Systemic Banks, Mortgage Supply, and Housing Rents*

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Abstract

We show that tighter mortgage lending standards after the Great Recession have led to higher housing rents. U.S. banks, especially those deemed systemically important, have increased their propensity to deny mortgage applications, particularly among FHA loan applicants and black and Hispanic borrowers. Tighter standards have increased demand for rental housing and led to higher rents, depressed homeownership rates, greater construction of multifamily housing, and lower rental vacancies. These effects are stronger in MSAs with barriers to using online lending platforms, such as age and internet accessibility, and where regulations inhibit competition among alternative lenders.

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1 Introduction

This paper studies the role of mortgage credit supply in the post-2007 crisis period. Following the crisis, homeownership rates collapsed while housing rents increased very quickly in many U.S. cities.[1] The number of cost-burdened renters (paying more than 30 percent of income for housing) has attained record levels, raising affordability concerns and prompting policy debates about what to do (Fernald et al. 2015). This paper shows that a contraction of mortgage credit supply has been a significant driver of the recent dynamics of rents and homeownership rates. The contraction was much stronger among FHA loan applicants and black and Hispanic borrowers. It intensified around 2011, following the implementation of major post-crisis regulatory overhauls, like the Dodd-Frank Act and various lawsuits against prominent mortgage lenders. Moreover, tighter mortgage standards have also prompted increases in multifamily construction.

There is an ongoing debate on what caused the 2007 crisis and what the appropriate policy responses are. Mian and Sufi (2009) provide evidence pointing to excessive credit supply towards low-income households as the cause of the crisis. Adelino, Schoar and Severino (2016) or Foote, Loewenstein and Willen (2016) argue that loans to low-income households were not the dominant driver of pre-crisis credit flows, and thus policies should not necessarily aim to restrict credit accessibility for these borrowers. Our results are consistent with the view that policy reforms have especially reduced the flow of credit towards households on the margin of homeownership, who are often lower-income, and that renters have been strained by the subsequent increase in housing rents.

The mechanism that we test was originally proposed by Linneman and Wachter (1989) and is formalized by Gete and Reher (2016).[2] It begins with a shock that contracts mortgage supply for some lenders. Then, frictions to substitute across lenders lead to more difficult access to credit, especially for the borrowers on the margin of homeownership, such as FHA loan applicants and black and Hispanic borrowers. Since downward house price rigidities prevent most households from buying without credit, households denied credit move from the market for homeownership to the rental market. An increase in the demand for rental housing, together with an imperfect short-run elasticity of supply, drove up housing rents and reduced rental vacancies.

We find that a one percentage point increase in the growth of mortgage denials leads to around a 2.3 percentage point increase in housing rent growth. To put this estimate into

[1] Based on the Zillow Rent Index, nominal rents grew at an average annual rate of around 3% over the 2011-2014 period.

[2] Ambrose and Diop (2014) and Acolin et al. (2016) provide empirical support using different periods and identification strategies.

context, the cross-sectional variation in rent growth is around 5 percentage points for most years. The estimate is 1.5 percentage points larger in MSAs without rent control. We also identify strong effects from credit tightening on the supply of rental housing through the construction of multifamily units. Moreover, we provide evidence of frictions to substitute across lenders: age of the borrowers, barriers to internet access and lack of competition among lenders or mortgage brokers. These frictions have prevented new lenders, especially online lenders that have played an increasingly important role in mortgage markets since the crisis, from filling the void left by the banks' retreat.

We explore several identification strategies, and all provide consistent results. In the benchmark strategy, we first estimate lenders' national propensity to deny a loan using fixed effects, and we purge the estimates from borrower, MSA, and time effects in a similar manner as Khwaja and Mian (2008) or Amiti and Weinstein (2013). Then we create a novel credit supply shock based on the wedge between Big-4 (Bank of America, Citibank, JP Morgan Chase and Wells Fargo) and non-Big-4 lenders' national propensity to deny a mortgage application over 2008-2014, weighted by the 2008 mortgage application market share of the Big-4 banks in the MSA. This shock captures the relative stringency of the Big-4's lending standards in a given year and the degree to which this tightening is felt in a given MSA.

It seems plausible to assume that the Big-4 banks were especially exposed to policy shocks. These are the only systemically important financial institutions lending in mortgage markets. Stein (2013) discusses how the Dodd-Frank Act subjected Big-4 banks to heightened oversight and higher liquidity and capital requirements. Calem, Correa and Lee (2016) show that the first stress test in 2011, which only applied to the largest banks, including the Big-4, had a negative effect on mortgage approval rates at those banks. Moreover, since the False Claims Act was first used publicly in the mortgage space in 2011, the Big-4 banks claim that they have suffered a large increase in the risk of being subject to fines and litigation in case a mortgage results in default.[3]

We then use the credit supply shock as an instrument for the mortgage application denial rate.[4] We control extensively for factors that may be correlated with housing rents and also explain the Big-4's market share, like, for example, income, population growth, age, unemployment, past housing prices, or proximity to a Big-4 headquarters. Additionally, denial rates only

[3]The Big-4 banks, plus Ally, paid $25 billion in 2012. In addition, each of them also faced other settlements that ranged from $82 million for Wells Fargo in 2015 to $16.65 billion for Bank of America in 2014 (Goodman 2015).

[4]Denial rates are strongly correlated with proxies for lending standards, such as the Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS). Interestingly we show that even if aggregate denial rates in mortgage markets have a clear downward trend since 2008, there are significant differences between Big-4 and non-Big-4 lenders.

vary with the Big-4 shock, not through the elasticity of housing supply which relates to the construction of rental units. This suggests that we are capturing a rental demand shifter, not a change in supply.

Our results are especially strong on the subsample of FHA loans and applications made by black and Hispanic borrowers, as these groups are more likely on the margin of homeownership. Moreover, the results persist when we construct MSA-level averages of individual lenders' shocks, weighting by the lenders' market shares, instead of using the credit supply shock based on the wedge between Big-4 and non-Big-4 lenders. This is similar to the Greenstone, Mas and Nguyen (2015) approach and is more agnostic about which lenders are subject to shocks.

We also used the instruments proposed by Adelino, Schoar and Severino (2013) and Loutskina and Strahan (2015) that exploit changes in the maximum loan limits that government-sponsored enterprises (GSEs) insure.[5] These instruments are well accepted in the literature as instruments for credit shocks (e.g. Dagher and Kazimov 2015). We obtained similar results with these instruments as in our baseline analysis. Exploiting the overidentification generated by these other instruments, we provide evidence that our credit supply shock is a valid instrument for denial rates. We also checked that our results are not driven by a mechanical effect of increased foreclosures due to the credit supply shock, which would restrict the supply of rentals.

In terms of contribution to the literature, to the best of our knowledge we are the first to show that tight credit supply in the post-2007 period has increased housing rents and depressed homeownership rates.[6] The existing literature on housing rents has thus far focused on other, non-credit drivers like population flows (Saiz 2007), shrinking leisure of high-income households (Edlund, Machado and Sviatchi 2015), income growth (Hornbeck and Moretti 2015, or Muehlenbachs, Spiller and Timmins, 2015) or households' expected duration of stay in a house (Halket and Pignatti 2015). Mezza, Sherland and Sommer (2015) show that student debt has affected the demand for homeownership.

The rest of the paper is organized as follows. Section 2 discusses the underlying theory. Section 3 has the main identification strategy and Section 4 has a variety of follow-up exercises. Section 5 studies new building permits, rental vacancies and house prices. Section 6 studies homeownership and frictions to substitute between lenders. Section 7 concludes. The Appendix

[5] The 2008 Economic Stimulus Act changed how these conforming loan limits are decided, creating endogeneity problems for post-2008 samples. We show how to slightly modify the Loutskina and Strahan (2015) instruments to avoid these problems.

[6] There is a large literature that analyzes whether easy access to credit caused house prices increases during the period preceding the 2007 crisis. See for example, Albanesi, DeGiorgi and Nosal (2016), Anenberg et al. (2016), Adelino, Schoar and Severino (2016), Ben-David (2011), DiMaggio and Kermani (2016), Driscoll, Kay and Vojtech (2016), Favara and Imbs (2015), Foote, Loewenstein and Willen (2016), Glaeser, Gottlieb and Gyourko (2012), or Mian and Sufi (2009) among others.

explains our data sources and the Online Appendix contains supplementary results.

2 Motivation and theory

In this section we describe the theory we want to test. As Figure 1 shows, following the recent financial crisis, housing rents have increased steeply in many MSAs. The rent-to-income ratio for the median MSA has risen by more following the Great Recession than it did over the previous 25 years combined. At the same time, the U.S. homeownership rate has collapsed to historic lows.

The large drop in homeownership suggests an important role for the extensive margin of rental demand. This margin depends on mortgage accessibility, as analyzed theoretically in Gete and Reher (2016). If there are short-term frictions to expand the supply of rental housing, then credit supply shocks can increase housing rents and lower the homeownership rate by encouraging more households to rent rather than own. Two such candidates for credit supply shocks are: (i) higher costs for the lender, for example, because of higher liquidity or capital requirements, or (ii) higher costs of loan default, for example, because regulators impose fines on loans which result in default.[7] Big-4 banks have been exposed to both factors.[8]

3 Benchmark specification

3.1 Propensity to Deny

We estimate a measure of the Big-4's relative tightening of credit supply that is purged of borrower, MSA, and time effects. We do so using yearly mortgage credit data from the Home Mortgage Disclosure Act (HMDA) since 2007.[9] HMDA data contain application-level information on the applicant and the outcome of the application. Since our focus is on households contemplating whether to rent or own, we only study applications for the purchase of owner-

[7] Wells Fargo's CEO told the Financial Times in August 2014: "If you guys want to stick with this programme of 'putting back' any time, any way, whatever, that's fine, we're just not going to make those loans and there's going to be a whole bunch of Americans that are underserved in the mortgage market." The CEO of JP Morgan CEO made similar remarks on an earnings call.

[8] Consistent with the theory, Figure 1 in the Online Appendix shows a positive correlation between MSAs with a large share of lending by the Big-4 banks in 2008 and growth in housing rents over the 2011-2014 period.

[9] By focusing on post-crisis years, we avoid structural breaks associated with the financial crisis. Also, the year 2007 is the first when the data are in electronic form on the HMDA webpage, and thus our first measured growth rate corresponds to the year 2008.

occupied, 1-to-4 family dwellings, which include single-family houses and also individual units within multi-unit buildings, such as condominiums. We focus on MSAs as the unit of analysis, as they are arguably the smallest geographical unit in which we cannot expect households to borrow in one location to buy in another one.

