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Fair market rent and the distribution of rents in Los Angeles

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A B S T R A C T

A unique data source is used to analyze the effect of the fair market rent (FMR) on the distribution of apartment rents in Los Angeles for 2007–2015. The data set includes the results of semi-annual surveys of rents in Los Angeles since 2007. The surveys include information on location, characteristics of the property, and a rating of the overall quality of the building exterior. Histograms suggest there is a tendency for rents to cluster at values around the FMR, particularly for small (studio and 1 bedroom) units. We also estimate a model explaining the probability that a unit's rent lies in a set of intervals, including regions just below and just above the FMR. The estimates suggest that the probability that the rent clusters around the FMR is significantly higher than would be expected given the underlying characteristics of the properties. An analysis of changes in rents over time suggests that the tendency for rents to cluster in the region just above the FMR is persistent for individual properties over time.

1. Introduction

Section 8 housing program provides vouchers to over 2 million low-income households annually. The program, which is managed by the US Department of Housing and Urban Development (HUD), is designed to subsidize rents for low-income households. HUD determines the expected cost of a medium quality apartment in a metropolitan area and sets the "Fair Market Rent" (FMR) by using the Decennial Census, the American Community Survey and random digit dialing telephone surveys. The FMR is usually set at the 40th percentile of metro area or county wide rents. Using the FMR as the benchmark, the local housing authorities set a local Payment Standard (PS), which is usually around 90–110% of the FMR. If the rent is below the PS, the household pays 30% of income in rent and the public housing authority pays the landlord the difference between the PS and 30% of the tenant's adjusted income, with the maximum subsidy capped at the difference between the PS and 30% of the adjusted income. Since 1998, tenants can choose an apartment where the rent exceeds the PS by no more than the PS plus 10% of adjusted income in the first year of lease, with the excess rent (i.e. difference between rent and PS) being borne by the tenant. Thus, the total rent contribution cannot exceed 40% of the household's adjusted income in the first year of lease (although the household can choose to pay more than 40% in subsequent years).

The PS produces a kink in the household's budget constraint. Letting R and Y represent the rent and the household's adjusted income, the subsidy is $S = R - .3Y$ for $.3Y \leq R \leq PS$ and $S = PS - .3Y$ if $PS < R \leq PS + 0.1Y$. This kink produces a tendency for rents to bunch at the PS in markets with a large number program participants. The household thus has an incentive to find an apartment for which the rent is as high as the PS because the subsidy will cover for the additional rent and the household can achieve higher utility by consuming more housing without sacrificing consumption of other goods. However, due to search costs, some recipients choose units that rent for less than the FMR.

Section 8 program provides incentives for landlords to alter rents. An advantage of charging a relatively low rent is it helps assure a large pool of potential tenants. Similarly, there is little incentive to set rents that are only slightly below the PS because Section 8 tenants do not incur the cost of higher rents. On the other hand, the fact that voucher recipients do not lose their subsidy unless the rent exceeds PS plus 10% of their income[1] means increase in the number of households who are able to afford units with rents somewhat above the PS, which in turn is likely to increase the mass of rents in this region. The kink in the household's budget constraint thus provides an incentive toward a bunching of rents near the PS.

Previous research on Section 8 housing program has focused on evaluating the benefits of the program (Carlson et al., 2011; Cutts and Olsen, 2002; Reeder, 1985; Weinberg, 1982), the effect of the program on property values and neighborhood characteristics (Baum-Snow and Marion, 2009; Eriksen, 2009; Galster et al., 1999), or their effect on residential mobility (Ladd and Ludwig, 1997; Turner, 1998). Research on the effects of the program on the distribution of rents has been hampered by a paucity of good data on market rents. The question is important because a tendency for landlords to raise rents up to the fair market value

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[1] The rent can increase above the PS plus 10% of income in subsequent years to avoid cost of moving.

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increases the cost of the program, while a tendency to lower rents to the FMR has the beneficial effect of making higher-quality housing available to participating households.

In this study, we take advantage of a unique data source to analyze the effect of the FMR on the distribution of apartment rents in Los Angeles for 2007–2015. A private firm, Applied Real Estate Analysis, Inc. (AREA), has conducted semi-annual surveys of rents in Los Angeles since 2005. AREA conducts biannual surveys by sending trained people to inquire about rents for rental housing. AREA also conducts less extensive surveys in New Orleans and Philadelphia. The objective of the surveys is to provide information to local housing authorities to help determine whether rents are reasonable for voucher units. The surveys include information on location, characteristics of the property, and a rating of the overall quality of the building exterior. The surveys provide a unique source of data on rents for individual housing units over an extended time. Although we would prefer to use the PS for our analysis, it is not available for our entire sample period. Hence, we use the FMR for our analysis while providing robustness tests using data on PS for the period for which it is available, August 2013 to December 2015.

Our analysis has three steps. First, we present histograms showing the distribution of rents over time. The evidence suggests that there is a tendency for rents to cluster at values just above the FMR, particularly for small (studio and 1 bedroom) units. Next, we estimate a model explaining the probability that the rent charged for a unit lies in a series of $25 intervals, including the regions just below and just above the FMR. The estimates confirm the results of the histograms: the probability that the rent is in the region just above the FMR is significantly higher than would be expected given the underlying characteristics of the properties. The findings using the PS for the subset of the data are consistent with the results using the FMR.

One advantage of the AREA data set is that it tracks many apartments over time. This feature of the surveys allows us to determine whether the tendency for rents to bunch near the FMR is persistent for individual units over time. A contingency table suggests that apartments with rents just below the FMR are no more likely to continue to have rents in this region over time than to have lower or higher rents. However, apartment with rents just above the FMR are more likely to continue to have rents in this region over time.

2. Section 8 program: overview

Housing vouchers are allocated under Section 8 of the US Housing and Community Development Act 1974. Section 8 voucher program was renamed Housing Choice Voucher (HCV) in 1998. Prior to the voucher program, the government had relied more on place-based housing programs, where housing was constructed and operated at below market rates for low income households. However, the importance of most of the supply based programs has declined due to concerns that they create areas of concentrated poverty and are not cost effective.

The voucher program, which is managed by HUD, is designed to allow low income households to rent in the private market. A household is eligible to receive a voucher if its income is less than 50% of the median income (adjusted for household size) in its metropolitan area. In addition, at least 75% of all housing vouchers must go to households with income not exceeding 30% of the adjusted median income for that area. The households apply to the Public Housing Authority (PHA) and vouchers are allocated through a waiting list.[2] Some groups like elderly, disabled or homeless are given priority and moved to the top of the waiting list.

The recipient of the voucher has 2–3 months to find an apartment that meets HUD's minimum habitability standard. The housing authority is responsible for inspecting the unit to determine if it meets quality standards and to determine whether the rent is reasonable.[3] Given high search costs and the likelihood of discrimination, only 69% of families and individuals who received vouchers from large metropolitan PHAs succeeded in using them to lease units under Section 8 program in 2000 (Finkel and Buron, 2001). However, housing authorities are able to use all the vouchers allocated to them despite the households' 69% success rate in finding a unit because the housing authorities can issue more vouchers than the allocated quotas.

Every year, HUD announces a FMR for each metropolitan area. The FMR, which varies by the number of bedrooms in a unit, is set at the 40th or 50th percentile of the gross housing rent (including utility costs) in the metropolitan area. HUD relies on the most recently available census data on rents paid, with an adjustment for the local CPI and with additional adjustments to weight toward recently occupied standard-quality rental units. Given the FMR, the PHA sets the PS at 90–110% of the FMR.[4] The budget allotted to the PHA does not vary with changes in FMR, and the PHA determines the extent of any increase in the PS (McCarty, 2006).

Fig. 1 represents the budget set for a Section 8 household, with the quantity of composite good (Q_X) represented on the vertical axis and the quantity of housing services (Q_H) represented on the horizontal axis. This representation is very similar to that of Olsen (2003) and Eriksen and Ross (2015). In the absence of a Section 8 voucher, the household faces the linear budget constraint ABCGH, where the price of the composite good is P_X and the price of housing services is P_H. The household is eligible for a subsidy if it obtains a Section 8 voucher and consumes housing services above the minimum quality of housing services (Q_H^{MIN}). The subsidy is the difference between the rent (P_H Q_H) and 30% of adjusted income (0.3Y), as long as the rent is below the payment standard indicated by the red horizontal line in Fig. 1. The maximum housing service a household is able to purchase by paying 30% of adjusted income is denoted by Q_H^{PS} in the figure, and the maximum subsidy is P_H Q_H^{PS} – 0.3Y.

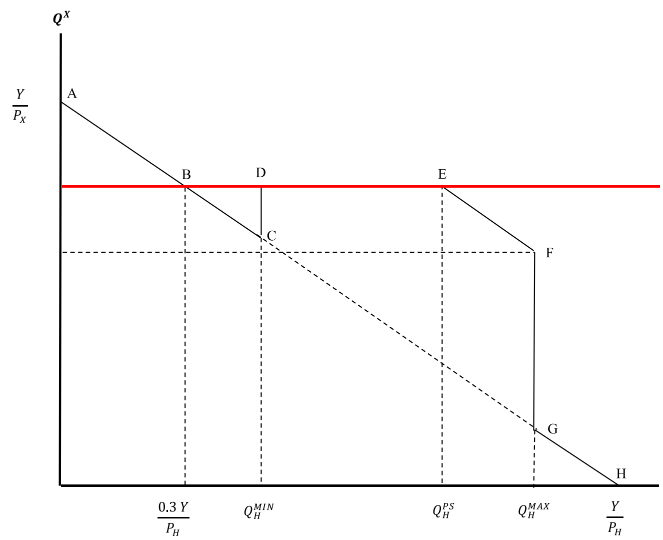
Since 1998, households may choose to rent a unit for higher than the PS, subject to contributing to no more than 40% of their adjusted income in the first year. If a household rents a unit above the PS, the maximum subsidy is capped at $P_H.Q_H^{PS}$ – 0.3Y and the difference between rent and the PS is borne by the household (EF). The household thus has an incentive to find an apartment for which the rent is between the rent ceiling and some rent, say $R_{Max,}$ such that the household's rent contribution does not exceed 40% of its adjusted income upon first occupancy but may contribute more in the subsequent years to avoid moving. Eriksen and Ross (2015) calculate R_{Max} to be 120% of the FMR for a household with three members who together earn 50% of the median income for the area. According to our calculations, the maximum rent for Los Angeles in 2015 is 124% of the FMR for a household with four members in a two bedroom apartment. However, the value of R_{Max} is unique to the household, and thus is not observable in our data set. The fact that some households are willing to pay rents higher than the PS increases the potential pool of renters who are willing to pay rents in a range higher but close to the PS.

