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Despite being eligible for use in any neighborhood, housing choice vouchers tend to be redeemed in low-opportunity neighborhoods. This paper investigates whether landlord behavior contributes to this outcome by studying the recent expansion of neighborhood-based voucher limits in Washington, DC. We conduct two waves of a correspondence experiment: one before and one after the expansion. Landlords heavily penalize tenants who indicate a desire to pay by voucher. The voucher penalty is larger in high-rent neighborhoods, pushing voucher tenants to low-rent neighborhoods. We find no evidence that indexing rents to small areas affects landlord acceptance of voucher tenants. The data can reject the claim that increasing rent limits by less than $3,000 per month can eliminate the voucher penalty. Neighborhood rent limits do shift lease-up locations toward high-rent neighborhoods in the year after the policy change, an effect that is large relative to the number of voucher households that move but small relative to all voucher tenants.

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1 Introduction

Participants in the largest federal housing program tend to live in neighborhoods with limited opportunities ((Galvez (2010), Jacob and Ludwig (2012), Horn et al. (2014)). For example, in 2016 the median Housing Choice Voucher (HCV) household in Washington, DC lived in a neighborhood at the 11th percentile of the quality index we use in this paper. Concentration of voucher families in high-poverty neighborhoods hinders a major goal of housing policy: moving families toward self-sufficiency and reducing inter-generational reliance on housing subsidies. Voucher families would likely have better outcomes if they were not concentrated in low-opportunity neighborhoods.[1]

Observers of housing policy have long debated whether residential sorting results from restrictions imposed on tenants versus their own preferences. In a speech on segregation and fair housing, President Nixon noted that freedom requires both the *right* and the *ability* to choose: "The right to move out of a mid-city slum... means little without the means of doing so" (Nixon (1971)). This type of thinking motivates a longstanding goal of federal housing policy, which is to ensure that people have the opportunity to choose housing in high-quality neighborhoods (Quadel Consulting Corporation (2001)), but observers debate whether the tendency of voucher recipients to live in certain neighborhoods indicates restrictions on tenants. In the same speech, Nixon pushed against breaking up demographically concentrated neighborhoods, saying, "It is natural and right that we have Italian or Irish or Negro or Norwegian neighborhoods...what matters is mobility: the right and the ability of each person to decide for himself where and how he wants to live, whether as part of the ethnic enclave or as part of the larger society" (Nixon (1971)). A similar argument echoes in policy debates today about the goals of federal housing policy and the best approach for enforcing fair housing laws (Carson (2015), The Editorial Board (2016)).

Landlord behavior represents a potential but under-researched restriction on where voucher tenants lease-up. The existing academic literature has largely focused on tenant choices, using models in which landlords typically rent to any tenant able to pay (e.g., Galiani et al. (2015)). Landlords, particularly in high-rent neighborhoods, might avoid voucher tenants due to higher maintenance costs, compliance costs, or their own or other tenants' (discriminatory) preferences. A series of recent correspondence and audit studies demonstrate that this is the case; landlords shape lease-up locations by screening out voucher tenants in large numbers (Phillips (2017), Moore (2018), Cunningham et al. (2018)). Geyer and Sieg (2013) also show that inferences about tenants' preferences can change dramatically when supply constraints are taken into account when studying public housing programs. Many jurisdictions have experimented with policies to change landlord responses to voucher tenants, but few studies rigorously evaluate the effectiveness of these efforts.

The adoption of small area fair market rents (SAFMRs) represents one policy change aimed at landlords that is gaining traction across the US. In HCV, tenants pay 30 percent of their income in rent and their local housing authority subsidizes the remaining amount. The standard implementation of the HCV program is for the local housing authority to subsidize a household's rent

[1] See research on the Moving to Opportunity (MTO) experiment (Ludwig et al. (2013), Chetty et al. (2016), and Aliprantis and Richter (2018))

up to a limit that is uniform across the voucher holder's metro area, referred to as the metro's fair market rent (FMR). Such a uniform limit skews the units available to tenants toward those in low-rent and low-quality neighborhoods. Paying a subsidy that rises and falls with neighborhood rents would increase the number of units eligible for vouchers in high-opportunity neighborhoods (Palm (2018)) and incentivize the participation of landlords with units previously out of range of the rent standards. These effects are the motivation behind SAFMRs. Though some debate has surrounded the policy, many cities in the US are moving toward neighborhood rent limits.[2]

This paper investigates whether paying higher rental subsidies in high-rent neighborhoods will lead more landlords to accept vouchers in such neighborhoods. We conduct two waves of a correspondence experiment, building on Phillips (2017) and testing how landlords respond to fictional potential tenants who indicate a desire to pay by voucher.

We first show that the results of our audit experiment are consistent with those in Phillips (2017): landlords assess a large penalty to voucher tenants. Among the fictional inquiries we sent to landlords in Washington, DC, inquiries that expressed a desire to pay with a voucher received 27 percentage points fewer responses, a gap that is seven times larger than the effect of listing a black-indicating name. The penalty for voucher tenants is larger in high-rent neighborhoods. The voucher penalty is 12 percentage points larger in a neighborhood at the 90th percentile of the rent distribution than at the 10th percentile. A differential penalty across neighborhoods can help explain why voucher tenants lease-up less often in high-opportunity neighborhoods and suggests that interventions aimed at landlords might help deconcentrate vouchers from high-poverty neighborhoods.

We then study an expansion of neighborhood-level rent limits in Washington, DC. DC was an early adopter of neighborhood-based rent limits, though their ability to allow rents to adjust to neighborhood conditions is limited by a cap imposed through a federal Moving to Work waiver. Our two waves of experimental data from 2015 and 2017 straddle a policy change that increased the top end of the neighborhood rent limits in high-rent DC neighborhoods from 130 percent to 175 percent of HUD's metro-wide FMR.

We find no evidence that indexing voucher limits to small areas affects landlord acceptance of voucher tenants in an economically significant way. In a triple-difference framework, we use variation over time, neighborhoods, and whether the inquiry requests payment by voucher to test whether the voucher penalty applied by landlords decreases over time in neighborhoods affected by this change relative to unaffected neighborhoods. We find no such evidence. This 'zero' is relatively precise, indicating that rent limits would need to increase by roughly $3,000 per month to eliminate the voucher penalty. Rent limits also change discontinuously at the border between neighborhoods affected and unaffected by the policy change. We test for whether landlord behavior shows a similar jump and find no evidence for such a change.

Our final contribution is to examine lease-up locations of voucher holders after the policy change.

[2] The Obama administration completed an administrative rule adopting neighborhood-level rent limits for HCV programs in January 2017. The Trump administration promptly rescinded this ruling. The ensuing court battle continued through December 2017, at which time a federal judge reinstated the original rule (Jan (2017)).

In spite of our null result on landlord behavior, we find suggestive evidence that lease-up locations improved. Specifically, the rate at which voucher households move into neighborhoods with increased limits increases relative to neighborhoods where the limits do not change. Relative to the number of movers, this short-run effect is large. Prior to the policy change, low-rent neighborhoods receive three times more new voucher tenants than high-rent neighborhoods. After the policy change, the rate of voucher tenants moving in equalizes. Overall, these results are quite similar to those of Collinson and Ganong (2018), who find that the adoption of SAMFR limits in Dallas led to improvements in neighborhood quality for voucher households that move.

Relative to the total stock of HCV tenants in DC, the effect we find on lease-up locations is small. The increase in tenants leasing up in high-rent neighborhoods represents only 3 percent of all HCV tenants because most tenants do not move in any given year. Whether increased neighborhood rent limits will lead to a long-term change in the geography of opportunity for voucher tenants in DC depends on how these effects evolve over time.

