Multifamily Rental Housing and Naturally Occurring Affordability - The Investor Perspective*

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Abstract

Housing unaffordability is becoming a key driver of poverty and low economic growth across urban areas worldwide. Multifamily rental housing (MFRH) plays a major role in providing rental accommodation in urban areas in the US and can help alleviate naturally occuring unaffordability. Given its importance in the economy and the high institutional ownership in the sector, it is surprising that so little is known about the financial performance of MFRH in comparison to single family owner-occupied housing. This paper is the first to provide property-level analysis of MFRH financial performance and its dependence of local levels of housing affordability. We construct four different measures of naturally occurring housing affordability at the zip code level - rent burden, rent affordability, home affordability, eviction rate. Using a large sample of securitized loan level data on multifamily properties across the US from 2003 to 2016 and combining it with census tract data, we explain three performance indicators at the property level - occupancy rate, capitalization (cap) rate and loan delinquency. We find that a building located in an affordable zip code is associated with a significantly higher cap rate. The transmission occurs through a loan channel since only properties for which the financing is associated with high loan-to-value (LTV) ratio, low mortgage rate or no previous delinquency show the significant positive relationship. In terms of occupancy rates, a property located in a less affordable area in terms of rents would be associated with a higher occupancy rate only if at the same time the area has high median house prices or income levels. For areas with low income, rent affordability has no significant effect on occupancy rates. This may be due to positive externalities making wealthy areas more desirable places to rent. Above results reveal that investors

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are not worse off by investing in affordable areas. In the contrary, their returns can be higher than when investing in less affordable areas given all else equal when they are subject to more scrutiny from the debt providers.

1 Introduction

Unlike the single-family housing market, the multifamily rental housing (MFRH) sector has been under-researched, mostly due to data limitations. In recent years, the rental market in large US cities has grown considerably; rental housing stock has grown much faster than the owner-occupied stock, at 10 percent between 2006 and 2014 (Center, 2016). MFRH units can be owned by real estate companies or institutional investors such as funds and rented to households, including low and moderate-income households. Affordable housing is to a large extent rental accommodation and can be counted within the MFRH market. According to the National Association of Home Builders (NAHB, 2017), the share of multifamily housing which is build to rent is currently 95 percent and the lowest was in 2005 at 47 percent. Since 2010 we observe a strong increase in multifamily housing starts which has reached the pre-crisis level. The provision of multifamily housing in addition to single-family housing is important for the rental market and can lead to naturally occurring housing affordability. We want to distinguish our definition of housing affordability from the general perception of what affordable housing stands for which is mostly associated with government subsidies and some form of government involvement. We are not interested in this but instead in market forces associated with rents, income and house prices which lead to rents or homes being less or more affordable. We call this type of housing affordability 'naturally occurring'.

Unlike the single-family rental market which has been dominated by private investors, the multifamily segment is treated as commercial real estate and institutional investors have increasingly been showing interest in this market. However, the financial performance of MFRH has hardly been studied and is still not understood. There are only a handful of studies examine the dynamics of MFRH investments and they relate in particular to MFRH loan performance. This paper is the first to assess how naturally occurring housing affordability across ZIP codes affects the financial performance of MFRH buildings. We assess the investment and loan performance of individual buildings whose loans have been securitized as Commercial Mortgage Backed Securities (CMBS) across affordable or non-affordable ZIP codes. That will help us identify whether the performance of buildings in non-affordable census tracts is better that in more affordable ones controlling for a host of property, loan and ZIP-code level characteristics. We use data for MFRH securitized into non-agency CMBS which are then bought by institutional investors. Therefore, the final investors in this market segment are essentially institutional investors bearing the underlying property risks. Understanding the financial performance of MFRH buildings located in ares with different levels of housing affordability may help incentivizing more institutional investors to invest in less affordable housing areas. Thus, the question which this study attempts to answer is how naturally occurring housing affordability across ZIP codes affects the financial performance of MFRH buildings. We use a number of different measures of affordability at the regional level. Our core measure is rental affordability defined as the ratio of median household rent in a given ZIP code to the median household income in the same ZIP code in a given year. Similarly we use the home affordability which is defined as above however instead of the rent, we use the median property price. Another measure of housing affordability we use is the rental burden defined as the percentage of people who live in the respective census tract and pay more than 30 percent of their gross income for housing. The last measure is the eviction rate. All the data stems from annual census tract surveys. The investment performance is assessed by looking at the occupancy rate of a building which is a core predictor of commercial real estate performance and at the capitalization (cap) rate of the building. The other part of the financial performance is the loan performance which is assessed by looking at delinquency probability of a loan in each year. The data for the financial performance is from Trepp. While the latter - default in MFRH has been explored in a couple of studies, the former relationship has not been assessed. In general, this is the first study to link housing affordability to the MFRH performance and approach the housing affordability issue from investor's point of view.