Thus, households have an incentive to consume more housing while holding the consumption of other goods constant by moving from a point

[2] The Los Angeles Times suggests that households in Los Angeles county have waited at least a decade for a voucher (http://www.latimes.com/local/lanow/la-me-ln-section-8-waiting-list-20170922-htmlstory.html). According to the Housing Authority of the City of Los Angeles (HACLA), the Los Angeles City Housing voucher list opened for 2 weeks in October 2017 after being closed for thirteen years. Over 600,000 applications were expected, only 20,000 of whom were randomly selected to be put on waitlist and the voucher list is now closed again.

[3] According to research done by Abt Associates (2001), the median housing authority rejects between ¼ - ½ units after first inspection. HUD also audits the housing authorities, with the rent reasonableness being one of the key components of audit. The study finds the authorities to be highly compliant in ensuring rent reasonableness (ICF Macro, 2009).

[4] HUD must approve rents in excess of this limit.



Note: The red line denotes the Payment Standard.

Fig. 1. Budget set of Section 8 household.

D to E. However, given high search costs, they might be willing to consume housing services less than E if it is not worth their time to search for a slightly better unit. This is likely to result in bunching below the PS, indicated by higher density below the PS than in the absence of the kink in the budget constraint. On the other hand, some households may also choose to consume on the EF segment of the budget constraint by paying 30–40% of their adjusted income, which would also increase the density above the PS.

Landlords have an incentive to charge rents just below the PS to take advantage of the fact that voucher recipients do not bear the cost of the difference between the actual and the FMR rent. The voucher system also creates an incentive for charging rents just above the FMR because some voucher recipients may be willing to pay more than 30% of their income for a unit. Together, the kink and notch in the budget constraint suggests that there may be a bunching of rents just below and just above the PS. Of course, these predictions are conditional on the characteristics of the unit as they are irrelevant for a unit that warrants either a rent much in excess or far below the PS. We use an interval regression procedure to control for the effects of observable housing characteristics while also taking into account the tendency toward a higher density of rents near the PS.

3. Literature review

The first experiment to study the impact of housing vouchers on rent was the Housing Assistance Supply Experiment (HASE) in 1975–1980. It was conducted in two small Midwestern cities, Green Bay, WI and South Bend, IN. All applicants who met the income eligibility criteria were given the voucher. Studies suggest that the changes in rents in these two experimental cities due to the experiment were not significantly different from the rest of the country (Barnett, 1979; Struyk and Bendick, 1981; Lowry and Rand Corporation, 1983; Rydell, 1982). The program had little effect on market rent. According to Susin (2002), subsidies under the HASE program were very close to lump sum transfers, and had minimal habitability standards that did not induce households to move out of their current homes and thus did little to increase housing demand.[5] However, rent expenditures increased by about 8% due to the experiment (Lowry and Rand Corporation, 1983). Some studies also found that landlords in the two cities were more likely to maintain their unit to meet the quality requirements for the program.

Susin (2002) analyzed a similar question at the national scale using the American Housing Survey (AHS). He finds that low-income households in metropolitan areas with more vouchers have witnessed faster rent increases than areas with fewer vouchers. He found that vouchers have increased rents by 16% in the 90 biggest metropolitan areas, a result that he attributed to low supply elasticities in low quality rental markets. According to his analysis, these estimates imply that vouchers caused total rents paid by low-income non-recipients to increase by \$8.2 billion while providing a subsidy of only \$5.8 billion to recipients, resulting in a net loss of \$2.4 billion. Some studies have raised concerns about omitted variable bias in Susin's paper as the past allocation of vouchers might have been correlated with some determinants of rent (Khadduri and Wilkins, 2008; Olsen, 2003; Schill and Wachter, 2001).

Collinson and Ganong (2015) address the potential endogeneity of voucher levels by using exogenous changes in FMR to analyze the effects of housing voucher generosity. The two sources of variation considered are the revision of the FMR in 2005 (when the FMR was adjusted using the 2000 Census) and a policy change in 2001 that raised the FMR from the 40th to the 50th percentile of rent in an area. They estimate that a one-dollar increase in rent ceiling leads to a 46 cent increase in rents over the next six years, with no commensurate improvements in housing or neighborhood quality. They also analyze the effect of "tilting" the rent ceiling toward the higher quality neighborhood, i.e., setting the FMR at the zip code level rather than having a single ceiling for the whole metro area (Dallas, Texas in 2011). They find that this tilting led to an increase in rent in expensive neighborhoods and a decline in rents in low cost neighborhoods.

Eriksen and Ross (2015) use a panel of individual housing units in the Annual Housing Survey (AHS) to analyze the effect of increasing the supply of vouchers on rents. Comparing rents for 2000 and 2002, they find that voucher recipients rent more expensive units after receiving the subsidy, with the largest rent increases reserved for units near the rent ceiling in cities with inelastic supply. Their results suggest that a 10% increase in the number of vouchers resulted in a 0.39% increase in rents for units near the FMR and a 0.95% decrease in rent for low quality units.[6] They also find that the increase in rents is highest for units in MSAs where supply is relatively inelastic.

Prior literature on section 8 vouchers has analyzed whether vouchers affect market rents by changing the demand of rental housing. Our paper analyzes a different question: do the incentives for bunching around the payment standard influence the distribution of rents?

4. Statistical approach for analyzing the distribution of rents near the FMR

The primary objective of this study is to determine whether the FMR produces a bunching of rents near the notch in the household's budget constraint produced by the FMR.[7] Studies of behavioral responses to notches typically are based on simple histograms (e.g., Chetty, 2012; Kleven and Waseem, 2012; Saez, 2010). The typical analysis involves estimating flexible functions for the number of observations lying within a series of bins, and then testing whether there is a discontinuity at the kink/notch – which, in this case, is the FMR. The approach has several drawbacks for an analysis of the distribution of rents. First, rents are heavily concentrated at focal points throughout the range of the

[5] The experiments also funded the development of an elaborate housing market model by the Urban Institute. De Leeuw et al. (1975) simulated a full-scale voucher program, with an increase in people served but a smaller increase in demand by each household. The results imply a 40% rise in household's price in the worst case scenario.

[6] Units near the FMR are those that are within 20% of the FMR while low quality units are whose rent is below 80% of the FMR in 1997.

[7] As discussed earlier, we would like to analyze whether there is bunching around the PS but in absence of the PS for the entire sample period, we are running our analysis using the FMR.

distribution. More importantly, the approach does not account for the characteristics of the property. For example, large units in areas with views are likely to have rents far in excess of the FMR.

To estimate the effect of the FMR on the distribution of rents, we take advantage of the discrete nature of the rent data to estimate a modified version of an interval regression model. Rents are nearly always recorded in increments of $25: rents such as $800 or $825 are common; rents of $810 or $830 are extremely rare. To account for the discrete nature of the data, we adopt a linear function for the underlying latent variable for the monthly rent, R, and we assume that the actual rent is set to a discrete value of θ_j if $\theta_j \le R \le \theta_{j+1}$, where θ is the set of discrete $25 focal points encompassing the range of contract rents observed in the data set. The linear equation for the underlying latent variable is $R = X\beta + u$, where X is a set of explanatory variables representing characteristics of the property and neighborhood and u is an error term.

The interval regression model follows from an assumption that the error term is normally distributed, in which case the probability that the rent for observation i is equal to θ_j is given by $P_{ij} = \Phi\left(\frac{\theta_{j+1} - X_i\beta}{\sigma}\right) - \Phi\left(\frac{\theta_j - X_i\beta}{\sigma}\right)$. The implied likelihood function is equivalent to the expression for an ordinal probit model, but the values for the boundaries between regions, θ_j, are known rather than estimated. As a result, a normalization such as $\theta_1 = 0$ is not required, and the standard error, σ, is identified.

This simple version of interval regression is simply an extension of a hedonic price function to situation where the dependent variable is discrete, and it simplifies to a standard hedonic regression when the dependent variable is continuous. The empirical question addressed here is whether there is a higher probability of observing rents near the FMR than would be expected given the observed set of housing characteristics, X.[8] To account for the potential of either an increase or a decrease in the probability that rent lies in the regions close to but above or below the FMR, we adjust the probability by a factor of λ_1 for the region $R_* \le R \le FMR$ and by a factor of λ_2 for the region $FMR < R \le R^*$, where R_* and R^* are pre-set rents below and above the FMR. For the standard interval regression model, $P_{i^*} = \Phi\left(\frac{FMR - X_i\beta}{\sigma}\right) - \Phi\left(\frac{R_* - X_i\beta}{\sigma}\right)$, $P_i^* = \Phi\left(\frac{R^* - X_i\beta}{\sigma}\right) - \Phi\left(\frac{FMR - X_i\beta}{\sigma}\right)$, and $P_{ij} = \Phi\left(\frac{\theta_{j+1} - X_i\beta}{\sigma}\right) - \Phi\left(\frac{\theta_j - X_i\beta}{\sigma}\right)$ in other regions. Continuing with this notation, we then adjust the expressions for the two regions near the FMR by the factors λ_1 and λ_2, and adjust all the probabilities by the factor $1/(1 + (\lambda_1 - 1)P_{i^*} + (\lambda_2 - 1)P_i^*)$ to assure that the adjusted probabilities sum to one. Using Λ_i to denote the denominator of this expression, the adjusted probabilities are the following:

$$\text{Just below the FMR:} \quad Prob(R_* \le R_i \le FMR) = \lambda_1 P_{i^*}/\Lambda_i \tag{1}$$

$$\text{Just above the FMR:} \quad Prob\left(FMR < R_i \le R^*\right) = \lambda_2 P_i^*/\Lambda_i \tag{2}$$

$$\text{Elsewhere} \quad Prob\left(\theta_j \le R_i < \theta_{j+1}\right) = P_{ij}/\Lambda_i \tag{3}$$

The parameters $\beta,\ \sigma,\ \lambda_1$, and λ_2 are estimated by maximizing the log-likelihood function implied by these probabilities.