The remainder of the paper is organized as follows: Section 2 provides background on the HCV program and recent policy changes in DC. Section 3 describes our experiment, as well as the HUD and Census data we use in our analysis. Section 4 measures landlord response to vouchers, and Section 5 measures responses to a change in voucher values. Section 6 concludes. Appendix A presents a simple model that helps us to interpret our estimates.

2 Background

2.1 The Housing Choice Voucher Program and Neighborhood Quality

The US Department of Housing and Urban Development's (HUD) Housing Choice Voucher (HCV) program provides subsidies for recipients to use in the private rental market for housing. Unlike project-based assistance that is tied to a specific location, voucher recipients can, in principle, lease-up in any neighborhood. In practice, voucher tenants typically live in low-quality neighborhoods (Galvez (2010)).

One reason voucher recipients move to low-quality neighborhoods is that their voucher has a uniform value within their city that is relatively low. Tenants pay 30 percent of their income in rent and their local housing authority pays the balance, up to some fair market rent (FMR) determined by HUD. Since the FMR is typically set at the 40th percentile of rent for the entire metro area, households have an incentive to concentrate in low-rent apartments, which are disproportionately located in low-rent neighborhoods.[3]

Washington, DC provides a clear illustration of how voucher recipients concentrate in low-quality neighborhoods when a uniform subsidy is provided in a bimodal rental housing market.

[3]The 40th percentile is for the distribution of gross rents paid by recent movers in the private market who are not voucher holders. If a tenant rents an apartment above the FMR, the tenant is responsible for the remaining amount of rent. Hence, tenants have a strong incentive to rent units below the FMR. 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.

As shown in Figure 1a, in DC many tracts have a median rent below $1,000 per month and many others have a median rent above $1,750 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.

If the voucher program aims to provide voucher holders opportunity through access to high-quality neighborhoods, one approach for policy would be to determine the value of a voucher at the level of specific neighborhoods. Determining the FMR in such small areas rather than an entire metro area would increase the eligible number of units in high-opportunity neighborhoods (Palm (2018)), and has been shown to increase lease-up in higher-quality neighborhoods in Dallas, Texas (Collinson and Ganong (2018)). HUD has conducted demonstrations of this "small area FMR" in five additional sites (Kahn and Newton (2013), Finkel et al. (2017)).

2.2 Small Area Fair Market Rents in Washington, DC

We consider a 2017 policy change in Washington, DC to investigate the impacts of small area FMRs on landlords and voucher holders. Through a Moving to Work waiver (Galvez et al. (2017)), DC received permission from HUD to move from city-wide to neighborhood-specific rent limits. This waiver was received in early 2015, prior to the first round of our experiment. 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 neighborhood and number of bedrooms. When introduced, the neighborhood-specific levels could not exceed 130 percent of the city-wide FMR.

Since DC exhibits a bi-modal 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. As a result, in January 2017 DC obtained a waiver to increase neighborhood rent limits up to 175 percent of the city-wide FMR. This change comes between the two waves of our experiment. Figure 2 displays the new rent limits for 2017. 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. Our analysis will investigate how the policy change in 2017 impacted voucher holders' outcomes in tracts that moved from limits at 130 percent of fair market rent to 175 percent of fair market rent.

3 Data

3.1 Experimental Design

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 apartment listings from an online classified ads 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 apartment listings during May and June of 2015. The resulting data were the same as those considered in Phillips (2017). In the second wave, we sent 4,264 inquiries to 1,810 apartment listings during July to August 2017. The two waves are identical unless otherwise noted.

We sent inquiries to apartments in Washington, DC that list monthly rent appropriate for a voucher. For a given inquiry, the research assistant first identified all apartments eligible for the experiment. In the first wave, apartments listed for rent greater than $1,500 were excluded. 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, be listed within the previous 24 hours, have a known location, be located inside the boundaries of the District of Columbia, not obviously a scam, and not a re-posting previously applied to. 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 apartment 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, twwo 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.

The language of an inquiry to a particular apartment listing was a randomly generated message comparable to those used in Hanson and Hawley (2011) and Ewens et al. (2014). 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 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 apartments. For the other half of apartments, we stratified or matched treatment, assigning black names at random but guaranteeing each apartment received half black and half white names. In the second wave, we similarly stratified assignment of name race for half of all apartments. For the other apartments, we assigned black names to all inquiries. We also assigned greetings, benedictions, 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.

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 apartment in the first wave rents for \$1,253 per month and has one bedroom. In the bi-modal DC rental housing market, online listings tend to come from the upper mode in high-rent, high-quality 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 apartment 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 by construction, and the average apartment is more expensive and larger because we increase the rent limit for entering the experiment. 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 apartment location. Following Ewens et al. (2014), we focus on only positive responses in which a landlord invites the applicant to see the apartment, explicitly provides a means for further contact, or responds that the apartment 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 apartment. We also observe neutral responses, where landlords provide or request more information but do not describe availability or reply only with availability.

3.2 HUD and Census Data

We use data from HUD's Picture of Subsidized Households. This data set indicates the number 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 2015, 2016, and 2017.

To characterize neighborhoods, we use tract-level data from the 2012-2016 American Community Survey (ACS). We follow Aliprantis and Richter (2018) and measure neighborhood quality as 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. 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.

Relative to the national distribution (Figure 3a), the Washington, DC metro area comprises primarily high-quality and expensive rental units (Figure 4a). We focus our analysis on the city of Washington, DC, i.e., the area covered by the DC Housing Authority. Within city limits, there is a bimodal distribution of high-rent units in high-quality neighborhoods and low-rent units in low-quality neighborhoods (Figure 5). The result is many high-rent units in high-quality neighborhoods and low-rent units in low-quality neighborhoods but few low-rent units in mid-quality neighborhoods (Figure 6a). While the middle of the rent and quality distribution exists in DC, HCV residents did not live in such neighborhoods in 2016 (Figure 6b).

Table 2 presents summary statistics about neighborhoods and HUD voucher recipients. Means are weighted by one of five different weights: census tract population, number of HUD voucher recipients in 2015 and 2017, and number of units included in the experiment in 2015 and 2017, respectively. These weights provide a snapshot of the relative differences in neighborhood context for the average DC resident, the average HUD recipient, and units in our experiment. Panel A presents statistics from the American Community Survey at the census-tract level. For instance, the average neighborhood median household income across all DC residents is \$77,000, whereas the average neighborhood income to which all HUD voucher recipients are exposed is just \$44,000-\$45,000. By contrast, the rental units in the 2015 wave of the experiment are exposed to average neighborhood incomes of \$81,000, and \$93,000 in the 2017 wave. Other key indicators of neighborhood quality, such as employment, poverty, and education, show that current voucher holders are more exposed to lower-quality neighborhoods than is the typical resident. Our experiment's listings are drawn from even higher-quality neighborhoods than the city average, which reflects the composition of the online rental market for voucher holders. Since the goal of neighborhood-based rent limits is to extend the voucher program to new neighborhoods and landlords, this sample provides a useful one in which to test the effects of the policy.

Panel B summarizes data on the HUD voucher program aggregated to the census-tract level. Unsurprisingly, voucher recipients are more exposed to neighborhoods with many more housing choice voucher-registered units than are either the typical resident or the units in our experiment. Despite the higher quality of neighborhood for the average unit in the experiment, there are some current HCV tenants and units in the neighborhoods where the experiment takes place.

4 Measuring Landlord Responses to Vouchers

4.1 Empirical Strategy

We can measure the tendency of landlords to avoid voucher tenants using a simple linear regression of a callback dummy on a treatment dummy estimated by ordinary least squares.

$$Y_{ikt} = \beta_0 + \beta_1 \tau_{ikt} + \beta_2 Post_t + \epsilon_{ikt}$$

Y_{ikt} is a dummy for whether the landlord k responds positively to inquiry i during year t. τ_{ikt} is a dummy for whether the inquiry includes a statement asking to pay by voucher. Since the probability of treatment varies between the 2015 and 2017 waves, we also include a year 2017 dummy $Post_t$. Then, β_1 measures the extent to which landlords avoid Section 8 tenants.