We also observe the top holding company for each lender in the data. We divide the mortgage lenders into those which are held by a Big-4 bank and those which are not: $l \in \{\text{Big4}, \ \text{NoBig4}\}$. Following a method similar to Khwaja and Mian (2008), we estimate the probability of loan denial, $\Pr(\text{denial}_{i,m,l,t} = 1)$, as a linear probability model,

$$\Pr(\text{denial}_{i,m,l,t} = 1) = X_{i,m,l,t}\beta + L_{l,t} + \alpha_{m,t} + \alpha_{m,l}, \tag{1}$$

where $X_{i,m,l,t}$ controls for the characteristics of individual borrowers (income, requested loan-to-income, and race of borrower i applying for a loan from lender type l in MSA m and year t).[10] The terms $\alpha_{m,t}$ and $\alpha_{m,l}$ control for lender, time, and regional shocks. The value $\alpha_{m,t}$ is the coefficient on an indicator variable which equals 1 if the borrower applies from MSA m in year t and equals 0 otherwise, and $\alpha_{m,l}$ is the coefficient on an indicator variable which equals 1 if the borrower applies from MSA m to a lender of type l and equals 0 otherwise.

We focus on denials as the gauge of credit supply because denials only involve two decisions: the borrower's choice to apply, and the lender's choice to deny or not to deny. This minimizes the impact of unobserved borrower characteristics in our estimation of (1). Figure 2 shows how aggregate denials are strongly correlated with a proxy of lending standards based on the Senior Loan Officer Survey (SLOOS). In addition, the trend is decreasing since 2008. However, this aggregate trend hides substantial heterogeneity, with Big-4 lenders increasing their denial rate while non-Big-4 lenders reduce it.

Our focus in (1) is on $L_{l,t}$, which is a vector of dummy variables for lenders of type l in year t. Specifically, our reference category is $l =$ "NoBig4 lenders" and $t = 2007$. Thus, $L_{l,t}$ should be interpreted as a given borrower's excess denial probability from applying to a lender of type l during year t, relative to the counterfactual of applying to a non-Big-4 lender in 2007. In other words, $L_{l,t}$ captures the lender specific component of the denial rates. For example, it may reflect a higher cost of funds or greater regulatory risk borne by lenders of type l in a given year. Importantly, $L_{l,t}$ does not confound either borrower or regional effects, since these are already captured by $X_{i,m,l,t}$ and the pair $(\alpha_{m,t}, \alpha_{m,l})$, respectively. To emphasize this interpretation, we refer to $L_{l,t}$ as the propensity to deny.

In Figure 3, we plot the propensity to deny, $L_{l,t}$, for Big-4 banks and for ordinary lenders.

[10] There are 21,709,935 observations used to estimate (1).

Section 4 contains an analogous plot for the subsample of FHA loans and another for black and Hispanic borrowers. Recall that the reference category is l = "NoBig4 lenders", and t = 2007. Thus, Figure 3 indicates that the Big-4 were systematically more likely to deny a loan application than ordinary lenders, and this difference has increased over time. In fact, ordinary lenders appear to have loosened their standards relative to 2007, when they denied 15.6% of applicants. That is, there is significant time variation in the *relative* stringency of the Big-4's approval standards. We exploit this relative variation in constructing our credit supply shock, as described below.

3.2 The credit supply shock

Having estimated the Big-4's propensity to deny in Section 3.1, we follow the Bartik methodology to construct a credit supply shock in MSA m and year t.[11] Denoting this shock by $V_{m,t}$, and recalling that $L_{l,t}$ denotes the estimated lender-year fixed effect from (1), we define

$$V_{m,t} = (L_{\text{Big4},t} - L_{\text{NoBig4},t}) \cdot \text{Share}_{m,08}, \tag{2}$$

where $\text{Share}_{m,08}$ denotes the share of applications going to Big-4 lenders from MSA m in year 2008. The shock $V_{m,t}$ captures the relative stringency of the Big-4's approval standards in a given year ($L_{\text{Big4},t} - L_{\text{NoBig4},t}$) and the degree to which this tightening is felt in a given MSA ($\text{Share}_{m,08}$). Importantly, an increase in $V_{m,t}$ corresponds to a reduction of credit supply because it means a higher denial rate.

Figure 4 plots year-by-year histograms of the estimated credit shocks $V_{m,t}$. Since $V_{m,t}$ is in units of denial rates, the x-axis shows the ratio of $V_{m,t}$ to the total mortgage denial rate in an MSA. This ratio describes the extent to which the Big-4 shock can account for total denials. There is substantial cross-sectional variation in the shock $V_{m,t}$ as well as temporal variation, evident by the outward shift in the distribution of $V_{m,t}$ over time. We use these sources of variation to study housing rents in the next subsection. Moreover, in Section 4.3 we will explore an alternative credit shock based on MSA-level averages of lender specific fixed effects estimated as in (1).

[11] Bartik (1991) developed a method of isolating local labor demand changes that are unrelated to changes in local labor supply. The "Bartik Instrument" averages national employment growth across industries using local industry employment shares as weights.

3.3 Housing rents

We use the shock $V_{m,t}$ in two ways: (i) directly to study the effect of credit supply on housing rents; and (ii) as an instrument for mortgage denial rates. This second approach provides estimates whose units are easier to interpret. Our rent data are from the Zillow Rent Index.[12] Table 1 contains the unconditional summary statistics of our sample.

First, we estimate the following Bartik regressions,

$$\Delta \log(\text{Rent})_{m,t} = V_{m,t-1}\beta + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}, \tag{3}$$

where α_m, α_t are MSA and year fixed effects, respectively. Throughout the paper, we use the notation $\Delta A_{m,t} \equiv A_{m,t} - A_{m,t-1}$, for some variable A. Our controls ($\Delta X_{m,t}$) are: the change in the log of the MSA's median inhabitant age, the change in the MSA's unemployment rate, the change in the log of the MSA's median household income, and the change in the log of the MSA's population; the once-lagged changes in each of these four variables; and the once-lagged change in the log rent in the MSA.[13] Finally, several times throughout the paper we consider the role of the elasticity of housing supply as measured by Saiz (2010). For the sake of consistency across specifications, we only include the 231 MSAs for which we have a record of this elasticity and a full set of controls. Our findings are consistent when we expand the sample.

We present our results from estimating (3) in Table 2.[14] Our point estimate for β is positive, significant, and similar with or without the set of controls. Tighter credit leads to higher housing rents. However, because the magnitude of the point estimate is difficult to interpret, we also use the credit supply shock $V_{m,t}$ defined in (2) as an instrument for the mortgage application denial rate.

It is likely that mortgage denial rates are themselves endogenous with respect to housing rents; for instance, lower rents may reduce denial rates as lower-quality borrowers choose to rent rather than apply for a mortgage. However, our instrument seems valid because, as we have argued, and will provide further evidence in the next section, neither the systematic tightening of the Big-4's approval standards ($L_{\text{Big4},t} - L_{\text{NoBig4},t}$) nor the historical presence of the Big-4 in

[12] The Zillow Rent Index has the advantage of not being affected by the composition of homes currently for rent, and thus facilitates comparisons across time. Moreover, it is superior to tracking the rent of a particular unit size over time, as it is not contaminated by shifts in demand which come simply from substitution between units of different size. The interpretation of the index is nominal dollars per month.

[13] We do not control for lagged house price growth because of its collinearity with lagged rent growth.

[14] We compute standard errors according to Driscoll and Kraay (1998(Driscoll and Kraay 1998)), allowing for autocorrelation of up to two years, and spatial correlation within a given year. Our choice of two years of autocorrelation follows a standard practice of allowing around $\sqrt{T}$ periods of autocorrelation, which, for our sample of 2008 to 2014, is around 2. Results are very similar if instead we cluster the standard errors by MSA.

an MSA (Share_m) are endogenous with respect to MSA-level rents.

Our first-stage regression equation is

$$\Delta \text{Denial Rate}_{m,t} = V_{m,t-1}\delta + \Delta X_{m,t}\eta + \lambda_m + \lambda_t + v_{m,t}, \tag{4}$$

where λ_m and λ_t are MSA and year fixed effects, and all other notation is the same as in (3). Table 2 in the Online Appendix contains the first-stage results. The point estimate for δ is consistent across specifications, and it suggests a tight link between denial rate growth and our Bartik credit supply shock. When interacting the shock $V_{m,t}$ with supply elasticity, the point estimate for the interaction is highly insignificant. If $V_{m,t}$ were a supply shifter, one might expect it to affect denial rates differently in areas with different values of housing supply elasticity. Thus, it does not appear that we are confounding a rental demand shifter with a rental supply shifter because (1) purged denial propensities of MSA-specific effects.

Using an overline ($\overline{\Delta \text{Denial Rate}_{m,t}}$) to denote the fitted value from the first-stage, the second-stage equation is

$$\Delta \log(\text{Rent})_{m,t} = \overline{\Delta \text{Denial Rate}_{m,t}}\beta + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}, \tag{5}$$

where the remaining notation is the same as in (3). The coefficient on $\Delta \text{Denial Rate}_{m,t}$ is the percentage point change in rent growth following a 1 percentage point increase in mortgage denial rates.

We present our estimates of specification 5 in Table 3. The positive and significant point estimates suggest an important role for credit availability, operating through denial rates, in explaining housing rent growth. Quantitatively, a 1 percentage point increase in mortgage denials leads to around a 2.3 percentage point increase in rent growth. To put this estimate into perspective, the cross-sectional variation in rent growth is around 5 percentage points for most years.

When including the interaction with supply elasticity, the point estimate for β is larger, and the interaction term is negative, though insignificant. This result suggests a role for physical supply in accommodating credit-induced rental demand, we discuss the supply-side response in greater detail in Section 5. In the fourth column of Table 3, we consider whether credit has a stronger impact on rent growth in states without rent control. The estimate for β is 1.5 percentage points higher for states without rent control than the estimate obtained in the baseline specification.[15]

[15] States with rent control are California, New York, New Jersey, Maryland, and the District of Columbia.

4 Other specifications

In this section we first do several checks to ensure that our findings are not driven by factors affecting both Big-4 presence in 2008 and housing rent growth over the 2008-2014 period. Second, we study the subsample of FHA loans and applications made by black and Hispanic borrowers, as these groups are more likely on the margin of homeownership. Third, we explore an alternative credit shock that does not build on the wedge between Big-4 and non-Big-4 banks. Fourth, we explore changes in the GSE conforming loan limit as another source of credit supply variation. We confirm the benchmark results. Moreover, the overidentification generated by these other instruments suggest that the shock $V_{m,t}$ is a valid instrument for denial rates. Fifth, we account for the possibility that credit supply may have affected rents through foreclosures.