The extended version of the interval regression model simplifies to the standard interval regression approach when $\lambda_1 = 1$ and $\lambda_2 = 1$, and it simplifies to a linear regression when these conditions hold and the dependent variable is continuous. If the underlying hedonic price function is correctly specified, it is appropriate to use data from the full housing market rather than restricting the analysis to rents near the FMR because the additional information helps to identify the hedonic price function. The implicit assumption is that the voucher program is not large enough to alter the coefficients of the hedonic price function; instead, it simply increases the mass of willingness to pay in the region near the FMR. Although this assumption seems reasonable, it does come at a cost: in addition to the usual assumption that any missing variables are uncorrelated with the error term, the estimation procedure relies on the normality assumption for its validity. Moreover, we cannot claim that our estimates are fully causal in nature.[9] However, our data set does include a large number of relevant explanatory variables, and it also allows us to conduct a supplementary analysis in which we check whether units with rents near the FMR are also likely to have rents in the same region later on.

Fig. 2(a) and (b) illustrate the change in the distribution when λ_1 and λ_2 are different from 1. In the first case, λ_1 and λ_2 are both greater than 1, which produces additional mass below and above the FMR. In the second case, λ_2 is again greater than 1, but λ_1 is less than 1. These values lead to additional mass just above the FMR, but a low mass in the region just below it. The rest of the distribution adjusts downward to account for relatively high increase in mass in the region just above the FMR.

Table 1 shows the values for R_* and R^* used in this study, along with the FMR. As an example, consider the case of a 1-bedroom apartment in 2008. The FMR is $1041, which lies between the focal points $1025 and $1050. We extend the range for R_* and R^* to the next set of focal points, $1000 and $1075 because it is reasonable to expect these values to also be influenced by the FMR. For the interval regression, we combine the year and bedroom categories and thus gain power by estimating a single regression. We include year fixed effects to control for time trends and dummy variables to account for heterogeneity in the number of bedrooms.

5. Data

AREA has conducted semi-annual surveys of rents in Los Angeles since 2005. They send a team of people to inquire about the availability of apartments in all areas of the city where rental units are available. The analysts record information on gross and net asking rents and such characteristics of the units as square footage, the number of bedrooms and bathrooms, and even such detailed features as whether microwaves and washer/dryers are included with the unit. We use gross asking rents (which include utilities) in our analysis, but for brevity we will refer to them as rents.[10] The survey also includes the analyst's assessment of the condition of the building on a 4-point scale, ranging from 1 (excellent) to 4 (poor). Although the data set is not a full panel, many units were surveyed more than once over the 2007–2015 period analyzed here. The surveys are conducted in two waves each year, first in February/March and then August/September.

Table 2 presents a list of the variables used in the study, along with their sample means. Fig. 3 shows average rents and the values for FMR by year. The sharp downturn in the housing market that began at the end of 2007 is reflected in Fig. 1, although average rents did not decline until 2009. The values of FMR continued to grow, and by 2009 the FMR was higher than the average rent for all three apartment sizes. The FMR began to decline in 2012 while average rents were again rising. By 2014, the values of FMR were again lower than average apartment rents for all three apartment sizes.

We also collected data for PS for July 2013 to December 2015 from

[8] Housing characteristics used in the interval regression explain approximately 73% of the variation in price.

[9] It is difficult to disentangle causality because the FMR is changing smoothly and on average the year to year variation in the FMR for our sample data is about 2%. Also, the PS and the FMR do not change at the same time.

[10] We drop observations which have gross rent more than $5000.

tenant and landlord newsletters published by the Housing Authority of the City of Los Angeles (HACLA).[11] HACLA set new PS values in July 1, 2013, July 1,2014[12] and December 15, 2015.[13] Table 3 shows the PS in levels and as a percentage of FMR for studio, 1 and 2 bedroom apartments. The ratio of PS to FMR increased to an average of 105.6% in July2014,[14] from an average of 96.7% in July 2013 as the FMR decreased during this period but the PS continued to rise.[15] Since, the PS is around 100% of FMR, we conduct our base analysis using the FMR while using the PS for period when it is available. We also conduct robustness tests using alternative ratios of PS to FMR.

6. FMR and the distribution of rents

Fair Market Rents change annually, and the rates vary by the number of bedrooms. However, the rates do not vary by neighborhood: one rate applies for any comparable property within Los Angeles. Fig. 1 shows the FMR for 0–2 bedroom apartments for Los Angeles over time. The FMR range from $789 for a studio apartment in 2007 to $1465 for a 2-bedroom unit in 2011.

The distribution of rents recorded in the AREA surveys for studio apartments for 2007–2010 is shown in Fig. 4.[16] The red lines show the FMR. The results suggest a significant degree of clustering around focal points, particularly even 100s and 50. For all years other than 2009, there appears to be a spike in the number of units charging rents in the region just above the FMR, i.e., for $FMR < R \leq R^*$. In contrast, 2009 and 2013 are the only years for which there is a large number of units in the region just below the FMR, for which $R_* \leq R \leq FMR$.

Figs. 5 and 6 show comparable histograms for 1 and 2 bedroom apartments for the period 2007–2010. For 1-bedroom apartments, there appears to be some bunching in the region just above the FMR for 2009 and 2011, while there is a large number of observations with rent just below the FMR in 2010 and 2013. For 2-bedroom apartments, there is a large number of units with rents just above the FMR for 2007, 2009, 2011 and 2012, and a large number of observations with rent just below the FMR in 2008, 2010 and 2012.

As discussed earlier the PS, creates a kink in the budget constraint and thus we would expect rents to bunch around the PS, resulting in a discontinuity around this point. We test whether there is a discontinuity at the fair market rent by combining the bedroom/year pairs and taking the difference between the rent and the corresponding FMR. The McCrary (2008) regression discontinuity test plot,[17] presented in Fig. A.4 in the appendix, suggests that the underlying density function of the difference between Rent and FMR is discontinuous at zero. The graph indicates that the density of rents below the FMR is high.

Although the histograms are suggestive, they do not show whether the results are statistically significant. Following Kleven and Waseem (2012), we use the cell counts from the histograms as dependent variables, with a cubic spline in rent as the primary explanatory variable.[18] Additional explanatory variables include an indicator that the rent ends with 50 or 100, along with variables indicating that the cell represents the regions just below and just above the FMR.

The results are presented in Table 4. The coefficients for the variable "Rent ends in 50 or 100" is always positive and statistically significant, indicating that rents cluster around values of 50 or 100. All the estimated coefficients for the variable indicating that a cell is just below the FMR are statistically insignificant, suggesting that there is not a significant bunching of rents just below the FMR. In contrast, the majority of the estimated coefficients are statistically significant for cells just above the FMR, indicating the presence of clustering of rents above the FMR. The results are similar when we change the cutoff value to 110% of the FMR, as summarized in Appendix Table A.2.

We repeat the rent frequency analysis using the PS for the two years for which we have the data and find our results to be consistent with those using the FMR. As suggested by the results in Table 5, there is no clustering below the PS but rents cluster above the PS for 2014–2015 period (surveys conducted in August/September 2014 and two rounds of survey in 2015).[19]

Although the results vary somewhat over time, they do suggest a relationship between the FMR and average rents. However, the results of this analysis cannot establish conclusively whether changes in rents are a direct result of changes in the FMR.

Table 6 shows the results of the interval regression model. In contrast to the spline regressions, the interval regression models take into account standard hedonic rent variables such as apartment size and neighborhood fixed effects.[20] The results suggest that there is a tendency for the rents to cluster around the FMR. The estimated values of both λ_1 and λ_2 are statistically significantly greater than 1, which implies a high concentration of rents both below and above the FMR.

The interval regression results differ somewhat from the rent frequency regressions (i.e. the spline method): the interval regressions indicate significant bunching on both sides of the FMR, while the spline only finds significant bunching above the FMR. The spline regressions do not control for characteristics of the units. Some units, such as particularly large ones or perhaps those located in particular neighborhoods, are unlikely to have rents near the FMR. On the other hand, there may be units with other characteristics or in certain neighborhoods that are relatively likely to have rents near the FMR based on the expected rent from the hedonic price function. The interval regression is designed to detect bunching beyond what would be expected simply given the characteristics of the units and their locations. There may be additional

[11] HUD does not receive information on the PS unless it exceeds the 90–110 band, in which case the high rent requires HUD's approval. We contacted HACLA and HUD's Los Angeles field office but were unable to get any information on PS for the City of Los Angeles, and economists at HUD and CBPP could not suggest an alternative way of obtaining the data.

[12] Effective March 2014 for new admissions and re-contracts.

[13] We went through all the newsletters from 2013 onwards and did not find any notification of changes in PS in July 2015. For the City of Los Angeles, the new PS used to be announced in February/March and would be effective July. However, recent newsletters indicate that the PS change is effective December for the period beginning December 2015. Thus, we assume that the PS did not change between the period July 2014 to December 2015 (effective March 1, 2016 for annual reexaminations) as we did not find any notification of changes in PS in the newsletter.

[14] Effective March 1, 2014 for new admissions and re-contracts.

[15] The FMR increased in October 2014 while the PS stayed the same. As result the ratio of PS to the FMR decreased marginally to an average of 103.7 in FY2015.

[16] The distribution of rents for studio, 1-bedroom and 2-bedroom apartments for 2011–2014 is shown in Appendix Figs. A.1–A.3 respectively.

[17] The z statistic of the McCrary (2008) regression discontinuity test is −6.92 and the p value is 4.40e-12, indicating that we can reject the null hypothesis of no sorting.

[18] We use six knots for all regressions, i.e., $y = \alpha + \sum_{j=1}^{3} \beta_j (R - R_0)^j + \sum_{k=1}^{6} \theta_k (R - R_k)^3 D_k$, where y is the frequency and R is the midpoint of the rent for the cell. $R_0, R_1, \ldots, R_7$ are equally spaced knots spanning the range of rent for the histogram, and D_k is a dummy variable that equals one if $R \geq R_k$ (Suits et al., 1978).

[19] The PS for the City of Los Angeles changed in July 2013, July 2014 (effective March 2014 for new admissions) and then in December 2015 (effective December 15, 2015 for new admissions and March 1, 2016 for annual reexaminations). Thus, we use the same PS for the three rounds of survey – August/September 2014, February/March 2015 and August/September 2015. The results do not change significantly even if we exclude the August/September 2015 period with estimated value of λ_1 and λ_2 at 1.430 (s.e. 0.08) and 1.298 (s.e. 0.08) respectively.

[20] The neighborhood definitions are taken directly from AREA, who delineate 38 neighborhoods across Los Angeles. We also include year fixed effects in the interval regression to control for time trends.