We can use other observable characteristics to test for whom the voucher penalty is greatest.

$$Y_{ikt} = \beta_0 + \beta_1 \tau_{ikt} + \beta_2 Post_t + \beta_3 \tau_{ikt} * X_{ikt} + \beta_4 X_{ikt} + \epsilon_{ikt}$$

The coefficient β_3 measures whether the voucher penalty is greater for inquiries or apartments with different X_{ikt}. In particular, we will focus on whether the penalty is greatest for apartments that post higher rents and are located in neighborhoods with high rent.

4.2 Results

We find that landlords avoid voucher tenants. The first column of Table 3 measures the simple difference in how landlords respond to inquiries requesting to pay by voucher versus those that do not. We pool across both waves of the experiment. As shown in the first row, landlords respond positively 29 percentage points less often to inquiries requesting to pay by voucher. This effect is large, seven times the effect of giving a black-indicating name, which, as shown in the second row, is 4 percentage points.

The voucher penalty increases with rent. Figure 7 displays the results graphically. The dashed lines show average (lowess smoothed) callback rates to tenants wishing to pay by voucher in the two waves of the experiment at different rent levels, while solid lines show the same for cash tenants. The gap between the lines measures the voucher penalty at a particular rent. At the lowest rent apartments, callback rates are similar, and in some cases, voucher tenants receive higher response rates. However, as rent increases, a gap appears such that tenants signaling a desire to pay by voucher receive much lower callback rates than those who give no such signal. The second column of Table 3 quantifies this result for an apartment's posted rent. The interaction between the voucher signal and monthly rent is the coefficient of interest. For each \$100 that the posted rent of an apartment increases, the gap between landlord responses to voucher and cash tenants widens by 0.75 percentage points. In the 2017 data, the 10th and 90th percentiles of the rent distribution in our data are \$2,950 and \$1,279 per month, respectively. Hence, the voucher penalty will be about 12 percentage points larger at the 90th percentile of the rent distribution than at the 10th percentile. The third column repeats this analysis, controlling for interactions between bedroom dummies and the voucher signal. Results are similar, which suggests that the voucher penalty increases with apartment quality, not just apartment size. Finally, the fourth and fifth columns split out the same result between the two years of the experiment, demonstrating that this result is stable over time.

These results indicate that landlord behavior could help explain why voucher tenants tend to lease up in low-opportunity neighborhoods. The existence of low-rent apartments does not guarantee that they will be available to voucher tenants. Since the voucher penalty increases with posted rent, the gap between the number of listed apartments truly accessibleto to voucher tenants grows with neighborhood rent. Even absent tenant preferences about different neighborhoods, voucher tenants would be directed to lower-rent, lower-opportunity neighborhoods on average.

5 Measuring Responses to a Change in Voucher Values

5.1 Empirical Strategies

In theory, voucher values that vary with neighborhood rent levels could increase high-rent landlords' willingness to accept vouchers and open new neighborhoods to voucher tenants. If landlords object to voucher tenants because of compliance costs, anticipated greater maintenance, other tenants' or neighbors' preferences, or prejudice, paying more could make a difference. However, this policy will only be effective if some landlords are on the margin between accepting and not accepting a voucher tenant over the price range affected by the increase in voucher limits. The effectiveness of paying more in high-rent neighborhoods is an empirical question.

We examine whether a change in neighborhood voucher values in Washington, DC affected landlords' acceptance of vouchers. As discussed above, Washington, DC received a waiver from HUD to set different voucher limits at the neighborhood level, as shown in Figure 8a. Prior to 2017, DC's waiver allowed it to set neighborhood limits based on neighborhood rent conditions up to a cap of 130 percent of fair market rent. In 2017 the cap expanded to 175 percent. Hence, rent limits increased in neighborhoods for which the city's preferred cap is above 130 percent of fair market rent. Figure 8 displays those neighborhoods in dark red.[4] Most of the western portion of the city, along with Capitol Hill and surrounding areas, saw rent limits increase. Rent limits in other neighborhoods, shown in light red, were not affected by this policy change. We can use this variation to test whether increasing neighborhood rent limits affects landlord behavior and lease-up locations.

We estimate the effects of higher rent limits in a difference-in-difference framework. First, consider a simple difference-in-difference estimated only on correspondence experiment inquiries

[4] The DC Housing Authority uses tax neighborhoods to set rent limits, and we cross-referenced tax neighborhoods with tracts to determine tract-level rent limits.

that request to pay by voucher:

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

Now, j indicates neighborhood. T_{ij} is a dummy for whether the inquiry was sent to an apartment in a neighborhood affected by the policy change, that is, with a 2017 rent limit above 130 percent of HUD's city-wide fair market rent. $Post_t$ is a dummy for the 2017 wave of the experiment. The coefficient of interest on the interaction of the two, γ_3, measures whether callback rates to voucher tenants increase more in neighborhoods where rent limits went up relative to neighborhoods where they did not. We estimate similar regressions in the voucher lease-up data, using tract-level measures from HUD.

We can use information from inquiries that do not request to pay by voucher in a triple-difference specification. The triple difference compares estimates from the above equation for inquiries requesting to pay by voucher and those that do not. More formally, we estimate:

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

The coefficient of interest is ψ_7, which measures whether the gap between voucher and cash inquiries falls over time in neighborhoods that receive rent 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 around the same time. 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 8a, several neighborhoods affected by the policy change border neighborhoods where rent limits were unaffected. 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 as well.

We measure this spatial discontinuity using a simple linear regression.

$$Y_{ijkt} = \phi_0 + \phi_1 \tau_{ijt} + \phi_2 Dist_k + \phi_3 \tau_{ijt} * Dist_k + \xi_{ijt}$$

In this specification, $Dist_j$ measures the distance between apartment k 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.

5.2 Results for Landlord Responses

We find no evidence that landlords respond to increased neighborhood rent limits. Figure 9 provides a graphical basis for this result. We plot landlord response rates against the new 2017 voucher payment limit for the apartment's neighborhood, split out by the year of the experiment and whether the inquiry requested to pay by voucher. The gap between solid and dashed lines measures the voucher penalty in different neighborhoods. The policy change increased rent limits in high-rent neighborhoods, so we should expect this gap to close on the right end of the graph, if the policy is effective. However, such a change is not apparent.

Table 4 helps quantify this result. The first column estimates the first stage relationship between the voucher value and the policy change in a simple difference-in-differences framework. The outcome is the monthly voucher rent limit in 1000s of dollars. We find a coefficient of 0.45 on the interaction between the "Above 130 percent" treatment and the year 2017 dummy. This value indicates that the rent limit increased by \$450 per month on average in tracts where the policy change increased the rent ceiling. This change is large, statistically significant, and passes all standard weak instrument tests.

The second column of Table 4 shows how landlord responses to voucher tenants changed in response to the policy. It estimates a simple difference-in-difference on the correspondence experiment data, restricting the sample to inquiries that request to pay by voucher. Callback rates were 7.9 percentage points lower in the high-rent neighborhoods that see their rent limits increase because they are above the old 130 percent of the fair market rent cap. However, the coefficient on the interaction in the third row shows that this gap does not close significantly in 2017. The positive coefficient of 0.024 indicates that the gap may have closed slightly, but this is not statistically significant. Column (3) estimates 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 close 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 rent limits. Any inference from the results in column (2) would overstate the benefits of increased rent limits. Thus, our preferred triple-difference specification in column (4) finds 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, though this estimate is not statistically significant.