Using a more than 200,000 building-year observations on multifamily housing across the entire US from 2003 to 2016, we find that housing affordability affects the performance of multifamily housing significantly. The lower the affordability, the lower the cap rate of a building. This is only the case however when the financing of the building is associated with high leverage, low mortgage rate or has not been delinquent before. In terms of occupancy rates, properties located in less affordable areas would be associated with higher occupancy rates only if the areas are associated with high house prices or high incomes. Assessing the link between MFRH performance and affordability would enable policy makers to tailor local housing affordability policies to address investor concerns and may lead to expanding affordable housing as an asset class.

2 Literature Review

Our paper related to three separate strands of literature - the studies on commercial real estate loan defaults, studies on multifamily housing property-level performance and studies on housing affordability. In terms of the loan performance, there have been only a few studies due to the limited data on commercial real estate loans. An early look at commercial real estate defaults is (Vandell, 1984), who argues that defaults can be driven by adverse cash flows or negative equity in the property. Quigley and Order (1995) use the contingent claim theory to explain mortgage defaults using Freddie Mac data. Commercial real estate borrowers would default following cash flow deficiencies if borrowing to overcome the deficiency reduces the equity in the property. This is when the value of the loan reaches the value of the property plus the transaction costs. Vandell et al. (1993) study commercial mortgage default risks at loan level for the first time using about 3,000 loans sourced from an insurance company. They show that default is predicted by loan terms and property values. Archer et al. (2002) find that the market is different from the single-family market with loan-to-value (LTV) ratios not been the main driver of multifamily mortgage defaults but instead property characteristics and the zip code location play a major role. Chen and Deng (2013) focus on the workout strategic decisions of commercial mortgages from the initial default 90-day delinquency to final foreclosure using 144 commercial mortgage backed securities (CMBS) deals.

While above papers have looked at the drivers of commercial mortgage default, there has been little account for the role of location of the property and how that can have an effect of the default dynamics. (Agarwal et al., 2012) investigate if the negative spillover effects from subprime mortgage originations result in higher default rates in the surrounding area but do not find evidence for that. Fernandes and Artes (2016) in turn find that accounting for spatial dynamics of small and medium sized companies' loans improves credit scoring models. Harding et al. (2008) highlight the importance of neighbouring characteristics for default. Yildirim (2008) shows that commercial real estate mortgage loans within the same location have correlated defaults. Seslen et al. (2010) also argue that insolvency which means negative cash flows is a trigger of default. They show that changes in MSA level property values and net operating income (NOI) are important factors in predicting mortgage default. Therefore, we argue that If the within-MSA characteristics are negatively associated with NOI growth, a measure of property financial health, it follows that they may be negatively associated with the ability to make required debt service payments on time, leading to an increase in the probability of delinquency. In terms of the local economic drivers, (An et al., 2013) are the first to look at the role of local traits at the MSA level associated with the commercial property market on commercial mortgage default. They argue that local economic variables can account for omitted information that in not captured in the property price indices at the more aggregate level. Furthermore, given the forward-looking nature of default, business cycle trends can affect borrower's expectations and defaults. The authors use 30,000 CMBS loans originated between 1998 and 2012 using Morningstar data. They find that local residential house price-related measures are a good proxy for local traits and explain commercial mortgage defaults. An et al. (2013) show that counties with high unemployment rates and low house price growth are associated with greater default risk.

In terms of multifamily housing property-level performance, there is hardly any academic research. Eppli and Tu (2018) look at the role of regional factors on the performance of apartment properties. They categorise markets by employment size and growth which serves as a proxy for property income growth potential and market liquidity. Markets with high expected employment growth are associated with high property appreciation and low capitalisation (cap) rates of apartment investments. Also, large MSAs would be expected to have lower liquidity risk and hence lower cap rates. While employment data matters for property performance, it also can affect commercial mortgage loan defaults.

In terms of housing affordability, there is a number of articles looking at it from different angles. What we are interested in is the link between housing affordability and property performance. A recent study by (?) use CoStar property-level data to assess the properties and performance of buildings classified as naturally occurring affordable housing. They find that low quality, small blocks (less than 20 units) and older buildings would fit into this category. They also argue that buildings build on average in 1952 fall within this category. The least affordable buildings are build on average in 2002. The MSAs with the highest stock of affordable housing are New York and Los Angeles.