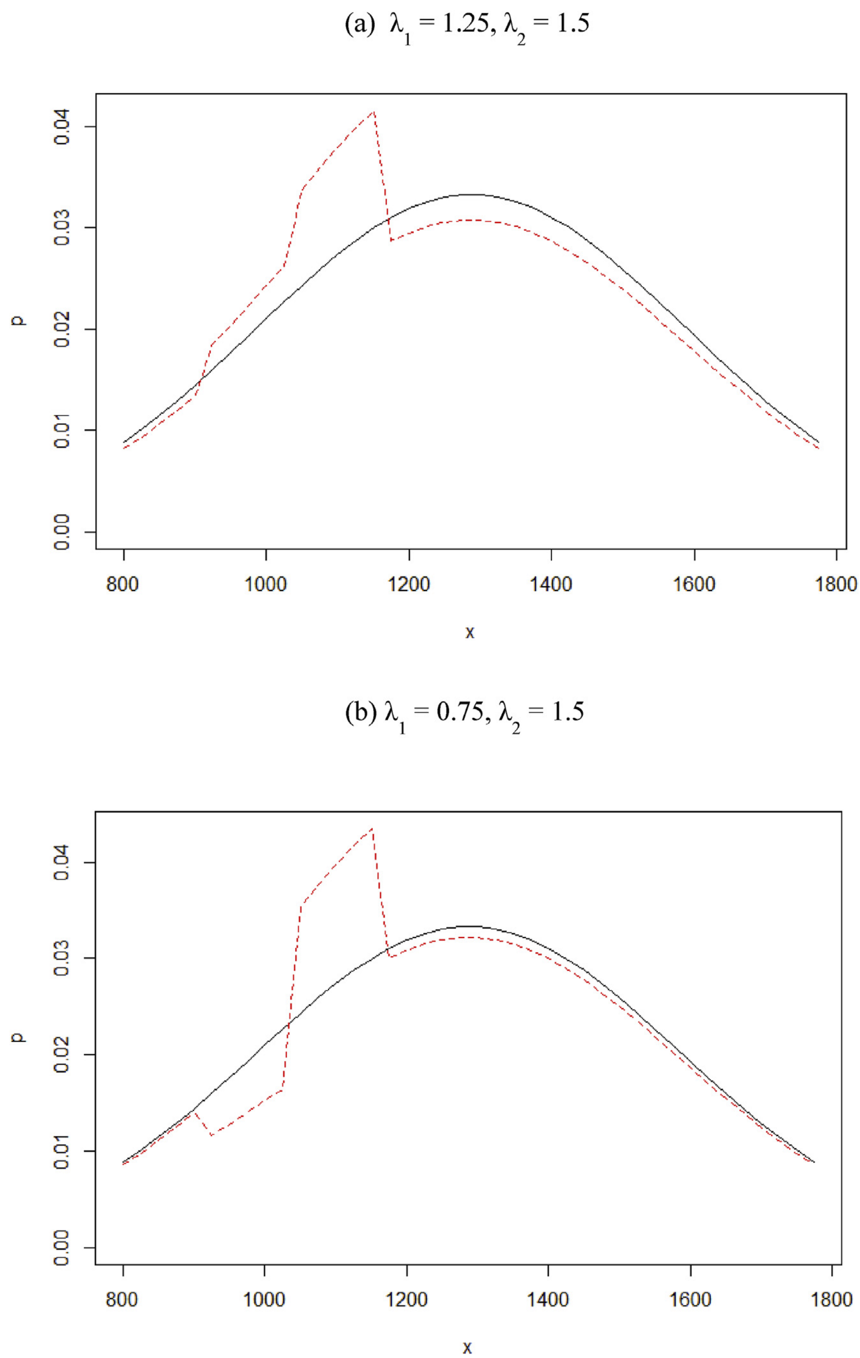


Fig. 2. Adjust probabilities for 925–1025 and 1050-1150.

bunching on one side of the FMR that is indicated by the interval regression but not by the spline method if the observed characteristics do not lead to a high probability of locating near the FMR but there does turn out to be significant bunching in that region of rents. Since this situation is exactly what we are trying to detect, the interval regression is a much preferable method in this context.

As a robustness check in Table 7, we re-compute the estimates of λ_1 and λ_2 using different ratios of the FMR. The robustness checks also help to account for the fact that the FMR is not identical to the PS. The coefficient for λ_1 is strongest at 90% of the FMR, which implies a strong presence of bunching below 90% of the FMR. Table 3 indicates that for our sample the PS is typically more than 95% of the FMR. However, our results indicate that maximum bunching occurs below the 90% of the FMR as indicated by the λ_1 coefficient. As an illustration, assume the FMR is $1030 when using 90% of the FMR. In this case, 90% of the FMR of $927, which is slightly below the PS which is $978 (assuming the PS is 95% of the FMR). Although we might expect most significant bunching in the $950 - $975 range, empirically we see rents clustering in the $900 to $925 region. This indicates that bunching is not tied strictly to a single point, and there is additional mass around the $900 region.

The fact that the rent distribution appears to have additional mass in the region below the FMR may simply indicate that the rent setting process is not as precise as theory suggests. However, it may also be due partly to differences in the timing of adjustment of the PS and the FMR, as the FMR is effective October 1 of the fiscal year while the PS was effective July 1 of the following year for upcoming annual re-examinations in much of our sample. Moreover, in a few instances, the rent was not affected by a new voucher payment standard until a second annual re-

Table 1
Rent intervals.

Year	R_*	FMR	R^*	$[R_{min}, R_*)$, Number Obs.	$[R_*, FMR]$, Number Obs.	$(FMR, R^*]$, Number Obs.	$(R^*, R_{max}]$, Number Obs.
Studio Apartments							
2007	800	843	875	331	77	92	326
2008	825	863	900	271	58	68	169
2009	875	904	950	438	61	29	66
2010	900	943	975	555	25	12	54
2011	925	973	1000	479	19	14	40
2012	925	961	1000	501	25	30	69
2013	875	911	950	302	62	38	128
2014	850	896	925	242	86	39	238
2015	875	913	950	200	50	37	287
1-Bedroom Apartments							
2007	975	1016	1050	755	164	83	785
2008	1000	1041	1075	509	51	59	604
2009	1050	1090	1125	712	44	79	238
2010	1100	1137	1175	1027	42	30	173
2011	1125	1173	1200	1047	29	40	165
2012	1125	1159	1200	1056	51	49	211
2013	1075	1101	1150	756	76	49	414
2014	1050	1083	1125	608	67	100	515
2015	1075	1103	1150	488	76	56	681
2-Bedroom Apartments							
2007	1225	1269	1300	525	106	112	1389
2008	1275	1300	1325	325	72	7	896
2009	1325	1361	1400	593	48	83	418
2010	1375	1420	1450	823	85	31	322
2011	1425	1465	1500	948	38	70	410
2012	1400	1447	1475	818	53	52	443
2013	1375	1421	1450	676	86	39	568
2014	1350	1398	1425	476	129	64	713
2015	1375	1424	1450	357	106	52	883

Table 2
Variable means.

Variable	Studio	1 Bedroom	2 Bedrooms
Monthly Rent	$875	$1098	$1567
500–750 s.f.	0.830	0.801	0.137
751–1000 s.f.	0.011	0.180	0.648
1001–1250 s.f.	0.001	0.009	0.145
1251–1500 s.f.	0.000	0.001	0.047
1501–2000 s.f.	0.000	0.001	0.019
2001 + s.f.	0.002	0.002	0.005
Dishwasher	0.121	0.262	0.416
Elevator	0.250	0.237	0.222
Fireplace	0.025	0.051	0.148
Microwave	0.114	0.125	0.197
Refrigerator	0.421	0.300	0.280
High-Rise Building	0.116	0.083	0.073
Mid-Rise Building	0.324	0.272	0.256
Exterior Rating = 1	0.029	0.048	0.075
Exterior Rating = 2	0.123	0.167	0.228
Exterior Rating = 3	0.726	0.720	0.651
2 Units in Building	0.037	0.060	0.096
3–4 Units in Building	0.051	0.089	0.126
5 + Units in Building	0.894	0.820	0.675
Single-Family Detached	0.002	0.003	0.062
1.5 Bathrooms	0.000	0.004	0.070
2 Bathrooms	0.000	0.002	0.364
Observations	5533	11,908	12,869

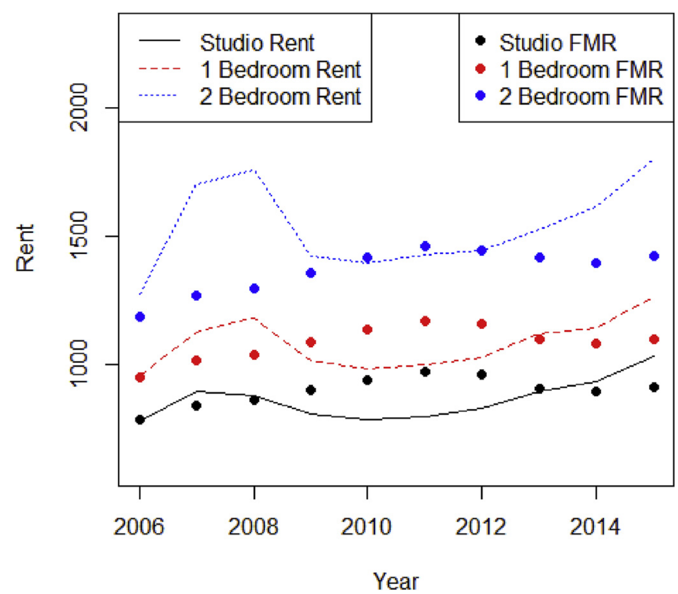


Fig. 3. Average rents and FMR by year.

examination if the tenant stayed in the same unit.[21] Since rents adjust annually, there is not a one to one correspondence between change in rents and the FMR. Finally, due to high search cost, some households may be willing to choose units that rent for less than the PS.

The value of λ_2 is strongest at 80% of the FMR, most likely because it is capturing some of the bunching below the true cutoff. Both coefficients are statistically greater than 1 for a broad range of values for the cutoff.

Table 3
Payment standard.

Payment Standard	Studio	1 Bedroom	2 Bedroom
Effective July 2013	911.0	1046.0	1350.0
As a % of FY2012 FMR	100.0	95.0	95.0
Effective July 2014	958.0	1156.0	1443.0
As a % of FY2013 FMR	106.9	106.7	103.2

There is also a monotonic decrease in magnitude as we move to cut offs

[21] As announced in the March–September 2013 HACLA's tenant newsletter.

