see the unit, though we classify some other text as positive following Ewens et al. (2014). See Appendix A for a full description of the experiment.

Signaling voucher status in an initial inquiry is within common practice. Practitioner organizations that work with tenants give conflicting advice. Some recommend disclosing one's voucher status immediately to avoid wasting time and resources pursuing dead-ends; this is particularly important for clients who lack private transportation. Others recommend delaying disclosure to avoid a negative first impression. In any case, all academic correspondence and audit studies on vouchers signal it at first contact (Phillips, 2017; Moore, 2018; Cunningham et al., 2018). Likewise, non-academic organizations that use audits for compliance purposes similarly signal vouchers at first contact (Scott et al., 2018).

Table 1 summarizes the design of the experiment. In the 2015 wave, the proportion of applicants listing a black or female name is 50 percent. The average unit in the first wave rents for $1,253 per month and has one bedroom. In the bimodal DC rental housing market, online listings tend to come from the upper mode in high-rent, high-opportunity neighborhoods. Thus, our experiment provides a good test of how landlords in such neighborhoods respond to voucher tenants. Since the voucher signal is assigned randomly and independently of all characteristics of the unit and all

other components of the messages, means for these baseline characteristics are the same for inquiries including the voucher statement (voucher) and those not (cash). Baseline balance is similar for the 2017 wave, though the proportion of inquiries with black names is higher and the average unit is more expensive and larger due to small changes in the design of the experiment.

3.2 Identification Strategies

We examine whether a change in neighborhood voucher payment limits in Washington, DC, affected landlords' acceptance of vouchers. We estimate the effects of higher rent limits in a difference-in-differences framework that uses variation across time and neighborhoods generated by the 2017 policy change. We estimate this model by ordinary least squares:

$$P_{ijt} = \beta_0 + \beta_1 T_j + \beta_2 Post_t + \beta_3 T_j * Post_t + \epsilon_{ijt}. \tag{1}$$

P_{ijt} measures the value of the neighborhood-specific voucher payment limit for unit i in tax neighborhood j during year t. T_j is a dummy for whether the unit is in a neighborhood affected by the policy change, that is, with a 2017 payment limit above 130 percent of HUD's city-wide fair market rent.[6] $Post_t$ is a dummy for years 2017 or later. The coefficient of interest is on the interaction of the two, β_3, which measures by how much more voucher payment limits increased in treatment neighborhoods compared to control neighborhoods.

We estimate a similar reduced form specification for final outcomes, again estimated by ordinary least squares:

$$Y_{ijt} = \gamma_0 + \gamma_1 T_j + \gamma_2 Post_t + \gamma_3 T_j * Post_t + \eta_{ijt}. \tag{2}$$

Y_{ijt} is an outcome indicator, for example, of whether a landlord responds positively to an inquiry to unit i in tax neighborhood j during year t. Other variables are defined as before. In the correspondence experiment data, γ_3 measures whether callback rates to voucher tenants increase more in neighborhoods affected by the policy. We estimate similar specifications using rental listings and voucher lease-up outcomes. When examining the lease-up outcomes, the level of observation is the neighborhood-year, and j indexes census tracts rather than tax neighborhoods.

This difference-in-differences specification relies on the typical parallel trends assumption. We assume that, in the absence of a policy change, the gap in outcomes between treated and control neighborhoods would remain constant over time. This assumption could be false if, for example, the neighborhood rental market is evolving differently in high-rent versus low-rent neighborhoods over time. To relax this assumption, we consider a triple-difference specification. For the correspondence experiment only, we can exploit the experimental variation in whether the fictional inquiry signals

[6] In Figure 1d, nearly all affected tracts are dark red, moving from 130% to exactly 175% of FMR. So, a treatment indicator explains nearly all variation created by the policy.

a desire to use a voucher, denoted by τ_{ijt}. More formally, we estimate:

$$Y_{ijt} = \psi_0 + \psi_1 T_j + \psi_2 Post_t + \psi_3 \tau_{ijt} + \psi_4 T_j * Post_t + \psi_5 T_j * \tau_{ijt} + \psi_6 Post_t * \tau_{ijt} + \psi_7 T_j * Post_t * \tau_{ijt} + \nu_{ijt} \tag{3}$$

The coefficient of interest is ψ_7, which measures whether the gap between voucher and cash inquiries decreases over time in neighborhoods that receive voucher payment limit increases, relative to those that do not.

The difference-in-differences and triple difference specifications described above could confound the effect of increased rent limits with other changes that particularly affect voucher tenants' access to high-rent neighborhoods in DC. For example, the DC Housing Authority introduced other policies and landlord outreach programs aimed at moving tenants to higher-rent neighborhoods. To guard against this possibility, we consider an alternative identification strategy that focuses on the spatial discontinuity in rent limits near the border of the policy change. As shown in Figure 1d, several affected neighborhoods border unaffected neighborhoods. Housing units, neighborhood conditions, and other policies will likely be similar on either side of these borders. If this is true, focusing on a narrow window around the border and comparing outcomes across the border will measure the effect of the policy in isolation from other policies or changes impacting both sides of the border.

We measure this spatial discontinuity using a simple linear regression.

$$Y_{ijt} = \phi_0 + \phi_1 T_j + \phi_2 Dist_i + \phi_3 T_j * Dist_i + \xi_{ijt} \tag{4}$$

In this specification, $Dist_i$ measures the distance between unit i and the policy border, measured as negative on the low side of the border and positive on the high side. Our coefficient of interest is ϕ_1, which measures the discontinuity in the outcome at the border. We implement this regression using 2017 data, since the border is created by the post-period variation in policy, and focus on the sample within 1 kilometer of the border. We use a parametric specification for simplicity; results are similar if we use common non-parametric regression discontinuity designs with optimal bandwidth selection.

4 Results

4.1 Quantifying Increases in Voucher Payment Limits

We first describe the variation in voucher payment limits used by each research design. Table 2 shows results from the difference-in-differences design. Column (1) estimates the relationship between the voucher payment limit and the policy change in a simple difference-in-differences framework as in Equation 1. The outcome is the monthly voucher rent limit in dollars. The positive coefficient of 668 on treatment confirms that high-rent neighborhoods had greater voucher rent limits, even before the policy change we study. The positive coefficient on the year 2017 dummy indicates that the housing authority raised voucher payment limits by an average of $286

per month in control tracts (because market rent was rising generally). The main coefficient of interest is the value of 455 on the interaction between treatment and the year 2017 dummy. This value indicates that the voucher limit increased by on average $455 per month more in treated tracts than in control tracts. This change is large and statistically significant.

The border discontinuity design generates even greater variation in voucher payment limits. Figure 4a displays the average voucher payment limit for listed properties by distance to the policy border. The monthly voucher limit does not vary much with distance to the border, except at the border itself. To the left, neighborhoods unaffected by the policy change have voucher limits that average just below $2,000 per month. On the right, neighborhoods affected by the policy change have voucher limits close to $3,000 per month. Column (1) of Table 3 quantifies the spatial discontinuity estimates using the strategy defined in Equation 4. The coefficient on the treatment neighborhood dummy is the focus and shows that voucher limits increase by $1,028 per month on average at the border.

4.2 Most Opportunity Landlords Do Not Respond to Increased Payment Limits

We use correspondence experiment data to test how landlords respond to changes in the voucher payment limit. The underlying experiment documents that high-rent landlords avoid voucher tenants, consistent with prior studies. In the first wave, landlords respond positively 50 percent of the time to cash tenants but only 23 percent of the time to voucher tenants, for a gap of 27 percentage points. This gap remains in the second wave at 29 percentage points. Figure 3 displays this voucher penalty and shows that it increases in the posted rent of the unit. Altogether, we begin with a context in which landlords frequently avoid voucher tenants and particularly so when marketing more expensive units. However, we find no evidence that paying landlords market rent in high-rent neighborhoods reduces the voucher penalty.

4.2.1 Difference-in-Differences Results

Table 2 summarizes the difference-in-differences results. The second and third columns estimate a simple difference-in-differences specification on the correspondence experiment data as in Equation 2. They split the sample of inquiries across the two columns into, respectively, those that request to pay by voucher and those that do not. Consider column (2). Prior to the policy change, callback rates to voucher inquiries were 8.8 percentage points lower in the high-rent neighborhoods. The positive coefficient of 0.024 on the interaction term indicates that the gap may have closed slightly, but this effect is not statistically significant with a confidence interval ranging from -7 to 12 percentage points. Column (3) estimates a placebo test of the same model for inquiries not requesting to pay by voucher. The interaction coefficient of 0.10 indicates that the gap between high- and low-rent neighborhoods actually does narrow for these tenants. This result suggests that it is important to control for other factors that change in high-rent neighborhoods over time other than the voucher payment limits. Any inference from the results in column (2) would overstate the benefits of increased rent limits. Thus, we estimate our preferred triple-difference specification from

Equation 3 in column (4) and find no evidence of positive landlord responses to higher payment limits. Taken literally, the triple interaction term of -0.080 indicates that the voucher penalty assessed by landlords actually became larger over time in neighborhoods with increased rent limits, relative to neighborhoods that did not change. However, this estimate is not statistically significant. Its 95 percent confidence interval rules out large improvements in landlord response. At the most optimistic end of this confidence interval, increasing the payment cap by $450 more per month increases positive landlord response rates by 5 percentage points, which is only one-sixth of the 29 percentage point voucher penalty applied by landlords.

4.2.2 Spatial Discontinuity Results

Results are similar if we test for discontinuities across the border between the areas affected and not affected by the policy change. Figure 4(b) verifies the validity of this research design using tenants who do not signal a desire to pay by voucher. Positive response rates from landlords are similar on either side of the border for tenants who do not mention the voucher program, as expected. Figure 4(c) previews the main result. Landlord responses to tenants signaling a desire to pay by voucher also show no discontinuity at the border, despite the large change in voucher payment limits. Table 3 quantifies these results. The main test for policy impacts is in column (2). The next three columns verify that housing units on either side of the border are similar in terms of how landlords respond to cash tenants (3), rent relative to city-wide FMR (4), and number of bedrooms (5). The negative and statistically insignificant coefficient in column (2) does not provide evidence that landlords respond more positively to voucher tenants on the side of the border with greater rent limits. At the edge of the 95 percent confidence interval, increasing the voucher payment cap by roughly $1,000 per month buys at most 14 percentage points of positive responses. As with estimates from the difference-in-differences design, spatial RD estimates suggest that eliminating the voucher penalty would require an exorbitant increase in the voucher payment limit.

4.2.3 Heterogeneity by Posted Rent

There are at least two reasons to examine effects by posted rent. First, the two waves of the experiment impose different sample restrictions based on posted rent. The greatest rents in the 2015 wave of our experiment equal 130 percent of the metro-wide FMR, while the 2017 wave includes amounts up to 175 percent of FMR. Imposing common limits can ensure that sample differences do not drive our results. Second, theory predicts that landlords may respond differently to vouchers depending on the posted rent of their unit. In a model where posted rents reflect a unit's quality, some landlords will avoid vouchers because the voucher fails to pay the going market rate for that unit. The simplest version of this model predicts that only landlords posting rent above the payment limit will avoid voucher tenants. Then, raising the voucher payment improves landlord responses but only among those units with posted rent between the old and new payment limits.

However, we find consistent results that, regardless of posted rent, landlords respond little to the increased payment limits. Table 4 estimates the triple-difference specification in various sub-samples depending on posted rent relative to the metro-wide FMR. The first column replicates the full-sample main result. The triple-interaction coefficient of -0.080 indicates that, if anything, landlords respond less positively to voucher tenants after the policy change. The second column imposes common support between the two waves of the experiment, limiting the sample to units posting rent no more than 130 percent of the metro-wide FMR. The negative and statistically insignificant triple-interaction coefficient of -0.048 matches our prior result that greater voucher payments show no sign of narrowing the voucher penalty imposed by landlords. The final three columns examine samples ranging from low to high posted rent. The triple-interaction coefficient for each sub-sample continues to be negative and statistically insignificant. Graphically, panel (d) of Figure 4 shows similar results limiting the border discontinuity design to units listed above 130 percent of FMR. Overall, we find no evidence that landlords respond to the availability of higher voucher payments differently depending on posted rent.

4.3 Higher Payment Limits Shift Where New Voucher Holders Locate

Higher payment limits increase voucher lease-up rates in high-rent relative to low-rent neighborhoods. Figure 5 summarizes these trends over time for treatment and control tracts. In the left panel, the dashed and solid lines show the average number of voucher tenants leased-up in neighborhoods that were and were not affected by the policy change, respectively. High-rent neighborhoods have far fewer voucher tenants, and we see only a small decrease in this gap after 2017. However, these numbers include both tenants with an existing voucher and tenants with new vouchers. The right panel focuses on just those tenants who have a new voucher. While high-rent neighborhoods attracted far fewer new voucher tenants than low-rent neighborhoods between 2012 and 2016, this trend dramatically changed in 2017, closing the gap.

Table 5 quantifies the change in lease-up locations. Column (1) shows a difference-in-differences specification with observations at the tract-year level. The outcome is the stock of vouchers leased in the tract. Consistent with the visual evidence, the coefficient of -78.3 on the treatment neighborhood dummy indicates that vouchers were much less common in high-rent treatment neighborhoods prior to 2017. The positive but statistically insignificant coefficient of 3.58 on the treatment-post interaction indicates no large difference in the time trends for the overall number of vouchers in treatment versus control neighborhoods. The 95% confidence interval excludes increases greater than 11% of the pre-policy gap between treatment and control neighborhoods. Column (2) shows the same specification using only new vouchers as the outcome. The policy increases the average number of new vouchers in treatment neighborhoods by 3.25 vouchers per tract. This effect is statistically significant and large in relative terms, eliminating the pre-policy gap of 3.20. The point estimates across columns (1) and (2) are similar in magnitude, suggesting any policy effects are concentrated among new voucher holders. Finally, column (3) shows that the results do not differ noticeably when narrowing focus to the treatment-control border. Altogether, we find that

increased payment limits dramatically change where the flow of new voucher tenants locate, leaving existing voucher holders unmoved.