3 Data, Variables, and Summary Statistics

3.1 Data

For this analysis, we use two main data sources. For the property and loan level information we use data from Trepp. For the housing affordability measures and regional characteristics we use data from the Census 5-percent Public Use Microdata Sample (PUMS) American Community Survey (ACS). The data is in annual frequency and available from 2000 to 2016. PUMS is a smaller census of 5 percent of census people which takes place every year as compared to the national census taking place every ten years. The estimation period is between 2003 and 2016 and includes about 200,000 observations.

Trepp collects information from non-agency CMBS of commercial real estate loans for all sectors and not just multi-family housing. In this paper, however, we only focus on the MFRH segment of the commercial real estate market and hence only look at multifamily loans securitized into CMBS. Loan level data for multifamily housing loans is also available from the Freddie Mac and Fannie Mae which have become active in the securitization business of multifamily loans following the Global Financial Crisis (GFC). Through this, their goal is to provide affordability to the US housing market. While Fannie Mae does not provide performance data of multifamily loans, Freddie Mac discloses performance data of multifamily loans. The Freddie Mac data between 2009 and 2018 contains 12,897 unique loans with 247,205 billion USD in combined issuance. Overall, Freddie Mac has provided financing for approximately 79,000 multifamily properties or around 9 million apartment units since 1993. As a comparison, our data from Trepp contains 103,011 unique loans between 2000 and 2016 and about a similar number of individual properties. The advantage of our data set is that we would also have property characteristics in addition to the loan characteristics including the exact location of the building. Deal and building characteristics include building occupancy rate, annual net operating income (NOI) per building, age of the building, number of apartments units, etc.

Further ways to control for the quality of the building we use proxies such as the age of the building, the number of units, location of the building in proximity to employment centers or large MSAs, urban sub-markets.

3.2 Variables

3.3 Summary Statistics

We have three outcome variables of interest - the occupancy rate of the building, its cap rate and the delinquency rate of each loan over time. The cap rate has not been provided in the data and we have calculated a proxy as the ratio of net operating income (NOI) divided by the value of the building at securitization. The other two variables are readily available from Trepp. Table 1 presents summary statistics. In our full sample, occupancy rates are on average 94% and this figure is on average, very consistent year over year with only an average change of 0.08% per year. However, there is substantial variation in the distribution of changes in occupancy rates with the 10th percentile value of change at -3.58% and the 90th percentile value of change at 3.83%. However, small changes in occupancy rates are associated with large changes in building NOI and delinquency. If a building had a positive change in occupancy rate the previous year the building NOI is, on average, $70,051 higher than if it had a negative change in occupancy rate; this difference equates to an approximately 13% higher value for NOI. Similarly, only 11.52% of buildings with a positive change in occupancy rate in the previous year have a delinquency in payment of their loan in the current year, as compared to 18.50% of buildings with a negative change in occupancy rate. Of course, these are only univariate results, but we will explore these relationships further as we expand the analysis within this study. The average cap rate is 5.33% and it has a similar standard deviation. Annually, the cap rate changed by 0.05%. We can see that the final dependent variable - the delinquency rate - takes a value of 9% on average with a variation of 29%. Delinquency (*delinq*) is a dummy variable taking the value of 1 if the loan has been delinquent in a given year. The loan is considered delinquent if the borrower is more than 30 days behind on payments. The variable *delinq_any* is also a dummy variable, it indicates if the loan has ever in the past been delinquent at least once. We can see that 13.4% of the loans have been delinquent at least once. It can then be the case that some of those loans default but a large proportion of them move back to not being delinquent and continue paying back the loan in the next period.