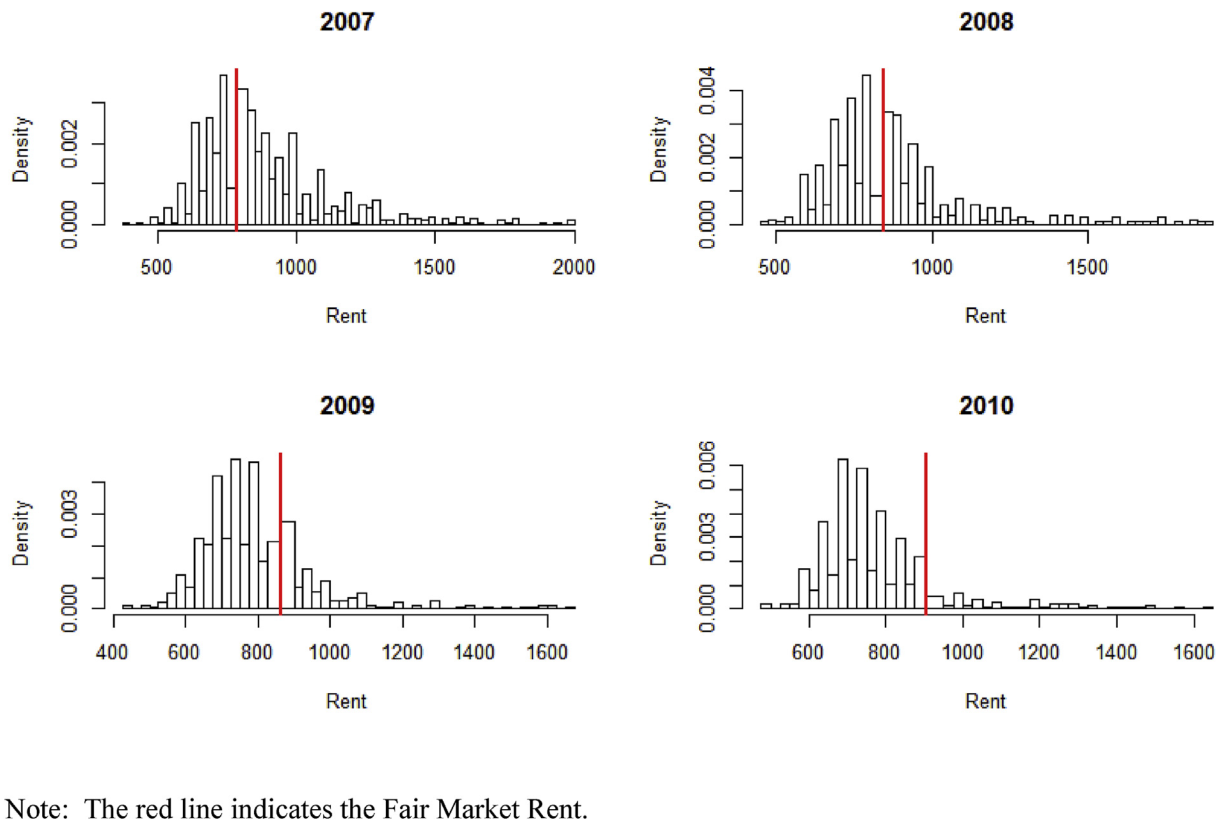


Fig. 4. Distribution of rents for studio apartments.

which are below or above the 90–110% band of the FMR. Thus, our estimates are robust to alternative values of the cutoffs, and suggest that there is a strong tendency toward a high density of rents near the FMR. Since the PS are typically within 90–110% of the FMR, these results also imply a tendency to bunch near the PS.

Our analysis has focused on the FMR rather than the PS because we have only limited data on the latter. As a further robustness check, we repeat the analysis using the PS for the period for which it is available, August/September 2013 to August/September 2015. The data on the PS are drawn from "Section 8 Tenant Newsletter" and "Section 8 Owner Newsletter", which is published by the Housing Authority of the City of Los Angeles (HACLA).

Table 8 summarizes the results for the rent interval regressions obtained using the PS in place of the FMR. The first column of the table suggest that the results are similar to those obtained using the FMR: the estimated values of λ_1 and λ_2 are both statistically greater than 1, and the estimates are very close to those presented for the FMR in Table 6. The second and third columns of the table summarize the results for placebo experiments that use the values of PS from November 2016 and November 2017 in place of the actual values, which are dates after those used for the interval regressions. If rents were clustering around the PS, we should expect clustering to be smaller or disappear around the "placebo" PS. We find that both λ_1 and λ_2 decrease monotonically as we move further away from the true PS (the PS had been increasing over this period). The results of the placebo test imply less bunching in the region near the placebo FMR values, particularly for the PS from November 2017.

Another potential concern could be that units that are just below the FMR are not comparable to units that are just above the cut off. Table A.1 in the appendix presents the differences in the characteristics below and above the FMR. The differences are not statistically significant except for a few categories where the differences are very small in magnitude.

In the next section, we test whether the pattern of bunching near the FMR kink is persistent over time for units that appear more than once in the sample.

7. Changes in rents over time

If the FMR directly influences rents, we would expect some persistence in the tendency for apartments to have rents near the FMR over time. We define four broad categories for rent: Rent $< R_*$, $R_* \leq$ Rent $\leq$ FMR, FMR $\leq$ Rent $< R^*$, and Rent $\geq R^*$. Since rental contracts typically are for a year, we analyze changes in rents over an interval of at least two years, which ensures that rents will not persist simply because the contract does not allow for changes over the time under consideration. Restricting the sample to individual apartments for which we observe rents for at least two survey periods that are two or more years apart produces 2955 pairs of rents.

The results for the full set of 2955 rent pairs are shown in Table 9. To understand how this table is constructed, consider the first column of results. Over the full 2007–2015 period, we observe 1375 instances where an apartment has Rent $< R_*$ in two survey periods that are at least two years apart. We have 1658 instances where the first observation in a pair has Rent $< R_*$, and we have 1771 instance where the second observation in a pair falls in this category. Thus, by chance we would expect to observe (1658/2955)x(1771/2955)$\times$2955 = 993.68 occasions where both observations in a pair have Rent $< R_*$. The variance for this cell is given by 993.68$\times$(1–1658/2955)x(1–1771/2955) = 174.75, which implies a T-value for the difference between the actual and expected number of occurrences of (1375–993.68)/13.22 = 28.85 (Agresti, 1996). Thus, the actual number of times when Rent $< R_*$ in both periods is greater than what we would expect to observe by chance alone.

Table 9 suggests that rents at the upper and lower ends of the distribution – i.e., when Rent $> R^*$ or Rent $< R_*$ are persistent over time. Rents are unlikely to fall in one end of the distribution in an early year and then in the other end of the distribution in a subsequent year. The more interesting case occurs when the rent in the earlier period is either

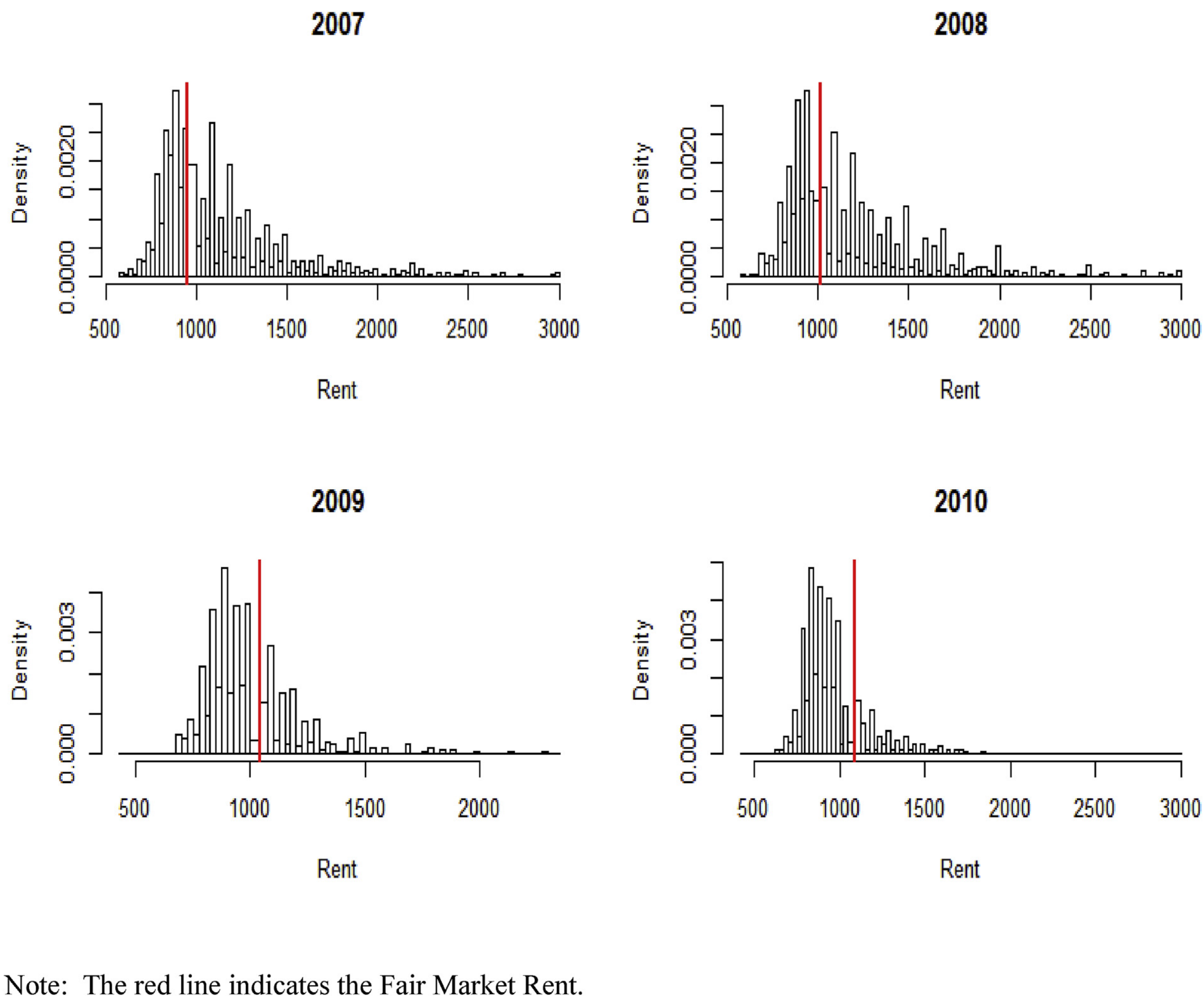


Fig. 5. Distribution of rents for 1-bedroom apartments.

just below or just above the FMR. Of 179 instances where rent is just below the FMR in the earlier period in a pair, there are only 15 occasions where we also observe $R_* \leq$ Rent $\leq$ FMR in the later period. Although this number is greater than the approximately 11 times we would observe this pattern by chance, the difference is not statistically significant. In contrast, we can reject the null hypothesis that the 21 occasions where the rent was just above the FMR in two periods is not greater than the approximately 9 times we would expect to observe this combination by chance.