The changes in lease-up locations we observe are similar to the prior literature. Other studies document changes in lease-up locations in response to higher voucher payment limits in high rent neighborhoods (Collinson and Ganong, 2018; Dastrup et al., 2019; Reina et al., 2019). The scale of the policy is also relatively similar. Our estimates imply that approximately 150 households per year move to opportunity in response to the policy we study. This value is small relative to the entire DC housing market and even the the voucher program, which leased 11,612 units in DC in 2017. However, the 150 households per year we see move is large relative a flow of approximately 500 new vouchers issued in DC in 2017 and similar to the number of movers for other policy changes. The policy in Bergman et al. (2019) provides programming to 200 households and induces 40% into opportunity moves. Similarly, the Baltimore Regional Housing Partnership (BRHP) studied by DeLuca and Rosenblatt (2017) has existed for about 15 years and currently serves about 4,000 families, which yields 267 families per year.

5 Discussion

5.1 Why Do Most Landlords Not Respond to Increased Payment Limits?

Understanding landlords' reasons for avoiding vouchers can help clarify why they do not adjust when payment standards change. Two primary motivations are available. First, landlords may use voucher status to statistically predict other tenant characteristics, like race or expected maintenance costs. Second, landlords might avoid vouchers because the costs of complying with inspections and other regulatory burdens of the voucher program are too high.

Our data show no signs that landlords use the voucher signal as a proxy for other characteristics. Table 6 uses OLS regressions to show how the voucher penalty varies with other characteristics of the listing and the tenant. Column (1) shows that voucher tenants receive positive responses 28 percentage points less often. This effect is large. By way of comparison, an inquiry with a Black-indicating name receives an economically and statistically significant 4 percentage point penalty. Columns (2) and (3) show that landlord responsiveness to cash tenants increases with rent, perhaps due to greater opportunity cost to the landlord of an empty unit. However, the voucher penalty also increases with rent, which is consistent with either statistical discrimination or regulatory burdens. We test for statistical discrimination as in Hanson and Hawley (2011) and Ewens et al. (2014) by examining how the voucher penalty varies in the presence of other information. Column (4) shows that the voucher signal decreases positive responses by 58% (35 pp) when not signalling other information, compared to 60% (19 pp) when also signaling that the tenant has bad credit or is a smoker. Similarly, the voucher penalty does not vary with implied race of the name on the inquiry. Our data are limited to race-indicating names and the initial landlord interaction. Race could be quantitatively important later on in the leasing process or in ways not captured by name, but our data provide no evidence of an interaction between voucher status and race.

Landlords' direct responses emphasize the cost of compliance. For the 2017 wave of the correspondence experiment, we code e-mails from landlords who explicitly reject the voucher in their response. Most (85%) provide no specific reason. But the responses of those who give a specific rationale are suggestive; they are split entirely among those concerned about program compliance (e.g. inspections) and those that say the program will not pay their listed rent. These responses are anecdotal but they match the qualitative literature, which argues that bureaucratic inefficiency often drives landlords away and the voucher program becomes attractive when it pays greater or more predictable rent than the private market (Garboden et al., 2018).

Landlords might compensate for perceived costs of the voucher by over-pricing lower quality units. Theory predicts that such effects would result in price bunching at the voucher payment limit; however, for landlords in opportunity neighborhoods in DC, we find no evidence that the voucher program offsets higher costs by paying a premium. Figure 6 plots histograms of the difference between posted rent and the neighborhood voucher payment limit for different samples of listings from 2017. Figure 6a shows all listings on the general market website from which we draw our experiment sample, and the distribution of rent is smooth. Figure 6b shows listings from a specialist website, DCHousingSearch.org, which targets subsidized tenants. Their listings show a large spike at zero, indicating that landlords price many units at exactly the voucher payment ceiling, presumably above market rent. However, Figures 6c and 6d show that this heaping exists only in low-rent neighborhoods. Together, these facts suggests that landlords can respond to the voucher program by charging above-market rent; however, landlords in high rent neighborhoods do not charge a premium, even in the presence of increased payment standards. If the voucher incurs additional costs but pays the same rent as a cash tenant in these neighborhoods, theory predicts landlords will not participate even when payment limits increase.

While the costs of program compliance and the absence of a rent premium explain landlord reluctance, other theories could rationalize the lack of a landlord response to increased payment limits. One possibility is that racial discrimination is occurring at a stage after first email responses, and landlords cite compliance costs to distract from this discrimination (Gap and to Opportunity Neighborhoods, 2021). Another possibility is that landlords are unaware of the policy change, though we have some anecdotal evidence that landlords are informed. Of nine landlord e-mails specifically mentioning payment standards, five accurately describe DCHA's system based on neighborhood and number of bedrooms, three are vague, and only one inaccurately refers to the prior system based on bedrooms but not neighborhood. We do not have representative data on landlord beliefs and cannot rule out the possibility that many landlords are unaware of the policy change, but most landlords who volunteer their opinions on voucher rent payments are well-informed.

5.2 Do Any Landlords Respond?

While most landlords do not respond to rising voucher payment limits, we identify a set of landlords who do respond by targeting listings to voucher tenants. Table 7 shows results from DCHousingSearch.org, a website that specializes in listings for subsidized tenants. For each tax

neighborhood-year between 2010 and 2018, we count the number of these specialist listings. The first column shows results for total listings. We use a difference-in-differences regression with the inverse hyperbolic sine of the number of listings as the outcome. The coefficient of -2.07 on the treatment neighborhood dummy indicates that high-rent neighborhoods see far fewer postings than low-rent neighborhoods prior to the policy change we study. The positive coefficient on the interaction between treatment neighborhoods and the period after the 2017 policy change indicates that the overall number of listings increases in high-rent neighborhoods relative to low-rent neighborhoods after 2017. The value of 0.48 indicates that the number of listings increased by 126 percent in treatment neighborhoods after the policy change relative to before it.[7] That increase comes on a relatively small base of 52 listings in treatment neighborhoods in 2015, but the percentage increase is so large as to be noticeable relative to the 310 new voucher holders located in treatment neighborhoods in 2015. The panel of voucher specialist listings also spans the limited introduction of neighborhood-based voucher payments in 2015, allowing us to test for its effect as well. For our treatment neighborhoods, this policy increased the voucher payment cap from 100 percent of FMR to 130 percent of FMR. The coefficient on the interaction between being a treatment tract and the years 2015-2016 indicates a similar increase in listings for this policy change. Taken together, the results are consistent with the policy changes inducing a response by some opportunity landlords who post listings targeted at voucher tenants.

The increase in specialist listings is concentrated for units with posted rent between the old and new payment caps. The final four columns of Table 7 estimate the difference-in-differences specification from the first column but only count the number of listings in specific rent ranges. For example, the fourth column counts only units listed between 130 percent and 175 percent of the metro-wide FMR. Units listed in this range were more expensive than neighborhood payment limits prior to 2017 but within them after 2017. The positive coefficient of 0.40 is statistically significant and the largest among the various rent ranges for 2017. This result indicates that the policy change not only generated voucher specialist listings in high-rent neighborhoods overall but particularly for units between the old and new voucher payment ceilings. The second row of Table 7 shows a similar pattern for the 2015 policy change with listings up to 130 percent of FMR increasing.

Landlords in high-rent neighborhoods who market to voucher tenants appear to be relatively unusual. Table 8 displays summary information for tax assessments for 2017 listings. Each column corresponds to a different set of listings. The first column shows listings associated with high-rent neighborhoods listed on DCHousingSearch.org. The remaining columns provide comparisons to all listings on DCHousingSearch.org and all listings on the majority market website. Compared to these broader sets of landlords, landlords who facilitate opportunity moves for voucher holders have three distinctive characteristics. First, they have relatively little experience specializing in voucher tenants despite being existing property owners. The vast majority had not listed a unit on the voucher specialist website prior to the policy change in 2017. Second, they are unusually

[7] As with log transformations, inverse hyperbolic sine coefficients only approximate percentages when working with dummy variables and large changes. Following Bellemare and Wichman (2019), we calculate percent changes as $\frac{sinh(\hat{y}_1)}{sinh(\hat{y}_2)} - 1$

exposed to both parts of DC's segmented housing market. They have 52 percent of their other units in high-rent treatment neighborhoods, compared to 28 percent for other voucher specialists and 85 percent for majority market landlords. Third, they operate on a surprisingly small scale. They own a mean of 11 properties, and a majority own only one; 79 percent own 5 properties or fewer. Their scale is small compared to voucher landlords overall (Garboden et al., 2018). Their properties are also small. Only 13 percent are multi-family high-rise buildings with more than three stories. These landlords do not appear to be overcoming the compliance costs of the voucher program via economies of scale.

5.3 How Do Tenants Relocate if Most Landlords Do Not Respond?

We find that increased voucher payment limits do not change the behavior of most landlords but do change where tenants locate; both of these facts can be true in a perfectly competitive market if the number of vouchers is small. The Becker model of discrimination in labor markets (Becker, 1971; Charles and Guryan, 2008) implies that wages depend on the discriminatory preferences of the marginal, not average, employer. In the housing context, if there are more landlords in a neighborhood who will accept vouchers than voucher tenants wanting to live there, then landlord preferences would not constrain tenants. The voucher program is small relative to the overall market, using only 3.6% of DC's housing units in 2015. In high-rent neighborhoods treated by the policy, vouchers have particularly small market shares with a median across tracts of 0.3% in 2015 and 0.6% in 2017. Higher voucher payment limits doubled the number of families moving to opportunity but only needed to convince less than 1% of landlords to agree to lease to a voucher holder for the usual market rent.

However, the group of interested landlords may not be sufficient to support a larger program of opportunity moves. A scaled-up policy that spread voucher tenants equally across neighborhoods would use 3.6% of housing units in each neighborhood. In our study, 20% of landlords respond positively to voucher tenant inquiries. Cunningham et al. (2018) find that only 69% of such inquiries turned into actual apartment showings. Kennedy and Finkel (1996) find that the median voucher tenant needs to see 5 units to successfully lease. Those figures would imply that only about 2.7% of contacted landlords would actually lease to a voucher tenant in an average neighborhood. This value is above the current concentration of voucher tenants in high-rent neighborhoods, 0.6%, but below the city-wide level of 3.6%. While only approximate, this comparison suggests that the voucher program exists in a middle ground. Typical efforts to move voucher households to opportunity in small numbers may be unconstrained by landlord preferences because vouchers are at present exceedingly rare in high-rent neighborhoods; however, scarcity of interested landlords might hamper attempts to help larger numbers of voucher tenants move to opportunity.

6 Summary and Concluding Remarks

This paper documents how landlords shape access to neighborhood opportunity and the extent to which increasing voucher payment limits can encourage landlords to facilitate moves to opportunity. We conduct two waves of a correspondence experiment, sending inquiries from fictional voucher tenants to rental housing listings in Washington, DC. These two experiments bracket a policy change in which DC increased voucher payment limits in high-rent neighborhoods. Most landlords in high-rent neighborhoods screen out voucher tenants. We find that most landlords do not change their screening decisions in response to higher voucher payment limits. A few do respond positively, though, and we identify a set of these landlords using specialist rental listings and property tax data. We find that these landlords begin to offer units in high-rent neighborhoods to voucher tenants at near-market values. The landlords owning these units are unusual. They are few in number, operate at small scale, and have properties exposed to a wide variety of neighborhoods. Their response to the increased payment limits is enough to equalize the flow of voucher tenants into, but not the stock in, high- versus low-rent neighborhoods.

Our results suggest that policies designed to move voucher tenants to opportunity may succeed at current scales but struggle to attract landlords at a larger scale. We estimate that approximately 150 households per year move to opportunity in response to the policy we study, which is similar in magnitude to other existing interventions (Bergman et al., 2019) but only increases the median share of housing used by vouchers in high-rent neighborhoods from 0.3% to 0.6%. If these magnitudes represent the upper range of programmatically and politically feasible housing mobility programs, such programs will need to persist over many years to change the stock of voucher tenant lease-up locations. Will the increased flow of voucher tenants to high-rent neighborhoods persist? The answer depends in part on whether more landlords can be drawn into the voucher program over time, and our finding that opportunity landlords on the margin are scarce and atypical may be cause for concern.

Our study focuses on one policy change in Washington, DC, but the implications extend more broadly. The policy we study is closely related to the Small Area Fair Market Rents (SAFMRs) that have begun to roll out nationally. Observing how landlords respond to an expansion of neighborhood-level voucher payment limits provides a preview of what to expect from this policy in other places. Our results should be particularly informative for places that share DC's sharp neighborhood sorting and tight relationship between opportunity and rent levels, that is, in the places where access to neighborhood opportunity likely matters most.

Our results should encourage innovative policymakers to expand engagement with landlords. Indirect landlord engagement through SAFMRs has shown some success in multiple, widely varying contexts. Housing authorities have already begun experimenting with a variety of more direct interventions, including landlord outreach and education, larger security deposits, insurance against damage to units, faster and more predictable inspections, payments that offset the opportunity cost of a vacant unit, certification of tenants' preparedness for renting, and active matching of landlords with tenants. Our results suggest this emphasis on experimenting with how to engage landlords is

well-placed.

However, evidence on which landlord engagement strategies best promote access to opportunity is lacking. As in other cities, greater voucher payment limits can encourage some moves to opportunity, but we also find concerning evidence that few opportunity landlords are on the margin of accepting a voucher. The scarcity and unusual characteristics of these marginal landlords raises a question of whether enough landlords would be willing to sustain access to opportunity. More work is needed to understand how landlords respond to mobility interventions at scale and over longer periods of time. Similarly, we have little evidence on the relative effectiveness of and the complementarities between the many other policies targeted at landlords. We do not know if they induce a similarly small and unusual set of landlords to engage with voucher tenants or if these higher-touch interventions reach a broader group of landlords. Evidence from this study and other recent work shows that public policy can help families access different neighborhoods, but it remains to be seen whether such policies can draw in enough landlords to support residential moves as a systematic response to unequal opportunity.

More broadly, the fact that landlords persistently avoid voucher tenants helps explain why some policies have more success in encouraging opportunity moves. The most successful strategies implement a complex packages of services (DeLuca and Rosenblatt, 2017; Bergman et al., 2019). Bergman et al. (2019) identify five different possible mechanisms behind their intervention's success, of which direct interaction with landlords is only one.[8] Our results indicate this mechanism is active. Landlords avoid voucher tenants and do so persistently. Few opportunity landlords are induced even by greater rent payments to participate in the voucher program. Costs of navigating the program may be more important. When complex mobility interventions engage directly and intensively with landlords who have little experience with vouchers, they may help demystify the voucher program in a way that paying greater rent alone does not. New mobility programs may be able to counteract negative perceptions of the voucher program by following models of landlord engagement, for example from Baltimore (Cossyleon et al., 2020). Extensive engagement with landlords is a fundamental ingredient for programs that facilitate opportunity moves.