Our primary explanatory variables of interest are the four measures of housing affordability which stem from annual census tract surveys. Our core measure is rental affordability defined as the ratio of median household rent in a given ZIP code to the median household income in the same ZIP code in a given year. Similarly we use the home affordability which is defined as above however instead of the rent, we use the median property price. Another measure of housing affordability we use is the rental burden. The rent burden is defined as the percentage of people which pay more than 30 percent of their income on rent or mortgage and tax expenses. This means that the rent burden is a measure for everyone's housing non-affordability and not just for renters. Home owners' rent burden is based on the mortgage and tax expenses; hence rent burden is a measure of cost associated with the actual usage of the property unit. On average, 52% of the properties in our sample are occupied by renters. The average rent burden across all census tracks is 30% but it varies largely from close to zero percent to about 50 percent in the 99th percentile. Home affordability is on average 4.5 meaning that a household would need on average 4.5 annual median gross salaries to pay for a median house in the given zip code for a given year. However, we also see large variations across the affordability with it being 2.65 in the 25th percentile and 17.7 in the 99th percentile. The distribution is somewhat skewed as the median value is 3.5 compared to a mean of 4.5 suggesting that there are some highly unaffordable areas in our sample. The average rent affordability is 0.02 meaning that a household pays 2% of the annual median household income on monthly rent. The median of the median gross rent is 921 USD per month and the median of the median household income is 47,895 USD per year. The median rent affordability is 3.52 suggesting a strong skew. Some areas have much higher rent affordability. The 25th percentile of rent affordability is 2.64 and the 99th percentile is

17.7. The last measure is the eviction rate which suggests that in 2.89% of the cases, the household is evicted, however the median is 1.84% suggesting that in some areas there are high proportions of eviction rates. The 25th percentile is 0.76% and the 99th percentile is 14.89%.

In addition to above explanatory variables, we control for a host of property and loan level characteristics. Some fixed characteristics of the loan at origination including the log of the LTV ratio at securitization, the log of the original balance on the loan, if the loan has a balloon repayment feature, if the loan has lock-out period for prepayment. We control for dynamic loan characteristics including the current interest rate on the loan - the mortgage rate. We also control for zip-code level demographics and household income changes. Table 1 also shows information about those variables. We can see that the average mortgage rate (actrate) is 6% with the maximum value of 10%. Given our sample period between 2006 and 2016, this seems like a high mortgage rate even for a commercial loan. The LTV at securitization is 69% with some large variation between 26% and 82% for the 1th and 99th percentile. We can see that most of the loans are balloon lock loans. The average age of the loans in our sample is 7 years with some dating back to 19 years. The buildings in our sample have on average 166 properties which would suggest that they are rather large multifamily complexes and hence mostly invested in by institutional investors. The buildings are build on average in 1975 with the oldest in 1900 and the newest in 2016. The 99th percentile is in 2011.

We also present the summary statistics by the highest and lowest quartiles for the four affordability measures in Table 2 and Table 3. While the properties are similar in many respects, the starkest difference is between the change in occupancy rates. For the high rent burden sample, the average change in occupancy is 0.17%, over an order of magnitude larger than the low rent burden sample, -0.07%. The cap rate and the delinquency rate are higher in the low rent burden. We observe very similar patterns for the home and rent affordability measures. The case for eviction rate is in reverse but follows the same pattern.

4 Methodology

We estimate an unbalanced panel for the years 2003-2016 with new loans entering and many existing loans exiting the sample over this time horizon.

Equation (1) illustrates the random effects panel regression strategy for estimating the effect of zip code level within city variation on changes in annual building occupancy rates.

$$Y_{it} = \beta X_{it} + \theta Z_{ct} + \alpha + u_{it} + \epsilon_{it} \tag{1}$$

X is a vector of control variables by loan i (only one loan is observed for each property) and time t, and Z is a vector of demographic and financial flow variables by zip code c and year t,α is the unknown intercept, u is the between-entity error and ϵ is the within-entity error. We cluster standard errors at the zip code level in each model. For the return on debt, we will estimate a continuous outcome and for delinquency, we will use a binary outcome and therefore specify this model as a logistic regression. After estimating the baseline model for delinquency, we will consider the competing risks of delinquency and prepayment (Ambrose and Sanders (2003) and Ciochetti et al. (2002)).

5 Results

Table 4 and Table 5 present baseline results for the occupancy rate and the cap rate respectively. For each case we estimate the effects of each of the four measures of affordability separately on either variable of interest.

5.1 Occupancy rate

Variations in occupancy rates are associated with changes in the demand for rental accommodation rather than the supply dynamics across zip codes. Changes in supply would not vary across zip codes within a given MSA but rather across larger regions due to differences in zoning or land availability.