The results indicate that any increase in limits would have to be very large to eliminate the voucher penalty assigned by the landlords we test. A simple instrumental variables model can summarize the results and quantify the precision of our null result. We start with the triple difference model from column (4). We then use the interaction between the post period and the policy treatment as an instrument for the voucher rent limit. Likewise, the triple-interaction between the post period, policy treatment, and voucher signal is an instrument for the interaction between the voucher limit and the voucher signal. Column (5) shows the results. The coefficient of interest is the interaction between the voucher limit and the voucher signal. The coefficient of -0.18 is negative and statistically insignificant. The edge of the 95 percent confidence interval is 0.09, indicating that increasing the voucher limit by $1,000 at most decreases the penalty assigned to voucher tenants by 9 percentage points. Rent limits would need to increase by at least $3,200 per month to eliminate the observed voucher penalty of 29 percentage points. Thus, we conclude that the landlords we observe are insensitive to the voucher payment limit.

Results are similar if we test for discontinuities across the border of the area affected by the policy change. Figure 10 displays this result graphically. Panel (a) shows that the monthly voucher limit increases by roughly $1,000 per month at the border. 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. At the border, there is a noticeable jump in the voucher limit. Panel (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 for tenants who do not mention the voucher program, as expected. Finally, panel (c) previews the main result. Landlord responses to tenants signaling a desire to pay by voucher show no discontinuity at the border, despite the large change in rent limits.

Table 5 quantifies the spatial discontinuity estimates. The coefficient on the policy change is the focus. Column (1) shows that voucher limits increase by $1,030 per month on average at the border. The next three columns verify that housing units on either side of the border are similar in terms of rent (2), number of bedrooms (3), and how landlords respond to cash tenants (4). The main test for policy impacts is in column (5). The negative and statistically insignificant coefficient does not provide evidence that landlords respond more positively to voucher tenants on the side of the border with greater rent limits. The instrumental variables specification in column (6) combines columns (1) and (5), using an indicator for the side of the border affected by the policy change as an instrument for the voucher limit. The coefficient on the voucher limit is again negative and statistically insignificant, -0.025. The edge of the 95 percent confidence interval is 0.096, indicating that a $1,000 increase in the monthly rent limit increases positive responses from landlords by 9.6 percentage points at most. As with estimates from the difference-in-differences design, this estimate suggests that eliminating the voucher penalty would require an exorbitant increase in the rent limit.

5.3 Results for Lease-Up Location

On the other hand, we find evidence that increasing voucher rent limits affects lease-up locations for voucher households that move. Figure 11 provides some initial graphical evidence. The left figure shows how the number of voucher tenants newly arriving in a census tract changed between 2012-2016 and 2017. Recall that the policy change largely increased rent limits in the Northwest portion of the city. Relative to historical norms, newly moving voucher tenants tend to move into these higher-rent neighborhoods rather than cheaper neighborhoods in far Southeast DC. As shown in the right figure, part of this trend appears to be driven by new neighborhoods opening to voucher tenants. This figure shows which tracts have changed in terms of whether they have any voucher tenants. Several high-rent tracts in the far northwest that previously had no voucher tenants received their first voucher tenants in 2017. Higher payment limits seem to be changing the map of where voucher tenants move in DC. Figure 12 provides similar evidence for the time series. Each sub-figure shows the average number of voucher tenants leasing up in a tract, splitting tracts into high-rent neighborhoods affected by the increased rent limits (where the 2017 limit is greater than 130 percent of FMR) versus those not affected. In the top left figure, 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 little to no evidence that this gap closes in 2017. However, these numbers include both old tenants remaining in their existing leases and new tenants who move. The top right figure focuses on just those tenants who move. While high-rent neighborhoods attracted far fewer voucher tenants than low-rent neighborhoods between 2012 and 2016, this trend dramatically changed in 2016. New movers are now just as likely to move to high-rent and low-rent neighborhoods.

Table 6 quantifies these results. Each column estimates a simple difference-in-difference specification on a panel of census tracts with a different outcome related to voucher lease-up. Column (1) examines the total number of vouchers in the tract. The first row shows the coefficient on the interaction between a dummy for whether the tract was affected by the policy change and a dummy for whether the observation comes from after the change went into effect. The coefficient of 4.74 indicates that the number of voucher tenants increased by about five households in tracts with increased limits, relative to tracts where the policy change did not affect the rent limit. This effect is small in absolute terms relative to the mean of 81.7 tenants per tract and not statistically significant. However, column (2) indicates that this effect exists and is quite large for newly arriving voucher tenants. The coefficient of 4.36 is statistically significant at the 1 percent level and indicates a large effect among this group. The average tract receives about four new voucher tenants in a given year, and the policy change has an effect roughly equal to this mean. As shown in the figures above, columns (3) and (4) confirm that the increase in vouchers is large in percentage terms and opens up new neighborhoods that previously had no voucher tenants. The likelihood that a tract has any voucher households increases by 11 percentage points in tracts with higher limits. Among the group of voucher tenants who are moving, higher rent limits affect lease-up locations and appear to induce moves into tracts where vouchers were totally absent.

Table 7 confirms that these results hold for only the set of tracts near the border of the policy change. The difference-in-differences specification could confound true policy effects with differential trends in high-rent neighborhoods. The similar pre-treatment trends in Figure 12 help alleviate this concern. However, other policy changes could drive our results if the DC Housing Authority conducts other policies in the same neighborhoods targeted for increases in rent limits. Such effects should be much more limited near the policy border, an area where neighborhoods and policy environments should be more similar. Table 7 replicates the voucher lease-up results using only tracts that touch the policy border. Results are quite similar.

6 Conclusion

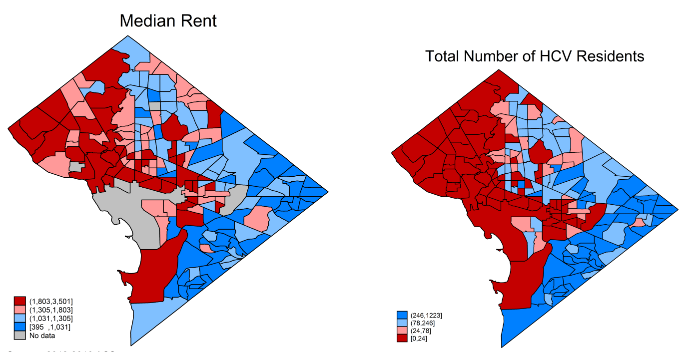
In this paper, we find that landlords respond little but tenants do manage to lease-up in better neighborhoods when subsidized housing vouchers pay more in high-rent neighborhoods. To test landlord responses, we conduct two waves of a correspondence experiment in Washington, DC. Landlords significantly penalize fictional tenants who express a desire to pay by voucher, responding positively to an initial e-mail inquiry about half as often. We find no evidence that this penalty decreases in neighborhoods where the DC Housing Authority (DCHA) increases the maximum voucher payment relative to neighborhoods that see no increase. Similarly, we observe no discontinuity in the voucher penalty at the border between neighborhoods with higher and lower rent limits. Null results in both models are relatively precise, indicating that DCHA would need to increase the rent limit by approximately $3,000 per month to eliminate the voucher penalty.

On the other hand, tenants become more likely to lease up in neighborhoods where vouchers pay more. Prior to the policy change, voucher tenants who move are about three times more likely to move to low rent neighborhood than to high-rent neighborhoods. In the year after vouchers in high-rent neighborhoods begin to pay more, voucher tenants become equally likely to move into high-rent versus low-rent neighborhoods. Some neighborhoods that previously had no voucher tenants also begin receiving voucher tenants. Thus, relative to the number of voucher tenants who move, the policy has a large effect on where voucher tenants lease up. However, there are few movers. The policy moves about four households per treated tract, or about 400 households in total, over one year. This represents about 3 percent of the roughly 15,000 voucher households in DC. Thus, overall effectiveness will depend on whether the one-year effects we observe persist and affect where people move each year over the next several years.