Landlords play a key role in allocating access to opportunity. In the economics literature, existing models of the housing market tend to simplify landlord behavior and thus explain location choice with tenant preferences and prices (Galiani et al., 2015). An alternative view suggests that frictions in the search process prevent opportunity moves (Bergman et al., 2019, 2020). Our results add to the evidence for this latter view. Similar to an extensive qualitative literature (Popkin and Cunningham, 2000; Rosen, 2014; Greenlee, 2014; Desmond, 2016; Garboden et al., 2018), our results indicate that landlords not only actively screen out voucher tenants but also are reluctant

[8] (Cossyleon et al., 2020) describe some of the BRHP's efforts to directly engage landlords as the program's assignment of a single contact person for landlords, offering information through a website, and mediating disputes between landlords and tenants. Bergman et al. (2019)'s discussion of mechanisms states, "Families identified five key mechanisms through which the CMTO program helped them move to opportunity: providing emotional support, increasing motivation to move to a high opportunity neighborhood, streamlining the search process by helping to prepare rental applications and 'rental resumes,' providing direct brokerage services and representation with landlords, and providing crucial and timely assistance for auxiliary payments that could prevent a lease from being signed."

to change even in the presence of much larger payment limits. Landlords actively and persistently shape where voucher holders locate.

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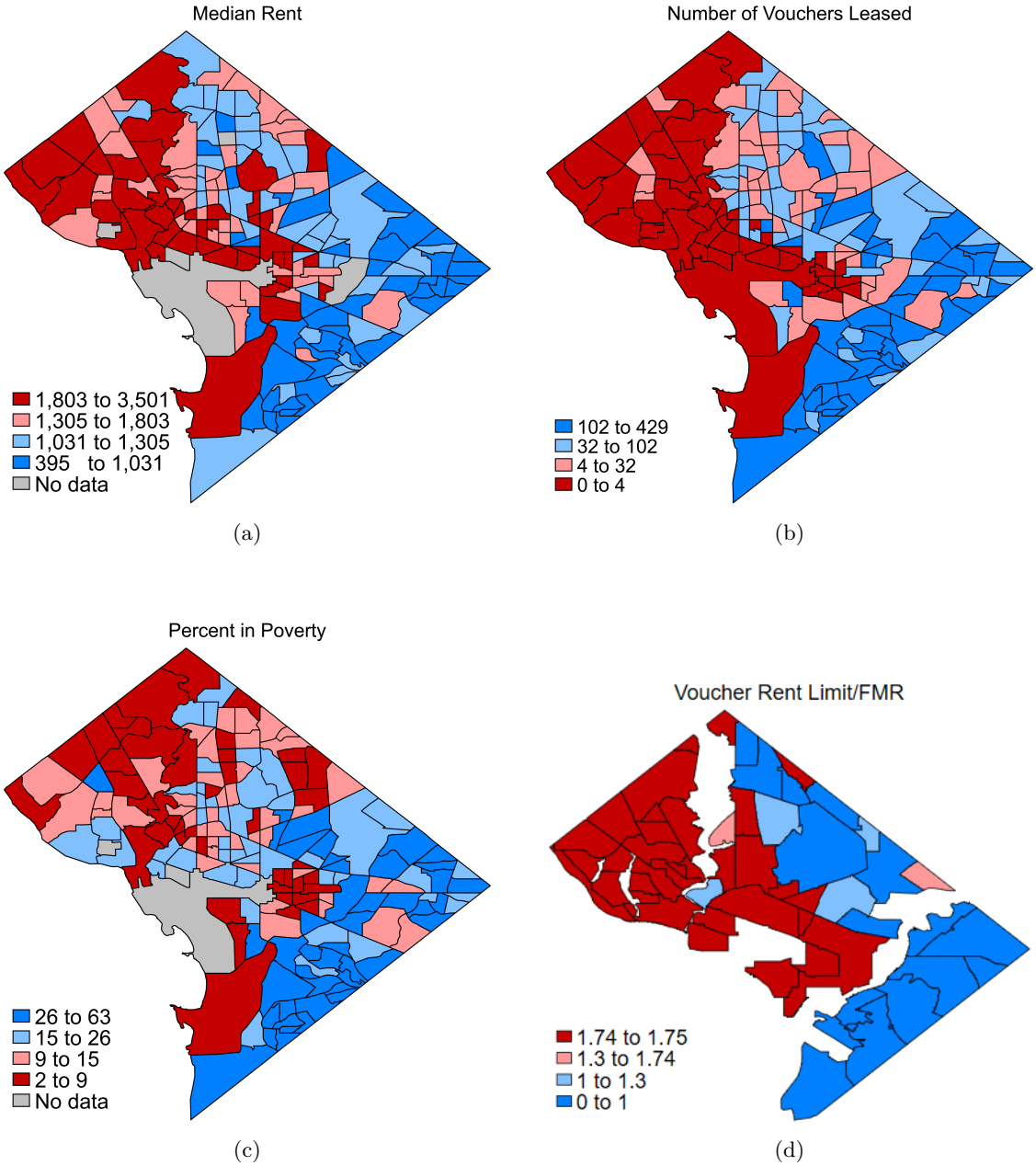


Figure 1: Neighborhoods in Washington, DC

Notes: Each figure shows a map of Washington, DC. Figure (a) shows median rent by census tract from the 2012-2016 ACS. Figure (b) shows the number of HCV residents leased-up by tract from HUD's 2015 Picture of Subsidized Households. Figure (c) shows poverty rates from the 2012-2016 ACS. Figure (d) shows the ratio of 2017 neighborhood voucher payment limits from DCHA and metro-wide FMR from HUD, by tax neighborhood. Source: US Census Bureau, US Department of Housing and Urban Development.

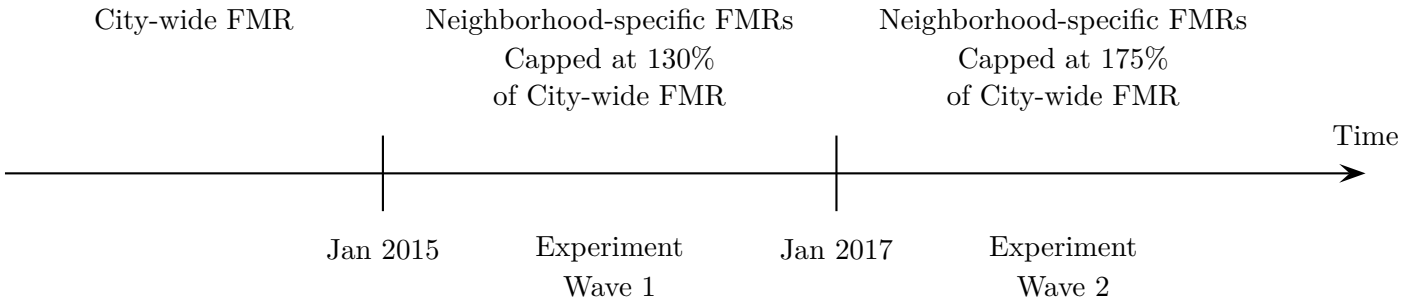


Figure 2: Timeline of Small Area Fair Market Rent (SAFMR) Policy in DC

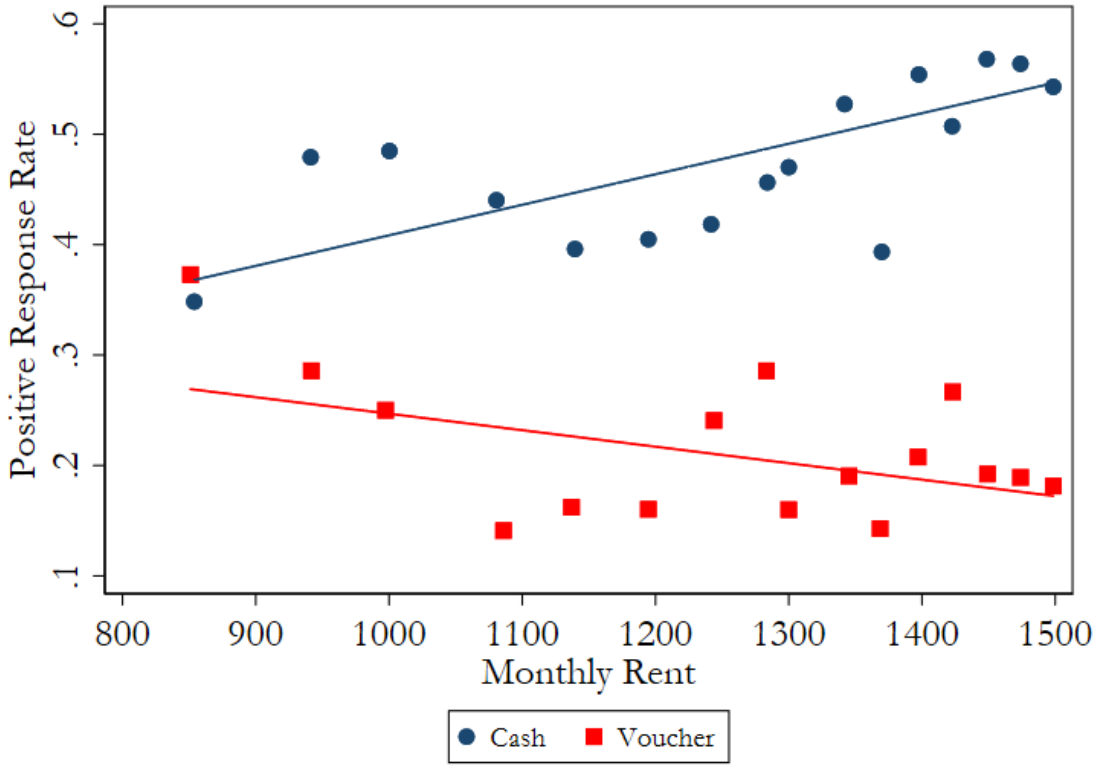
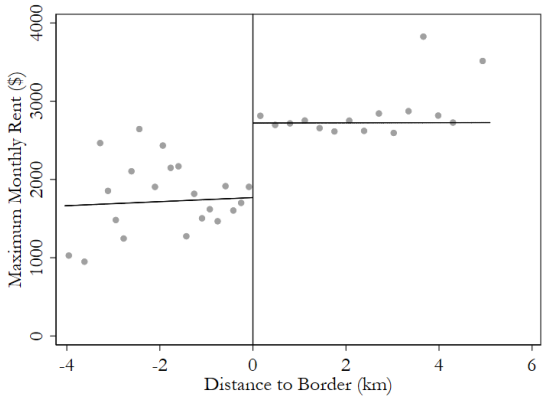
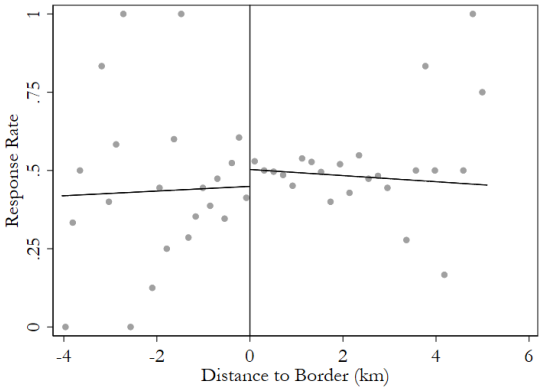


Figure 3: Probability of Positive Landlord Response, by Voucher Signal and Posted Rent

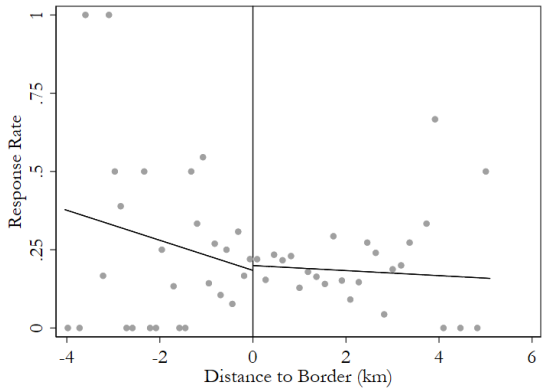
Notes: Each line shows data from the experiment and is a linear fit of the relationship between a landlord positive response dummy and the posted rent of the unit. Dots show group means for posted rent bins with equal sample size. Each line/dot is limited to the sub-sample of the indicated voucher signal treatment. The sample is also limited to units with rent between the 1st and 99th percentiles of the rent distribution of both waves. Source: Correspondence experiment.