4.1 Dealing with the endogeneity of Big-4 share

While the propensity to deny, $L_{l,t}$, does not confound unobserved regional effects, one might wonder whether MSAs with a higher share of mortgage applications to Big-4 lenders in 2008 might, in some way, be disposed to unobserved rent shocks over the post-2008 period. If this were the case, then $V_{m,t}$ would not be a valid credit supply shock for the purposes of studying housing rents. We do several checks to deal with this potential problem.

Figure 2 in the Online Appendix shows that there is large heterogeneity across MSAs in the share of mortgage applications to Big-4 lenders in 2008. Figure 3 in the Online Appendix shows the geographic distribution of 2008 Big-4 shares. There is not a profound east-west or north-south geographic divide that may generate candidates for unobserved rent shocks over the post-2008 period. Neither are Big-4 shares concentrated in large cities that have attracted attention for their cost of living and might be candidates for unobserved rent shocks. For robustness, we redid the analysis of Section 3.3 excluding California from the data, and the results remain quite similar.[16]

Next, we re-estimate our core specifications of Section 3.3 but using a different definition of the Bartik shock that we denote as $W_{m,t}$. The difference relative to the $V_{m,t}$ shock defined in (2) is that now we use weights s_m that are orthogonal to factors that may be correlated with housing rents and also explain Big-4 market share, like for example income, population growth, age, unemployment, past housing prices or proximity to a Big-4 headquarter. We proceed in three steps

[16] Table 5 in the Online Appendix contains the results.

First we regress the 2008 Big-4 market share on a large set of variables that may affect both this market share and rent dynamics over the 2008-2014 period,

$$\text{Share}_{m,08} = Z_m\beta + \epsilon_m. \tag{6}$$

The controls Z_m are: the 2000-2008 change in the log of median household income, the log of population, the log of median inhabitant age, the unemployment rate, and log rents, measured by the Zillow Rent Index, as well as the 2007-2008 change in each of these variables. We also control for whether the MSA is in a state which contains or is close to the headquarters of a Big-4 bank.[17] Table 4 contains the results. Interestingly, MSAs in states with or close to a Big-4 headquarters had a higher Big-4 share in 2008, suggesting a role for geography in credit supply.

Second, we extract the residual from (6), which we denote s_m,

$$s_m = \text{Share}_{m,08} - Z_m\hat{\beta}. \tag{7}$$

This residual is the component of a city's Big-4 share which is orthogonal with respect to pre-2008 fundamentals that may also affect housing rents. We refer to s_m as the idiosyncratic component of an MSA's 2008 Big-4 share.

Third, we use s_m to construct the new Bartik shock

$$W_{m,t} = (L_{\text{Big4},t} - L_{\text{NoBig4},t}) \cdot s_m. \tag{8}$$

Then, we re-produce the core analysis of Tables (2)-(3) using our revised shock $W_{m,t}$ instead of $V_{m,t}$. The results are in Online Appendix Table 4 and are within a similar range. In fact, the point estimate for the impact of denial rates on rent growth is 3.1, compared with 2.3 from Table (3).

4.2 FHA and minority applicants

We now perform a robustness check based on two subsamples for whom a mortgage rejection likely has a stronger effect on the rent-own decision: FHA loan applicants and black and Hispanic applicants. First, we focus exclusively on FHA loans. We begin by re-estimating (1) among the subset of applications for FHA loans. We denote the estimated lender-year fixed

[17] These states are: California (Wells Fargo), North Carolina (Bank of America), and New York, New Jersey, or Connecticut (JP Morgan and Citigroup).

effects as $L_{l,t}^{FHA}$. Second, we focus on loans to black and Hispanic applicants, which, to simplify language, we call minority loans. That is, we re-estimate (1) among the subset of applications by minorities, and we denote the estimated lender-year fixed effects as $L_{l,t}^{Min}$.

Figure 5 plots these lender-year fixed effects. They represent the excess probability of denial faced by the applicants from applying to lenders of type $l \in \{\text{Big4}, \text{NoBig4}\}$ in year t, relative to the baseline of $l =$ "NoBig4 lenders", and $t = 2007$. Both lender groups appear more stringent when considering only FHA loans, but the Big-4 tightened their approval standards for FHA borrowers substantially more than non-Big-4 lenders over our sample period. This is consistent with Big-4 lenders' apprehension of legal repercussions from mistakes in the underwriting of government-insured loans.[18] Concerning minority loans, after controlling for MSA, time, and individual borrower characteristics, Big-4 banks are more likely to deny applications made by black or Hispanic borrowers, although this relative stringency varies less than with FHA loans.

We then construct an analogue to the credit supply shock in (2),

$$Y_{m,t} = (L_{\text{Big4},t}^{FHA} - L_{\text{NoBig4},t}^{FHA}) \cdot \text{Share}_{m,08}, \tag{9}$$

$$M_{m,t} = (L_{\text{Big4},t}^{Min} - L_{\text{NoBig4},t}^{Min}) \cdot \text{Share}_{m,08}. \tag{10}$$

where, as in (2), $\text{Share}_{m,08}$ denotes the fraction of mortgage applications from MSA m to Big-4 banks in 2008. We use the share of total mortgage applications to define $\text{Share}_{m,08}$, rather than the share of FHA or minority loan applications, to further avoid endogeneity concerns related to the fraction of FHA or minority borrowers in a given MSA in 2008.

We re-estimate the Bartik (3) and instrumental variable (5) specifications using $Y_{m,t}$ and $M_{m,t}$ in place of $V_{m,t}$. Online Appendix Tables 6 and 7 contain the results. The estimates indicate that both the credit shocks $Y_{m,t}$ and $M_{m,t}$, can significantly explain housing rents. We obtain results similar to our baseline estimate from Table 3. A 1 percentage point increase in the growth of loan denials leads to a 2.1 percentage point increase in rent growth when using the FHA-based credit shock, and to a 2.3 percentage point increase when using the minority-based credit shock.

[18] In a July 2014 conference call with analysts, JP Morgan's CEO remarked "The real question for me is should we be in the FHA business at all. Until they come up with a safe harbor or something, we are going to be very, very cautious in that line of business."

4.3 MSA average shocks

Now we explore a credit supply shock which is more agnostic as to which lenders were affected by the shock. We do not divide the lenders into Big-4 and non-Big-4. Instead, for each year, we rank lenders according to national application share in that year. We assign a unique identifier to each lender. For lenders whose share is outside the top 20, we assign an identifier of 0. Thus, for each year, lender identifiers are in the set $l \in \{0, ..., 20\}$. Then, we estimate (1) year-by-year and extract an equivalent of the lender fixed effect $L_{l,t}$. In this setting, $L_{l,t}$ represents the excess denial probability from applying to lender l in year t relative to a lender outside the top 20 ($l = 0$) in that year. We weight these fixed effects by the application market share $\text{Share}_{m,l,t}$ of lender l in MSA m in year t to construct an "MSA average credit supply shock", $G_{m,t}$, as

$$G_{m,t} = \sum_{l=0}^{20} L_{l,t} \text{Share}_{m,l,t}. \tag{11}$$

The reason we do not use 2008 shares is because it is not always clear how to track lenders outside the Big-4 over time. For example, Taylor, Bean & Whitaker was a top-20 lender in 2008, but shut down its operations in 2009.

Our results in Table 5 show that $V_{m,t}$ and $G_{m,t}$ are strongly correlated and that when $G_{m,t}$ is used to instrument for denial rates, we find again that higher denial rates lead to higher housing rents. The estimated coefficient on denial rates is 1.4, which is within the range of our benchmark estimate.

4.4 Variation in conforming loan limits

Now we explore the set of instruments used by Loutskina and Strahan (2015). These include (i) the fraction of mortgage applications from a given region in year $t-1$ for a loan within $\pm 5\%$ of the conforming loan limit in year t, which we denote $\text{AtLimit}_{m,t-1}$, and (ii) this fraction multiplied by the change in the log conforming loan limit from year $t-1$ to year t, which we denote $\text{AtLimit}_{m,t-1} \times \Delta \log(\text{ConfLimit})_{m,t}$.

We need to depart slightly from the method of Loutskina and Strahan (2015) because the 2008 Economic Stimulus Act has changed how the conforming loan limits are decided. Prior to 2008, conforming loan limits were uniform across MSAs and depended only on prior national house prices. However, the Economic Stimulus Act designated certain MSAs as high-cost, and thus subject to a less restrictive conforming loan limit. While Loutskina and Strahan (2015) effectively argue that these two instruments are orthogonal to local demand over the 1994-2006 period, the second instrument is not exogenous over our 2009-2014 period because, as of 2008, a city's designation as "high-cost" varies each year according to local demand conditions. Thus, we cannot include the interaction term $\text{AtLimit}_{m,t-1} \times \Delta \log(\text{ConfLimit})_{m,t}$ in our set.[19] We address this issue by replacing the change in the log conforming loan limit from year $t-1$ to year t with the MSA's inverse elasticity of housing supply, as estimated by Saiz (2010). The idea is that this inverse elasticity is meant to capture the degree of house price growth in an MSA, and thus is a reasonable proxy for the change in the log conforming loan limit from year $t-1$ to year t.

We structure the rest of the exercise similarly to our instrumental variables analysis in Section 3.3. First, we consider the first-stage impact of our expanded instrument set on the change in denial rates,

$$\begin{aligned} \Delta\text{Denial Rate}_{m,t} = V_{m,t-1}\delta_1 + \text{AtLimit}_{m,t-1}\delta_2 + \left(\text{AtLimit}_{m,t-1} \times \text{Elasticity}_m^{-1}\right)\delta_3 + ... \\ ... + \Delta X_{m,t}\eta + \lambda_m + \lambda_t + \upsilon_{m,t}, \end{aligned} \tag{12}$$

where the notation is the same as in (4). Our second-stage equation is the same as in (5), with rent growth as our outcome of interest.