The contrast between the empirical results for landlord responses and lease-up locations presents a puzzle that has several possible solutions. Two possibilities seem most likely. First, landlords other than the ones we observe in our experiment may drive lease-up in new neighborhoods. Two separate groups of landlords may serve the different components of DC's bimodal housing market, and the policy may only affect landlords already familiar with vouchers. If the policy causes landlords who already serve voucher tenants but who do not post online to diversify into high-rent neighborhoods, we would observe the collection of results in this paper. Second, landlords may respond at stages beyond the initial inquiry. Higher voucher payments could help avoid situations where landlords eliminate voucher tenants at the time of the showing or during inspections, and we cannot observe this stage of the process. It is also possible that changes in tenants' behavior could drive our results, though this would require tenants to have incorrect expectations. A larger payment from the housing authority to the landlord has no immediate value to tenants but could make them more optimistic about their chances in high-rent neighborhoods, changing search locations. If tenants have rational expectations, though, these changes in tenant behavior only occur if landlords respond to the policy (c.f. the model in the appendix of Collinson and Ganong (2018)). We can also eliminate a few of the possibilities. It is unlikely for example that other local policy changes drive the change in lease-up we observe. The DCHA actively pursued other policies to move voucher tenants into high-rent neighborhoods during the sample period, but these policies should not cause the changes in lease-up specifically near the rent-limit border that we observe.

While our empirical results are complex, they provide some clear and policy-relevant information. First, it is challenging to engage mainstream landlords in housing voucher programs. Such landlords apply a very large penalty to voucher tenants when screening initial inquiries, and housing authorities would have to pay much, much higher rents to bring these landlords in. These results suggest that engaging mainstream landlords in voucher programs may require other complementary interventions. On the other hand, paying greater amounts in higher-rent neighborhoods can help voucher tenants move to those neighborhoods. A significant debate revolves around whether adopting small area fair market rents can help people move to high-opportunity neighborhoods. Our results support and clarify previous results from Dallas. A similar policy in DC does increase the rate at which tenants move into high-rent neighborhoods. As in Collinson and Ganong (2018), we find these effects for the short run and for voucher tenants who move, though in any given year only a small proportion of voucher tenants move. Neighborhood-based rent limits help some voucher households move to higher-quality neighborhoods immediately after introducing this policy, but the long-run effects of this policy change remain to be seen.

7 Figures



(a) (b)

Figure 1: Neighborhoods in Washington, DC

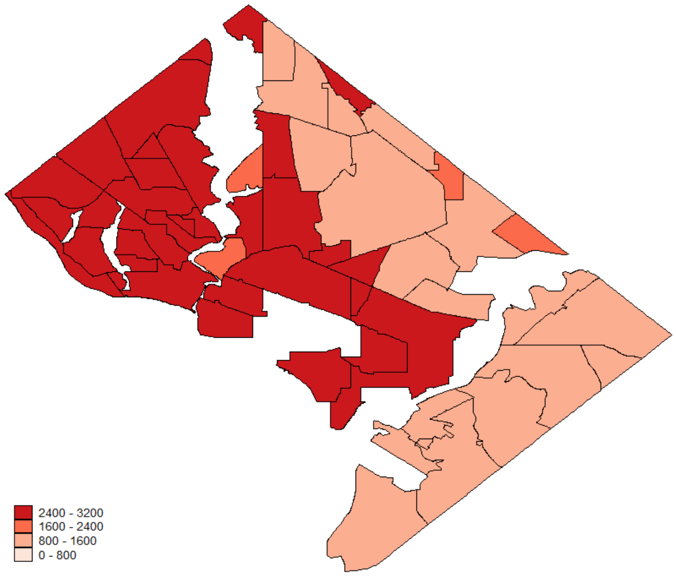
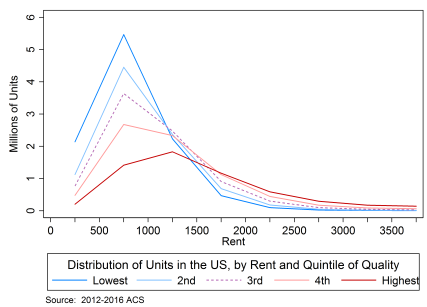
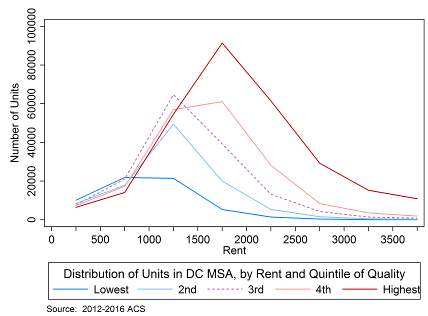


Figure 2: The Neighborhood-Specific Value of a Housing Choice Voucher in Washington, DC 2017

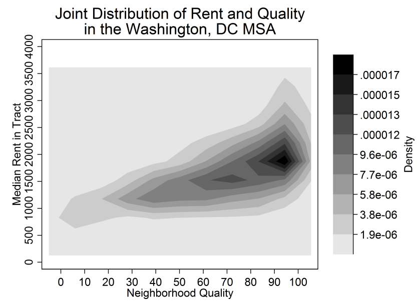


(a)

Figure 3: The Joint Distribution of Median Rent and Quality in the US

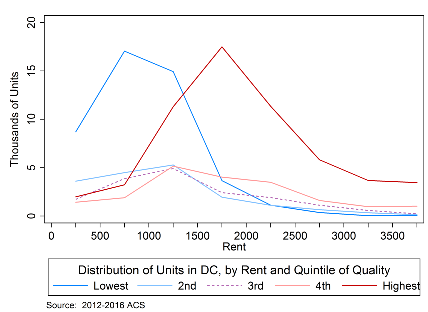


(a)

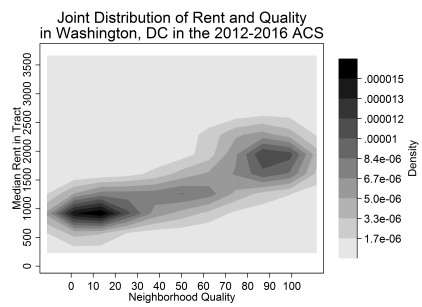


(b)

Figure 4: The Joint Distribution of Median Rent and Quality in the Washington, DC MSA

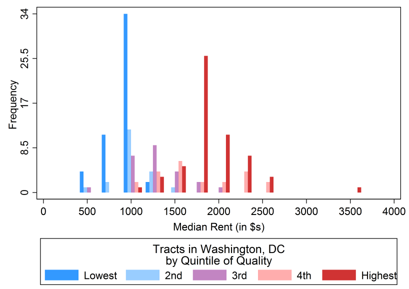


(a)

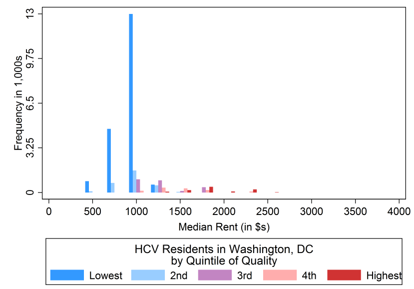


(b)