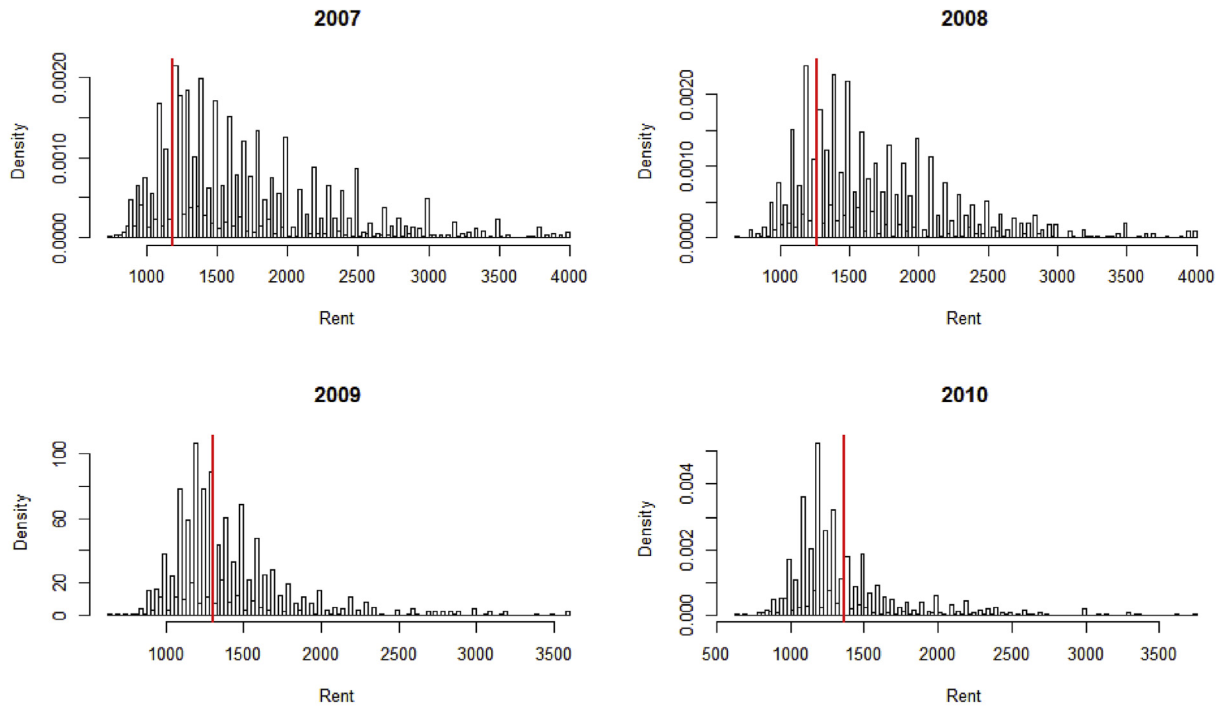
Table 10 presents contingency tables for the three sets of apartment sizes. The table suggests that this pattern of a relatively high probability of persistence for rents just above the FMR is confined to studio and 1-bedroom apartments. The coefficient is positive but not statistically significant for 2-bedrooms apartments. We suspect that the insignificant result for 2-bedrooms apartments is explained by asking too much of a data set with a relatively small number observations within individual cells, but we cannot rule out the possibility that a larger data set would produce similar results. In no case do we observe persistence for rents falling just below the FMR. For 2-bedroom apartments, we also find that a significant number of apartments shift from being rented below the FMR in the earlier period to above the FMR in the latter period.

An important caveat to these results is that we do not observe whether the units are occupied by voucher recipients or households that do not receive subsides. Thus, we cannot determine whether the tendency for persistence in rents above the FMR is due to voucher recipients or unsubsidized households to be in this same range over time, or if the status of the renter occupying the unit changes over time.

8. Conclusion

The Housing Choice Voucher program creates a kink in an eligible household's budget constraint at the payment standard. Since households pay the same share of income when they choose apartments with rents at or just below the PS, they have an incentive to find apartments with rents close to the PS. However, due to high search cost, some households are willing to choose units that rent for less than the PS. On the other hand, some households also have an incentive to rent above the PS as they can consume more housing by paying up to 40% of the adjusted income in the first year of the lease and a higher percentage in the subsequent year of lease. Thus, the program provides the potential for a bunching of rents at levels just below and just above the PS.

We test this prediction using a methodology that simultaneously accounts for the bunching of rents near the FMR and the tendency for rents to be charged in increments of $25. The empirical approach is based on an extension of the interval regression model, with extra mass added to the regions just below and just above the FMR. This method is preferable over the standard spline regressions as it controls for the characteristic of the unit and their location. Using a unique survey of rental units in Los Angeles for 2007–2015, we find a tendency for bunching of rents in these two regions. The tendency for rents to cluster above the FMR is more



Note: The red line indicates the Fair Market Rent.

Fig. 6. Distribution of rents for 2-bedroom apartments.

Table 4
Rent frequency regressions.

Variable	Studio Apartments		1 Bedroom		2 Bedroom	
	Coef.	T-Value	Coef.	T-Value	Coef.	T-Value
2007						
Rent ends in 50 or 100	0.913	7.669	0.933	10.033	1.432	13.279
$R_* \leq R \leq PS$	0.094	0.236	−0.054	−0.146	0.035	0.074
$FMR < R \leq R^*$	1.291	2.422	0.565	1.153	1.927	2.974
2008						
Rent ends in 50 or 100	0.949	7.666	1.002	10.126	1.305	13.412
$R_* \leq R \leq FMR$	−0.285	−0.708	−0.467	−1.189	0.072	0.168
$FMR < R \leq R^*$	1.311	2.446	0.694	1.344	−0.572	−0.978
2009						
Rent ends in 50 or 100	0.526	4.616	0.709	5.663	1.126	10.994
$R_* \leq R \leq FMR$	0.213	0.640	−0.744	−1.704	−0.473	−1.132
$FMR < R \leq R^*$	0.749	1.684	1.212	2.104	1.715	2.976
2010						
Rent ends in 50 or 100	0.761	5.951	0.570	6.059	0.967	9.822
$R_* \leq R \leq FMR$	0.120	0.327	−0.294	−0.799	0.321	0.781
$FMR < R \leq R^*$	0.851	1.717	0.952	1.892	0.941	1.657
2011						
Rent ends in 50 or 100	0.606	5.453	0.520	4.814	1.090	11.654
$R_* \leq R \leq FMR$	0.270	0.728	−0.686	−1.708	−0.562	−1.404
$FMR < R \leq R^*$	1.430	3.067	1.308	2.391	1.584	2.884
2012						
Rent ends in 50 or 100	0.752	4.756	0.680	6.946	0.972	10.779
$R_* \leq R \leq FMR$	0.162	0.314	−0.027	−0.076	−0.136	−0.348
$FMR < R \leq R^*$	1.928	3.056	1.259	2.566	1.201	2.273
2013						
Rent ends in 50 or 100	0.725	5.941	0.897	8.154	1.176	11.893
$R_* \leq R \leq FMR$	0.178	0.465	−0.673	−1.607	−0.283	−0.635
$FMR < R \leq R^*$	1.084	2.102	0.715	1.244	0.801	1.312
2014						
Rent ends in 50 or 100	0.899	7.384	0.725	6.913	1.314	11.619
$R_* \leq R \leq FMR$	0.015	0.039	−0.307	−0.741	0.628	1.327
$FMR < R \leq R^*$	0.773	1.527	1.358	2.490	1.299	2.062
2015						
Rent ends in 50 or 100	0.804	6.780	1.123	12.140	1.435	14.155
$R_* \leq R \leq FMR$	−0.408	−1.107	−0.106	−0.290	−0.109	−0.246
$FMR < R \leq R^*$	0.622	1.295	1.255	2.622	1.189	1.995

Note. The regressions also include cubic splines for rent as explanatory variables.

Table 5
Rent Frequency Regressions using Payment Standards. Note. The regressions also include cubic splines for rent as explanatory variables.

Variable	Studio Apartments		1 Bedroom		2 Bedroom	
	Coef.	T-Value	Coef.	T-Value	Coef.	T-Value
2013–2014						
Rent ends in 50 or 100	0.739	4.787	0.753	7.304	1.140	11.357
$R_* \le R \le PS$	0.005	0.010	−0.573	−1.440	−0.276	−0.616
$FMR < R \le R^*$	0.886	1.415	0.082	0.153	−0.434	−0.701
2014–2015						
Rent ends in 50 or 100	0.915	8.167	1.116	11.633	1.509	13.757
$R_* \le R \le PS$	0.250	0.662	−0.180	−0.491	−0.164	−0.343
$PS < R \le R^*$	1.890	3.857	1.664	3.429	1.301	2.025

Table 6
Estimation results for probability parameters.

Using FMR			
Constant	1385.144	Exterior Rating = 1	380.528
	(28.32)		(10.50)
500 + s.f.	39.652	Exterior Rating = 2	195.113
	(9.60)		(9.68)
Bedroom = 0	−500.288	Exterior Rating = 3	78.63
	(6.56)		(9.15)
Bedroom = 1	−301.596	1.5 Bathrooms	127.14
	(4.73)		(7.39)
Dishwasher	104.596	2 Bathrooms	125.078
	(4.25)		(4.95)
Elevator	12.478	2 + Bathrooms	401.024
	(5.41)		(7.99)
Fireplace	130.625	2 Units in Building	−22.79
	(4.47)		(8.22)
Microwave	171.983	3–4 Units in Building	−98.807
	(4.09)		(8.74)
View	93.01	5 + Units in Building	−169.595
	(6.00)		(7.81)
Single-Family Detached	376.661	λ_1	1.594
	(8.38)		(0.04)
High-Rise Building	94.692	λ_2	1.455
	(7.04)		(0.04)
Mid-Rise Building	−25.81	σ^2	260.197
	(5.24)	Log likelihood	−113103.69
Sample size: 30310			

Note. Standard errors are in parentheses. The regressions also include controls for neighborhood and year fixed effects. Base category is 2 bedroom apartments.