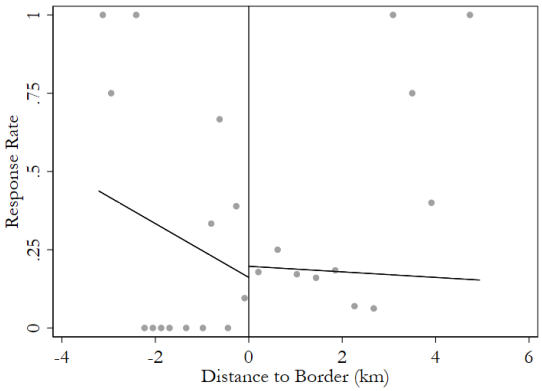
(a) Voucher Limit



(b) Landlord Responses - Cash Tenants



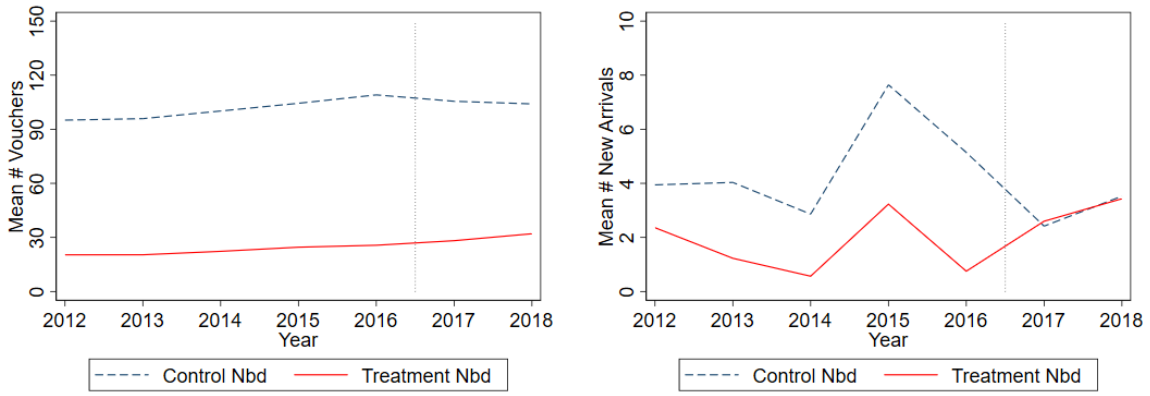
(c) Landlord Responses - Voucher Tenants



(d) Landlord Responses - Voucher, Rent > 130% FMR

Figure 4: Border Discontinuity Effects

Notes: Each sub-figure shows a regression discontinuity plot with optimal bandwidth and bin width selection from Calonico et al. (2017). Treatment neighborhoods are defined as in Figure 1d. The running variable is distance to the nearest border with a tax neighborhood of different treatment status. The running variable is negative in control neighborhoods and positive in treatment neighborhoods. Each plotted point shows the average of the outcome for a particular bin, and the two lines shows the best local linear fit within the given bandwidth. The outcome in (a) is the value of the neighborhood-specific voucher payment limit; all others use a landlord positive response dummy. All figures limit the sample to 2017 inquiries that send a voucher signal, except (c) which limits the sample to those that do not. Figure (d) also limits the sample to units with posted rent above 130 percent of FMR. Source: Correspondence experiment.

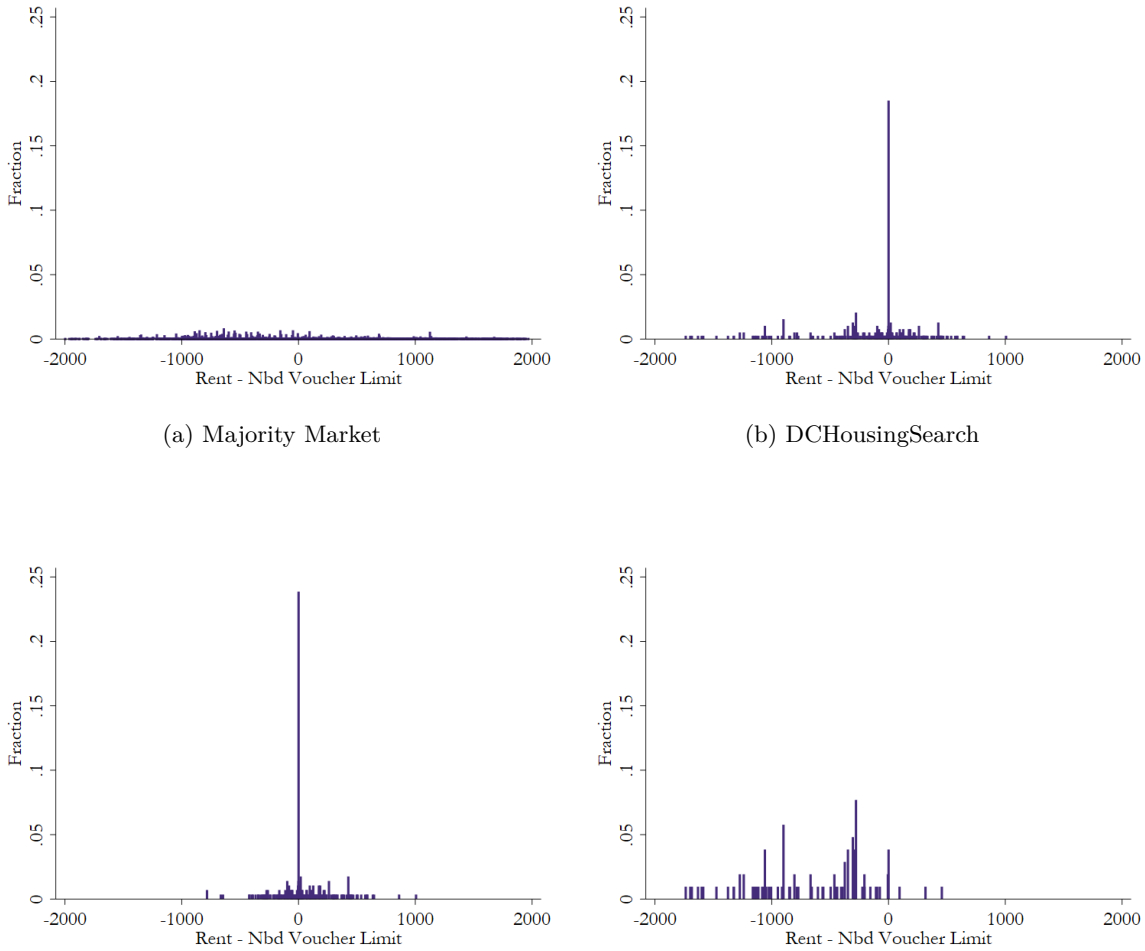


(a) Number of Vouchers

(b) Number of Newly Leased Vouchers

Figure 5: Number of Vouchers, Tracts Affected vs. Unaffected by Policy Change

Notes: Data are from the HUD Picture of Subsidized Households. Each line shows an average across census tracts by year and treatment status. The treatment dummy indicates that the tax neighborhood of the unit had a voucher payment limit greater than 130 percent of metro-wide FMR in 2017. The left pane shows the number of vouchers in use, deflating the "number of vouchers available" in the data by usage and reporting rates. The right panel shows the number of newly leased vouchers. Source: US Department of Housing and Urban Development.



(a) Majority Market

(b) DCHousingSearch

(c) DCHousingSearch - Control Neighborhoods

(d) DCHousingSearch - Treatment Neighborhoods

Figure 6: Frequency of Listings, by Posted Rent Relative to Neighborhood Rent Limit in 2017

Notes: Each graph shows a histogram for data from 2017. The horizontal axis measures the simple difference between the posted rent and the neighborhood-specific voucher payment limit for that unit's neighborhood, i.e. zero indicates a unit listed for exactly the voucher limit. Bin width is 1. Each sub-figure examines a subset of observations from rental listings over the listed data sources and neighborhoods. The treatment dummy indicates that the tax neighborhood of the unit had a voucher payment limit greater than 130 percent of metro-wide FMR in 2017. Source: Correspondence experiment, Social Serve.

Table 1: Experiment Summary Statistics

	Cash	Voucher	All
A. Year 2015			
Voucher	0.00	1.00	0.25
	(0.00)	(0.00)	(0.43)
Black	0.49	0.50	0.49
	(0.50)	(0.50)	(0.50)
Female	0.50	0.50	0.50
	(0.50)	(0.50)	(0.50)
Monthly Rent	1,252	1,255	1,253
	(212)	(221)	(214)
Bedrooms	0.9	1.0	0.9
	(0.7)	(0.8)	(0.8)
Positive Response	0.50	0.23	0.43
	(0.50)	(0.42)	(0.50)
N	2,010	658	2,668
B. Year 2017			
Voucher	0.00	1.00	0.50
	(0.00)	(0.00)	(0.50)
Black	0.75	0.75	0.75
	(0.43)	(0.43)	(0.43)
Female	0.49	0.51	0.50
	(0.50)	(0.50)	(0.50)
Monthly Rent	2,046	2,056	2,051
	(701)	(663)	(682)
Bedrooms	1.3	1.3	1.3
	(1.0)	(0.9)	(0.9)
Positive Response	0.48	0.19	0.33
	(0.50)	(0.39)	(0.47)
Sq. Ft.	849	881	865
	(500)	(909)	(735)
N	2,115	2,149	4,264

This table shows data from the experiment. Each cell shows means with standard deviations in parentheses. The first, second, and third columns show inquiries that signal use of a voucher, those that do not, and the combined sample, respectively. Source: Correspondence experiment.

Table 2: Effect of Increasing Rent Limits on Landlord Voucher Penalty, Triple Difference

	(1) All Voucher Limit ($)	(2) Voucher Response	(3) Cash Response	(4) All Response
Treatment Nbd X 2017	454.8***	0.024	0.10**	0.10**
	(54.8)	(0.048)	(0.048)	(0.048)
Treatment Nbd	668.0***	-0.088*	-0.067*	-0.067*
	(34.6)	(0.047)	(0.034)	(0.034)
2017	286.4***	-0.047	-0.090**	-0.090**
	(42.7)	(0.043)	(0.040)	(0.040)
Treatment Nbd X 2017 X Voucher				-0.080
				(0.064)
Voucher X 2017				0.043
				(0.056)
Treatment Nbd X Voucher				-0.021
				(0.054)
Voucher				-0.26***
				(0.047)
Control Baseline Mean	1324.3	0.48	0.48	0.48
R^2	0.66	0.0074	0.0025	0.092
N	6857	2778	4079	6857

The sample comes from the two correspondence experiments. Each column shows the results of a linear regression (or linear probability model). The outcome is a landlord positive response dummy except in the first column, which uses the voucher payment limit as the outcome. The treatment dummy indicates that the tax neighborhood of the unit had a voucher payment limit greater than 130 percent of metro-wide FMR in 2017. The voucher dummy is an indicator that the inquiry states a desire to pay by voucher. The sample for the final three columns is inquiries signalling use of a voucher, those without such a signal, and the full sample, respectively. Coefficients for all covariates are listed. Standard errors are in parentheses and are clustered by tax neighborhood. Source: Correspondence experiment.

Table 3: Effect of Increasing Rent Limits on Landlord Voucher Penalty, Border Discontinuity

	(1) Voucher Voucher Limit ($)	(2) Voucher Response	(3) Cash Response	(4) Voucher Rent	(5) Voucher Bedrooms
Treatment Nbd	1028.1***	-0.026	0.041	0.0074	-0.11
	(115.5)	(0.084)	(0.087)	(0.061)	(0.21)
Distance to Border (km)	180.2	0.073	0.073	0.32***	-0.091
	(191.0)	(0.12)	(0.12)	(0.10)	(0.37)
Treatment Nbd X Distance	-318.0	-0.081	-0.11	-0.30**	-0.32
	(212.6)	(0.14)	(0.15)	(0.11)	(0.41)
Control Mean	1759.3	0.33	0.33	1.08	1.82
R^2	0.47	0.00070	0.0027	0.10	0.041
N	882	882	854	877	882

The sample comes from inquiries in the 2017 correspondence experiment, restricted to those within 1 km of the border between tracts treated and untreated by the policy. Each column shows the results of a linear regression with the variable listed in the column headings as the outcome. The treatment dummy indicates that the tax neighborhood of the unit had a voucher payment limit greater than 130 percent of metro-wide FMR in 2017. Distance is negative for control neighborhoods and positive for treatment neighborhoods. All columns use only the sub-sample of inquiries sending a voucher signal, except the third column, which uses only those not sending the signal. Coefficients for all covariates are listed. Standard errors are in parentheses and are clustered by listing. Source: Correspondence experiment.

Table 4: Effect of Increasing Rent Limits on Landlord Voucher Penalty, Triple Difference, Heterogeneity by Posted Rent

	(1) All Response	(2) Under 130% FMR Response	(3) 40% to 70% FMR Response	(4) 70% to 100% FMR Response	(5) 100% to 130% FMR Response
Treatment Nbd X 2017 X Voucher	-0.080	-0.048	-0.13	-0.11	-0.12
	(0.064)	(0.063)	(0.22)	(0.10)	(0.12)
Voucher X 2017	0.043	0.058	-0.11	0.046	0.18*
	(0.056)	(0.056)	(0.13)	(0.082)	(0.11)
Treatment Nbd X Voucher	-0.021	-0.021	0.12	-0.043	0.13
	(0.054)	(0.054)	(0.17)	(0.076)	(0.080)
Treatment Nbd X 2017	0.10**	0.079	-0.16	0.25***	0.13***
	(0.048)	(0.048)	(0.13)	(0.076)	(0.046)
2017	-0.090**	-0.11**	0.11	-0.13**	-0.21***
	(0.040)	(0.041)	(0.076)	(0.059)	(0.036)
Treatment Nbd	-0.067*	-0.067*	0.0020	-0.19***	-0.14***
	(0.034)	(0.034)	(0.100)	(0.046)	(0.041)
Voucher	-0.26***	-0.26***	-0.073	-0.19***	-0.46***
	(0.047)	(0.047)	(0.095)	(0.066)	(0.075)
Control Baseline Mean	0.54	0.54	0.34	0.52	0.68
R^2	0.092	0.077	0.033	0.078	0.11
N	6857	5067	403	1713	2924

The sample comes from the two correspondence experiments. The sample varies across columns, limiting the sample to listings with posted rent relative to the city-wide FMR in the range shown at the top of the column. The first column replicates column (4) of Table 2. Each column shows the results of a linear regression (linear probability model) with a landlord positive response dummy as the outcome. The outcome is a landlord positive response dummy. The treatment dummy indicates that the tax neighborhood of the unit had a voucher payment limit greater than 130 percent of metro-wide FMR in 2017. The voucher dummy is an indicator that the inquiry states a desire to pay by voucher. Standard errors are in parentheses and are clustered by tax neighborhood. Source: Correspondence experiment.

Table 5: Effect of Increasing Rent Limits on Number of Vouchers Leased-Up per Tract

	(1) Vouchers	(2) New Arrivals	(3) New Arrivals
Treatment Nbd X Post-2017	3.58	3.25***	2.86***
	(2.84)	(0.77)	(0.90)
Post-2017	3.88*	-1.77***	-2.04***
	(2.09)	(0.45)	(0.56)
Treatment Nbd	-78.3***	-3.20***	-4.20***
	(8.95)	(0.80)	(1.01)
Treatment Nbd X Post X Border			1.58
			(1.77)
Post-2017 X Border			0.89
			(0.93)
Treatment Nbd X Border			3.20**
			(1.52)
Border Tract			-2.58***
			(0.95)
Control Baseline Mean	100.9	4.74	4.74
R^2	0.29	0.025	0.038
N	1253	1192	1192

The sample comes from the HUD Picture of Subsidized Households. The unit of analysis is a tract-year. Each column shows the results of a linear regression with the outcome listed at the top of the column. The treatment dummy indicates that the tract of the unit had a voucher payment limit greater than 130 percent of metro-wide FMR in 2017. The border dummy refers to tracts that border a tract with a different value of the treatment indicator. Coefficients for all covariates are listed. Standard errors are in parentheses and are clustered by tract. Sample sizes are lower after the first column due to dropping observations in the first year for which the outcome can neither be observed nor imputed with first differences. Source: US Department of Housing and Urban Development.