The impact of the conforming loan limit instruments on denial rates is theoretically unclear. On the one hand, a large number of applicants at the threshold coupled with an increase in the threshold could reduce denial rates, as lenders can potentially sell these mortgages to a GSE. On the other hand, an increase in the threshold could induce lower-quality borrowers to apply for relatively large loans, thereby increasing observed denial rates. Alternatively, lenders might be unwilling to sell their loans to the GSEs, perhaps for fear of legal or regulatory repercussions, and so an increase in the loan limit would lead to an increase in denials to the extent that borrowers respond to the higher limit by requesting larger loan sizes. Indeed, Online Appendix Table 8 indicates that the latter effect dominates over our period: the conforming loan limit instruments are positively correlated with denial rates over our sample period. To explore this further, Online Appendix Table 9 shows that increases in the conforming loan limit, as gauged by our instruments $\text{AtLimit}_{m,t-1}$ and $\text{AtLimit}_{m,t-1} \times \text{Elasticity}_m^{-1}$, led to a greater fraction of denials attributed to the borrower's debt-to-income, but they led to an insignificant change in the fraction of denials attributed to the borrower's collateral quality.[20]

We present our second-stage estimates in Table 6. Note that our point estimates are similar,

[19] Our data on conforming loan limits are at the county-year level, and begin in 2008. Full details are in the Appendix.

[20] HMDA allows lenders to optionally report the primary reason for loan denial from a selection of possible reasons, including debt-to-income ratio and collateral quality.

though slightly larger, to those obtained in our baseline instrumental variables analysis in Table 3, with an estimated impact of denial rates on rent growth of 2.4 to 3.5, compared with around 2.3 from our baseline. Moreover, Hansen's J-statistic is consistently insignificant across specifications, whether or not the Big-4 Bartik shock, $V_{m,t}$, is included in the instrument set. When $V_{m,t}$ is included, the C-statistic for the difference-in-Sargan test that $V_{m,t}$ is a valid instrument is also insignificant. That is, we fail to find evidence that our instrument set, and in particular $V_{m,t}$, suffers from a lack of validity. Quantitatively, our various specifications suggest that a 1 percentage point increase in the growth or mortgage denials leads to between a 1.4 and 3.5 percentage point increase in rent growth.

4.5 Foreclosures

In this subsection we consider whether the growth in rents might have resulted from an alternative channel through which Big-4 banks may have induced more foreclosures. Higher foreclosures would artificially reduce the available housing stock in an area and lead to increases in rents and decreases in homeownership. To test for such an effect, we re-estimate our baseline Bartik and instrumental variables specifications from equations 3 and 5, except that we include the change in the MSA-level foreclosure rate as an additional independent variable.

In the first column of Online Appendix Table 10, we estimate (3) on the subsample of 81 MSAs for which we have foreclosure data using our full set of controls from Section 3. We also include the change in the foreclosure rate as an additional control. The estimated coefficient on the credit supply shock $V_{m,t}$ is significant, although the point estimate differs from that of Table 2 because of the change in sample. Moreover, foreclosures themselves do not appear to have a significant effect on housing rents. In our instrumental variables specification (5), we find that foreclosures neither affect the estimated impact of denial rates on rent growth, nor do they have a significant effect on rents themselves. That is, we continue to find that the Big-4's credit supply shock works through denial rates, not through a foreclosure-induced constriction of rental supply. This finding is consistent with Mian, Sufi and Trebbi (2015), who find that U.S. foreclosures peaked early in 2008, at the beginning of our observation window.

5 Construction, vacancies and housing prices

To this point, we have focused primarily on the response of housing rents to tightening mortgage supply. In this section, we study the effect on other housing variables of interest.

5.1 Construction

We consider the response of multifamily construction to rental demand. With an outward shift in rental demand, one might expect builders to respond with increased construction of multifamily properties. To test this hypothesis, we use data on the number of permits issued for the construction of multifamily units, which we obtain from the Census' annual Building Permits Survey.[21] We then estimate our Bartik specification (3) but now with the change in the log of multifamily permits issued as our outcome. Similarly, we estimate a variant of the instrumental variables model (5) except that we replace the second-stage outcome with the change in the log of multifamily permits issued.

Table 7 contains the results.[22] We find a role for credit supply on the construction of multifamily units. In fact, the estimates indicate that the impact is quite large, with a 1 percentage point increase in denial rates leading to between a 41.7 and 49.5 percentage point increase in the growth of multifamily permits. This strong result suggests that the recent demand-driven rent growth may weaken substantially as this construction is completed.

5.2 Rental vacancy rates

We next analyze the impact of mortgage supply on rental vacancy rates. Our theory predicts that the credit-induced rental demand should lead to a tighter rental market and thus, for a given stock of rental units, to reduced vacancy rates. To explore this possibility, we use data on the fraction of vacant rental properties from the Housing Vacancy Survey. As we did with multifamily permit issuance, we then estimate our Bartik specification (3) but with the change in the rental vacancy rate as the outcome. We also estimate the instrumental variables model (5) with the change in the rental vacancy rate as the second-stage outcome.

Table 8 contains the results. In all specifications, we find a negative point estimate on the coefficients of interest, consistent with the theory discussed above. However, while economically significant, the estimates are not statistically significant. This may result from the relatively small sample of 58 MSAs for which we have data on rental vacancies.

[21] We define multifamily units as the sum of 2 unit shelters, 3-4 unit shelters, and 5+ structure shelters. Our permit data covers 218 MSAs.

[22] We obtain similar results if we focus on the share of multifamily permits among total building permits.

5.3 Housing prices

The effects of our credit supply shock on house prices is theoretically unclear. On one hand, higher rents could raise house prices according to the logic of standard asset pricing, as house prices represent the discounted sum of flow payoffs, or rents. On the other hand, restricted access to credit implies a reduction in demand for owner occupied properties and thus a lower house price, all else equal. To explore possible heterogeneity, we partition the sample into MSAs with a high (top third) and low or moderate (bottom two thirds) price-to-income ratio in 2008. Those MSAs in the high group have $\text{Affordable}_m = 0$, and the remaining MSAs have $\text{Affordable}_m = 1$. The idea is that, in housing markets where the median home is more affordable, the median house is more likely to be priced by households on the margin of homeownership.

Table 9 analyzes the effects of credit supply on house prices. The first column studies the effect of the Bartik shock $V_{m,t}$ directly. In the second column, we use $V_{m,t}$ as an instrument for rent growth. In both specifications, we interact the variable of interest with Affordable_m. The result of the table is that the effect of credit supply on house prices depends on whether the median house price is affordable, and thus likely priced by those on the margin of homeownership. While house prices rise with credit-induced rent growth, there also appears to be an attenuating effect: the reduced demand for owner occupied housing by the marginal household pushes down the median house price. Both columns deliver this same message.

6 Homeownership and frictions to replace the Big-4

To evaluate whether the increase in rents indeed comes through the channel of housing tenure choice, we now consider whether mortgage supply impacts homeownership rates. Next, we ask whether there exist frictions in mortgage markets that could inhibit would-be homeowners from obtaining credit from a less stringent lender than a Big-4 bank.

6.1 Homeownership

First, we replicate regression (3) except that we now consider homeownership rates, rather than housing rents, as our outcome of interest. We also estimate a variant of the instrumental variables model in (4) and (5) except that we replace the second-stage outcome with the change in homeownership rates.

Table 10 contains the results. The coefficients for the credit shock $V_{m,t}$ are negative and significant, suggesting that the tightening of the Big-4's approval standards has led to lower homeownership rates and thus affected rents through a housing tenure choice channel. A 1 percentage point increase in the growth of denial rates leads to around a 2.4 percentage point reduction in a city's growth in homeownership. Finally, as a measure of robustness, we re-perform our analysis of homeownership rates on the subsample of FHA loan applicants and black and Hispanic borrowers, and we obtain very similar results. These results are shown in Online Appendix Tables 15 and 16.

6.2 Frictions to substitute among lenders

Implicit in our analysis to this point is a notion that there are frictions which make it difficult for rejected borrowers to find new sources of credit. In this subsection we explore two possible sets of frictions to substitute across lenders: internet accessibility and competition among credit suppliers. Households in regions with more frictions encounter greater difficulty substituting towards more lenient lenders and should feel the effects of the Big-4's tightening more strongly. We study homeownership rates as our outcome since housing tenure choice is the key channel through which mortgage supply affects rents in our theory.

6.2.1 Internet accessibility

We first consider internet accessibility. As documented by Lux and Greene (2015), online lenders without branches have been the group of lenders with the fastest growth over the period that we analyze. We employ two measures of internet accessibility. First, Bull and Gulamhuseinwala (2016) show that older borrowers encounter greater difficulty transitioning to an online platform than younger borrowers. Thus, age appears to be an important barrier to borrowing from online lenders. To evaluate this effect, we compute the ratio of inhabitants older than 50 to inhabitants between ages 25 and 49 in a given MSA during 2008, the first year of our sample period, and then standardize this ratio to have a mean of 0 and a standard deviation of 1. We then interact the credit supply shock $V_{m,t}$ defined in (2) with this ratio, denoted by Older_m. That is, we estimate the regression

$$\Delta \text{HR}_{m,t} = V_{m,t-1}\beta_1 + (V_{m,t-1} \times \text{Older}_m)\beta_2 + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}, \tag{13}$$

where $\text{HR}_{m,t} \in [0,1]$ denotes the homeownership rate.

Second, we use the Forbes.com Wired Rank of city-by-city internet accessibility. This index ranks cities according to a weighted average of the percent of internet users with high-speed connections, the number of companies providing high-speed internet, and the number of public wireless internet hotspots in a city. To assess the importance of internet access in mitigating credit supply shocks, we estimate

$$\Delta \mathrm{HR}_{m,t} = V_{m,t-1}\beta_1 + (V_{m,t-1} \times \mathrm{LowInternet}_m)\beta_2 + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}, \tag{14}$$

where $\mathrm{LowInternet}_m$ indicates whether the MSA was not ranked in the top 25 by the Forbes.com index in 2008.[23]

Our estimates of (13) and (14) are presented in the first two columns of Table 11. The tightening of lending standards captured by $V_{m,t}$ led to stronger effects on homeownership in MSAs with either an older population or with less internet availability.

It is possible that age or internet inaccessibility are proxies for, say, regulation. To account for this possibility, we include an interaction between our credit supply shock, $V_{m,t}$, and the Wharton Residential Land Use Regulation Index (WRLURI) developed by Gyourko, Saiz and Summers (2008). This index measures the stringency of regulations on residential growth in a given MSA, where higher values indicate greater stringency. It is standardized to have a mean of 0 and standard deviation of 1. The results, presented in columns three and four of Table 11, suggest that our measures of internet accessibility do not confound regulatory disposition. Thus, it appears that credit supply has a stronger impact on the marginal household's choice of tenure where it is more difficult for that household to maneuver online lending.