Table 7
Robustness for interval regression.

	λ_1		λ_2	
	Coefficient	Standard Error	Coefficient	Standard Error
65% of FMR	0.446	(0.03)	1.015	(0.04)
70% of FMR	1.151	(0.04)	1.897	(0.05)
80% of FMR	2.644	(0.06)	3.110	(0.07)
90% of FMR	2.864	(0.06)	2.567	(0.06)
95% of FMR	1.987	(0.05)	1.756	(0.04)
100% of FMR	1.594	(0.04)	1.455	(0.04)
105% of FMR	1.211	(0.03)	1.426	(0.04)
110% of FMR	1.176	(0.03)	1.128	(0.04)
120% of FMR	1.068	(0.04)	0.828	(0.03)
125% of FMR	0.826	(0.03)	0.864	(0.03)

Note. The regression specification is same as that of Table 6.

Table 8
Interval Regression results using Payment Standards.

	Key Result	Placebo Experiments	
	Payment Standard	PS from Nov. 2016	PS from Nov. 2017
Constant	1158.697	1112.917	1109.603
	(65.53)	(60.55)	(59.03)
500 + s.f.	80.127	93.155	92.956
	(22.18)	(20.51)	(20.05)
Bedroom = 0	−502.923	−503.531	−502.509
	(13.49)	(12.95)	(12.66)
Bedroom = 1	−324.125	−326.037	−325.377
	(10.05)	(9.64)	(9.43)
Dishwasher	106.864	111.062	110.366
	(8.52)	(8.26)	(8.09)
Elevator	32.686	32.859	33.116
	(10.86)	(10.51)	(10.28)
Fireplace	93.164	100.55	100.179
	(9.28)	(8.92)	(8.74)
Microwave	157.459	147.553	146.822
	(8.10)	(7.79)	(7.63)
View	310.488	303.735	302.98
	(11.10)	(10.65)	(10.46)
Single-Family Detached	338.075	337.895	337.87
	(17.84)	(17.15)	(16.81)
High-Rise Building	40.509	40.998	41.178
	(14.37)	(13.86)	(13.57)
Mid-Rise Building	−39.85	−38.211	−37.915
	(10.27)	(9.93)	(9.72)
Exterior Rating = 1	507.029	474.1	473.306
	(35.81)	(34.02)	(33.34)
Exterior Rating = 2	312.725	284.46	283.223
	(34.86)	(33.07)	(32.42)
Exterior Rating = 3	174.317	139.392	138.918
	(33.84)	(32.07)	(31.44)
1.5 Bathrooms	146.779	141.927	142.124
	(16.37)	(15.71)	(15.38)
2 Bathrooms	102.713	96.651	96.408
	(10.24)	(9.79)	(9.58)
2 + Bathrooms	348.173	342.607	343.119
	(20.78)	(19.98)	(19.58)
2 Units in Building	−50.119	−44.136	−43.36
	(17.03)	(16.23)	(15.90)
3–4 Units in Building	−108.054	−102.713	−101.735
	(17.81)	(17.00)	(16.65)
5 + Units in Building	−182.964	−178.136	−177.174
	(16.10)	(15.46)	(15.14)
λ_1	1.578	1.348	1.161
	(0.08)	(0.07)	(0.08)
λ_2	1.463	1.188	0.849
	(0.08)	(0.07)	(0.06)
σ^2	264.952	257.139	255.213
Log likelihood	−30528.652	−30308.921	−30416.184
Sample size	8138	8138	8138

Neighborhood and year fixed effects included, Includes only 0, 1 and 2 bedrooms. Standard errors are in parentheses.

consistent over time than in the region below the FMR. An analysis of rent changes for the subset of observations for which rents are observed over several periods suggests that units with rents that are just above the FMR in a period are also likely to have rents in the region just above the FMR two or more years later.

Appendix

Table 9
Contingency table of rent changes with 0–2 bedrooms.

Earlier Period	Later Period				
	Rent < R_*	$R_* \leq$ Rent $\leq$ FMR	FMR $\leq$ Rent < R^*	Rent $\geq$ R^*	Row Total
Rent < R_*	Actual = 1375	101	58	124	1658
	Expected = 993.68	100.43	90.33	473.55	
	T-Value = 28.85	0.09	−5.28	−28.69	
$R_* \leq$ Rent $\leq$ FMR	109	15	16	39	179
	107.28	10.84	9.75	51.13	
	0.27	1.34	2.12	−2.07	
FMR $\leq$ Rent < R^*	88	10	21	42	161
	96.49	9.75	8.77	45.98	
	−1.40	0.08	4.37	−0.71	
Rent $\geq$ R^*	199	53	66	639	957
	573.55	57.97	52.14	273.34	
	−30.05	−0.82	2.40	31.82	
Column Total	1771	179	161	844	2955

Note. The data set includes 2955 pairs of rents for apartments over intervals of at least 2 years.

Table 10
T-values for rent changes.

Earlier Period	Later Period				
	Rent < R_*	$R_* \leq$ Rent $\leq$ FMR	FMR $\leq$ Rent < R^*	Rent $\geq$ R^*	Row Total
Studio Apartments					
Rent < R_*	9.55	−0.10	−3.46	−9.30	414
$R_* \leq$ Rent $\leq$ FMR	−0.57	0.05	1.14	0.03	50
FMR $\leq$ Rent < R^*	−0.15	−0.30	2.83	−1.14	45
Rent $\geq$ R^*	−11.34	0.29	1.51	12.31	106
Column Total	416	48	29	122	615
1 Bedroom					
Rent < R_*	18.71	−0.11	−3.29	−18.93	718
$R_* \leq$ Rent $\leq$ FMR	−0.66	1.60	−0.04	−0.05	66
FMR $\leq$ Rent < R^*	−2.77	1.02	3.64	0.54	66
Rent $\geq$ R^*	−18.48	−1.20	1.75	20.20	346
Column Total	770	59	74	293	1196
2 Bedrooms					
Rent < R_*	18.99	0.22	−2.88	−18.41	526
$R_* \leq$ Rent $\leq$ FMR	1.24	0.55	2.84	−2.84	63
FMR $\leq$ Rent < R^*	0.12	−0.68	0.97	−0.22	50
Rent $\geq$ R^*	−19.68	−0.19	1.19	19.88	505
Column Total	585	72	58	429	1144

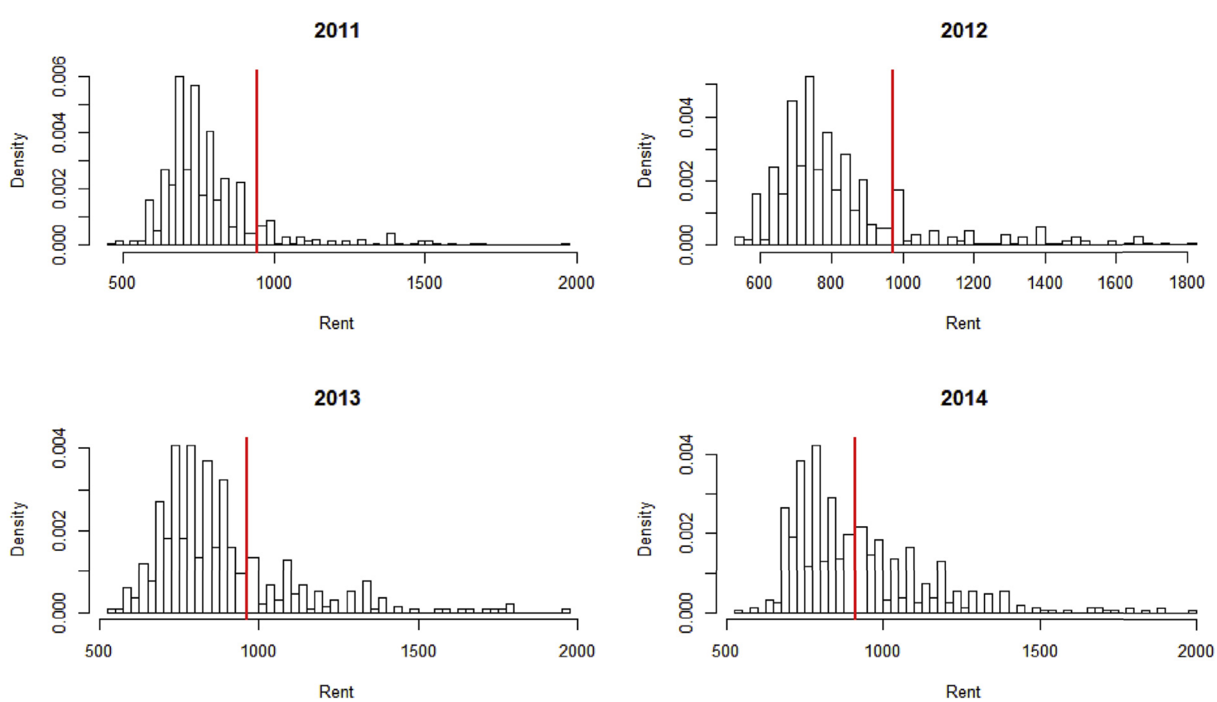
Note. The data set includes pairs of rents over intervals of at least 2 years.

Table A.1
Balance test.