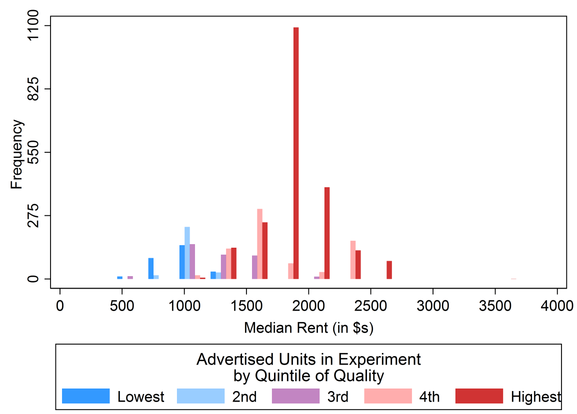
Figure 5: The Joint Distribution of Median Rent and Quality in Washington, DC



(a) All Units in DC



(b) HCV Residents



(c) The Experiment

Figure 6: HCV Residents in DC

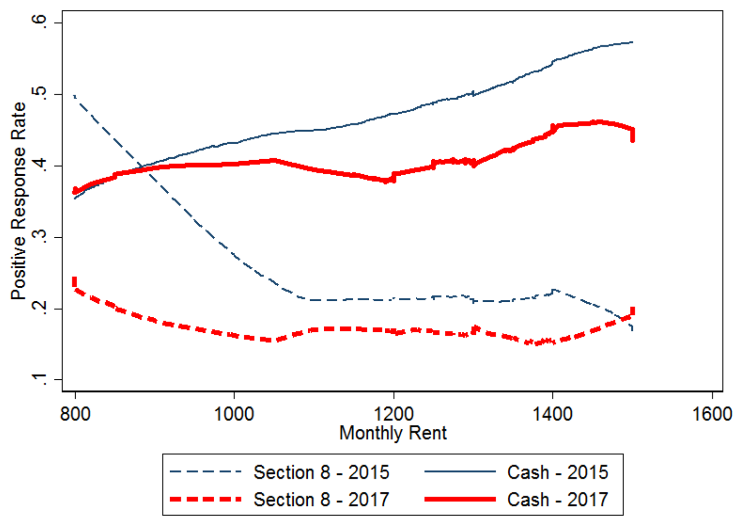
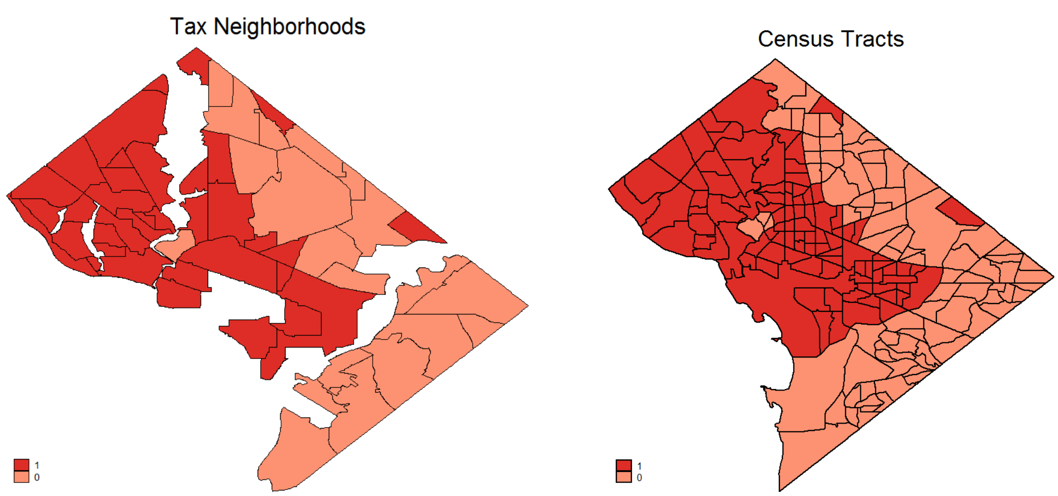


Figure 7: The Probability of Positive Response $\alpha(r, X)$



(a)

(b)

Figure 8: Changes in Rent Limits

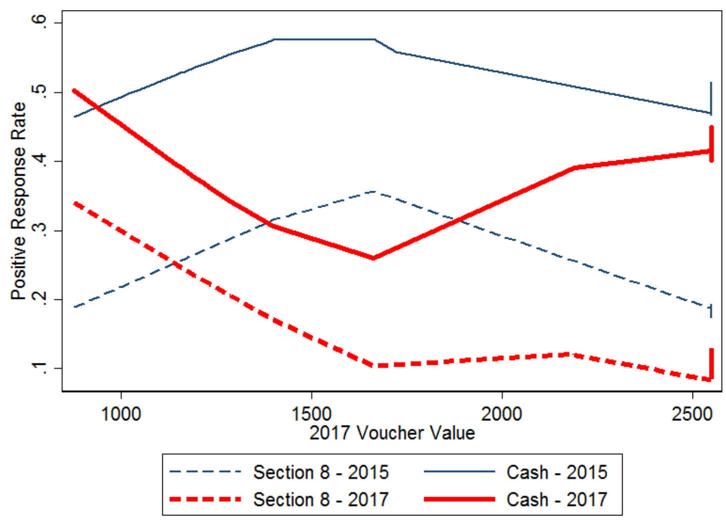
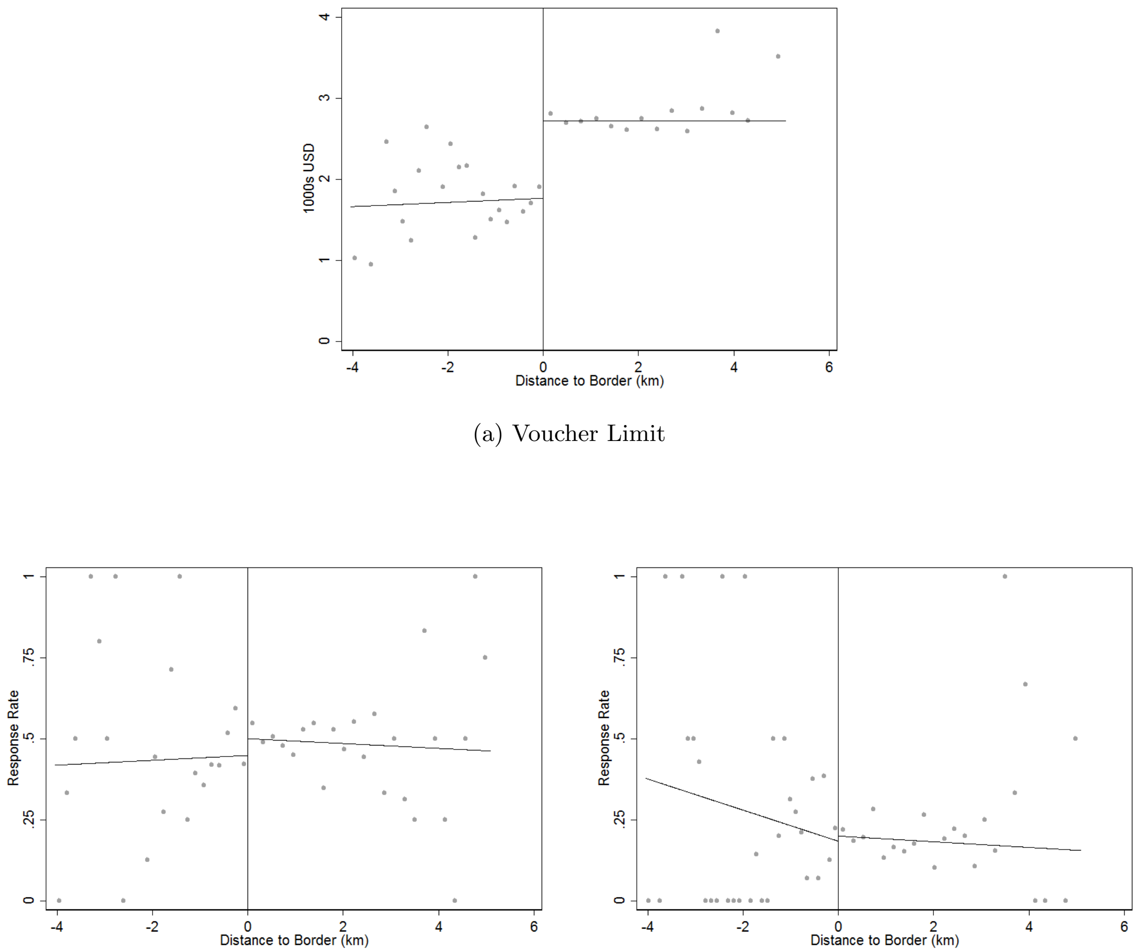