6.2.2 Competition among lenders and mortgage brokers

We consider as a second friction the role of competition among lenders and the mortgage brokers who connect lenders with borrowers. If non-Big-4 lenders operate in an uncompetitive market, borrowers should encounter more difficulty finding alternative sources of credit if denied by a Big-4 bank. Similarly, if mortgage brokers face little competition, they may lack the incentive to connect borrowers with more lenient lenders. In both cases, the Big-4's stringency should have a stronger impact in regions where there is little competition among either lenders or mortgage brokers.

First, we focus on the role of mortgage brokers. According to Backley et al. (2006) at least two thirds of mortgage loan transactions are intermediated by a mortgage broker. If mortgage

[23] The results are similar if we instead use, for example, the top 20 as the cutoff.

brokers have sticky relationships with lenders, then brokers may keep sending customers to those lenders even if their standards are higher. To explore this possibility, we construct a measure of barriers to entry based on the heterogeneity across states in the regulation of mortgage brokers. Specifically, 48 states require mortgage brokerage firms to carry a license, while 18 states impose the additional requirement that individual brokers also be licensed.[24] According to Backley et al. (2006), this additional licensing requirement represents a relevant cost to operating as a mortgage broker, and so we use it to approximate lack of competition in mortgage markets. Our regression equation for this analysis is

$$\Delta \mathrm{HR}_{m,t} = V_{m,t-1}\beta_1 + (V_{m,t-1} \times \mathrm{License}_m)\beta_2 + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}, \tag{15}$$

which has an interaction between $V_{m,t-1}$ and an indicator of whether MSA m requires individual mortgage brokers to carry a license.

Second, we focus on competition among non Big-4 lenders. To measure such competition, we construct a Herfindahl-Hirschman index (HHI) of loan applications among non-Big-4 lenders in a given MSA during the year 2008, the start of our sample period.[25] To ease interpretation, we standardize the HHI so that it has a mean of 0 and a standard deviation of 1. The corresponding regression equation is

$$\Delta \mathrm{HR}_{m,t} = V_{m,t-1}\beta_1 + (V_{m,t-1} \times \mathrm{HHI}_m)\beta_2 + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}, \tag{16}$$

which is of the same form as (15).

The first column of Table 12 presents the estimates of (15). We again find an important role for credit supply, and the negative point estimate on the interaction with $\mathrm{License}_m$ is consistent with a theory in which lack of competition among mortgage brokers strengthens this role. However, because the estimate for the interaction term is not significant, it is difficult to draw strong conclusions. The estimates of (16) in the second column of Table 12 indicate that credit supply has a stronger impact on homeownership where non-Big-4 lenders face little competition, with a negative, significant coefficient on HHI_m.

As before, one might be concerned that $\mathrm{License}_m$ or HHI_m could in fact proxy for, say, land-use regulations that make homeownership rates more responsive to credit supply. To account for this possibility, we again include an interaction between our credit supply shock, $V_{m,t}$, and

[24] As of 2006, these 18 states were Arkansas, California, Florida, Hawaii, Idaho, Louisiana, Maryland, Montana, Nevada, North Carolina, Ohio, Oklahoma, South Carolina, Texas, Utah, Washington, West Virginia and Wisconsin.

[25] The results are quite similar if we construct the HHI in terms of originations, rather than applications. We prefer to use applications because our credit shock $V_{m,t}$ is defined in terms of application share.

the Wharton Residential Land Use Regulation Index (WRLURI). If, indeed, either License_m or HHI_m are simply proxies for land-use regulation, the estimated coefficients on their interactions with $V_{m,t}$ in (15) and (16) should change substantially. Columns three and four of Table 12 present our results from this test. Interestingly, there appears to be some connection between regulation of mortgage brokers and land-use regulation, as the point estimate for the interaction with License_m in the third column is much smaller. However, the estimate for the interaction with HHI_m is quite similar whether or not we account for land-use regulation, suggesting that our measure of competition among non-Big-4 lenders does not confound regulatory preferences. In fact, the negative and significant coefficients on the interaction between $V_{m,t}$ and WRLURI suggest that land-use regulation strengthens the impact of credit supply on homeownership.

7 Conclusions

In this paper, we showed that tighter mortgage credit explains a significant component of the increase in housing rents and lower homeownership rates since the 2007 financial crisis. Our benchmark specification instrumented for denial rates with a new measure of a credit supply shock. This shock captures the relative stringency of the Big-4's lending standards in a given year and the degree to which this tightening is felt in a given MSA. For cities where the Big-4 received 25% of mortgage applications in 2008, denial rates were 1.1 percentage points higher because the Big-4 tightened standards relative to other lenders over 2008-2014. Additionally, rents were 2.5% higher, and the homeownership rate was 1.8 percentage points lower in these MSAs. We obtain similar results when we use alternative instruments such as changes in the maximum loan limits that the GSEs insure, or when we use an average credit supply shock among active lenders in the MSA.

Our results suggest that recent regulatory changes may have unintended consequences and result in less accessible credit for some borrowers and higher housing rents; Ambrose, Conklin and Yoshida (2016) present results that point in the same direction. The results also indicate that the price effect of the resulting rental demand will weaken as supply expands to accommodate more renters. This finding may signal that high rent growth is self-moderating through increased supply, without the need for rent controls.

Finally, we explored several frictions that have prevented new lenders from filling the void left by the Big-4 banks. For example, borrowers' age or frictions inhibiting internet usage appear to be barriers to substituting towards new online lenders. The increase in housing rents will recede as borrowers become more accustomed to online banking. We also find an important role for market power among lenders in amplifying the impact of credit supply on housing tenure choice. These frictions may be more persistent.

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Appendix: Data Sources

In this section, we describe our data sources, how we cleaned them, and the key variables used in our analysis.

Housing rents and prices

Our rent data cover 320 MSAs from 2007 through 2014 at a yearly frequency. Data for rents and prices are from Zillow. To measure rents, we use the Zillow Rent Index (ZRI), and the particular series we use is the "Quarterly Historic Metro ZRI". The ZRI measures the median monthly rent for each MSA and has units of nominal dollars per month. Zillow imputes this rent based on a proprietary machine learning model taking into account the specific characteristics of each home and recent rent listings for homes with similar characteristics. The median is computed across all homes in an MSA, not only those which are currently for rent. Thus, unlike pure repeat-listing indices, the ZRI is not biased by the current composition of for-rent properties. To measure house prices, we use the Zillow Home Value Index (ZHVI), based on the series "Quarterly Historic Metro ZHVI". The ZHVI is computed using a methodology analogous to that of the ZRI. Although the ZRI and the ZHVI are available quarterly, we only retain the values corresponding to the fourth quarter of each year because our mortgage data are at the yearly frequency.

We merge all datasets based on year and the MSA's 2004 core based statistical area (CBSA) code. For sub-metro areas of the largest MSAs, we use the CBSA division code. Since Zillow does not identify MSAs using Census Bureau codes, we created a crosswalk file between Zillow and CBSA codes. The crosswalk matches cities based on their name in Zillow and their Census name. In general, the Zillow data are much broader, covering 906 cities. However, after merging with the cities for which we have the mortgage data described below, we have rent data for 320 MSAs.

Mortgage data

Data on mortgage credit come from the Home Mortgage Disclosure Act (HMDA). The frequency of the data is yearly. HMDA data contain application-level information on the requested loan size, loan purpose, property type, and application status for mortgage requests received by both depository institutions and independent mortgage companies. We observe the self reported income, race, and gender of the borrower, as well as an identifier of the lender receiving the application. Since our focus is on how credit affects rents through housing tenure choice, we only retain mortgage applications for the purchase of a 1-to-4 family, owner-occupied home. In terms of HMDA variables, we retain applications satisfying the following conditions: occupancy = 1 (owner occupied), property type = 1 (1-to-4 family), loan purpose = 1 (for-purchase), and action taken $\neq$ 6 (loan not purchased by institution). To maximize data quality, we additionally require that applications were not flagged for data quality concerns (edit status = "NA") and have a non-empty MSA code. We identify denied and originated loans as those with action taken = 3 and action taken = 1, respectively. FHA loans are those with loan type = 2.

Our data on MSA population and income also come from HMDA as part of the FFIEC Census Report. The FFIEC directly reports median family income for each MSA and census tract, and the population for each census tract. We compute MSA-level population by summing across census tracts belonging to an MSA. In terms of demographics, we identify applicants as black if the applicant's primary race = 3 and as Hispanic if the applicant's primary race = 5 and the applicant's ethnicity = 1.

We merge the HMDA's application-level data by lender and year with the HMDA reporter panel. The reporter panel contains each lender's name, total assets, and top holding company. Within each year, we classify a lender as belonging to the Big-4 if its top holding company is one of the Big-4 banks. To account for slight changes in institutional names over time, we identify the Big-4 banks as those whose names possess the strings "WELLS FARGO", "BANK OF AMERICA", "CITIG", or "JP". Using our classification scheme, if a Big-4 bank acquires another institution in, say, 2010, then that institution would be classified as a non-Big-4 lender in 2009 but as belonging to the Big-4 in 2010.

Elasticity and regulation data

The house price elasticity of supply at the MSA level comes from Saiz (2010). We have elasticity data for 241 MSAs. The Wharton Residential Land Use Regulation Index (WRLURI) comes from Gyourko, Saiz and Summers (2008) and covers 290 MSAs. The WRLURI is standardized to have a mean of 0 and standard deviation of 1, and higher values indicate more stringent regulation. Our data on licensing rules for mortgage brokers come from Backley et al. (2006), according to whom, as of 2006, 48 states require mortgage brokerage firms to carry a license, while 18 states impose the additional requirement that individual brokers also be licensed. These 18 states are Arkansas, California, Florida, Hawaii, Idaho, Louisiana, Maryland, Montana, Nevada, North Carolina, Ohio, Oklahoma, South Carolina, Texas, Utah, Washington, West Virginia and Wisconsin. Finally, our data on state-level rent controls come from the National Multifamily Housing Council, according to which the states practicing rent control are California, New York, New Jersey, Maryland, and Washington, D.C. Since the Washington D.C. metro area spans Alexandria, Virginia, we do not classify it as practicing rent control in our baseline analysis. However, the results of Table 3 are quite similar in magnitude and precision if we instead classified Washington, D.C. as an MSA where rent control is practiced.

Homeownership and vacancy data

Homeownership rates and vacancy rates for rental properties are available for a selection of 75 MSAs from the U.S. Census Bureau's Housing Vacancy Survey at quarterly frequency dating back to 2005, though over our sample period we only observe data for 70 of these. The national homeownership rate is available at a quarterly frequency dating back to 1980. As we did with the Zillow data, we only retain the fourth-quarter value for homeownership and vacancy rates, to match the annual frequency of our mortgage data.