Table 6: Linear Probability Model of Landlord Response on Inquiry Characteristics

	(1)	(2)	(3)	(4)	(5)
	Positive Response	Positive Response	Positive Response	Positive Response	Positive Response
Voucher	-0.28***	-0.14***	0.034	-0.35***	-0.044
	(0.012)	(0.032)	(0.10)	(0.022)	(0.10)
Black Name	-0.043***	-0.043***	-0.043***	-0.052***	-0.060***
	(0.012)	(0.012)	(0.012)	(0.016)	(0.016)
Bad Credit/Smoker	-0.18***	-0.19***	-0.18***	-0.25***	-0.25***
	(0.012)	(0.012)	(0.012)	(0.016)	(0.016)
Monthly Rent - 100s		0.0055***	0.010***		0.010***
		(0.0015)	(0.0020)		(0.0020)
Voucher X Rent		-0.0079***	-0.012***		-0.012***
		(0.0016)	(0.0022)		(0.0022)
Voucher X Black				0.023	0.042*
				(0.023)	(0.023)
Voucher X Bad Credit/Smoker				0.16***	0.15***
				(0.022)	(0.022)
BedroomXVoucher Dummies	No	No	Yes	No	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes
Mean of Dep. Var.	0.37	0.37	0.37	0.37	0.37
R^2	0.12	0.13	0.13	0.13	0.14
N	6932	6932	6932	6932	6932

The sample comes from the two correspondence experiments. Each column shows the results of a linear regression (linear probability model) with a landlord positive response dummy as the outcome. The voucher treatment is an indicator that the inquiry states a desire to pay by voucher and the black name variable is an indicator for an inquiry with a black-indicating name. Coefficients for all covariates are listed unless indicated. Standard errors are in parentheses and are clustered by rental listing. Source: Correspondence experiment, Social Serve.

Table 7: Effect of Increasing Rent Limits on Number of Voucher Specialist Listings (Inverse Hyperbolic Sine), by Rent Relative to FMR

	(1) All arsinh(Listings)	(2) < 100% FMR arsinh(Listings)	(3) 100-130% FMR arsinh(Listings)	(4) 130-175% FMR arsinh(Listings)	(5) > 175% FMR arsinh(Listings)
Treatment Nbd X Post-2017	0.48***	0.10	0.32	0.40**	0.031
	(0.15)	(0.12)	(0.19)	(0.16)	(0.031)
Treatment Nbd X 2015-2016	0.33**	0.20*	0.37*	0.059	0.025
	(0.13)	(0.11)	(0.18)	(0.057)	(0.026)
Treatment Nbd	-2.07***	-2.01***	-0.83***	-0.0084	0.0084
	(0.36)	(0.35)	(0.20)	(0.031)	(0.0084)
Year FE	Yes	Yes	Yes	Yes	Yes
Control Mean Listings	12.9	11.1	1.67	0.090	0
Mean of Dep. Var.	1.27	0.98	0.54	0.16	0.013
R^2	0.37	0.43	0.15	0.12	0.017
N	513	513	513	513	513

The sample comes from listings posted to DCHousingSearch.org between 2010 and 2018. In the first column, the outcome is the inverse hyperbolic sine of the number of listings by tax neighborhood and year. The inverse hyperbolic sine is similar to a log transformation but accounts for zeros. The latter columns restrict this count to listings with posted rent (relative to fair market rent) in the listed range. Since the unit of observation is the neighborhood-year, the sample size is the same in each column. Each column shows the results of a linear regression. The treatment dummy indicates that the tax neighborhood of the unit had a voucher payment limit greater than 130 percent of metro-wide FMR in 2017. Coefficients for all covariates are listed unless indicated. Standard errors are in parentheses and are clustered by tax neighborhood. Source: Social Serve.

Table 8: Summary of Property Holdings for Landlords Listing Units for Rent

	(1) DCHousingSearch.org High Rent	(2) DCHousingSearch.org All	(3) Majority Market Website All
Pre-2017 DCHousingSearch Listing: Any	0.24	0.40	0.21
Pre-2017 DCHousingSearch Listing: Proportion	0.09	0.21	0.01
Listed Property Sold After 2015	0.24	0.22	0.13
Proportion in Treatment Tracts (if >1 Unit)	0.52	0.28	0.85
# Properties	11	8	127
# Properties: 1	0.55	0.44	0.31
# Properties: 2-5	0.24	0.33	0.16
# Properties: 6-25	0.14	0.18	0.21
# Properties: 26+	0.07	0.05	0.32
Type: Single Family	0.22	0.26	0.09
Type: Multi-Family 0-2 Stories	0.65	0.65	0.33
Type: Multi-Family 3+ Stories	0.13	0.09	0.58
Avg. Lot Area (sqft)	7,178	8,134	13,608
Avg. Assessed Value (millions)	2.0	3.6	15.8
Avg. Assessed Value: Land (millions)	0.7	0.8	3.2
Avg. Assessed Value: Improvements (millions)	1.3	2.8	12.6
N	42	341	3696

This table shows the results of matching rental listings to DC property tax records. For any given listing, we match it to a DC property tax record. Within property tax records, we identify other properties with the same owner address, which we use to calculate landlord holdings information for any given listing. There are two exceptions: sale date information is only for the listed property, not the landlord network, and property location excludes the listed property. Each column summarizes landlord characteristics for a different sample of rental listings. The first column shows all listings on DCHousingSearch.org in treatment tracts with posted rent between 130 percent and 175 percent of FMR. The second columns shows all listings on DCHousingSearch.org. The final column shows all listings on the majority market website. All columns are restricted to listings in the year 2017 that successfully match to DC property tax records (which primarily requires having an exact address on the listing). All reported statistics are means. Source: Majority market website, Social Serve, Washington, DC, Integrated Tax System Public Extract.

A Data Appendix

A.1 Lease-Up Data

We use data from HUD's Picture of Subsidized Households. This data set indicates the number and characteristics of households receiving various HUD-supported programs by census tract. We extract data on the number of households leased-up with Housing Choice Vouchers in each census tract of Washington, DC, in each year between 2012 and 2019. One of our main outcomes is the number of vouchers leased up in a tract in a given year. The data list the "number of subsidized units available" in a given tract. To be consistent with city-wide values of vouchers available, the underlying data take the number of vouchers actually in use and inflate them proportional to vouchers not in use.[9] To recover the actual number of vouchers leased up, we reverse this process and deflate the tract-level voucher numbers by the city-wide voucher usage rate. Another outcome of interest is the number of households with a new voucher they received in the past year who are in a tract in a given year. This value is directly observed in the data for most tracts. For a few tracts, though, it is censored due to small values. For these few tracts, we impute the number of new vouchers with the difference in the number of leased-up vouchers between the present year and the previous year. Finally, the HUD data are at the tract level rather than the tax neighborhood. We map the policy variation to census tracts as shown in Appendix Figure 8.

A.2 Listings Data

The rental listings used for the correspondence experiment are derived from a majority market website. The website is large; it listed units at a rate of about 80,000 per year during our 2017 sample period, compared to 162,670 rented units in DC reported by the 2017 ACS. Our sample includes listings from both 2015 and 2017. For both waves we can observe posted rents, locations, and some unit characteristics (e.g., number of bedrooms, square feet). However, for the 2017 wave we recorded a large sample of rental listings that did not fit the screening criteria for the experiment. This larger set of listings can be used to better characterize the state of the full rental market. Unfortunately, we do not have a similar sample of listings for the 2015 wave.[10] The listings in 2017 from the majority market website therefore serve two purposes: 1) as the source of subjects for the correspondence experiment, and 2) as microdata that characterizes landlords in the market.

Toward the second purpose, we supplement the majority market site listings with rental listings from a voucher specialist website. SocialServe.com is a non-profit organization that operates DCHousingSearch.org with funding from the DC Department of Housing and Community Development (DHCD). The site specializes in hosting listings for subsidized tenants and income-restricted housing units. SocialServe.com provided a database of all units listed on its site between 2010 and 2018. Its specialized nature makes the site less extensive; there are 453 total listings in 2017.

[9] Thanks to Ed Olsen for bringing this fact to our attention.

[10] In each wave, we screen listings to avoid duplicate correspondence with the same landlord, limit to a range of rents relevant to the experiment, and otherwise restrict the sample. Listings that failed this screen in 2015 were discarded, while in 2017 they were preserved.

The data include information that can be observed publicly on its website: address, posted rent, number of bedrooms, etc. These listings include many landlords seeking voucher tenants, which provides a useful sample of listings targeted specifically at subsidized households. Local government also encourages landlords affected by certain affordable housing initiatives to list on the site. For example, new development in DC often falls under inclusionary zoning restrictions that require developers to reserve a certain number of rent-restricted units for low- or moderate-income households. Since we wish to focus on listings with market rent, we always restrict these data to exclude any listings tagged as corresponding to inclusionary zoning or posted with a rent schedule other than simple rent (e.g., income-based rent). We also eliminate units with six or more bedrooms, for which voucher payment limits are not clearly defined.

A.3 Property Tax Data

Rental listings by themselves do not provide information on landlords, so we match the rental listings from both sources described above to property assessments from DC property tax records. We match properties between the listing and tax data sets using a fuzzy matching algorithm based on the address. Within the tax assessment data we identify properties owned by the same landlord using the address to which the DC tax authority sends the property tax bill. For a given property matched to an online rental listing, we identify all other properties in DC with the same tax bill address and hence the same assumed owner. To the extent that a single property manager pays tax bills for multiple owners, we will measure property manager networks rather than owner networks. The tax data also include owner names; however, many of these are LLC shell names that would lead to under-aggregating of multi-property ownership. We choose to risk the former error of over-aggregating owner networks, as property managers who both pays taxes and screens potential tenants for a landlord are relevant agents for our purposes.

A.4 Design of Correspondence Experiment

We conducted two waves of a correspondence experiment examining how landlords respond to tenants who state a desire to pay with a subsidized housing voucher. Research assistants sent e-mails from fictional applicants to real rental housing listings from the majority market site. Since the inquiries were from fictional people, we could control and randomly assign the entire content of the initial e-mail from the applicant to the landlord. In the first wave of the experiment, we sent 2,668 fictional inquiries to 1,336 real rental listings during May and June of 2015. The resulting data are the same as those considered in Phillips (2017). In the second wave, we sent 4,264 inquiries to 1,810 rental listings during July and August 2017. The two waves are identical unless otherwise noted.

We sent inquiries to rental listings in Washington, DC whose monthly rent is appropriate for a voucher. For a given inquiry, the research assistant first identified all units eligible for the experiment. In the first wave, we only include units listed for monthly rent of no more than $1,500. The second wave targeted any units whose rent was less than or equal to the highest voucher limit

in the city for the unit's size. For efficiency units, the highest rent limit during the study was $2,560; for five-bedroom units, it was $5,766. Eligible units also had to be monthly rentals, listed since the previous work-day (typically the previous 24 hours), of known location, located inside the boundaries of the District of Columbia, not obviously a scam, and not a re-posting to which we previously applied. During the second wave, we also eliminated postings for roommates and ads by recognized landlords to whom we had already applied. Once a set of units had been screened for eligibility, a subset was randomly selected to receive inquiries. A given unit may have received multiple inquiries. During the first wave, there was an initial period where each unit was randomly selected to receive only one or two inquiries, which was later changed to two or four. In the second wave every unit had an equal chance of receiving one, two, or four inquiries. For units receiving multiple inquiries, the e-mails were sent in random order with at least one hour between them.

Our analysis focused on a signal statement indicating that the fictional tenant wished to use a housing voucher to subsidize rent. Since most people refer to the Housing Choice Voucher program by its prior name, Section 8, we focused on this language. In particular, selected inquiries received one of the following statements:

- I'm looking for a place that takes Section 8.
- I would also like to know if you accept Section 8 vouchers.
- Also, I would plan to pay with a Section 8 voucher.
- I plan to pay with Section 8.

We randomly and independently selected inquiries to include this statement versus omitting it. An inquiry without reference to Section 8 was intended to indicate a cash tenant. In the first wave, one-quarter of all e-mails included a voucher statement; in the second wave this increased to one-half.

Signaling voucher status in an initial inquiry is within common practice. Practitioner organizations that work with tenants give conflicting advice. Some recommend disclosing one's voucher status immediately to avoid wasting time and resources pursuing dead-ends; this is particularly important for clients who lack private transportation. Others recommend delaying disclosure to avoid a negative first impression. In any case, all academic correspondence and audit studies on vouchers signal it at first contact (Phillips, 2017; Moore, 2018; Cunningham et al., 2018). Likewise, non-academic organizations that use audits for compliance purposes similarly signal vouchers at first contact (Scott et al., 2018).

The language of an inquiry to a particular rental listing was a randomly generated message comparable to those used in Hanson and Hawley (2011) and Ewens et al. (2014). See Appendix Figure 7 for an example. All other characteristics were assigned randomly and orthogonal to the main voucher signal treatment. As in Ewens et al. (2014) we randomly and independently assigned one-third of the applicants to include positive quality signals (professional employment, good references, and/or good credit), one-third to include negative signals (smoker and/or bad

credit), and one-third to have no signal statement of quality. Names were chosen at random from the same list as in Bertrand and Mullainathan (2004). The sex signaled by the name was chosen randomly, independently, and in equal proportion. Name-indicated race was also assigned randomly, though the exact assignment rule varied. In the first wave, we assigned black-indicating names randomly and independently with a probability of 0.50 for half of all units. For the other half of units, we stratified or matched treatment, assigning black names at random but guaranteeing that each unit received half black and half white names. In the second wave, we similarly stratified assignment of name race for half of all units. For the other units, we assigned black names to all inquiries. We also assigned greetings, valedictions, etc. randomly. We avoided detection by drawing the components of each e-mail at random and without replacement so that landlords receiving as many as four e-mails in the experiment received truly unique e-mails. In 2017, minor differences from the text of messages used in 2015 were introduced to help obscure the experiment from detection.