The sample size in Table 4 ranges between 148,735 and 165,791 unique building-year observations. The main variables of interest are the coefficients for the affordability measures. We can see that three of the four affordability measures are significant at the 1% confidence level. Only rent burden seem not to be significant. The effect of home and rent affordability is positive on occupancy rate meaning that the higher the unaffordability of the area, the higher the occupancy rate. This means that multifamily housing buildings located in unaffordable zip codes would be associated with higher occupancy. In the case of eviction rates we observe a negative relationship. We can see that the higher the eviction rate of the area the lower the occupancy rate of a building located in that area would be. This suggests a negative spillover effect from evictions in a given zip code to other buildings and potentially to less occupancy. This may suggest that areas in which housing is affordable may be associated with evictions and hence lower occupancy. To better understand the channels from affordability to occupancy rate we distinguish between four quartiles of occupancy rates. The higher the quartile the higher the occupancy rate. The coefficient in each quartile is the difference of the occupancy rate change from quartile 1. In addition to that, we restrict our sample on the highest and lowest quartile of median household income (columns 1 and 2) and house price (columns 3 and 4). The results are presented in Table 7. We only use rent affordability as the measure of affordability as it is significant in the baseline results and is most adequate for the MFRH market. What becomes apparent is that rent affordability has only a significant impact on occupancy rates when the building is located in a high income zip code (Model (1)) or a high house price zip code (Model (2)). Another observation is that the buildings located in the least affordable areas (quartile 4) are those which have the significantly higher occupancy rates as buildings located in the most affordable areas (quartile 1). Being in the least affordable area which at the same time has the most expensive real estate is the case in which occupancy rate will be 50% higher than being in the most affordable area with the most expensive real estate. Affordability would not matter is the building is located in the bottom quartile of areas in terms of income or house prices. This suggests that the issue of affordability when it comes to occupancy rates of buildings would only matter when those buildings are located in the most expensive or most economically developed zip codes. Since affordability has a negative effect on occupancy, we argue that there is a negative externality channel in place associated with evictions.

Going back to Table 4, we can see that the change in household income at the zip code level does not have significant effects on occupancy rates of buildings. The percentage of African-American and Hispanic population has a significantly negative effect on occupancy rates. Moreover, the higher the number of renter occupiers the higher the occupancy rate which would suggest that such areas in general do not only attract more tenants but also they can do that more easily.

In terms of the building-level characteristics, we see that buildings which have loans with high loan-to-value (LTV) ratios at seciritization are associated with lower occupancy rates. This is an important observation for financial market regulators and financiers since loans are covered by the rental income of those commercial buildings. Buildings with high LTV ratios are regarded as more risky and that seems to feed in through the way they manage their properties and find tenants. Buildings with more units and larger buildings in general have lower occupancy rate as it is harder for them to fill a large number of units and such buildings may be less attractive to tenants. Older buildings also have lower occupancy rates which is associated with the quality of living. Surprisingly, buildings which have been renovated recently have less occupancy rate. This may be associated with high rent being charged or some of the renovation costs outsources to tenants reducing the tenant numbers.

5.2 Cap rate

Table 5 presents the baseline results for the cap rate. We see that only two of the four affordability measures are significant at the 5% confidence level. Those measures are the rent burden and rent affordability. They both affect the cap rate in a negative way suggesting that the higher the unaffordability, the lower the cap rate. This result holds when controlling for other zip code level demographics and economic fundamentals. The result shows that buildings located in affordable areas have higher profitability as compared to buildings located in less affordable areas. This is an important finding against the conventional wisdom that affordability has negative effects on profitability. In order to further investigate what may explain this relationship, we split the sample into buildings with (1) high versus low LTV ratio, (2) with high mortgage rate versus low mortgage rate and (3) with no previous delinquency versus having been previously delinquent. The results are presented in Table 6. The results for the control variables remain robust are therefore not shown. We can clearly see that only buildings which have a loan associated with a high LTV ratio, a low mortgage rate or have not been delinquent before are significant. This suggests that the effect of affordability of the area is only then associated with a positive effect on the cap rates when those buildings have some specific loan characteristics. This result suggests that the affordability of the area may be reflected in the mortgage terms and hence indirectly affect the profitability of the building through a loan channel. It seems that buildings which have not been delinquent on the loans are rewarded for being in affordable areas.

6 Conclusion

In this study, we examine the relative importance of local naturally occurring housing affordability at the zip code on MFRH financial performance. We use four different measures of naturally occurring housing affordability - rent burden, the eviction rate, the home affordability and rent affordability. Combing a large sample of loan level data on multifamily housing across the entire US from 2003 to 2016 with annual census tract level data, we explain three performance indicators at the property level - occupancy rate, capitalization rate and loan delinquency. We find that housing affordability affects the performance of multifamily housing significantly. We find that buildings located in affordable areas are associated with significantly higher cap rates. The transmission occurs through the loan channel since only properties for which the financing of the building is associated with high leverage, low mortgage rate or no previous delinquency are able to deliver the positive relationship. In terms of occupancy rates, properties located in less affordable areas would be associated with higher occupancy rates only if the areas are associated with high house prices or high incomes. This may be due to negative externalities and negative spillovers of evictions. Assessing the link between MFRH performance and affordability would enable policy makers to tailor local housing affordability policies to address investor concerns and may lead to expanding affordable housing as an asset class.