Figure 9: The Probability of Positive Response $\alpha(\bar{r}_j, X)$ where Voucher Limit in Nbd j is $\bar{r}_j$

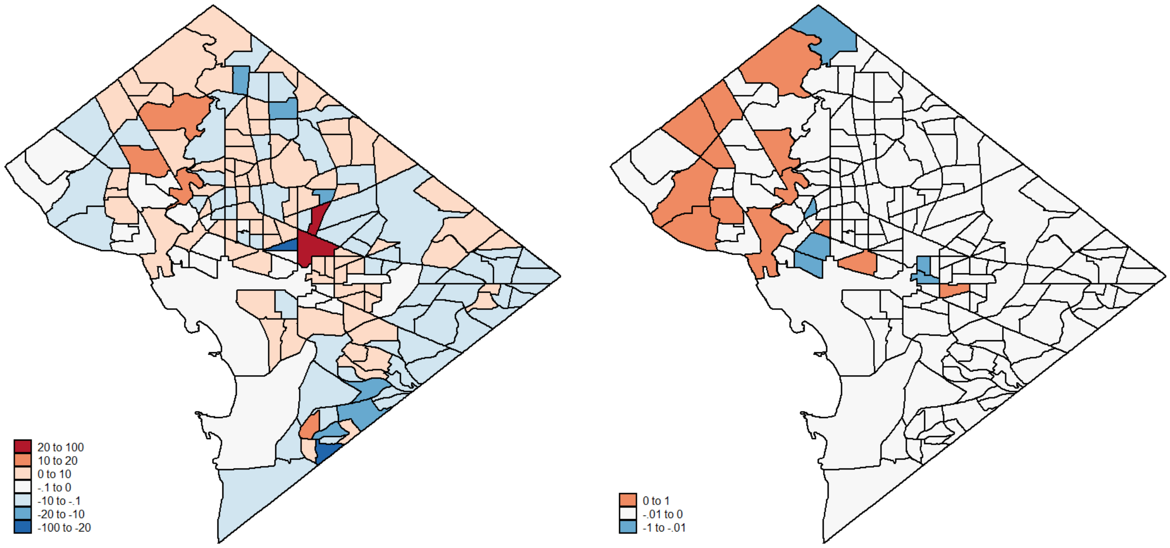


(a) Voucher Limit

(b) Landlord Responses - Cash Tenants

(c) Landlord Responses - Voucher Tenants

Figure 10: Border Discontinuity Effects



(a) Number of New Arrivals

(b) Any Voucher Residents

Figure 11: Change in Voucher Residents by Census Tract, 2017 vs. 2012-2016 Mean

Figure 12: HCV Residents by Tracts Affected and Unaffected by Policy Change

8 Tables

Table 1: Correspondence 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	1252	1255	1253
	(212)	(221)	(214)
Bedrooms	0.9	1.0	0.9
	(0.7)	(0.8)	(0.8)
Positive Response	0	0	0
	(1)	(0)	(0)
N	2010	658	2668
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	2046	2056	2051
	(701)	(663)	(682)
Bedrooms	1.3	1.3	1.3
	(1.0)	(0.9)	(0.9)
Sq. Ft.	849	881	865
	(500)	(909)	(735)
N	2115	2149	4264

The sample comes from two correspondence experiments. The top panel shows the first wave from May to June 2015 and the bottom panel shows the second wave conducted in July and August 2017. Each cell shows means with standard deviations in parentheses. The first and second columns split out inquiries not signaling use of a voucher vs. signaling use of a voucher, and the final column shows statistics for the combined sample.

Table 2: Neighborhood Summary Statistics

	All	Voucher 2015	Voucher 2017	Exp 2015	Exp 2017
A. General Population (ACS)					
Med HH Income	77	44	45	81	93
	(41)	(21)	(23)	(38)	(35)
Med Home Value	490	316	319	521	565
	(233)	(125)	(130)	(223)	(194)
Median Rent	1401	1045	1060	1430	1608
	(516)	(276)	(294)	(406)	(419)
Share Employed	62	51	52	67	70
	(14)	(11)	(12)	(13)	(11)
% Poverty	19	29	29	16	14
	(13)	(13)	(13)	(11)	(9)
Share College	50	24	25	57	67
	(29)	(18)	(19)	(26)	(22)
N	441706	26497	25591	1481	2213
B. Voucher Tenants (HUD)					
Avg HH Income	16	16	15	16	16
	(4)	(3)	(3)	(3)	(4)
HCV Units Available	96	204	202	69	51
	(103)	(121)	(117)	(82)	(69)
% Occupied	77	74	79	74	79
	(3)	(1)	(0)	(1)	(0)
HCV Tenants	223	379	354	184	135
	(183)	(243)	(222)	(149)	(123)
Avg Rent	1777	1930	1606	1936	1616
	(188)	(79)	(78)	(89)	(94)
Avg Family Rent	436	427	419	433	429
	(94)	(79)	(78)	(89)	(94)
% Moved Last Year	7	9	4	8	10
	(9)	(10)	(6)	(9)	(14)
N	441706	26497	25591	1481	2213

This table shows neighborhood statistics and tract-level characteristics from the 5-year 2012-2016 ACS (top panel) and the 2016 HUD Picture of Subsidized Housing (bottom panel). Statistics are means with standard deviations in parentheses. The columns use different weights. The columns weight respectively by tract total population, number of voucher holders in 2015, number of voucher holders in 2017, number of experimental inquiries in 2015, and number of experimental inquiries in 2017.

Table 3: Landlord Responses to a Voucher Signal

	Combined	Combined	Combined	2015	2017
Voucher	-0.29***	-0.15***	0.027	0.44***	-0.028
	(0.012)	(0.032)	(0.10)	(0.14)	(0.058)
Black	-0.041***	-0.041***	-0.041***	-0.060***	-0.026
	(0.012)	(0.012)	(0.012)	(0.017)	(0.016)
Monthly Rent - 100s		0.0057***	0.011***	0.031***	0.0084***
		(0.0016)	(0.0020)	(0.0066)	(0.0025)
Voucher X Rent		-0.0075***	-0.012***	-0.053***	-0.011***
		(0.0016)	(0.0022)	(0.010)	(0.0028)
BedroomXVoucher Dummies	No	No	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	No	No
Mean of Dep. Var.	0.37	0.37	0.37	0.43	0.33
R^2	0.090	0.093	0.099	0.085	0.10
N	6932	6932	6932	2668	4264

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 dummy is an indicator that the inquiry states a desire to pay by voucher and the black dummy 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 apartment listing.