We measure how landlords respond to the fictional inquiries via e-mail. Most often, landlord responses can be linked to the original inquiry because landlords respond through the listing service's system and/or because the listing number is referenced. In the few cases where this is not possible, the inquiry e-mail accounts are uniquely matched to applicant names. We then match manually given the timing of the inquiry, the timing of the response, and the listing location. Following Ewens et al. (2014), we focus on only positive responses in which a landlord invites the applicant to see the unit, explicitly provides a means for further contact, or responds that the unit is available while providing or requesting more information. We code as negative those responses indicating the unit is no longer available or that some stated trait of the applicant is incompatible with the listing. We also observe neutral responses, where landlords provide or request more information but do not describe availability or reply only with availability.

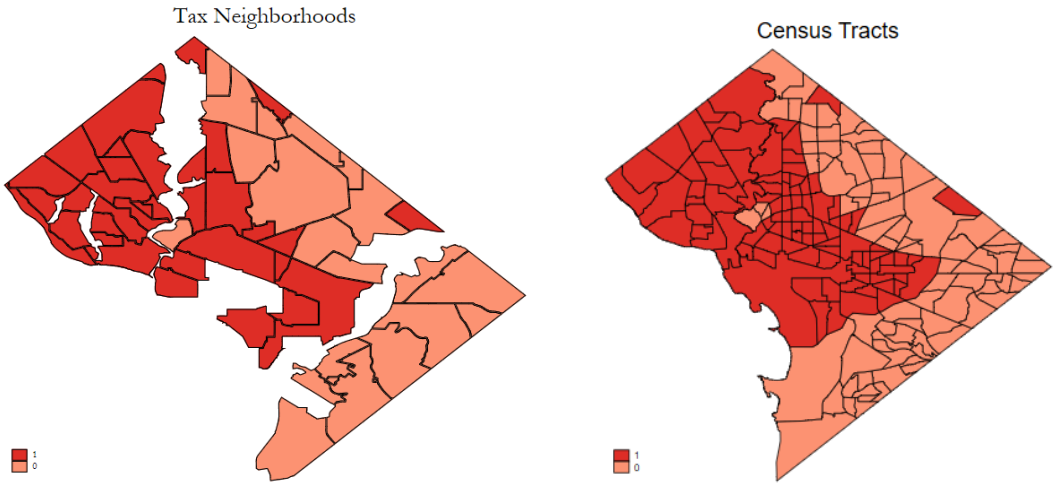
B Appendix Tables and Figures

Hi,

My name is Meredith O'Brien, I am responding to your [redacted] posting for an apartment listed at INSERT RENT AMOUNT/month. I have a long and consistent rental history if you would like references. I plan to pay with Section 8. Is the place still available?

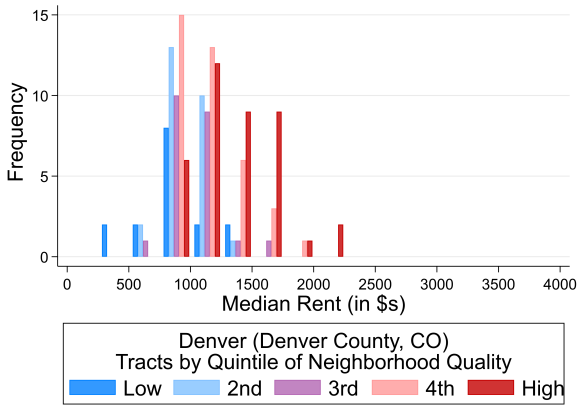
Thank you for your time,
Meredith O'Brien

Figure 7: Example Inquiry

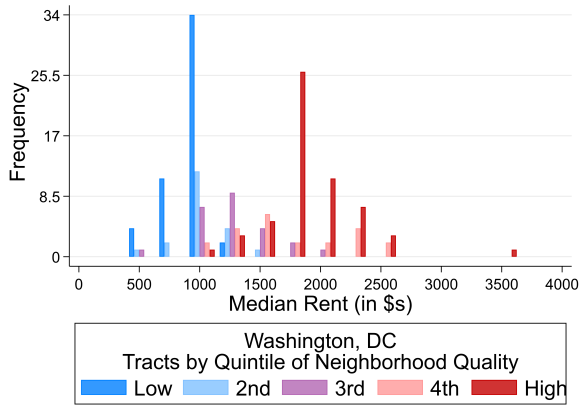


(a) Tax Neighborhoods (b) Census Tracts

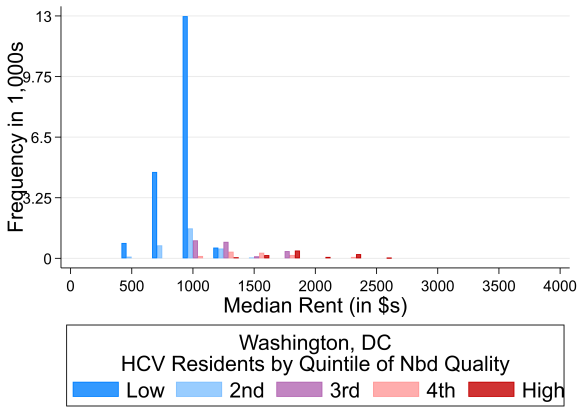
Figure 8: Changes in Rent Limits Notes: Neighborhoods in dark red indicate those that had a voucher payment limit greater than 130 percent of metro-wide FMR in 2017. Neighborhoods in light red had a voucher payment limit less than or equal to 130 percent of metro-wide FMR in 2017. Source: Author calculations.



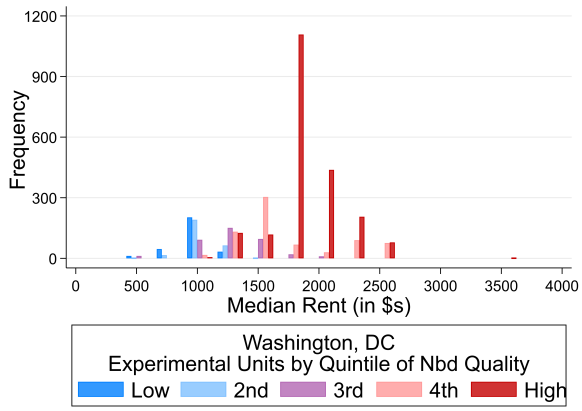
(a) US Median (Denver)



(b) DC - All Residents



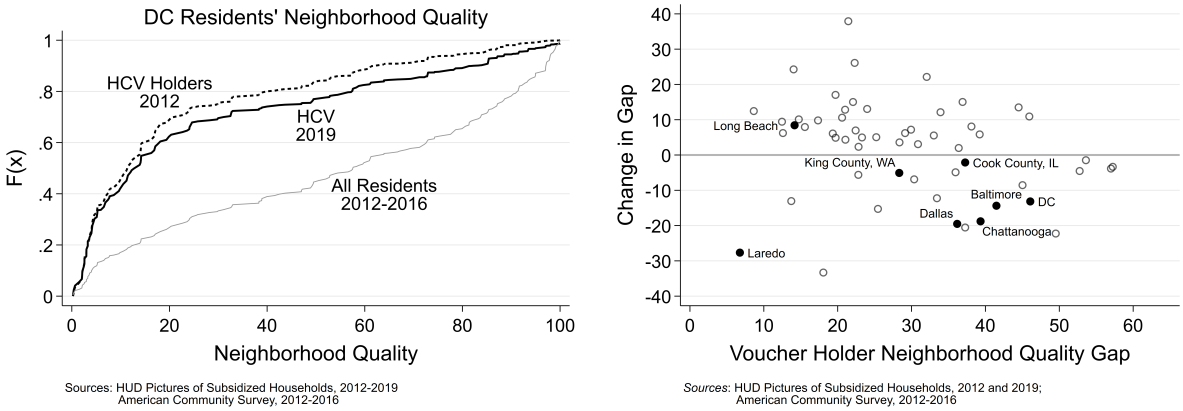
(c) DC - HCV Residents



(d) DC - Experimental Units

Figure 9: Joint Distribution of Median Rent and Neighborhood Quality

Notes: Each figure shows a two-way histogram counting the frequency of census tracts with a particular rent range and quality index quintile. Figures (a) and (b) assign one observation per tract in Denver County, CO and DC, respectively. Figures (c) and (d) weight tracts by the number of vouchers and number of listings used in the experiment, respectively. The opportunity index is the first principal component of the poverty rate, the unemployment rate, the employed to population ratio, the share with a HS diploma, the share with a BA, and the share of families with children under 18 that are single-headed from the ACS. Each of these variables is first put into percentiles of the national distribution (in terms of population living in census tracts with these characteristics). We denote quality as the tract's percentile in the distribution of the resulting index/principal component. Source: US Census Bureau, US Department of Housing and Urban Development, correspondence experiment.

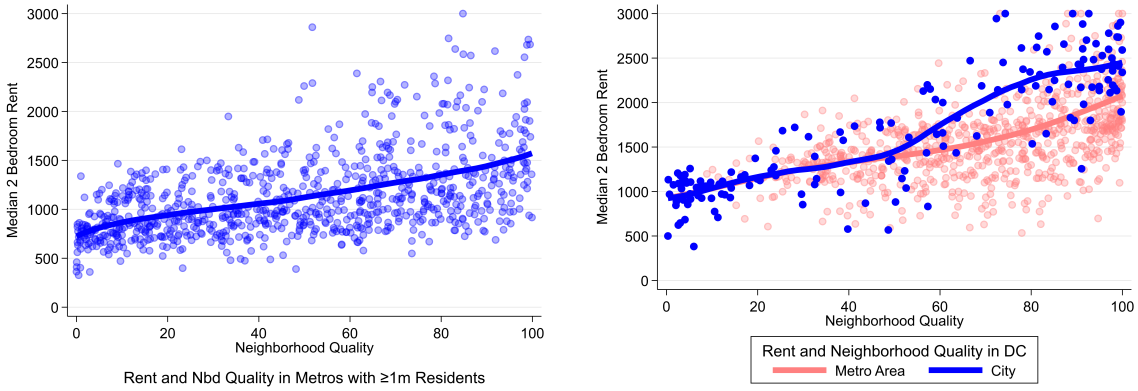


(a) DC

(b) Large Metros and SAFMR Demonstration Sites

Figure 10: DC and Metros with Prominent HCV Programs

Note: Neighborhood quality is measured as in Figure 9. The left panel shows CDFs of neighborhood quality for different populations in DC. In the right panel, the *gap* measured on the x-axis is the area between the neighborhood quality CDFs of HCV residents in 2012 and all residents in the 2012-2016 American Community Survey (ACS). The *change in gap* on the y-axis is the area under the CDF of HCV residents in 2012 and the CDF of HCV residents in 2019 as a percentage of the area measured in the *gap*. The sample includes the central county of metros with at least 1 million residents (hollow circles); the entire Dallas and Baltimore MSAs (solid circles); DC (solid circle); and the SAFMR demonstration sites (solid circles).



(a) Largest Counties in Metros with $\geq 1m$ Population

(b) Washington, DC

Figure 11: Neighborhood Quality and Median Rent

Note: The left panel shows a random sample of 1,000 tracts from the 54 MSAs (the largest county in each MSA) with populations of at least 1,000,000 in the 2012-2016 ACS. The right panel shows tracts in the city of Washington, DC, and the entire DC metro area. The neighborhood quality index in both figures is the first principal component of the poverty rate, the unemployment rate, the employed to population ratio, the share with a HS diploma, the share with a BA, and the share of families with children under 18 that are single-headed from the ACS. Each of these variables is first put into percentiles of the national distribution (in terms of population living in census tracts with these characteristics). We denote quality as the tract's percentile in the distribution of the resulting index/principal component. Source: US Census Bureau.

Table 9: Average Neighborhood Context for Different Groups of DC Households

	All	Voucher	Experiment	DCHousingSearch.org	Treatment Tracts	Control Tracts
Median Rent	1449	1023	1642	1121	1666	1214
	(548)	(359)	(448)	(455)	(484)	(517)
Poverty Rate	18	27	14	25	13	23
	(14)	(12)	(10)	(14)	(8)	(16)
Med HH Income	87	49	100	58	106	67
	(46)	(28)	(39)	(36)	(37)	(46)
Share College	56	29	71	34	73	39
	(29)	(22)	(21)	(26)	(18)	(28)
Share Employed	63	54	71	55	72	54
	(14)	(12)	(12)	(14)	(12)	(12)
Opportunity Atlas Percentile Rank	28	8	36	10	36	18
	(29)	(11)	(31)	(15)	(31)	(23)
Poverty Percentile Rank	44	21	51	27	53	34
	(29)	(21)	(26)	(25)	(26)	(28)
Quality Percentile Rank	57	25	73	32	75	36
	(34)	(27)	(26)	(34)	(24)	(32)
Child Opportunity Index Percentile Rank	57	22	75	29	77	34
	(36)	(28)	(28)	(35)	(24)	(35)
Vouchers	62	151	34	117	35	90
	(74)	(87)	(50)	(83)	(48)	(85)
New Vouchers	2.6	5.5	2.0	4.5	3.5	1.7
	(8.0)	(9.8)	(5.9)	(7.8)	(9.7)	(5.6)
N	564,615	291,347	273,268	15,257	4,316	453

Neighborhood statistics and tract-level characteristics from the 5-year 2013-2017 ACS. The middle panel of opportunity indices are transformed into national percentile ranks using data from (Chetty et al., 2018), the ACS, (Aliprantis and Richter, 2020), and (Noelke et al., 2020); we use the Opportunity Atlas ranking based on children's income given parents with incomes at the 25th percentile of household income. The last two HCV variables are from the 2017 HUD Picture of Subsidized Households. The number of voucher holders with a new voucher is censored for values 10 and below; in these cases we impute this with the annual change in the number of vouchers. Statistics are means with standard deviations in parentheses. The columns are weighted averages for tracts. The columns weight respectively by tract's total population (ACS 2013-2017), number of vouchers (HUD 2017), number of listings in the 2017 wave of the experiment, and number of unit listings in DCHousingSearch.org in 2017. The final two columns weight by total population but limit the sample to tracts affected vs. unaffected, respectively, by the policy we study. Source: US Census Bureau, US Department of Housing and Urban Development, correspondence experiment, Social Serve.