	Below FMR	Above FMR	Difference	t value
Bedroom = 0	0.259	0.254	0.005	0.344
Bedroom = 1	0.336	0.385	−0.05	−2.903
Bedroom = 2	0.405	0.361	0.044	2.55
Dishwasher	0.272	0.3	−0.028	−1.728
Elevator	0.232	0.272	−0.04	−2.591
Fireplace	0.066	0.077	−0.011	−1.206
Microwave	0.096	0.131	−0.034	−3.085
View	0.017	0.023	−0.006	−1.189
Single-Family Detached	0.015	0.018	−0.003	−0.72
High-Rise Building	0.064	0.087	−0.023	−2.486
Mid-Rise Building	0.32	0.341	−0.021	−1.266
Exterior Rating = 1	0.033	0.033	0	−0.032
Exterior Rating = 2	0.182	0.222	−0.04	−2.779
Exterior Rating = 3	0.739	0.709	0.03	1.918
1.5 Bathrooms	0.031	0.029	0.002	0.296
2 Bathrooms	0.172	0.146	0.026	1.951
2 + Bathrooms	0.003	0.008	−0.005	−1.984
2 Units in Building	0.063	0.064	0	−0.044
3–4 Units in Building	0.09	0.093	−0.003	−0.299
5 + Units in Building	0.798	0.788	0.011	0.736

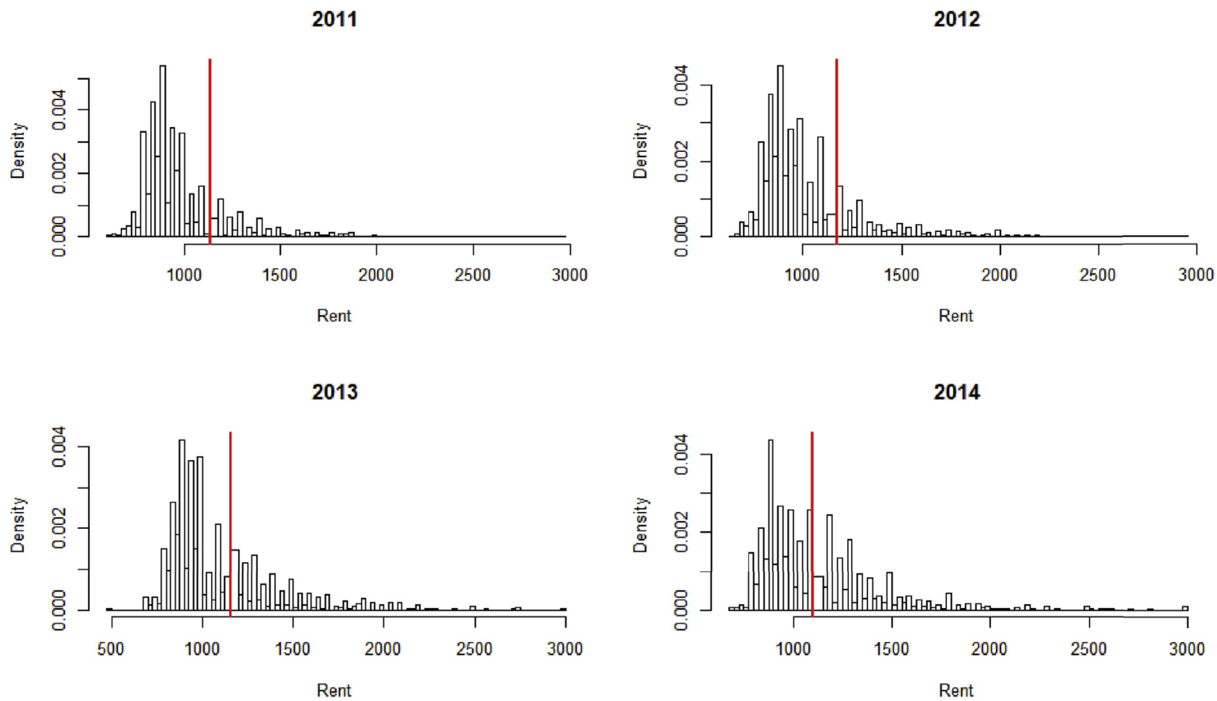
Table A.2
Rent frequency regressions with 110% of FMR.

Variable	Studio Apartments		1 Bedroom		2 Bedroom	
	Coef.	T-Value	Coef.	T-Value	Coef.	T-Value
2007						
Rent ends in 50 or 100	0.908	7.581	0.922	10.071	1.415	12.981
$R_* \le R \le FMR$	−0.025	−0.063	−0.013	−0.036	0.597	1.255
$FMR < R \le R^*$	1.082	2.106	0.536	1.145	1.694	2.631
2008						
Rent ends in 50 or 100	0.929	7.469	1.004	10.058	1.317	13.420
$R_* \le R \le FMR$	0.521	1.269	−0.187	−0.496	0.069	0.163
$FMR < R \le R^*$	1.519	2.975	0.955	1.872	1.168	2.012
2009						
Rent ends in 50 or 100	0.523	4.534	0.686	5.359	1.079	10.511
$R_* \le R \le FMR$	−0.005	−0.012	0.309	0.709	0.584	1.356
$FMR < R \le R^*$	0.976	2.092	1.165	1.950	1.634	2.790
2010						
Rent ends in 50 or 100	0.798	5.841	0.582	6.234	0.957	9.721
$R_* \le R \le FMR$	0.415	0.971	−0.020	−0.055	0.050	0.119
$FMR < R \le R^*$	1.337	2.579	1.731	3.500	1.657	2.890
2011						
Rent ends in 50 or 100	0.603	5.382	0.509	4.795	1.092	11.589
$R_* \le R \le FMR$	−0.373	−1.059	0.536	1.314	0.284	0.700
$FMR < R \le R^*$	0.889	1.854	1.790	3.252	1.187	2.125
2012						
Rent ends in 50 or 100	0.689	4.423	0.690	7.094	0.958	10.692
$R_* \le R \le FMR$	−0.373	−0.780	0.062	0.171	−0.083	−0.220
$FMR < R \le R^*$	0.935	1.455	1.801	3.621	1.655	3.158
2013						
Rent ends in 50 or 100	0.685	5.704	0.894	8.039	1.174	12.085
$R_* \le R \le FMR$	−0.078	−0.195	0.282	0.644	−1.056	−2.439
$FMR < R \le R^*$	0.397	0.793	1.676	2.834	1.795	3.026
2014						
Rent ends in 50 or 100	0.891	7.619	0.708	6.885	1.359	12.078
$R_* \le R \le FMR$	0.544	1.358	−0.059	−0.153	−0.179	−0.399
$FMR < R \le R^*$	1.319	2.617	1.463	2.834	1.214	1.978
2015						
Rent ends in 50 or 100	0.802	6.787	1.122	12.169	1.425	14.256
$R_* \le R \le FMR$	0.639	1.590	−0.182	−0.530	−0.746	−1.775
$FMR < R \le R^*$	1.214	2.401	1.164	2.530	1.958	3.388



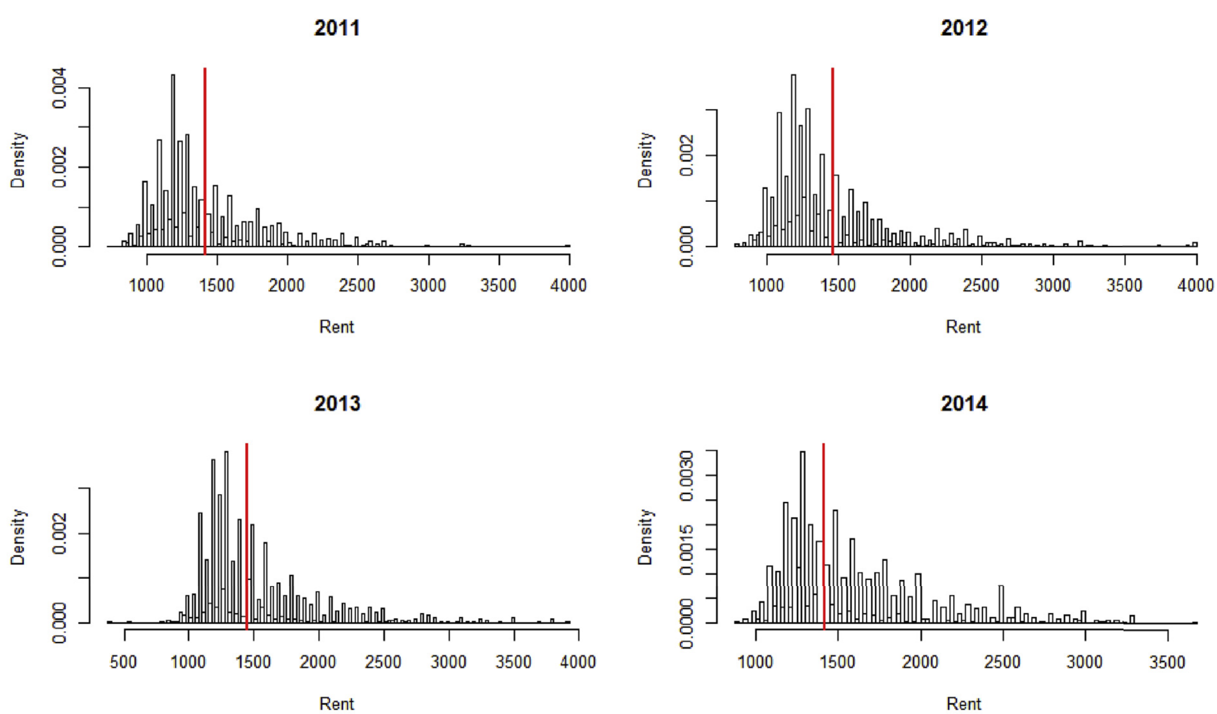
Note: The red line indicates the Fair Market Rent.

Fig. A.1. Distribution of Rents for Studio Apartments.



Note: The red line indicates the Fair Market Rent.

Fig. A.2. Distribution of Rents for 1-Bedroom Apartments.



Note: The red line indicates the Fair Market Rent.

Fig. A.3. Distribution of Rents for 2-Bedroom Apartments.

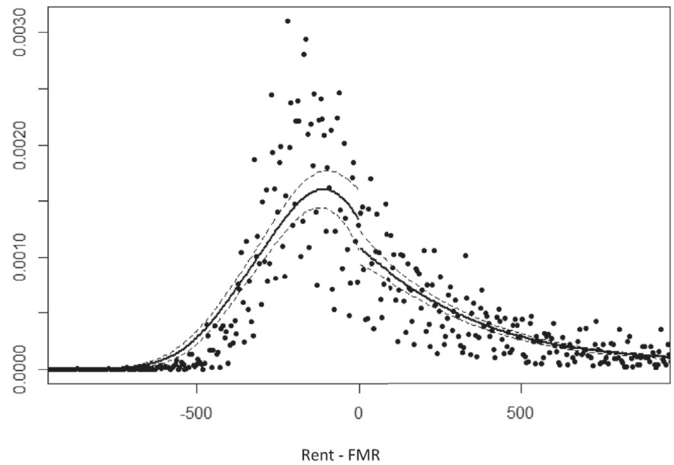


Fig. A.4. Histogram of the difference between Rent and FMR.

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