Other variables

We also rely on the following data sources:

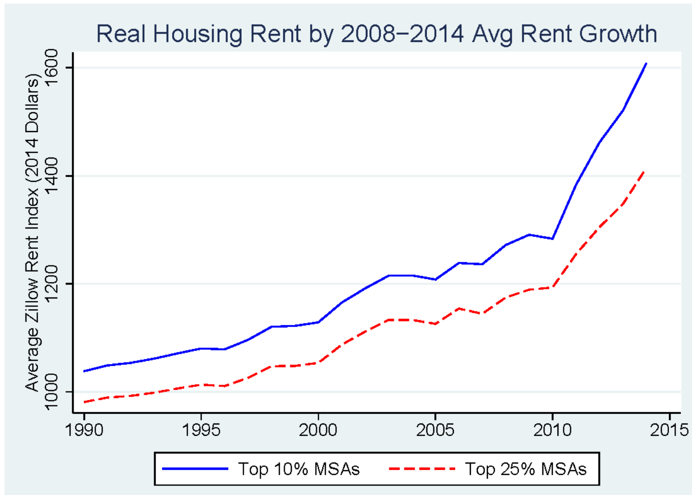
- Age data and unemployment data at the MSA level are from the American Community Survey 1-Year Estimates, provided by the U.S. Census Bureau.
- Data on multifamily permits come from the Census Bureau's annual Building Permits Survey. We define multifamily units as the sum of 2 unit shelters, 3-4 unit shelters, and 5+ structure shelters. Our permit data covers 218 MSAs.
- Our data on conforming loan limits is at the county-year level and begins in 2008. The data are provided by the Federal Housing Finance Agency (FHFA). We merge this dataset to our HMDA dataset by county and year prior to collapsing to the MSA-year level. For MSAs that have counties with different conforming loan limits, we take the application-weighted average conforming loan limit among counties.
- Foreclosure data comes from Zillow. Specifically, Zillow measures the percentage of home sales in a given month in which the home was foreclosed upon within the previous year. As with the other Zillow data, we retain only the value corresponding to the end of the year. We have data for 81 such MSAs.

- Our data on internet accessibility comes from the Forbes.com Wired Index ("America's Most Wired Cities"). This index ranks cities according to (i) the percentage of home internet users with high-speed connections, (ii) the number of companies providing high-speed internet access, and (iii) the number of public wireless internet hot spots per capita. It then generates a composite ranking based on a weighted average of each city's ranking in these three categories. We use the 2008 ranking in our analysis.

- Our data on the percentage of banks tightening standards comes from the Federal Reserve's Senior Loan Officer Survey (SLOOS). Specifically, we use the series Net Percentage of Domestic Banks Tightening Standards for Prime Mortgage Loans (DRTSPM). We choose this series because it is the SLOOS series with the most consistent coverage over our sample period. The Federal Reserve administers SLOOS quarterly to a panel of up to 60 large, geographically diverse domestic commercial banks.

To summarize, there are 231 MSAs with a full set of controls, elasticity and rent data which we use in our rent regressions. In addition, there are 60 MSAs we use in our homeownership regressions, 218 MSAs we use in our building permit regressions, and 58 MSAs we use in our vacancy rate regressions.

Figures



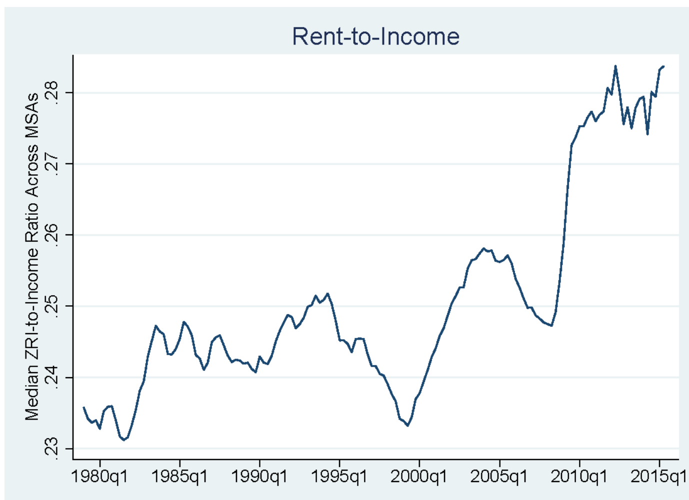


Figure 1. Dynamics of Real Housing Rents and Rent-to-Income. The top panel plots real housing rents over the 1991-2014 period in 2014 dollars for MSAs ranking in the top 10% and top 25% of 2008-2014 rent growth, respectively. Nominal rents are measured using the Zillow Rent Index. The translation to real rents is done using the Consumer Price Index excluding shelter. The bottom panel plots the median ratio of rent-to-income for the MSAs in our sample.

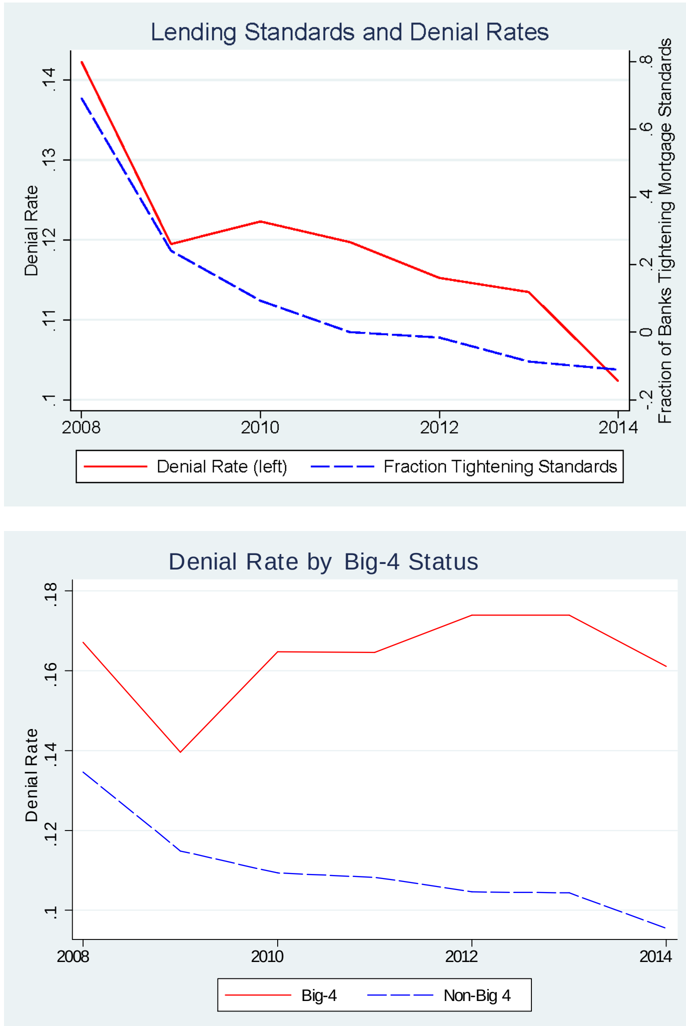


Figure 2. Lending Standards, Denial Rates and Compositional Effects. The top panel plots national denial rates along with the fraction of banks tightening lending standards for prime mortgage loans, based on the Senior Loan Officer Survey (SLOOS). The correlation between the two series is 0.921 with a p-value of 0.003. The bottom panel plots the aggregate denial rates for the Big-4 banks (Bank of America, Citibank, JP Morgan and Wells Fargo) and for non-Big-4 lenders.

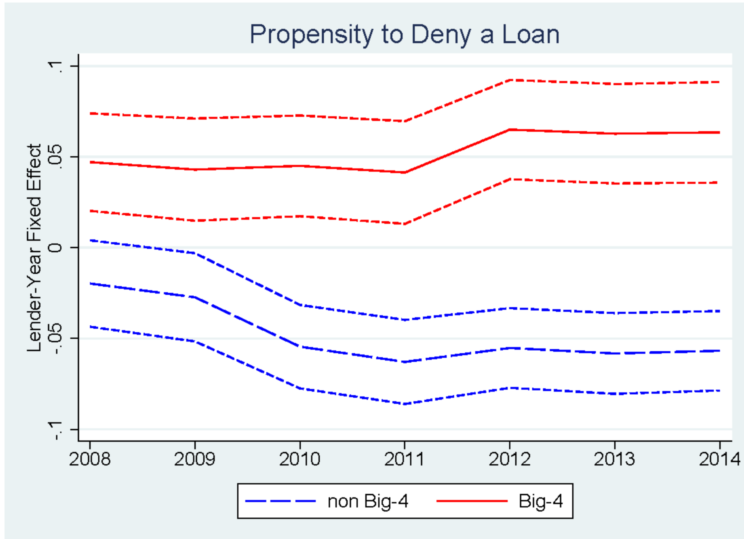


Figure 3. Propensity to Deny of Big-4 Banks and Other Lenders. This figure plots the lenders' fixed effects estimated in equation (1). The dashed lines correspond to a 95% confidence interval, computed with heteroskedasticity robust standard errors. The reference lender-year category is non Big-4 lenders in 2007, for which the loan denial probability was 0.156.

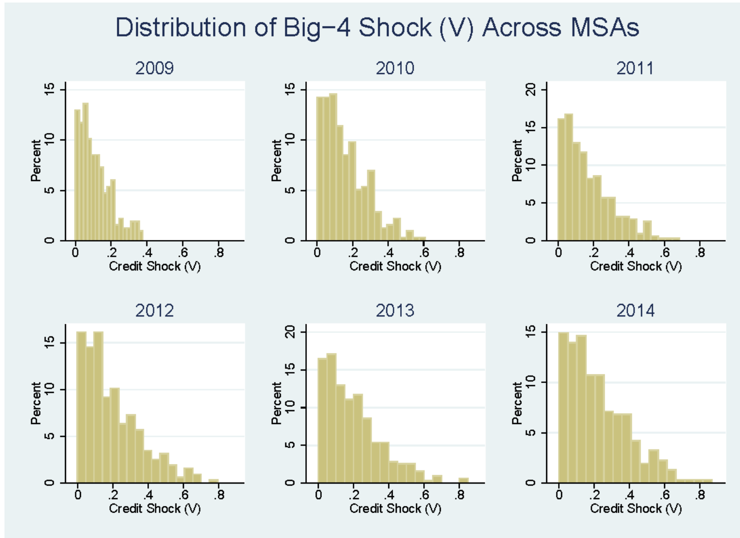


Figure 4. The Distribution of the Big-4 Bartik Shock ($V_{m,t}$). This figure plots a histogram of the Big-4 Bartik shock $V_{m,t}$ defined in equation (2). This shock is the product of the share of an MSA's mortgage applications to Big-4 banks in 2008 and the difference in the denial propensity of Big-4 and non Big-4 lenders in a given year. Since $V_{m,t}$ is in units of denial rates, we plot the histogram year-by-year with the x-axis showing the ratio of $V_{m,t}$ to the total mortgage denial rate in an MSA.