C Appendix: A Model of Landlord Decisions

C.1 Summary of Model

The workhorse neighborhood choice model in economics treats rental housing as a competitive market with landlords accepting any tenant who can pay market rent (e.g. Galiani et al. (2015)). Such a model simplifies two aspects of the voucher program that are the focus of our empirical analysis. First, landlords may actively screen tenants based on voucher status. While the qualitative literature provides many examples of such behavior (Popkin and Cunningham, 2000; Rosen, 2014; Greenlee, 2014; Desmond, 2016; Garboden et al., 2018), this issue has been largely ignored by the economics literature.[11] Second, landlords might change the rent they charge in response to the voucher program. There is contrasting quantitative evidence on the prevalence of this behavior. On one hand, Collinson and Ganong (2018) find that increasing metro-wide voucher payment limits increases rent paid without much effect on unit or neighborhood quality. Desmond and Wilmers (2019) use hedonic regressions to show that vouchers in Milwaukee over-pay by about 10 percent relative to observably similar units. McMillen and Singh (2018) find some evidence from Los Angeles that equilibrium rents cluster around voucher limits set by FMR. On the other hand, Olsen (2019) summarizes a series of HUD studies that show little voucher premium. He argues that the voucher program pays market rent on average due to sufficient enforcement of rent reasonableness and offsetting voucher premia in high-rent vs. low-rent neighborhoods. Eriksen and Ross (2015) examine how increasing the number of vouchers in a market affects pricing. They find no overall effect on rents charged but do find rent increases near FMR when housing supply is inelastic.

We build a theoretical model in which the way landlords screen and set prices in response to the voucher program depends on market conditions. Our model makes three predictions:

1. Landlords screen out the least attractive prospective tenants, particularly when facing a rental market with high demand.

2. Some landlords will price units at exactly the FMR that applies to their unit, regardless of the unit's market rent. This scenario will only obtain with weak enforcement of rent reasonableness and for landlords who rent primarily to voucher tenants.

3. Increasing voucher payment caps may attract two types of landlords to the voucher program: First, landlords who anticipate no additional cost of working with voucher tenants but who have units priced at market rates just above the old payment cap and, second, landlords who view participation as costly but are enticed by charging above-market rent at the new payment limit. Other landlords do not respond.

While the full specification of the model and our numerical results can be found in the next section, here we outline the reasoning leading to these predictions. We suppose that landlords

[11] A notable exception is Geyer (2017). Analogous behavior in other markets, like the labor market, has been studied extensively.

screen, or choose whether to accept or reject a tenant, based on the expected maintenance cost m the tenant will generate due to factors such as late rent; damage to the property; externalities operating through the preferences of the landlord's other tenants; the pecuniary, time, and energy costs of complying with program regulations; and contributions to utility arising from non-pecuniary factors such as altruism or prejudice. We show that in an extension of the McCall (1970) model the landlord's decision rule is based on a reservation expected maintenance cost where the landlord accepts if $m < m^*$ and rejects if $m > m^*$.

Landlord value functions are of the form

$$v(m) = \max \left\{ \frac{r-m}{1-\beta}, \quad \beta\,\pi \int v(m')dF(m') \right\} \tag{5}$$

where the maximization is over accepting the tenant or rejecting him and waiting to draw a new tenant with expected maintenance m' next period. Here π is the probability of encountering a tenant next period, β is the discount rate, r is posted rent, and $F(m')$ characterizes the landlord's beliefs about the distribution of maintenance costs he may encounter next period. Some related value functions are shown in Figure 12a, where the kink in these figures occurs at m^*.

Prediction 1 is illustrated in Figure 12a. As π increases, the reservation maintenance cost m^* will become smaller and smaller. This predicts that in a rental market with high demand such as the market in Washington, DC, landlords will tend to reject all but the most attractive prospective tenants. This type of screening could very easily lead to screening out voucher tenants, particularly in high-rent neighborhoods. If voucher tenants have higher maintenance costs on average, landlords will screen them out, particularly when landlords are in the most advantageous situations. We formalize this idea in Appendix **??** by allowing $F(m)$ to depend on observable characteristics.

Proceeding by backward induction, we cast the landlord's pricing decision in terms of choosing the slack s to add to market rent, $r = r^m + s$, to solve the problem

$$\max_s \mathbb{E}[v(m|r^m, s, r^{FMR}, \ell)]. \tag{6}$$

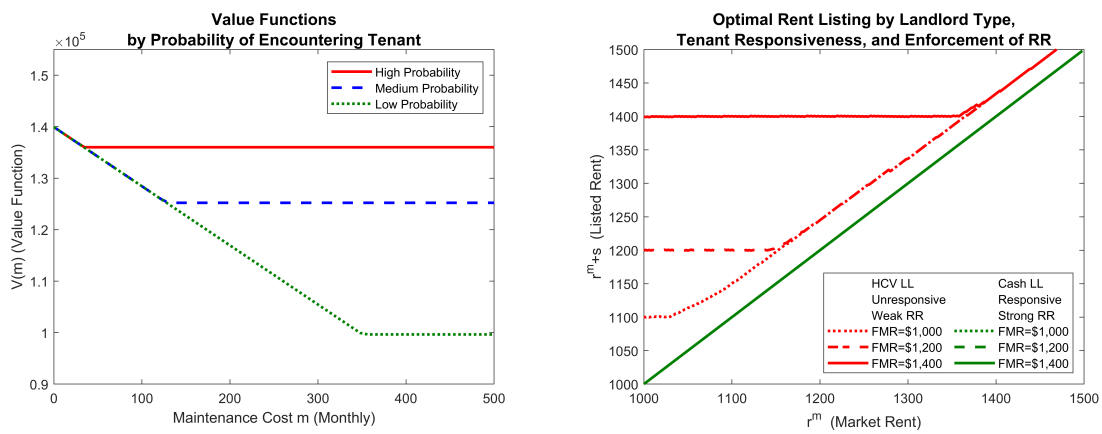
The goal is to choose slack to maximize expected value for the landlord. In Appendix **??** we illustrate this problem graphically as finding the highest point on an expected value curve.

In the model we allow for two types of tenants τ, "cash" and "voucher." Cash tenants are always driven away by rent increases, while voucher tenants only respond to rent increases when required to by payment limits or rent reasonableness enforcement. We also allow for two types of landlords ℓ, cash and voucher specialists, who differ in whether they view voucher tenants as adding substantially to maintenance costs.

Prediction 2 is illustrated in Figure 12b. A voucher landlord with a unit below the fair market rent (FMR) will set s so that $r = r^m + s = r^{FMR}$. In other words, voucher specialists will tend to list their unit at the FMR, since the benefit of increased rental income will outweigh the costs from driving away cash tenants. In contrast, a cash landlord with a unit below FMR will list his unit near the market rent. For these landlords the benefit of increased rental income must also

be weighed against the increased maintenance costs associated with the voucher tenants they are more likely to encounter after raising the listed rent.

Figure 12b also provides the basis for Prediction 3. Consider a landlord who owns a unit with market rent of $1,250. The landlord will not rent to voucher tenants when facing an FMR of $1,200, regardless of the enforcement of rent reasonableness or the type of landlord. If the FMR applied to the unit were to increase to $1,400, then a voucher landlord would rent the unit to a voucher tenant at the new FMR. Such an increase in FMR would also induce a cash landlord to rent the unit to a voucher tenant if he believed that voucher tenants had maintenance costs similar to those of cash tenants.



(a) Landlord's Accept/Reject Decision

(b) Landlord's Pricing Decision

Figure 12: The Landlord's Decisions

Note: The left panel shows the value functions of a cash landlord in Case 2 of Assumption A1 with weak enforcement of rent reasonableness and slack of $35. The right panel shows the optimal pricing decision rule for voucher and cash specialist landlords under various assumptions about the responsiveness (as measured by $\pi(s)$) of cash tenants to slack (pricing above market rent) and the enforcement of rent reasonableness (the highest level of slack permitted for voucher tenants). Source: Author calculations using model data.

C.2 Full Model

Consider the following model of landlord decision making. Suppose there is a fixed supply of housing units, and that landlord ℓ owns unit i in neighborhood j, and no other units. In the remainder of the analysis we will assume that we are focusing on one landlord ℓ with one unit of quality $q_i \in [0, 100]$ in a neighborhood of opportunity $opp_j \in [0, 100]$. We therefore suppress notation specifying ℓ, i, and j until we explicitly begin to investigate heterogeneity along these dimensions.

We model two choices made by the landlord. The first choice is the rent at which to advertise their unit. We frame this choice of the listed rent $r = r^m + s$ in terms of the slack s added to the competitive market rent of the unit, r^m, with the enforcement of rent reasonableness entering through the maximum slack $\overline{s}$ in the landlord's choice set. The second choice of the landlord is a discrete time optimal stopping problem of when to accept a tenant. Proceeding in terms of backward induction, we first assume that the landlord has set some rent level r and must decide

whether or not to accept a tenant he has encountered.

Our model has two types of tenants, $\tau \in \{C, H\}$ (cash and HCV), and two types of landlords, $\ell \in \{C, H\}$ (cash and HCV specialists).[12]

C.2.1 The Landlord's Problem of Whether to Accept or Reject a Tenant

After their choice of posted rent, r, the landlord must make a second decision as to whether to accept renter k with observed characteristics X_k as the tenant of his unit. Upon accepting an applicant as his tenant, each month the landlord will expect to earn

$$r - \mathcal{P}(X_k), \qquad \text{where} \qquad \mathcal{P}(X_k) = \int_{\mathcal{M}} m \; dF(m|X_k)$$

where m arises from factors such as late rent, maintenance to the unit after damage (possibly caused by tenants), and the monetary, time, and energy costs of complying with government regulations. Note that the expected maintenance cost is a function of the landlord's beliefs about the distribution of maintenance costs conditional on a tenant's observed characteristics, F_ℓ .

In a simple search model where accepted matches continue in perpetuity, the landlord will follow a reservation maintenance cost strategy. That is, upon matching with renter k, the landlord will accept the renter as a tenant if the expected maintenance cost is less than a reservation value m^*, or if

$$r - \mathcal{P}(X_k) > r - m^*.$$

To see that the landlord follows a reservation maintenance cost decision rule in our model, consider the case of just cash renters. The landlord's value function when encountering renter k is

$$v(\mathcal{P}(X_k)) = \max\left\{\frac{r - \mathcal{P}(X_k)}{1-\beta}, \beta \int v(m')dF(m')\right\}, \tag{7}$$

where the maximization is over accepting the tenant or rejecting him and waiting to draw a new tenant with expected maintenance m' next period. The textbook results from the McCall model can be extended to this model.[13] This establishes that the landlord's decision rule is based on a reservation expected maintenance cost where the landlord accepts if $\mathcal{P}(X_k) < m^*$ and rejects if $\mathcal{P}(X_k) > m^*$, and that one can characterize the reservation maintenance cost using the equation

$$m^* = r - \beta \int_0^{m^*} \left(m^* - m'\right) dF(m') \quad \text{where} \tag{8}$$
$$f(m') = \int_{\mathcal{X}} f(m|x)f(x|r)dx.$$

In the case of heterogeneity of tenants along the dimension of either paying with cash or a voucher, $\tau \in \{C, H\}$, let $\pi^C(r)$ be the probability of encountering a cash tenant and $\pi^H(r)$ be the

[12] We refer to housing choice vouchers (HCV) and vouchers interchangeably.

[13] See Chapter 5 of Ljungqvist and Sargent (2000).

probability of encountering an HCV tenant, where we assume that both of these probabilities are functions of the rent already listed by the landlord and that the landlord can encounter at most one tenant per period. We will at times denote the total probability of encountering a tenant next period by $\pi(r) = \pi^C(r) + \pi^H(r)$. We generalize the landlord's value function to

$$v(\mathcal{P}(X_k)) = \max\left\{\frac{r - \mathcal{P}(X_k)}{1-\beta}, \beta\left[\pi^C(r)\int v(m')dF(m'|\tau = C) + \pi^H(r)\int v(m')dF(m'|\tau = H)\right]\right\}, \tag{9}$$

and characterize the reservation maintenance cost in Equation 8 as

$$m^* = r - \beta\left[\pi^C(r)\int_0^{m^*}\left(m^* - m'\right)dF(m'|\tau = C) \quad + \quad \pi^H(r)\int_0^{m^*}\left(m^* - m'\right)dF(m'|\tau = H)\right],$$

both subject to the constraint that $\pi^C(r) + \pi^H(r) \leq 1$.

C.2.2 The Landlord's Rent Listing Problem

Proceeding by backward induction (i.e., assuming the landlord's optimal decision rule in the second period), consider the landlord's problem of the rental price at which to list his unit. We assume that the rent listed by the landlord r is

$$r = r^m + s,$$

a combination of the market rent for his unit and some amount of slack s. We suppose there are two types of landlords: cash specialists and HCV specialists, which we will denote by $\ell \in \{C, H\}$. Landlord types differ in the responsiveness of their probability of encountering tenants as a function of the slack they choose, $\pi^C(s|\ell)$ and $\pi^H(s|\ell)$. As well, different types of landlords have different beliefs about the distribution of HCV tenants' maintenance costs, $F(m|\ell, \tau = H)$.