7 Tables and Figures

Table 1: Descriptive statistics

	count	mean	sd	min	max
occrate	273069	94.0357	6.3026	0.72	100
changeoccrate	224793	0.0836	3.8772	-65.82	76
caprate	124318	5.3306	5.3373	-61.05	664
capratechange	91037	0.0517	0.3427	-4.95	5
delinq	324756	0.0942	0.2920	0.00	1
rentburden	324358	30.6498	7.7554	0.00	100
homeafford	320478	4.5290	3.3223	0.00	55
rentafford	324250	0.0210	0.0101	0.00	0
medianhouseholdincome	324750	52364.2319	24400.9711	0.00	250001
mediangrossrent	324260	988.4933	374.5073	0.00	3501
medianpropertyvalue	320483	231965.5272	189540.0357	0.00	2000001
povertyrate	324760	12.2610	11.3711	0.00	86
pctrenteroccupied	324760	52.9799	23.8659	0.00	100
renteroccupiedhouseholds	324760	1376.1184	819.5632	0.00	8537
evictionfilings	291191	95.7443	160.6017	0.00	3629
evictions	289126	36.9013	48.9590	0.00	522
evictionrate	289126	2.8981	3.2400	0.00	100
evictionfilingrate	291191	7.4437	13.0394	0.00	662
securltv	318520	69.3219	11.7788	10.00	138
lnorigbal	294608	15.2723	1.0720	12.96	18
actrate	319106	6.1062	1.5052	0.00	10
balloon	324756	0.9299	0.2554	0.00	1
lock	324756	0.8009	0.3993	0.00	1
loanage	323987	7.0526	5.2270	0.00	45
units	311631	166.2356	265.7241	1.00	47432
propyear	306552	1975.8975	24.2712	163.00	2016
reno_recent	324760	0.1087	0.3112	0.00	1

Table 2: Mean values across top and bottom quartiles of affordability measures (1)

	(1)	(2)	(3)	(4)
	Low rent burden	High rent burden	Low eviction rate	High eviction rate
occrate	93.68	94.37	95.06	93.32
changeoccrate	-0.07	0.17	0.04	0.12
caprate	5.57	5.21	5.29	5.24
capratechange	0.04	0.06	0.06	0.05
delinq	0.11	0.09	0.07	0.11
rentburden	21.95	40.73	30.50	31.38
homeafford	3.46	5.89	5.96	3.94
rentafford	0.02	0.03	0.02	0.02
medianhouseholdincome	61473.03	42212.08	60473.84	47943.87
mediangrossrent	944.37	998.26	1136.62	938.93
medianpropertyvalue	223509.68	225643.04	338114.19	192213.26
povertyrate	6.51	18.97	10.44	14.81
pctrenteroccupied	46.40	57.17	54.20	54.44
renteroccupiedhouseholds	1308.20	1343.92	1419.53	1429.21
evictionfilings	77.17	94.56	33.77	213.45
evictions	27.86	40.74	4.62	92.44
evictionrate	2.43	3.25	0.32	7.28
evictionfilingrate	6.46	7.74	2.71	16.41
securltv	70.47	69.02	66.56	70.29
lnorigbal	15.34	15.18	15.17	15.30
actrate	6.31	6.09	5.99	6.15
balloon	0.94	0.93	0.92	0.94
lock	0.86	0.78	0.74	0.83
loanage	6.27	7.57	7.01	7.35
units	177.65	151.66	134.10	181.77
propyear	1978.30	1974.11	1971.83	1976.09
reno_recent	0.11	0.11	0.10	0.11
N	81565	81310	72823	108051

Table 3: Mean values across top and bottom quartiles of affordability measures (2)

	(1)	(2)	(3)	(4)
	High home afford	Low home afford	High rent afford	Low rent afford
occrate	92.89	95.63	93.74	94.51
changeoccrate	0.01	0.12	-0.00	0.17
caprate	5.59	5.06	5.49	5.07
capratechange	0.04	0.06	0.04	0.06
delinq	0.13	0.07	0.11	0.08
rentburden	28.38	33.68	26.14	37.15
homeafford	2.14	8.69	3.23	6.68
rentafford	0.02	0.03	0.01	0.03
medianhouseholdincome	50670.91	51790.16	68043.87	35295.10
mediangrossrent	851.38	1181.00	888.31	1010.85
medianpropertyvalue	110407.39	428413.91	229981.62	231440.54
povertyrate	11.38	15.15	5.55	21.96
pctrenteroccupied	41.40	70.03	32.53	71.85
renteroccupiedhouseholds	1048.83	1844.60	902.02	1694.31
evictionfilings	91.18	67.50	52.10	120.38
evictions	38.79	27.76	19.79	50.03
evictionrate	3.70	1.75	2.35	3.27
evictionfilingrate	8.62	4.10	5.89	7.89
securltv	72.25	64.16	71.12	68.10
lnorigbal	15.25	15.04	15.29	15.18
actrate	6.36	5.99	6.23	6.06
balloon	0.94	0.91	0.93	0.93
lock	0.87	0.71	0.83	0.77
loanage	6.88	7.31	6.54	7.59
units	188.28	115.13	168.94	156.55
propyear	1980.96	1964.71	1980.86	1969.94
reno_recent	0.11	0.10	0.11	0.11
N	79659	84425	80415	81584

Table 4: Baseline results for occupancy rate

	(1) Rent burden	(2) Eviction rate	(3) Home afford	(4) Rent afford
L.rent-burden	0.00496			
	(0.00498)			
L.eviction-rate		-0.0485***		
		(0.0110)		
L.homeafford			0.0724***	
			(0.0230)	
L.rentafford				15.95***
				(2.983)
L.hhincomechange	-0.0829	-0.0675	-0.0338	-0.0369
	(0.139)	(0.144)	(0.136)	(0.136)
L.population	0.0000153	0.0000142	0.0000282	0.0000242
	(0.0000167)	(0.0000172)	(0.0000176)	(0.0000171)
pct-af-am	-0.0194***	-0.0165***	-0.0185***	-0.0201***
	(0.00227)	(0.00249)	(0.00229)	(0.00222)
pct-hispanic	-0.00554**	-0.00586**	-0.00560**	-0.00665***
	(0.00244)	(0.00247)	(0.00242)	(0.00240)
renter-occupied-households	0.000108**	0.000131**	0.0000328	0.0000502
	(0.0000536)	(0.0000584)	(0.0000580)	(0.0000540)
lnsecurltv	-1.630***	-1.666***	-1.498***	-1.630***
	(0.172)	(0.186)	(0.180)	(0.171)
lnorigbal	0.661***	0.648***	0.596***	0.656***
	(0.0845)	(0.0898)	(0.0876)	(0.0844)
actrate	-0.0774	-0.0588	-0.0716	-0.0801
	(0.0491)	(0.0518)	(0.0496)	(0.0490)
balloon	-0.847***	-0.892***	-0.831***	-0.850***
	(0.250)	(0.254)	(0.250)	(0.249)
lock	0.644***	0.701***	0.648***	0.642***
	(0.109)	(0.115)	(0.109)	(0.109)
loanage	0.145***	0.150***	0.144***	0.143***
	(0.0129)	(0.0127)	(0.0125)	(0.0126)
units	-0.00543***	-0.00542***	-0.00520***	-0.00542***
	(0.000695)	(0.000721)	(0.000694)	(0.000695)
propyear	-0.00877***	-0.00689***	-0.00702***	-0.00872***
	(0.00177)	(0.00187)	(0.00191)	(0.00176)
reno_recent	-0.374***	-0.395***	-0.375***	-0.370***
	(0.104)	(0.108)	(0.104)	(0.104)
largebuilding	-1.561***	-1.594***	-1.444***	-1.541***
	(0.110)	(0.115)	(0.112)	(0.109)
Constant	112.1***	108.6***	108.8***	112.0***
	(3.537)	(3.713)	(3.775)	(3.506)
Observations	165791	148735	163973	165777
Obs. Year FE	Y	Y	Y	Y
Orig. Year FE	Y	Y	Y	Y
Originator FE	Y	Y	Y	Y

Random effects panel regression results displayed. Standard errors clustered at the loan level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Baseline results for cap rate

	(1) Rent burden	(2) Eviction rate	(3) Home afford	(4) Rent afford
L.rent-burden	-0.00754**			
	(0.00330)			
L.eviction-rate		0.0188		
		(0.0441)		
L.homeafford			0.0100	
			(0.00873)	
L.rentafford				-6.713**
				(3.285)
L.hhincomechange	0.0591	0.0546	0.0580	0.0261
	(0.0638)	(0.0714)	(0.0631)	(0.0632)
L.population	0.0000142	0.0000141	0.0000175*	0.00000970
	(0.00000934)	(0.0000102)	(0.0000103)	(0.0000100)
pct-af-am	-0.00372	-0.00528***	-0.00386	-0.00381
	(0.00246)	(0.00190)	(0.00241)	(0.00253)
pct-hispanic	-0.00131	-0.00112	-0.00161	-0.00118
	(0.00150)	(0.00142)	(0.00143)	(0.00158)
renter-occupied-households	0.0000561	0.0000142	0.0000473	0.0000835**
	(0.0000379)	(0.0000497)	(0.0000423)	(0.0000407)
lnsecurltv	1.942***	1.883***	1.940***	1.944***
	(0.185)	(0.232)	(0.189)	(0.185)
lnorigbal	-1.370***	-1.380***	-1.369***	-1.368***
	(0.107)	(0.101)	(0.107)	(0.107)
actrate	-0.172**	-0.207**	-0.204***	-0.171**
	(0.0716)	(0.0843)	(0.0760)	(0.0717)
occrate	0.0927***	0.0945***	0.0925***	0.0928***
	(0.00466)	(0.00528)	(0.00470)	(0.00468)
balloon	-0.828***	-0.874***	-0.837***	-0.829***
	(0.206)	(0.197)	(0.206)	(0.206)
lock	-0.233***	-0.230***	-0.236***	-0.233***
	(0.0607)	(0.0649)	(0.0607)	(0.0607)
loanage	0.103***	0.0923***	0.0974***	0.101***
	(0.0130)	(0.0143)	(0.0124)	(0.0123)
units	0.00410***	0.00416***	0.00415***	0.00410***
	(0.000533)	(0.000519)	(0.000541)	(0.000533)
propyear	0.000545	0.00144	0.00160	0.000581
	(0.00161)	(0.00177)	(0.00152)	(0.00158)
reno_recent	-0.0994	-0.129	-0.0980	-0.105
	(0.0792)	(0.0877)	(0.0809)	(0.0800)
largebuilding	1.085***	1.129***	1.075***	1.083***
	(0.113)	(0.124)	(0.115)	(0.113)
Constant	0.793	-0.440	-1.076	0.681
	(3.150)	(3.475)	(2.935)	(3.112)
Observations	80243	72763	79608	80213
Obs. Year FE	Y	Y	Y	Y
Orig. Year FE	Y	Y	Y	Y
Originator FE	Y	Y	Y	Y

Random effects panel regression results displayed. Standard errors clustered at the loan level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Loan channel for cap rate

	(1) High LTV	(2) Low LTV	(3) High rate	(4) Low rate	(5) No delinq	(6) Delinq
L.rentafford	-9.602*	-3.898	0.272	-9.750**	-7.492**	1.267
	(5.760)	(2.704)	(8.010)	(4.042)	(3.695)	(4.691)
Observations	52222	27991	25338	54875	61208	19005
Controls	Y	Y	Y	Y	Y	Y
Obs. Year FE	Y	Y	Y	Y	Y	Y
Orig. Year FE	Y	Y	Y	Y	Y	Y
Originator FE	Y	Y	Y	Y	Y	Y

Random effects panel regression results displayed. The model has the same controls as Table 4. Standard errors clustered at the loan level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Local fundamentals channel for occupancy rate quartiles using rent affordability

	(1) High income	(2) Low income	(3) High house prices	(4) Low house prices
rentaffordquartile=2	0.478***	-0.513	0.263*	-0.170
	(0.168)	(0.347)	(0.149)	(0.234)
rentaffordquartile=3	0.723***	-0.470	0.351**	-0.127
	(0.191)	(0.388)	(0.154)	(0.286)
rentaffordquartile=4	0.695**	-0.396	0.506***	-0.0807
	(0.313)	(0.420)	(0.193)	(0.326)
Observations	38957	43342	33891	45397
Controls	Y	Y	Y	Y
Obs. Year FE	Y	Y	Y	Y
Orig. Year FE	Y	Y	Y	Y
Originator FE	Y	Y	Y	Y

Random effects panel regression results displayed. Rentaffordquartile equal to 2, 3 or 4 shows the coefficient for rent affordability in each quartile in relation to the first quartile. The model has the same controls as Table 4. Standard errors clustered at the loan level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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