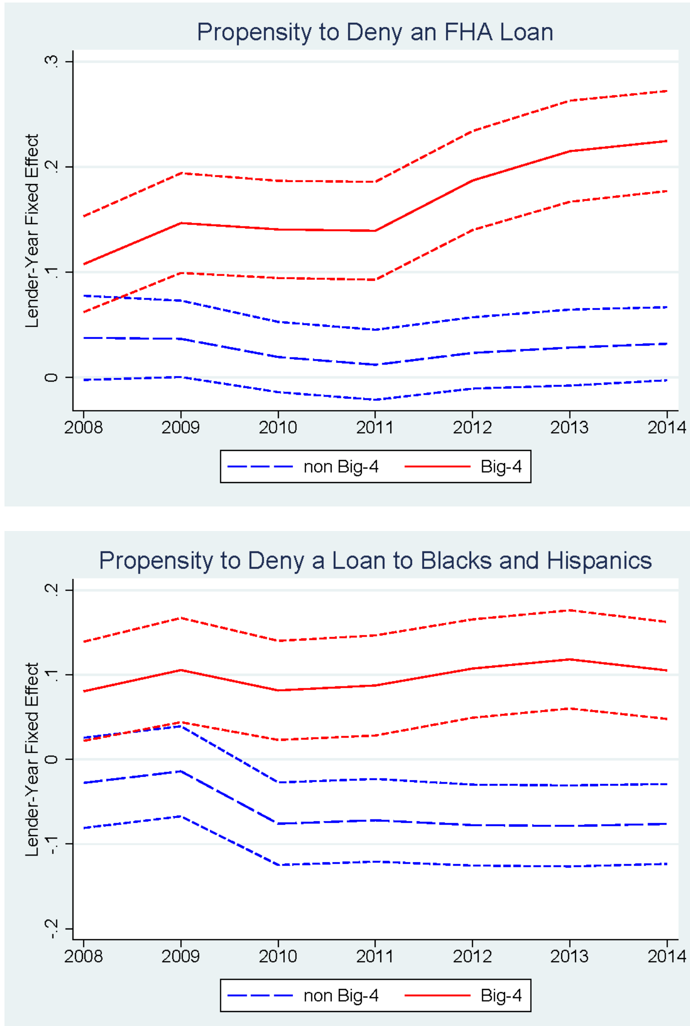


Figure 5. Propensity to Deny Mortgages to FHA Borrowers and to Blacks and Hispanics. The top panel plots the lenders' fixed effects estimated in equation (1) for FHA loans. The dashed lines correspond to a 95% confidence interval, computed with heteroskedasticity robust standard errors. The reference lender-year category is non Big-4 lenders in 2007, for which the denial probability for FHA loans was 0.148. The bottom panel plots the lenders' fixed effects estimated in equation (1) for loan applications by blacks and Hispanics, which we call minority loans. The dashed lines correspond to a 95% confidence interval, computed with heteroskedasticity robust standard errors. The reference lender-year category is as in the top panel and the corresponding denial probability for minority loans was 0.256.

Tables

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
$\Delta\log(\text{Rent}_{m,t})$	2222	0.027	0.059	-0.292	0.57
$\Delta\log(\text{Income}_{m,t})$	2222	0.012	0.042	-0.343	0.215
$\Delta\log(\text{Population}_{m,t})$	2222	0.014	0.067	-0.655	1.123
$\Delta\text{Unemployment Rate}_{m,t}$	2137	0.001	0.022	-0.086	0.088
$\Delta\log(\text{Rent}_{m,t})$	1926	-.008	.073	-.457	.28
$\Delta\log(\text{Age}_{m,t})$	2137	0.005	0.021	-0.158	0.17
$\Delta\text{Denial Rate}_{m,t}$	2222	-0.005	0.02	-0.216	0.19
$\Delta\text{Homeownership Rate}_{m,t}$	487	-0.007	0.033	-0.108	0.165
$\Delta\log(\text{Multifamily Permits}_{m,t})$	1902	-0.272	1.305	-5.862	4.533
$\Delta\text{Vacancy Rate}_{m,t}$	494	-0.004	0.037	-0.163	0.15
$\Delta\text{Foreclosure Rate}_{m,t}$	666	0	0.006	-0.021	0.053
Elasticity_m	1682	2.605	1.436	0.627	12.148
$\text{Big-4 Share}_{m,08}$	2204	0.168	0.12	0	0.579

Note: This table displays summary statistics of the key variables in our sample, which covers 2008-2014. The subscripts t and m denote years and MSAs, respectively. Rent is measured by the Zillow Rent Index, and Price is measured by the Zillow Home Value Index. Income is the median household income in the MSA. Age is the median inhabitant age in an MSA. Denial rate is the fraction of mortgage applications denied. Multifamily permits is the number of permits issued for the construction of 2-to-4 unit dwellings and 5-or-more structure dwellings. Vacancy rate is the vacancy rate among rental properties. Foreclosure rate is the fraction of home sales which were foreclosed upon during the previous year. Elasticity is the MSA level elasticity of housing supply as estimated by Saiz (2010). Big-4 Share is the fraction of mortgage applications to Big-4 banks in 2008 for the purchase of owner-occupied, 1-to-4 family properties.

Table 2: Housing Rents in Bartik Regressions

Outcome:	$\Delta\log(\text{Rent}_{m,t})$	$\Delta\log(\text{Rent}_{m,t})$
$V_{m,t-1}$	1.373	1.373
	(0.004)	(0.009)
MSA-Year Controls	No	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.019	0.108
Number of Observations	1380	1380

Note: P-values are in parentheses. This table estimates equation 3. The subscripts t and m denote years and MSAs, respectively. The sample period is 2008-2014. The credit shock $V_{m,t}$ is defined in equation 2. It is the product of the share of an MSA's mortgage applications to Big-4 banks in 2008 and the difference in the denial propensity of Big-4 and non Big-4 lenders in a given year. The MSA-year controls are the change in log of median household income, the log of population, the log of median inhabitant age, the unemployment rate, the once-lagged change in each of these four variables, and the once-lagged change in log rents. Online Appendix Table 1 has the coefficient estimates for these controls. All specifications include MSA and year fixed effects. Standard errors are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods.

Table 3: Housing Rents based on IV Estimation (Stage 2)

Outcome:	Δlog(Rent$_{m,t}$)	Δlog(Rent$_{m,t}$)	Δlog(Rent$_{m,t}$)	Δlog(Rent$_{m,t}$)
ΔDenial Rate$_{m,t}$	2.342	2.329	3.056	3.789
	(0.006)	(0.013)	(0.126)	(0.005)
ΔDenial Rate$_{m,t}$ $\times$ Elasticity$_m$			-0.333	
			(0.427)	
ΔDenial Rate$_{m,t}$ $\times$ Rent Control$_m$				-2.479
				(0.197)
MSA-Year Controls	No	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Underidentification test (p-value)	0.151	0.155	0.144	0.145
Number of Observations	1380	1380	1380	1380

Note: P-values are in parentheses. This table estimates equation 5. The subscripts t and m denote years and MSAs, respectively. The sample period is 2008-2014. Denial rate is the fraction of mortgage applications from MSA m in year t denied by lenders. The estimator is 2SLS, and the instrument for denial rates is the credit shock $V_{m,t}$ defined in equation 2. This shock is the product of the share of an MSA's mortgage applications to Big-4 banks in 2008 and the difference in the denial propensity of Big-4 and non Big-4 lenders in a given year. The MSA-year controls are those described in Table 2. Online Appendix Table 3 has the coefficient estimates for these controls. Elasticity denotes the elasticity of housing supply as estimated by Saiz (2010). Rent Control indicates whether the MSA practices rent control. All specifications include MSA and year fixed effects. Standard errors are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods.

Table 4: Determinants of Big-4 Share in 2008

Outcome:	$\text{Share}_{m,08}$
$\Delta \log(\text{Rent})_{m,07\text{-}08}$	0.043
	(0.731)
$\Delta \log(\text{Income})_{m,07\text{-}08}$	0.012
	(0.945)
$\Delta \log(\text{Population})_{m,07\text{-}08}$	0.008
	(0.991)
$\Delta \log(\text{Age})_{m,07\text{-}08}$	0.259
	(0.604)
$\Delta\text{Unempl Rate}_{m,07\text{-}08}$	1.629
	(0.004)
$\Delta \log(\text{Price})_{m,07\text{-}08}$	-0.393
	(0.000)
$\Delta \log(\text{Rent})_{m,00\text{-}08}$	0.973
	(0.017)
$\Delta \log(\text{Income})_{m,00\text{-}08}$	-1.248
	(0.049)
$\Delta \log(\text{Population})_{m,00\text{-}08}$	-0.072
	(0.201)
$\Delta \log(\text{Age})_{m,00\text{-}08}$	-1.397
	(0.225)
$\Delta\text{Unempl Rate}_{m,00\text{-}08}$	-16.720
	(0.000)
$\Delta \log(\text{Price})_{m,00\text{-}08}$	0.366
	(0.469)
Big-4 Headquarter_m	0.073
	(0.000)
R-squared	0.363
Number of Observations	258

Note: P-values are in parentheses. This table regresses MSA-level share of mortgage applications to the Big-4 banks in 2008 on MSA-level controls, as in equation 6. The controls are the 2000-2008 change in the log of median household income, the log of population, the log of median inhabitant age, the unemployment rate, log rents, log house prices, as well as the 2007-2008 change in each of these variables. Big-4 Headquarter denotes whether the MSA is located in a state with or close to the headquarters of a Big-4 bank. These states are: California (Wells Fargo), North Carolina (Bank of America), and New York, New Jersey, or Connecticut (JP Morgan and Citigroup). Standard errors are heteroskedasticity robust.