This landlord heterogeneity results in a generalized version of the value function specified in Equation 9. We now also account for the institutional rule that landlords cannot accept voucher tenants at a rent above the FMR that applies to their unit's local area. The resulting value function

is:[14]

$$v(m|r^m, s, r^{FMR}, \ell, \tau) = \max \Bigg\{ \mathbf{1}\{\tau = C\} \times \frac{r^m + s - m}{1-\beta} + \mathbf{1}\{\tau = H\} \times \min \left\{ \frac{r^{FMR} - m}{1-\beta}, \left(\frac{r^m + s - m}{1-\beta} \right) \right\}, \tag{10}$$

$$\beta \Bigg[\pi^C(s|\ell) \int v(m'|r^m, s, r^{FMR}, \ell, \tau = C)\, dF(m'|\ell, \tau = C) \; + \; \pi^H(s|\ell) \int v(m'|r^m, s, r^{FMR}, \ell, \tau = H)\, dF(m'|\ell, \tau = H) \Bigg] \Bigg\}.$$

The slack decision faced by a landlord is

$$\max_s \mathbb{E}[v(m|r^m, s, r^{FMR}, \ell)] = \max_s \; \pi^C(s|\ell) \int_{\mathcal{M}} v(m|s, \ell, \tau = C)\, dF(m|\ell, \tau = C) \; + \; \pi^H(s|\ell) \int_{\mathcal{M}} v(m|r^m, s, r^{FMR}, \ell, \tau = H)\, dF(m|\ell, \tau = H). \tag{11}$$

C.2.3 Landlord Types

Landlord types differ along two dimensions: the responsiveness of their probability of encountering tenants as a function of the slack they choose, $\pi^C(s|\ell)$ and $\pi^H(s|\ell)$, as well as their beliefs about the distribution of HCV tenants' maintenance costs, $F(m|\ell, \tau = H)$. We formally specify these differences in terms of the following assumptions:

Assumption A1: Differences in $\pi(s|\ell)$

We consider two cases of $\pi(s|\ell)$. In both cases, charging greater slack drives away cash tenants. In Case 1, the housing authority strictly enforces rent reasonableness, and the landlord is less likely to encounter both cash and HCV tenants if he increases the slack in his rent listing. In Case 2, the landlord is less likely to encounter cash tenants after increasing slack, but HCV tenants tend to fill this void. In this context we could think about π^C as representing the probability of the event "the most attractive/lowest $\overline{m}$ tenant encountered by the landlord is a cash tenant" and π^H analogously. These cases are summarized in Table 10 and shown in Figure 16 for high, medium, and low levels of responsiveness to slack (i.e., elasticity of π with respect to slack).

[14] Under this specification, HCV tenants are able to rent up in a unit listed above the FMR at the FMR. We also investigated specifying the first line of Equation 10 as $\left(\frac{r^m+s-m}{1-\beta}\right) \times \left(1 - \mathbf{1}\{r^m + s > r^{FMR},\ \tau = H\}\right)$ to capture an HCV tenant being unable to lease up in a unit listed above the FMR. We found that the choice between these specifications had no qualitative implications for our simulation results.

Table 10: Cases by Tenant Responsiveness to Slack

Case	Overall Probability	Cash Tenants	HCV Tenants
Case 1	$d\pi(s)/ds < 0$	$d\pi^C(s)/ds < 0$	$d\pi^H(s)/ds < 0$
Case 2	$d\pi(s)/ds \approx 0$	$d\pi^C(s)/ds < 0$	$d\pi^H(s)/ds \lesseqgtr 0$

Note: In Case 1 cash and HCV tenants both respond negatively to slack. In Case 2 cash tenants respond negatively to slack, but HCV tenants replace the "missing" cash tenants. In this sense one can think of π^τ as the probability that the most attractive tenant encountered is of type τ.

Assumption A2: Differences in $F(m|\ell, \tau = H)$

The distributions of expected maintenance costs $F(m|\ell, \tau)$ used in our simulations are shown in Figure 14. The expected maintenance costs of cash tenants is the same for all landlord types. For HCV specialist landlords, the expected maintenance cost distribution for HCV tenants is assumed to be slightly higher than the distribution for cash tenants. For these landlords the relatively similar maintenance cost distributions for cash and HCV tenants could be driven by beliefs about actual costs, experience in screening HCV applicants, or an addition of warm glow utility to the actual costs faced by HCV tenants. This last interpretation seems quite plausible; Greenlee (2014) documents that one third of landlords renting to HCV tenants report doing so out of a desire to help individuals they consider less fortunate than themselves, and Rosen (2014) interviews landlords who renovate units to tailor them to renting to voucher tenants.

For cash landlords, the expected maintenance costs of cash and HCV tenants are quite different. These landlords may not be familiar with the HCV program and might consider the prospect of an initial inspection especially burdensome. Also plausible is that these landlords have previously participated in the HCV program and found the experience costly; Garboden et al. (2018) find that two thirds of landlords who refuse voucher tenants had once accepted them, and Zuberi (2019) finds that many landlords express frustration in their interactions with their local PHA.

C.2.4 Model Predictions

We consider three model predictions. The most important components of these predictions are shown in Figure 15, but details about the components of this figure are shown in Figures 16-18.

First, our model predicts that as the overall probability of encountering a tenant $\pi = \pi^C + \pi^H$ goes up, the reservation maintenance cost m^* goes down. The reason can be seen from looking at the hypothetical value functions in Figure 15a. The downward sloping line is the value from accepting a tenant with maintenance cost m, and the horizontal line is the continuation value of rejecting a tenant (of any maintenance cost m). Increasing the probability of encountering a tenant raises the horizontal line, which in turn decreases the m at which the downward sloping and horizontal lines intersect. Since this point of intersection occurs at m^*, raising π decreases m^*.

Second, our model makes predictions about rent listing when rent reasonableness is strictly enforced (implying that HCV tenants are also deterred by slack, resulting in Case 1). The green

lines in Figure 15b shows objective functions $\mathbb{E}[v(m|r^m, s, r^{FMR}, \ell)]$ from Problem 11 for cash and HCV landlords when rent reasonableness is strictly enforced. We can see that the objective functions are both maximized by setting $s = 0$. Thus, the model predicts that with strict enforcement of rent reasonableness, cash and HCV landlords behave similarly in that they both list their unit at the market rent.

Third, our model makes predictions about rent listing decisions when rent reasonableness is weakly enforced (implying that HCV tenants need not be deterred by slack, resulting in Case 2). Under weak enforcement HCV landlords would also be less likely to encounter cash tenants after increasing the slack in their listed rent, but this decrease would be offset by HCV tenants able to fill this absence (Case 2 of A1). The red line in Figure 15b shows the resulting objective function $\mathbb{E}[v(m|r^m, s, r^{FMR}, \ell)]$ from Problem 11 for an HCV landlord. We can see that HCV landlords will maximize their objective function by setting s to list their unit at its FMR, or by choosing s so that $r = r^m + s = r^{FMR}$. By increasing slack, HCV landlords increase the income stream from a leased-up unit. While they face a tradeoff in that increasing slack chases away cash tenants, HCV tenants will fill this void. And since HCV landlords do not face such a different maintenance cost distribution for HCV tenants than cash tenants, this tradeoff will initially increase their objective function. Once slack hits the maximum allowed under rent reasonableness (or overall rent hits the unit's FMR), the HCV landlord will no longer benefit from increasing slack. Doing so will chase away cash tenants but will no longer increase the stream of income associated with a lease-up, and therefore will decrease the landlord's objective function.

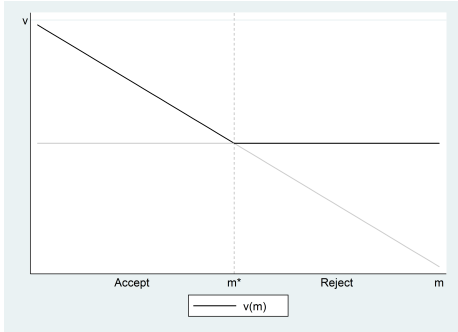


Figure 13: The Function $v(m)$

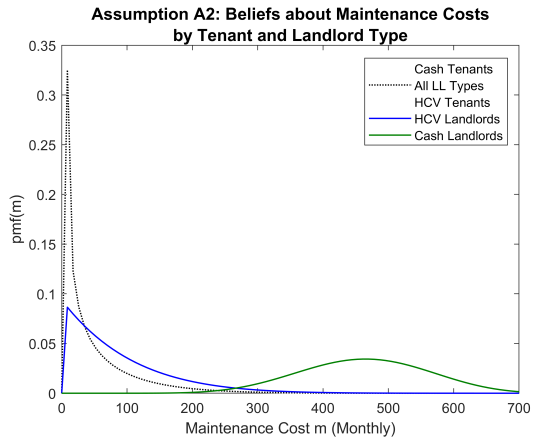
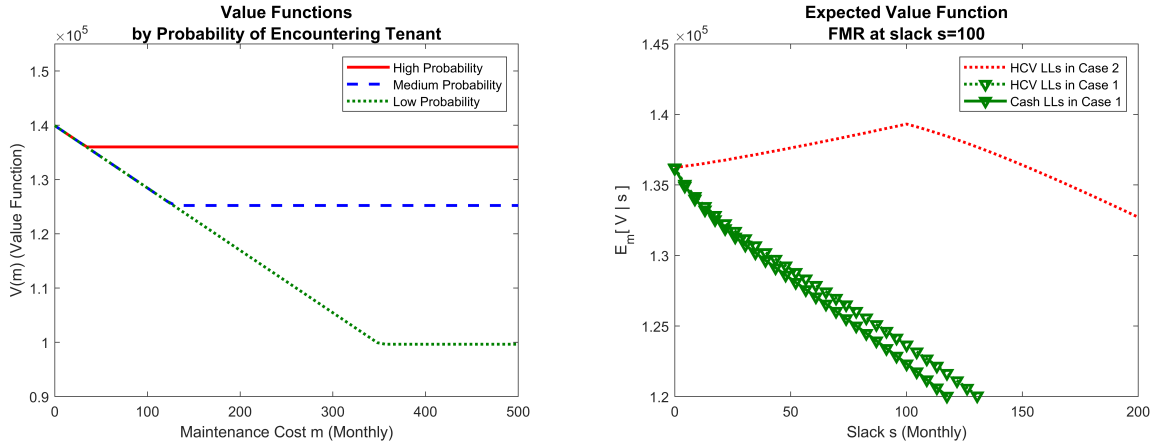


Figure 14: Assumption A2 by Landlord Type

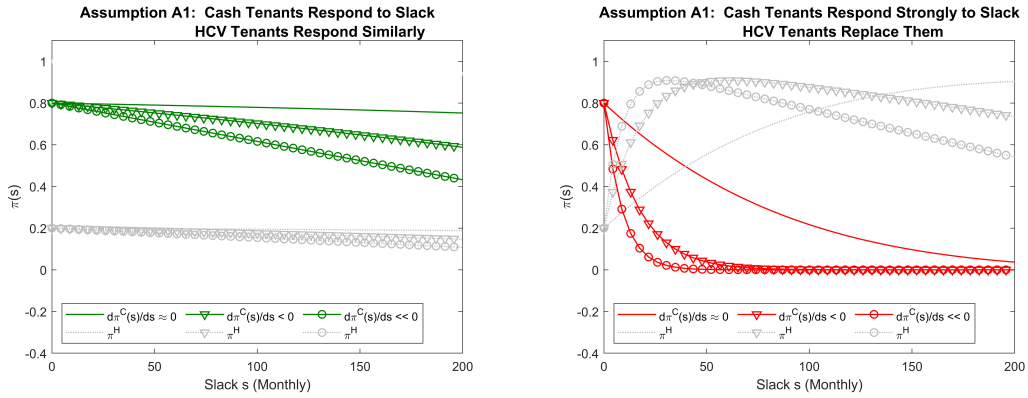


(a) Landlord's Accept/Reject Decision

(b) Landlord's Slack Decision

Figure 15: The Landlord's Decisions

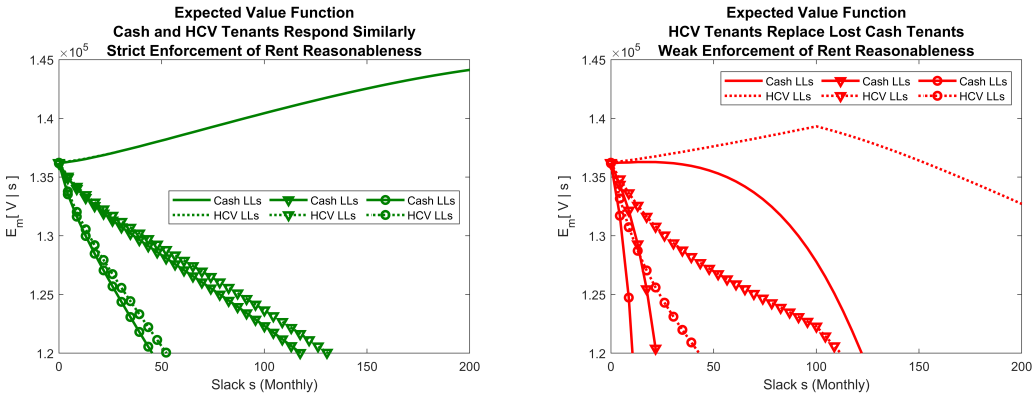
Note: The left panel shows the value functions of a cash landlord in Case 2 of Assumption A1 with weak enforcement of rent reasonableness and slack of \$35. The right panel shows the expected value function as a function of slack s for landlords under Case 2, in which cash tenants respond strongly and negatively to increased slack, but HCV tenants are unresponsive to slack and therefore make up the difference. Source: Author calculations using model data.



(a) Case 1

(b) Case 2

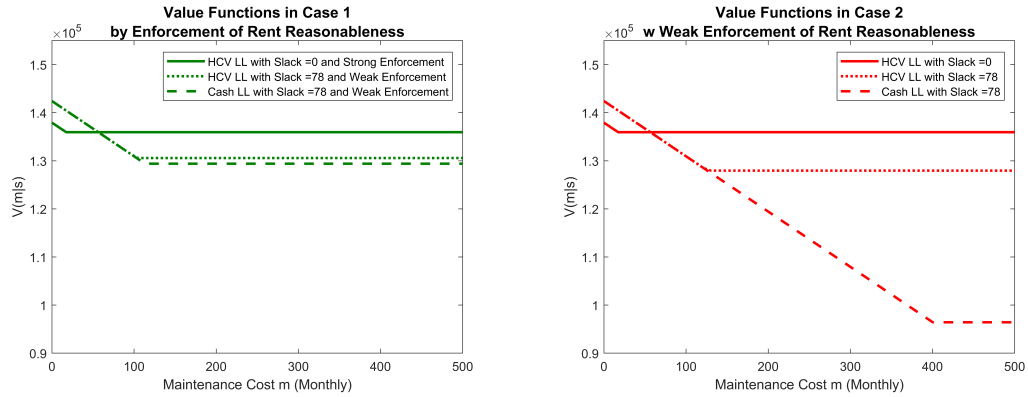
Figure 16: Two Cases of π when $\pi^C(0) = 0.80$ and $\pi^H(0) = 0.20$



(a) Case 1 w Strong Enforcement

(b) Case 2 w Weak Enforcement

Figure 17: Expected Value Function in the Two Cases from Figure 16



(a) Case 1 by Enforcement

(b) Case 2 w Weak Enforcement

Figure 18: Value Functions in the Two Cases from Figures 16 and 17