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

	First Stage All Voucher Limit	Reduced Form Voucher Response	Reduced Form Cash Response	Reduced Form All Response	IV All Response
Above 130% X 2017	0.45***	0.024	0.10**	0.10**	
	(0.040)	(0.049)	(0.044)	(0.044)	
Limit Above 130%	0.67***	-0.088**	-0.068**	-0.068**	-0.23**
	(0.019)	(0.039)	(0.030)	(0.030)	(0.093)
2017	0.29***	-0.047	-0.090**	-0.090**	-0.16**
	(0.037)	(0.043)	(0.039)	(0.039)	(0.069)
Above 130% X 2017 X Voucher				-0.080	
				(0.061)	
Voucher X 2017				0.043	0.099
				(0.053)	(0.091)
Above 130% X Voucher				-0.020	0.10
				(0.047)	(0.13)
Voucher				-0.26***	-0.015
				(0.039)	(0.16)
Voucher Limit X Voucher					-0.18
					(0.14)
Voucher Limit (1000s USD)					0.23**
					(0.10)
Mean of Dep. Var.	2.24	0.20	0.49	0.37	0.37
R^2	0.66	0.0072	0.0025	0.091	0.066
N	6879	2807	4125	6932	6879

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 dummy is an indicator that the inquiry states a desire to pay by voucher and the black dummy is an indicator for an inquiry with a black-indicating name. The indicator of above 130 percent indicates a neighborhood rent limit above 130 percent of FMR in 2017. The final column estimates an instrumental variables model using the policy*2017 and policy*2017*voucher signal interactions as instruments for the voucher limit and the voucher limit*voucher signal. Coefficients for all covariates are listed unless indicated. Standard errors are in parentheses and are clustered by apartment listing.

Table 5: Effect of Increasing Rent Limits on Landlord Voucher Penalty, Border Discontinuity

	First Stage Voucher Voucher Limit	Balance Voucher Rent	Balance Voucher Bedrooms	Balance Cash Response	Reduced Form Voucher Response	IV Voucher Response
Above 130%	1.03***	-9.55	-0.11	0.041	-0.026	
	(0.085)	(121.1)	(0.16)	(0.074)	(0.064)	
Distance to Border (km)	0.18	448.4**	-0.091	0.073	0.073	0.077
	(0.14)	(201.3)	(0.26)	(0.11)	(0.094)	(0.10)
Above 130% X Distance	-0.32**	-547.9**	-0.32	-0.11	-0.081	-0.089
	(0.16)	(226.3)	(0.29)	(0.13)	(0.11)	(0.12)
Voucher Limit (1000s USD)						-0.025
						(0.062)
Mean of Dep. Var.	2.49	2110.3	1.34	0.48	0.21	0.21
R^2	0.47	0.018	0.041	0.0027	0.00070	0.0036
N	882	882	882	854	882	882

The sample comes from inquiries in the two correspondence experiments, 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 (linear probability model) with a landlord positive response dummy as the outcome. The voucher dummy is an indicator that the inquiry states a desire to pay by voucher and the black dummy is an indicator for an inquiry with a black-indicating name. The indicator of above 130 percent indicates a neighborhood rent limit above 130 percent of FMR in 2017. The final column estimates an instrumental variables model using the high side of the border as an instrument for the voucher limit. Coefficients for all covariates are listed unless indicated. Standard errors are in parentheses and are clustered by apartment listing.

Table 6: Effect of Increasing Rent Limits on Tract-Level Voucher Lease-Up

	# Vouchers	# New Arrivals	IHS # Vouchers	Any Vouchers
Post X Limit Above 130% of FMR	4.74	4.36***	0.38***	0.11***
	(3.41)	(1.28)	(0.085)	(0.031)
Post	1.64	-2.61***	-0.029	-0.022
	(2.59)	(0.69)	(0.034)	(0.015)
Limit Above 130% of FMR	-107.7***	-4.40***	-2.51***	-0.22***
	(12.3)	(1.10)	(0.26)	(0.044)
Mean of Dep. Var.	81.7	3.95	3.78	0.86
R^2	0.30	0.028	0.33	0.087
N	1074	1013	1074	1074

The sample comes from the HUD Picture of Subsidized Housing. 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. 'IHS' refers to inverse hyperbolic sine. The indicator of above 130 percent indicates a neighborhood rent limit above 130 percent of FMR in 2017. Coefficients for all covariates are listed unless indicated. Standard errors are in parentheses and are clustered by tract.

Table 7: Effect of Increasing Rent Limits on Tract-Level Voucher Lease-Up, Only Border Tracts

	# Vouchers	# New Arrivals	IHS # Vouchers	Any Vouchers
Post X Limit Above 130% of FMR	11.9*	7.37**	0.44**	0.17**
	(6.61)	(3.07)	(0.17)	(0.076)
Post	-2.67	-1.94**	-0.11	-0.067
	(3.42)	(0.91)	(0.084)	(0.046)
Limit Above 130% of FMR	-44.1**	-1.32	-0.84	-0.026
	(20.2)	(1.61)	(0.51)	(0.079)
Mean of Dep. Var.	71.0	3.45	3.94	0.91
R^2	0.076	0.033	0.044	0.013
N	318	303	318	318

The sample comes from the HUD Picture of Subsidized Housing. 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. 'IHS' refers to inverse hyperbolic sine. The indicator of above 130 percent indicates a neighborhood rent limit above 130 percent of FMR in 2017. We restrict the sample to tracts that border a tract with a different value of this 130 percent indicator. Coefficients for all covariates are listed unless indicated. Standard errors are in parentheses and are clustered by tract.

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A Search Model Derivations

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

$$v_{u,k}(m) = \max\left\{\frac{r_u - m}{1-\beta}, \beta \int v_{u,k}(m')dF_{u,k}(m')\right\}, \tag{1}$$

where the maximization is over accepting the tenant or rejecting them 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.[5] This establishes that the landlord's decision rule is based on a reservation expected maintenance cost where the landlord accepts if $m < m^*_{u,k}$ and rejects if $m > m^*_{u,k}$, and that one can characterize the reservation maintenance cost using the equation

$$m^*_{u,k} = r_u - \beta \int_0^{m^*_{u,k}} \left(m^*_{u,k} - m'\right) dF_{u,k}(m') \quad \text{where} \tag{2}$$

$$f_{u,k}(m') = \int_{\mathcal{X}} f_k(m|x) f_u(x|r_u)dx.$$

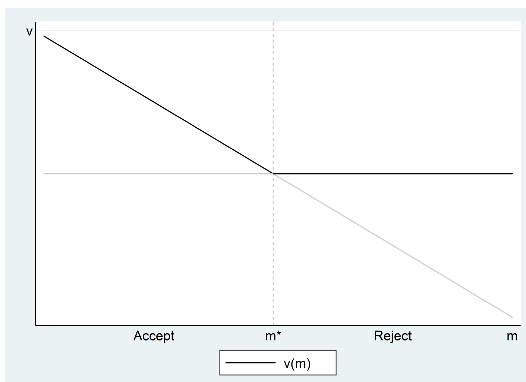

Figure 13: The Function $v(m)$

In the case of cash and section 8 renters, let π be the probability of encountering a cash renter and $1-\pi$ be the probability of encountering a Section 8 renter. Then the landlord's value function can be generalized to

$$v_{u,k}(m) = \max\left\{\frac{r_u - m}{1-\beta}, \beta\left[\pi \int v_{u,k}(m')dF^C_{u,k}(m') + (1-\pi)\int v_{u,k}(m')dF^S_{u,k}(m')\right]\right\}, \tag{3}$$

and the characterization of the reservation maintenance cost in Equation 2 can be generalized to

$$m^*_{u,k} = r_u - \beta\left[\pi \int_0^{m^*_{u,k}} \left(m^*_{u,k} - m'\right) dF^C_{u,k}(m') \quad + \quad (1-\pi) \int_0^{m^*_{u,k}} \left(m^*_{u,k} - m'\right) dF^S_{u,k}(m')\right]. \tag{4}$$

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