Table 5: MSA Average Shocks

Outcome:	$V_{m,t}$	Δlog(Rent$_{m,t}$)	Δlog(Rent$_{m,t}$)
$G_{m,t}$	0.297		
	(0.000)		
ΔDenial Rate$_{m,t}$		1.480	1.386
		(0.018)	(0.078)
MSA-Year Controls	No	No	Yes
MSA FE	No	Yes	Yes
Year FE	No	Yes	Yes
Underidentification test (p-value)		0.124	0.125
Number of Observations	1611	1380	1380

Note: P-values are in parentheses. The subscripts t and m denote years and MSAs, respectively. The sample period is 2008-2014. The credit shock $V_{m,t}$ is defined in equation 2 as the product of the share of an MSA's mortgage applications to Big-4 banks in 2008 and the difference in the denial propensity of Big-4 and non Big-4 lenders in a given year. The credit shock $G_{m,t}$ is defined in equation 11 as the weighted average of the denial propensity of the lenders of the MSA. The first column shows the correlation between V and G. The second and third columns use G as an instrument for denial rates, based on 2SLS estimation. The MSA-year controls are as in Table 2. All specifications include MSA and year fixed effects. The MSA-year controls are those described in Table 2. Standard errors are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods.

Table 6: Denial Rates and Rent Growth with Various IVs (Stage 2)

Outcome:	$\Delta\log(\text{Rent}_{m,t})$	$\Delta\log(\text{Rent}_{m,t})$	$\Delta\log(\text{Rent}_{m,t})$	$\Delta\log(\text{Rent}_{m,t})$
ΔDenial Rate$_{m,t}$	2.762	2.384	3.505	2.622
	(0.000)	(0.002)	(0.003)	(0.007)
CLL Instruments	Yes	Yes	Yes	Yes
$V_{m,t-1}$ as an Instrument	No	Yes	No	Yes
MSA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
J-statistic (p-value)	0.371	0.488	0.335	0.346
C-statistic (p-value)		0.481		0.350
Number of Observations	1380	1380	1380	1380

Note: P-values are in parentheses. This table estimates equation 5 with an expanded instrument set. The subscripts t and m denote years and MSAs, respectively. The sample period is 2008-2014. CLL denotes conforming loan limit. Denial Rate is the fraction of mortgage applications from MSA m in year t denied by lenders. The credit shock $V_{m,t}$ is defined in equation 2. The estimator is 2SLS, and the instruments for ΔDenial Rate$_{m,t}$ are (i) the fraction of applications in year t-1 within 5% of the conforming loan limit in year t, (ii) the interaction of this fraction with the inverse elasticity of housing supply in MSA m, and (iii) possibly $V_{m,t-1}$. Columns (2) and (4) include $V_{m,t-1}$ in the instrument set, and columns (1) and (3) exclude it. All specifications include MSA and year fixed effects. The MSA-year controls are those described in Table 2. Standard errors are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods. The C-statistic corresponds to the difference-in-Sargan test that $V_{m,t-1}$ is a valid instrument.

Table 7: New Building Permits

Outcome:	Δlog(Multifam Permits)$_{m,t}$	Δlog(Multifam Permits)$_{m,t}$
$V_{m,t-1}$	29.796	
	(0.001)	
ΔDenial Rate$_{m,t}$		49.529
		(0.000)
MSA-Year Controls	Yes	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.480	
Underidentification test (p-value)		0.143
Number of Observations	1223	1223

Note: P-values are in parentheses. The subscripts t and m denote years and MSAs, respectively. The sample period is 2008-2014. Multifamily Permits denotes the number of new building permits issued for the construction of 2-4 unit shelters and 5-or-more structure shelters. The credit shock $V_{m,t}$ is as estimated from 1. In the second column, the estimator is 2SLS, and the instrument for denial rates is the credit shock $V_{m,t}$ defined in equation 2. All specifications include MSA and year fixed effects. The MSA-Year controls are the change in log of median household income, the log of population, the log of median inhabitant age; the unemployment rate; the once-lagged change in each of these four variables; and the once-lagged change in the outcome variable. Online Appendix Table 11 has the coefficient estimates for these controls. Standard errors are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods.

Table 8: Rental Vacancies

Outcome:	ΔVacancy Rate$_{m,t}$	ΔVacancy Rate$_{m,t}$
$V_{m,t-1}$	-0.923	
	(0.078)	
ΔDenial Rate$_{m,t}$		-2.501
		(0.223)
MSA-Year Controls	Yes	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.290	
Underidentification test (p-value)		0.186
Number of Observations	348	348

Note: P-values are in parentheses. The subscripts t and m denote years and MSAs, respectively. The sample period is 2008-2014. Vacancy Rate is the fraction of rental properties vacant in MSA m and year t, from the Housing Vacancy Survey. The credit shock $V_{m,t}$ is defined in equation 2. In the second column, the estimator is 2SLS, and the instrument for denial rates is the credit shock $V_{m,t}$. All specifications include MSA and year fixed effects. The MSA-Year controls are the change in log of median household income, the log of population, the log of median inhabitant age; the unemployment rate; the once-lagged change in each of these four variables; and the once-lagged change in the outcome variable. Online Appendix Table 12 has the coefficient estimates for these controls. Standard errors are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods.

Table 9: House Prices, User Cost, and Affordability

Outcome:	$\Delta\log(\text{Price}_{m,t})$	$\Delta\log(\text{Price}_{m,t})$
$V_{m,t-1}$	3.428	
	(0.015)	
$V_{m,t-1}\times\text{Affordable}_m$	-3.037	
	(0.005)	
$\Delta\log(\text{Rent})_{m,t}$		2.979
		(0.210)
$\Delta\log(\text{Rent})_{m,t}\times\text{Affordable}_m$		-2.215
		(0.010)
MSA-Year Controls	Yes	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.582	
Underidentification test (p-value)		0.281
Number of Observations	1224	1224

Note: P-values are in parentheses. The subscripts t and m denote years and MSAs, respectively. The sample period is 2008-2014. Price denotes the Zillow Home Value Index. The variable Affordable_m is a dummy equal to 1 if the MSA's price-to-income ratio in 2008 was in the bottom 2/3 of the sample. The credit shock $V_{m,t}$ is defined in equation 2. The second column uses $V_{m,t-1}$ as an instrument for $\Delta\log(\text{Rent})_{m,t}$ based on 2SLS estimation. The MSA-Year controls are the change in log of median household income, the log of population, the log of median inhabitant age, the unemployment rate, the once-lagged change in each of these four variables, and the once-lagged change in the outcome variable. All specifications include MSA and year fixed effects. Standard errors are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods.

Table 10: Homeownership Rates

Outcome:	$\Delta \text{HR}_{m,t}$	$\Delta \text{HR}_{m,t}$
$V_{m,t-1}$	-1.003	
	(0.000)	
ΔDenial Rate$_{m,t}$		-2.367
		(0.011)
MSA-Year Controls	Yes	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.082	
Underidentification test (p-value)		0.189
Number of Observations	358	358

Note: P-values are in parentheses. The subscripts t and m denote years and MSAs, respectively. The sample period is 2008-2014. HR denotes the homeownership rate as computed by the U.S. Census Housing Vacancy Survey. The credit shock $V_{m,t}$ is defined in equation 2. In the second column, the estimator is 2SLS, and the instrument for denial rates is the credit shock $V_{m,t}$. The MSA-Year controls are the change in log of median household income, the log of population, the log of median inhabitant age, the unemployment rate, the once-lagged change in each of these four variables, and the once-lagged change in homeownership rate. Online Appendix Tables 13 and 14 have the coefficient estimates for these controls. All specifications include MSA and year fixed effects. Standard errors are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods.

Table 11: Age and Internet Access as Frictions to Substitute Across Lenders

Outcome:	$\Delta \mathrm{HR}_{m,t}$	$\Delta \mathrm{HR}_{m,t}$	$\Delta \mathrm{HR}_{m,t}$	$\Delta \mathrm{HR}_{m,t}$
$V_{m,t-1}$	-1.620	-0.293	-1.336	0.238
	(0.000)	(0.294)	(0.000)	(0.117)
$V_{m,t-1} \times \mathrm{Older}_m$	-0.510		-0.509	
	(0.002)		(0.003)	
$V_{m,t-1} \times \mathrm{LowInternet}_m$		-0.941		-1.136
		(0.009)		(0.000)
$V_{m,t-1} \times \mathrm{WRLURI}_m$			-0.398	-0.538
			(0.198)	(0.055)
MSA-Year Controls	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-Squared	0.084	0.085	0.086	0.087
Number of Observations	358	358	358	358

Note: P-values are in parentheses. This table estimates equations 13 and 14. The subscripts t and m denote years and MSAs, respectively. The sample period is 2008-2014. HR denotes the homeownership rate as computed by the U.S. Census Housing Vacancy Survey. The credit shock $V_{m,t}$ is defined in equation 2. Older is the standardized ratio of an MSA's ratio of inhabitants aged ≥ 50 to inhabitants aged 25 to 49 in 2008. LowInternet is an indicator as to whether the MSA was not ranked in the top 25 by Forbes.com Wired Rank of internet accessibility in 2008. The MSA-Year controls are those used in Table 10. Online Appendix Table 17 has the coefficient estimates for these controls. All specifications include MSA and year fixed effects. Standard errors are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods.

Table 12: Competition among Brokers and Lenders and Frictions to Substitute Across Lenders

Outcome:	$\Delta HR_{m,t}$	$\Delta HR_{m,t}$	$\Delta HR_{m,t}$	$\Delta HR_{m,t}$
$V_{m,t-1}$	-0.791	-3.378	-0.329	-3.057
	(0.001)	(0.001)	(0.532)	(0.002)
$V_{m,t-1} \times \text{License}_m$	-0.223		-0.381	
	(0.284)		(0.232)	
$V_{m,t-1} \times \text{HHI}_m$		-2.583		-2.769
		(0.023)		(0.019)
$V_{m,t-1} \times \text{WRLURI}_m$			-0.438	-0.690
			(0.199)	(0.042)
MSA-Year Controls	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-Squared	0.082	0.107	0.084	0.111
Number of Observations	358	358	358	358

Note: P-values are in parentheses. This table estimates equations 15 and 16. The subscripts t and m denote years and MSAs, respectively. The sample period is 2008-2014. HR denotes the homeownership rate as computed by the U.S. Census Housing Vacancy Survey. The credit shock $V_{m,t}$ is defined in equation 2. License denotes whether the MSA is in one of the 18 states which require individual mortgage brokers to be licensed. HHI denotes the standardized Herfindahl-Hirschman index among applications to non Big-4 lenders in 2008. WRLURI is the Wharton Residential Land Use Regulation Index developed by Gyourko, Saiz and Summers (2008). The MSA-year controls are those used in Table 10. Online Appendix Table 18 has the coefficient estimates for these controls. All specifications include MSA and year fixed effects. Standard errors are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods.