Systemic Banks, Mortgage Supply and Housing Rents*

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Abstract

Using an instrumental variables analysis, we show that systemically important U.S. banks have increased their propensity to deny mortgage applications. Tighter mortgage standards have increased demand for rental housing and led to higher rents, depressed homeownership rates, greater construction of multifamily housing, and lower rental vacancies. We provide evidence of frictions that have prevented new lenders from filling the void left by the Big-4 banks, such as barriers to using online lending platforms or regulations which make relationships between mortgage brokers and lenders stickier.

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1 Introduction

Following the recent financial crisis, housing rents have increased very quickly in many U.S. cities, creating serious affordability concerns. For example, based on the Zillow Rent Index, nominal rents have been growing at an average annual rate of around 3% over the 2011-2014 period, with a cross-sectional standard deviation that has increased from 4.7% over 2008-2010 to above 6.8% in 2012. In nearly all of the 10 most populated cities the median rent grew faster than inflation and also substantially faster than the median renter income. These dynamics have put the number of cost-burdened renters (paying more than 30 percent of income for housing) at record levels (Fernald et al. 2015).

In this paper we test if the rent increases may, in part, result from an inward shift of the mortgage supply curve that has generated an outward shift in the demand for rental housing. That is, U.S. lenders have tightened their lending standards in mortgage markets, making it more difficult for potential homebuyers to obtain credit. Without a mortgage, these households have become renters. Higher demand for rental units has driven up housing rents and reduced rental vacancies, as the supply of rental housing is not perfectly elastic in the short-run. Moreover, homeownership rates decrease, since downward price rigidities prevent most households from buying without credit. As time goes by, the supply of rental housing increases through, for example, the construction of multifamily units.

Our identification strategy centers on the four banks classified as systemically important financial institutions: Bank of America, Citibank, JP Morgan Chase and Wells Fargo. We refer to these banks as the Big-4. Big-4 lenders systematically denied more mortgage applications in the post-crisis period, and this effect has been stronger since 2011. In 87% of the cities in our sample, the Big-4's share of mortgage volume fell over the 2008-2014 period, and it fell by more than 22 percentage points in 10% of the cities. After the financial crisis, these banks have been subject to heightened oversight and higher liquidity and capital requirements (Stein 2013). Moreover, 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.[1] 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).

We create a credit supply shock based on the wedge between Big-4 and non-Big-4 lenders'

[1] 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.

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 is inspired by the Bartik methodology popular in labor economics.[2] The 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.[3]

We then use the credit supply shock as an instrument for the mortgage application denial rate. We cannot directly regress housing rents on mortgage denial rates because denial rates are likely endogenous with respect to rents; for instance, lower rents may reduce denial rates as lower-quality borrowers choose to rent rather than apply for a mortgage.

The previous instrument is valid to the extent that neither the systematic tightening of the Big-4's approval standards nor the historical presence of the Big-4 in an MSA are endogenous with respect to MSA-level rents. We therefore estimate the lenders' national propensity to deny a loan following Khwaja and Mian (2008), and we purge the estimates from borrower, MSA, and time effects. 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 trends or proximity to a Big-4 headquarter.

We find that the tightening of mortgage credit supply has contributed to higher housing rents. A one percentage point increase in the growth of mortgage denials leads to around a 2.3 percentage point increase in housing rent growth. This estimate seems plausible given that 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. Moreover, first-stage regressions in the instrumental variable analysis suggest that we are not confounding a rental demand shifter with a rental supply shifter: denial rates move only through the Big4-shock, not through the elasticity of housing supply which relates to the construction of rental units.

To further test our instrument we use the instruments proposed by Loutskina and Strahan (2015) that are well accepted in the literature as instruments for credit shocks (e.g. Dagher and Kazimov 2015). These exploit changes in the maximum loan limits that government-sponsored enterprises (GSEs) insure.[4] We obtained similar results with these instruments as in our baseline analysis. Moreover, we exploit the overidentification generated by these other instruments to

[2] 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] 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.

[4] 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.

provide evidence that our credit supply shock is a valid instrument for denial rates.

To confirm the theory that credit supply has affected housing rents through a housing tenure choice channel, we study the impact of credit supply on homeownership rates. The results confirm that households unable to get credit move from the market for homeownership to the rental market. Moreover, we check that our results are not driven by a mechanical effect of, say, increased foreclosures due to the credit supply shock, which would restrict the supply of rentals. As a natural follow-up, we consider supply-side responses to this surge in rental demand. We find that tighter credit explains a significant component of the increase in construction of multifamily units, and it can explain a reduction in rental vacancies. This result suggests that rent increases will weaken as supply expands to accommodate more renters.

Our results require frictions which have prevented new lenders from filling the void left by the Big-4 banks. We provide evidence of two frictions. First, we consider the importance of barriers to switch to online lenders. Online lenders have played an increasingly important role in mortgage markets since the crisis (Lux and Greene 2015). They should be less able to fill any gap left by the Big-4 banks in MSAs with barriers to internet access, which we measure using the Forbes index of city-by-city internet accessibility.[5] A similar effect should hold in cities with an older population, as older individuals may encounter greater difficulty transitioning to online lending (Bull and Gulamhuseinwala 2016). Our results suggest that the Big-4 banks' tighter standards have had a greater impact on homeownership in MSAs where internet accessibility appears to be lower. As a second friction, we exploit variation in historical competition among non-Big-4 lenders in an MSA, as well as regulations governing barriers to entry among mortgage brokers. A lack of competition among either non-Big-4 lenders or mortgage brokers reduces incentives for these alternative providers of credit to replace the Big-4.

Since applicants for Federal Housing Administration (FHA) insured loans tend to be lower-income and thus closer to the margin of homeownership, we reperform our baseline analysis on this subsample in isolation, and we obtain similar results. Interestingly, however, our baseline results disappear when we look at the pre-2011 sample. In this period, we would not expect to find meaningful Big-4 shocks, since the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank) was approved in the second half of 2010 and not implemented until 2011, and the False Claims Act was first used publicly in the mortgage space in 2011.

Our paper makes three main contributions to the literature. First, to the best of our knowledge we are the first to study the link between credit supply and housing rents. A number of recent papers have identified credit supply shocks and studied their impact on house

[5]Nguyen (2015) provides related evidence by showing that physical bank branches still play an important role in facilitating credit access in the U.S.

prices (e.g. Anenberg et al. 2016, Adelino et al. 2013, DiMaggio and Kermani 2015, Driscoll et al. 2016, Favara and Imbs 2015 or Glaeser et al. 2012). The general consensus is that outward shifts in credit supply have a significant, positive impact on house prices, although the magnitude of the impact is still in contention. The literature so far has focused on other drivers of housing rents like population flows (Saiz 2007), shrinking leisure of high-income households (Edlund et al. 2015), income growth (Hornbeck and Moretti 2015 or Muehlenbachs et al. 2015) or households' expected duration of stay in a house (Halket and Pignatti 2015).

Second, our results reinforce the literature started by Linneman and Wachter (1989) that access to credit determines tenure choice decisions. Gete and Reher (2016) formalize the theory. Acolin et al. (2016) document that changes in access to mortgage credit alter the probability that individual households become homeowners. Ambrose and Diop (2014) propose and test a model in which tighter credit pushes borrowers previously qualified enough to get a mortgage into the rent category. Mezza et al. (2015) show that student debt has affected the demand for homeownership.

Third, we are among the first papers to show a link between the regulatory and litigation changes that followed the 2007-2008 financial crisis, credit supply, and economic outcomes.[6] Basten and Koch (2015) find that countercyclical capital buffers shifted mortgage market share to more resilient banks, but did not necessarily reduce the riskiness of less resilient banks' loan portfolio. Gissler et al. (2016) show that the Qualified Mortgage regulation proposed in 2011 led to higher uncertainty, and consequently banks issued fewer loans. Calem et al. (2016) show that the first stress test in 2011 had a negative effect on the share of jumbo mortgage originations and approval rates at stress-tested banks.

In terms of econometric strategy, we are similar to Amiti and Weinstein (2013) and Greenstone et al. (2015), in that we use the Khwaja and Mian (2008) fixed effects estimator to identify a credit supply shock. Like Amiti and Weinstein (2013), we link the estimated denial rate shocks to specific events, such as the 2010-2011 regulatory overhaul and the litigation of systemically important lenders. Moreover, by exploiting cross-sectional variation in mortgage market competition, our identification strategy is similar to that of Scharfstein and Sunderam (2015), who document the impact of such competition on the transmission of monetary policy.

The rest of the paper is organized as follows. Section 2 motivates the paper and discusses the underlying theory. In Section 3.1, we estimate the national component of the Big-4 and non-Big-4 lenders' propensity to deny a mortgage application. Section 3.2 describes the credit

[6] Broadly, we also connect with a growing body of papers which has studied the recent impact of credit supply on economic outcomes (e.g. Chodorow-Reich 2014, Dagher and Kazimov 2015, Loutskina and Strahan 2015 or Mondragon 2014, among others).

shock and Section 3.3 has the main identification strategy. Section 4 checks the robustness of the previous results. Section 5 studies supply-side responses, such as new building permits and rental vacancies. Section 6 confirms that mortgage supply affected rents through a housing tenure choice channel by looking at homeownership, and Section 6.1 studies frictions to substitute between lenders. We conclude in Section 7. The Appendix explains our data sources in detail. An Online Appendix contains supplementary results.

2 Motivation and theory

In this section we briefly discuss the recent dynamics of rental markets and homeownership decisions, and 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. In fact, as illustrated by Figure 2, 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, as shown in Figure 3.

The previous figures suggest 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 capital requirements if equity is more expensive than debt, or (ii) higher costs of loan default, for example, because regulators impose fines on loans which result in default. Big-4 banks have been exposed to both factors. Since Dodd-Frank's implementation, these systemic banks are required to maintain higher capital ratios, and to satisfy other regulations which likely increase their cost of lending. Moreover, these banks claim that they have suffered a large increase in the risk of being subject to fines and litigation in case of mortgage default.

Consistent with the theory, Figure 4 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. This correlation motivates us to study whether tightening mortgage supply was a significant force among the various factors driving up rents over the post-Recession period.

3 Rents, mortgage supply, and the Big-4

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 use yearly mortgage credit data from the Home Mortgage Disclosure Act (HMDA) since 2007.[7] 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-occupied, 1-to-4 family dwellings, which include single-family houses and also individual units within multi-unit buildings, such as condominiums.

We also observe the top holding company for each lender in the data. We divide the space of mortgage lenders into those which are held by a Big-4 bank and those which are not: $l \in \{\text{Big4, NoBig4}\}$. The Big-4 banks are Bank of America, Citigroup, JP Morgan Chase, and Wells Fargo. 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

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

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).[8] The terms $\alpha_{m,t}$ and $\alpha_{m,l}$ control for lender, time, and regional shocks.[9]

The reason we focus on denials, as opposed to originations, as the gauge of credit supply, is that denials only involve two decisions: the borrower's choice to apply, and the lender's choice to deny or not to deny. On the other hand, originations encode information about a third decision, the borrower's choice to accept the loan offer. Since we seek to minimize the impact of unobserved borrower characteristics in our estimation of (1), we believe denials are the relevant outcome to study given our focus on credit supply shocks.

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, $L_{l,t}$

[7]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. By focusing on post-crisis years, we avoid structural breaks associated with the financial crisis.

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

[9]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.

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 5, we plot the propensity to deny, $L_{l,t}$, for Big-4 banks and for ordinary lenders. Section 4.2 contains an analogous plot for the subsample of FHA loans. Recall that the reference category is $l =$ "NoBig4 lenders", and $t = 2007$. Thus, Figure 5 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 popular in labor economics to construct a credit supply shock in MSA m and year t. Denoting this shock by $V_{m,t}$, and recalling that $L_{l,t}$ denotes the estimated lender-year fixed effect from (1), we define

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

where Share_m denotes the share of applications going to Big-4 lenders in 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 $(L_{t,\text{Big4}} - L_{t,\text{NoBig4}})$ and the degree to which this tightening is felt in a given MSA (Share_m). Importantly, an increase in $V_{m,t}$ corresponds to a reduction of credit supply because it means a higher denial rate. That is, it constitutes an *inward* shift of the credit supply schedule.

Figure 6 shows that there is considerable variation in the estimated credit shocks $V_{m,t}$. The figure plots year-by-year histograms of the estimated credit shocks. 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. Loosely-speaking, this ratio describes the extent to which the Big-4 shock can account for total denials. Given that all the histograms have a large mass above 0.5, there is substantial cross-sectional variation in the shock $V_{m,t}$. There is also significant temporal variation, as 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.

3.3 Credit supply and housing rents

This subsection contains our main analysis. We use the $V_{m,t}$ shock 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.[10] Table 1 contains the summary statistics of our sample.

First, we estimate the following regressions that are similar to the Bartik regressions popular in labor economics,

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

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, measured by the Zillow Rent Index.[11] Several times throughout the paper, we consider the role of the elasticity of housing supply 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.

We present our results from estimating (3) in Table 2.[12] Our point estimate for β is positive, significant, and similar with or without the set of controls. Tighter credit leads to higher housing

[10] The Zillow Rent Index is described in detail in the Appendix. It has the advantage of not being affected by the composition of homes currently for rent, and thus facilitates comparisons across time. Moreover, we believe it is superior to tracking the rent of a particular unit size (e.g. one bedroom apartment) 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.

[11] Our data sources are described in detail in the Appendix. The first two of these controls are from the American Community Survey's 1-year estimates, and the second two are from the Federal Financial Institutions Examination Council (FFIEC) Census Report.

[12] Standard errors are computed according to 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 between 1 and 2.

rents. Though not the focus of our analysis, our results in the Online Appendix indicate that rent growth is higher in cities with greater population growth and where the median age of inhabitants is falling.

Second, we use the credit supply shock $V_{m,t}$ defined in (2) as an instrument for the mortgage application denial rate. Our purpose is to lend an interpretation to the magnitude of our previous point estimates by estimating the effect of $V_{m,t}$, working through mortgage availability as gauged by denial rates, on rent growth.

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, we have argued (and we will provide further evidence in the next section) that neither the systematic tightening of the Big-4's approval standards ($L_{t,\text{Big4}} - L_{t,\text{NoBig4}}$) nor the historical presence of the Big-4 in 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 3 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. The shock alone describes 12% of the variation in denial rate growth. Moreover, when interacting the shock $V_{m,t}$ with supply elasticity, the point estimate for the interaction is highly insignificant.[13] This result is intuitive, since the Big-4's propensity to deny ($L_{\text{Big4,t}}$) should not have a stronger effect on denial rates across regions with different supply elasticities, given that the denial propensity is purged of MSA-specific effects. That is, it does not appear that we are confounding a rental demand shifter with a rental supply shifter, since, if $V_{m,t}$ were truly a supply shifter, one might expect it to affect denial rates differently in areas with different values of housing supply elasticity.

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 $\Delta\text{Denial Rate}_{m,t}$ may

[13] The t-ratio is 0.043.

be interpreted as 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 4. 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 the growth of mortgage denials leads to around a 2.3 percentage point increase in rent growth. This seems plausible given that the cross-sectional variation in rent growth is around 5 percentage points for most years. There is mild evidence of a role for physical supply in mitigating the effect of credit supply on rents: when including the interaction with supply elasticity, the point estimate for β is larger, and the interaction term is negative, though insignificant.[14] We interpret our results as consistent with a role for physical supply in accommodating credit-induced rental demand, although we take up this issue in greater detail in Section 5. In the fourth column of Table 4, we consider whether credit has a stronger impact on rent growth in states without rent control. The estimate for β is 3.8 for states without rent control, which is 1.5 percentage points higher than the estimate obtained in the baseline specification.[15]

Finally, we also estimated the core IV specifications on pre-2011 data and obtained highly insignificant results.[16] This is consistent with our theory, since Dodd-Frank was approved in the latter half of 2010 and was not implemented until 2011, and the False Claims Act was first used publicly in the mortgage space in 2011. That is, the major regulatory impact on the Big-4 did not occur during the pre-2011 subperiod.

4 Robustness

In this section we perform four sets of tests to confirm the robustness of the previous results. First, we do several checks to control for the possibility that cities with a strong Big-4 presence in 2008 might have responded to the 2007 housing collapse in a way which put upward pressure on rent growth over the 2008-2014 period. Second, we explore another source of variation in credit supply over our sample period: changes in the GSE conforming loan limit. We follow Loutskina and Strahan (2015) who construct a similar instrument to study the effect of credit-induced house price movements on local economic activity. This exercise provides a robustness check on the previous results. Moreover, the overidentification generated by these other instruments allows us to study whether the credit supply shock $V_{m,t}$ is a valid instrument

[14]The p-value for β in this specification is 0.126.
[15]States with rent control are California, New York, New Jersey, Maryland, and the District of Columbia.
[16]Results are available on request.

for denial rates. Third, we focus exclusively on FHA loans. The Big-4 retreated strongly from FHA borrowers over our sample period, and thus it is appropriate to consider whether we obtain similar results when focusing our attention on such loans. Fourth, we control for an alternative channel whereby the Big-4 shock may have affected rents through foreclosures.

4.1 Idiosyncratic Big-4 share

While we have argued in Section 3.1 that 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 7 shows that there is large heterogeneity across MSAs in the share of mortgage applications to Big-4 lenders in 2008. Figure 8 shows the geographic distribution of 2008 Big-4 shares. Notably, this share is not concentrated in large, east coast MSAs which have recently attracted attention for their cost of living, and thus might be candidates for unobserved rent shocks. Neither is there a profound east-west or north-south geographic divide that may generate candidates for unobserved rent shocks over the post-2008 period. For robustness, we redid the analysis of Section 3.3 excluding California from the data and the results remain quite similar.[17]

Next, we re-estimate our core specifications of Section 3.3 but using a different definition of the $V_{m,t}$ shock. We denote this revised shock as

$$W_{m,t} = (L_{t,\text{Big4}} - L_{t,\text{NoBig4}}) \cdot s_m. \tag{6}$$

The difference relative to the $V_{m,t}$ shock defined in (2) is that now we use weights 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 trends or proximity to a Big-4 headquarter.

That is, first we regress the 2008 Big-4 market share on a large set of variables that may

[17] These regressions are available upon request.

affect both this market share and rent dynamics over the 2008-2014 period,

$$\text{Share}_m = Z_m\beta + \epsilon_m. \tag{7}$$

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 reasonably close to the headquarters of a Big-4 bank.[18] Table 5 contains the results. As expected, longer-term movements in income, population flows, rents, unemployment and age over 2000-2008 are correlated with 2008 Big-4 share. With the exception of unemployment, shorter-term movements in these variables over 2007-2008, the post-crisis period, appear unrelated. 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 (7), which we denote s_m,

$$s_m = \text{Share}_m - Z_m\hat{\beta}. \tag{8}$$

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 $W_{m,t}$ defined in equation (6) and reproduce the core analysis of Tables (2)-(4) except that we use our revised shock $W_{m,t}$ instead of our baseline $V_{m,t}$ from (2). The revised results are in Table (6) and are quite similar. In fact, the point estimate for the impact of denial rates on rent growth is 2.2, which is nearly unchanged from the estimate of 2.3 from Table (4).

4.2 FHA sample

We now turn to FHA insured loans, and we begin by re-estimating (1) among the subset of applications for FHA loans. We denote the estimated lender-year fixed effects as $L_{l,t}^{FHA}$. These lender-year fixed effects, which we call the propensity to deny, are plotted in Figure 9. They represent the excess probability of denial faced by FHA 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 $t =$

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

2007.

FHA borrowers are often characterized as closer to the margin of homeownership. 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.[19]

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

$$Y_{m,t} = (L^{FHA}_{t,\mathrm{Big4}} - L^{FHA}_{t,\mathrm{NoBig4}}) \cdot \mathrm{Share}_m, \tag{9}$$

where, as in (2), Share_m 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 Share_m, rather than the share of FHA applications, to further avoid endogeneity concerns related to the fraction of FHA borrowers in a given MSA in 2008. Thus the shock $Y_{m,t}$, like the baseline shock $V_{m,t}$, has the same form as a Bartik shock. Accordingly, we re-estimate our baseline Bartik (3) and instrumental variable (5) specifications using $Y_{m,t}$ in place of $V_{m,t}$.

Tables 7 and 8 contain the estimates of this exercise. In our Bartik specification, the estimates of Table 7 indicate that the FHA-based credit shock $Y_{m,t}$ has a significant role in explaining housing rents. Moreover, the estimates of Table 8 suggest that this FHA-based shock, working through denial rates, has contributed to rent growth. In particular, a 1 percentage point increase in the growth of loan denials leads to a 2.1 percentage point increase in rent growth. This effect is quite close to our baseline estimate of 2.3 from Table 4, which suggests that the Big-4's retreat from FHA borrowers played a significant role in the credit-induced rent growth over our sample period.

4.3 Variation in conforming loan limits

In this subsection 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 ±5% of the conforming loan limit in year t, which we denote $\mathrm{AtLimit}_{m,t-1}$, and (ii) this fraction multiplied by the change in the log conforming loan limit from year $t-1$ to year t. We need to depart slightly from the method of Loutskina and Strahan (2015) because the

[19] 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."

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.[20] 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 baseline 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,

$$\begin{aligned} \Delta\text{Denial Rate}_{m,t} = V_{m,t-1}\delta_1 + \text{AtLimit}_{m,t-1}\delta_2 + \left(\text{AtLimit}_{m,t-1} \times \text{Elasticity}_m^{-1}\right)\delta_3 + ... \\ ... + \Delta X_{m,t}\eta + \lambda_m + \lambda_t + \upsilon_{m,t}, \end{aligned} \tag{10}$$

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 6 indicates that the latter effect dominates over our period: the conforming loan limit instruments are positively correlated over our sample period. To explore this further, Online Appendix Table 7 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

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

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.[21]

We present our second-stage estimates in Table 9. Note first that our point estimates are similar, though slightly larger, to those obtained in our baseline instrumental variables analysis in Table 4, 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 baseline results coupled with this robustness exercise suggest that a 1 percentage point increase in the growth or mortgage denials leads to between a 2.2 and 3.5 percentage point increase in rent growth.

4.4 Foreclosures

In this subsection we consider whether the growth in rents associated with the Big-4's stringency might have resulted from an alternative channel in 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. We display our results for the Bartik specification in Table 10 and our IV specification in Table 11.

In the first column of 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. In the second column, we include the change in the foreclosure rate as an additional control. In both columns, the estimated coefficient on the credit supply shock $V_{m,t}$ is significant and the point estimates are nearly the same. Moreover, foreclosures themselves do not appear to have a significant effect on housing rents. In Table 11, we repeat this exercise for our instrumental variables specification (5). Similarly, 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 et al. (2015), who

[21] 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.

find that U.S. foreclosures peaked early in 2008, at the beginning of our observation window.

5 Effects on construction and vacancies

To this point, we have focused primarily on the price response of housing rents to tightening mortgage supply. In this section, we consider the quantity response. The results of this section suggest that the price effect of the resulting rental demand will weaken as supply expands to accommodate more renters.

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.[22] We then estimate our Bartik specification with the change in the log of multifamily permits issued as our outcome,

$$\Delta \log(\text{Multifamily Permits})_{m,t} = V_{m,t-1}\beta + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}. \tag{11}$$

Table 12 contains the results. The estimated coefficients for the credit shock $V_{m,t}$ are positive and significant, which suggests that the Big-4's tightening approval standards has led to increased construction of multifamily units. We obtain similar results if we focus on the share of multifamily permits among total building permits.[23]

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

$$\Delta \log(\text{Multifamily Permits})_{m,t} = \overline{\Delta\text{Denial Rate}_{m,t}}\beta + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}. \tag{12}$$

Based on the estimates shown in Table 13, we again find a role for credit supply, working through mortgage denial rates, 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

[22] 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.

[23] Results are available on request.

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 with the change in the rental vacancy rate as the outcome

$$\Delta \text{Vacancy Rate}_{m,t} = V_{m,t-1}\beta + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}. \tag{13}$$

We also estimate the instrumental variables model (5) with the change in the rental vacancy rate as the second-stage outcome,

$$\Delta \text{Vacancy Rate}_{m,t} = \overline{\Delta \text{Denial Rate}_{m,t}}\beta + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}. \tag{14}$$

Table 14 contains the estimates of (13) and Table 15 has the estimates of (14). In all specifications, we find a negative point estimates 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.

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, and thus whether it affects housing rents through households on the margin of homeownership. 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.

First, we replicate regression (3) except that we now consider homeownership rates, rather than housing rents, as our outcome of interest. Specifically, letting $\text{HR}_{m,t} \in [0,1]$ denote the homeownership rate in MSA m and year t, we estimate

$$\Delta\text{HR}_{m,t} = V_{m,t-1}\beta + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}. \tag{15}$$

Table 16 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.

Second, we 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,

$$\Delta\text{HR}_{m,t} = \overline{\Delta\text{Denial Rate}_{m,t}}\beta + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}. \tag{16}$$

Our results, presented in Table 17, suggest that a tightening of approval standards contributes to a reduction in homeownership rates. 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. This impact supports the results of the previous analysis.

6.1 Frictions to substitute among lenders

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 higher 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.

6.1.1 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 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

$$\Delta\text{HR}_{m,t} = V_{m,t-1}\beta_1 + (V_{m,t-1} \times \text{Older}_m)\beta_2 + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}. \tag{17}$$

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

$$\Delta\text{HR}_{m,t} = V_{m,t-1}\beta_1 + (V_{m,t-1} \times \text{LowInternet}_m)\beta_2 + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}, \tag{18}$$

where LowInternet_m indicates whether the MSA was not ranked in the top 25 by the Forbes.com index in 2008.[24]

Our estimates of (17) and (18) are presented in the first two columns of Table 18. 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 et al. (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 18, 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 to maneuver online lending.

6.1.2 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

[24] The results are similar if we instead use the top 20 as the cutoff.

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 brokers have sticky relationships with lenders, then brokers may keep sending customers to those lenders even if their standards are higher. For example, a given broker may have established personal relationships with correspondents at a given lending institution, or she may be familiar with a given lender's application protocol. In this case, barriers to entry among mortgage brokers would effectively introduce barriers to entry among lenders. This friction may have entrenched Big-4 lenders in regional mortgage markets, making these regions more susceptible to the Big-4's systematic tightening of approval standards. A related theory is that mortgage brokers reduce the frictions associated with obtaining a mortgage: fewer mortgage brokers make it more difficult to match households with new lenders.

To explore this possibility, we construct a measure of barriers to entry among mortgage brokers. We follow the analysis of Backley et al. (2006) 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.[25] According to Backley et al. (2006), this additional licensing requirement represents a relevant cost to operating as a mortgage broker, and so, based on the theory outlined in the previous paragraph, we use it to approximate barriers to entry among lenders and the lack of competition in mortgage markets. Our regression equation for this analysis is

$$\Delta \mathrm{HR}_{m,t} = V_{m,t-1}\beta_1 + (V_{m,t-1} \times \mathrm{License}_m)\beta_2 + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}, \tag{19}$$

which is the analogue of (15), now with 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.[26] To ease interpretation, we

[25] 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.

[26] 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.

standardize the HHI so that it has a mean of 0 and a standard deviation of 1. The corresponding regression equation is

$$\Delta \mathrm{HR}_{m,t} = V_{m,t-1}\beta_1 + (V_{m,t-1} \times \mathrm{HHI}_m)\beta_2 + \Delta X_{m,t}\gamma + \alpha_m + \alpha_t + u_{m,t}, \tag{20}$$

which is of the same form as (19).

The first column of Table 19 presents the estimates of (19). 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 (20) in the second column of Table 19 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 in Section 6.1.1, one might be concerned that regions with tighter licensing requirements for mortgage brokers or with relatively monopolistic lenders have a natural preference for regulation. Thus, $\mathrm{License}_m$ 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 the Wharton Residential Land Use Regulation Index (WRLURI). If, indeed, either $\mathrm{License}_m$ or HHI_m are simply proxies for land-use regulation, the estimated coefficients on their interactions with $V_{m,t}$ in (19) and (20) should change substantially. Columns three and four of Table 19 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 $\mathrm{License}_m$ 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. To sum up, our results point to an important role for market power among lenders and mortgage brokers in amplifying the impact of credit supply on housing tenure choice.

7 Conclusions

In this paper, we analyzed the effect of changes in mortgage supply on the recent dynamics of housing rents. We instrumented for mortgage denial rates with a new measure of a credit supply shock. We constructed the shock as the wedge between Big-4 and non-Big-4 lenders' national propensity to deny a mortgage loan over 2008-2014, weighted by the 2008 mortgage application market share of the Big-4 banks in the MSA. This shock was purged of borrower, MSA, and time effects. It 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. We did multiple robustness checks and found no evidence against the instrument's validity. We also obtained similar results using credit supply instruments already established in the literature.

Consistent with a housing demand channel, we find that tighter credit explains a significant component of the increase in housing rents, lower homeownership ratios and rental vacancies, and higher construction of multifamily units. A 1 percentage point increase in the growth of mortgage denials leads to around a 2.3 percentage point increase in housing rent growth. Moreover, a 1 percentage point increase in the growth of denial rates also leads to around a 2.4 percentage point reduction in a city's growth in homeownership. 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 et al. (2016) presents results that point in the same direction.

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. Our results suggest that the increase in housing rents will recede as borrowers become more accustomed to online banking.

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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 covers 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). 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). 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. 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 population for each census tract. We compute MSA-level population by summing across census tracts belonging to an MSA.

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. Thus, 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 et al. (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 4 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 (HVS) 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 comes 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).
- 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 end of the year, or December. We have data for 81 such MSAs.

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

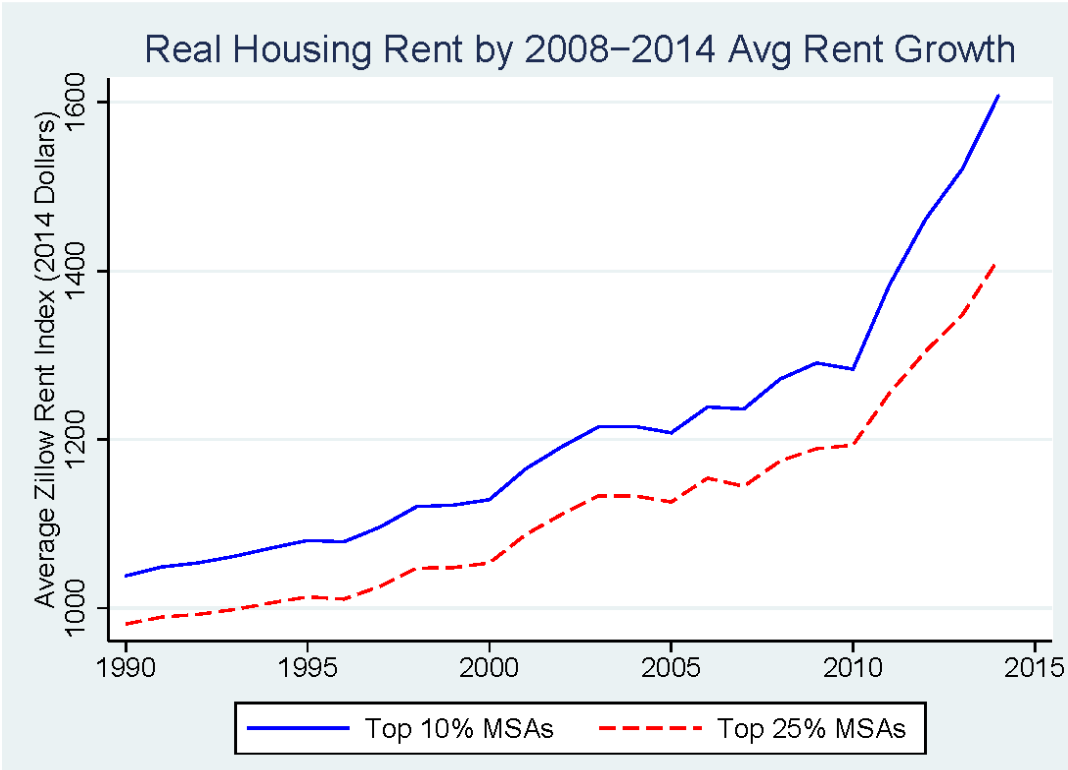

Figure 1. Dynamics of Real Housing Rents. This figure plots real housing rents over the 1991-2014 period in 2014 dollars for MSAs ranking in the top 10% and top 25% of 2008-2014 rent growth, respectively. Nominal rents are measured using the Zillow Rent Index. The translation to real rents is done using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

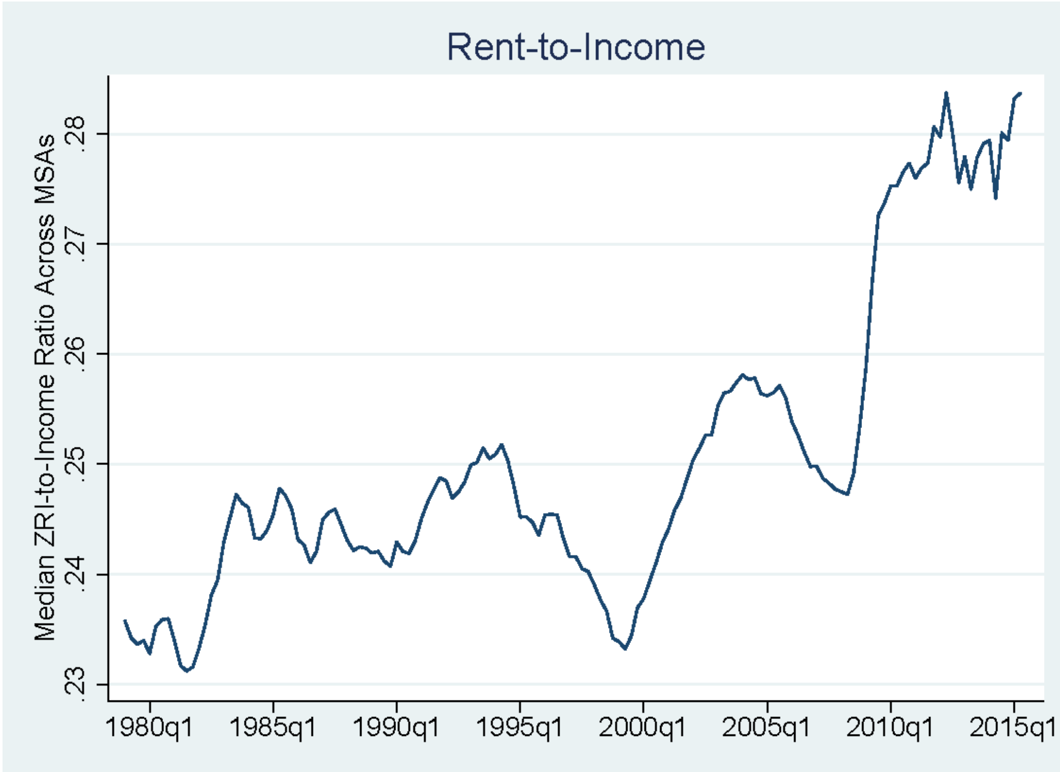

Figure 2. Rent-to-Income. This figure plots the median ratio of rent-to-income for the MSAs in our sample.

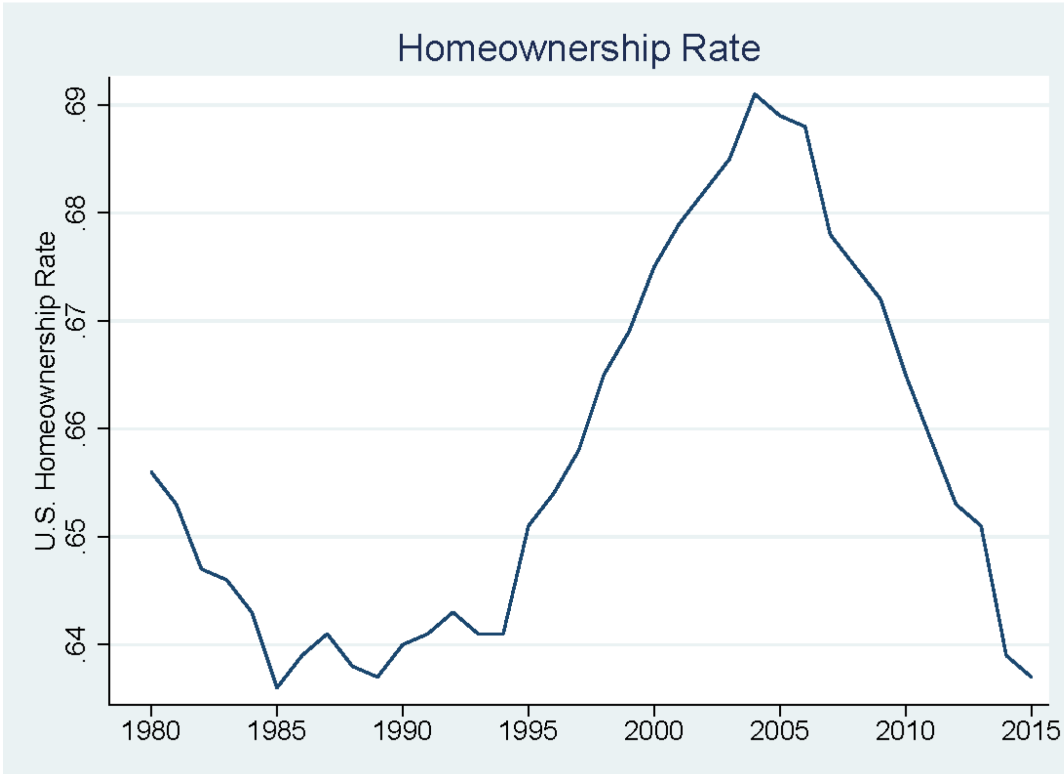

Figure 3. Homeownership Rate. This figure plots the dynamics of the U.S. homeownership rate. The data correspond to the fourth quarter of each year.

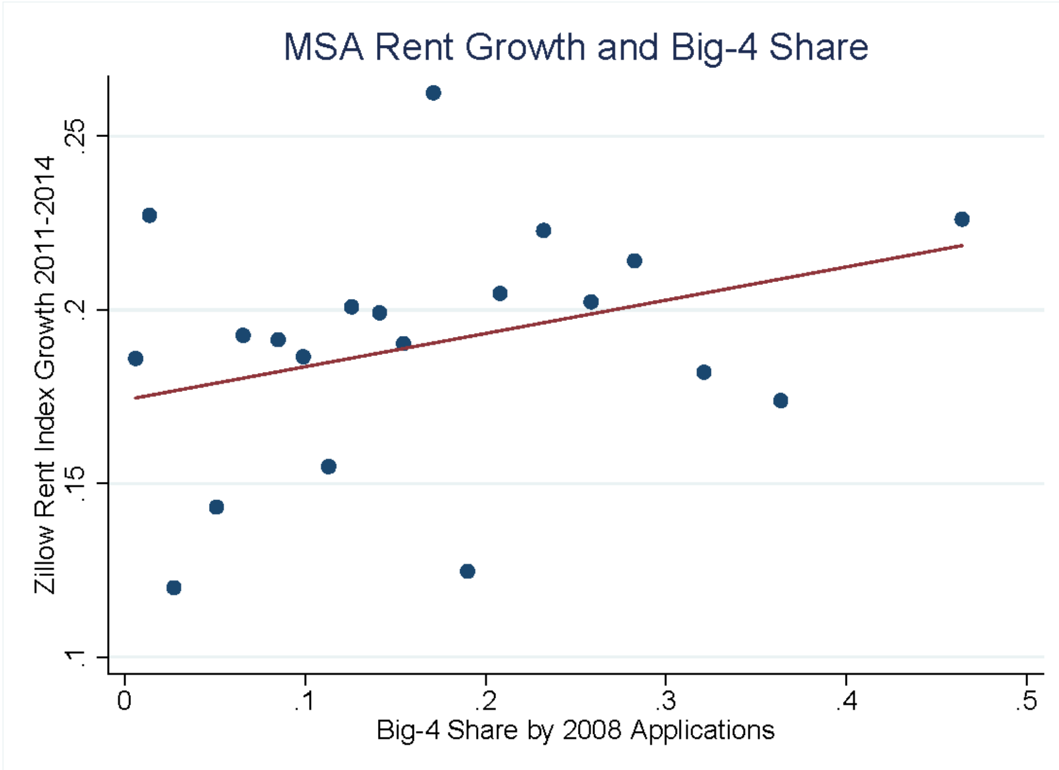

Figure 4. Big-4 Market Presence and Rent Growth (2011-2014). This figure plots the application share of Big-4 banks in 2008 and cumulative growth in the Zillow Rent Index at the MSA level from 2011-2014. For ease of appearance, the points are grouped into equal-sized bins of around 15 MSAs each. The slope of the best fit line is 0.096 with a heteroskedasticity robust standard error of 0.055 and corresponding p-value of 0.085.

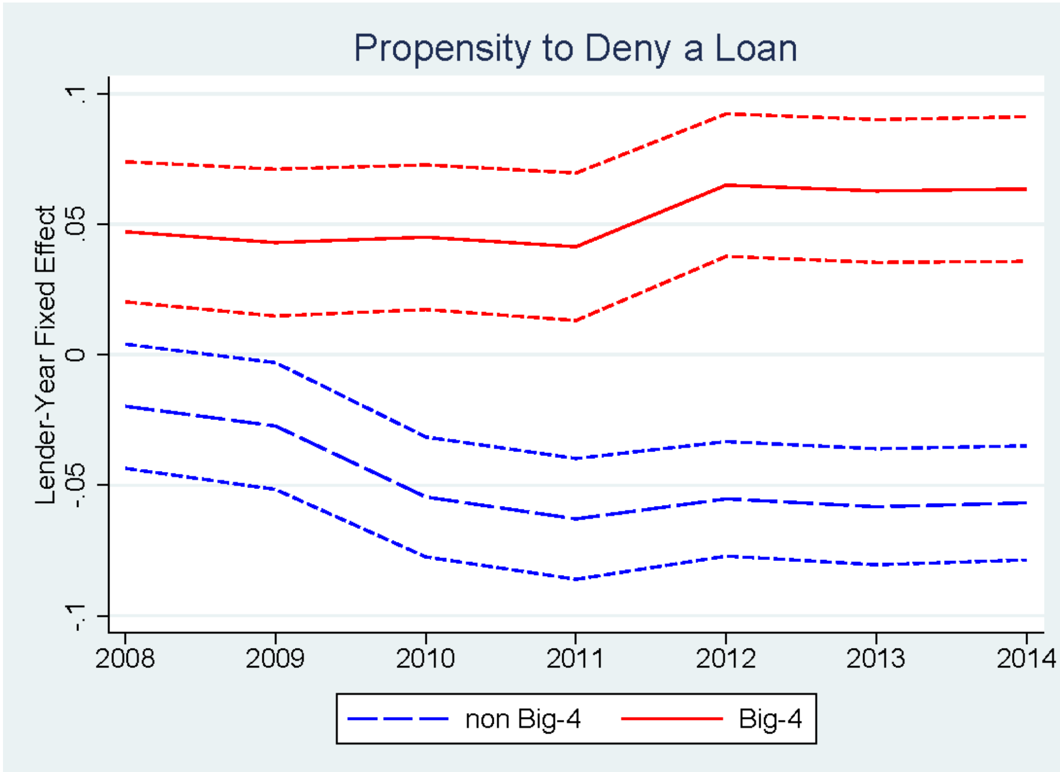

Figure 5. Propensity to Deny of Big-4 Banks and Other Lenders. This figure plots the lenders' fixed effects estimated in equation (1). The dashed lines correspond to a 95% confidence interval, computed with heteroskedasticity robust standard errors. The reference lender-year category is non Big-4 lenders in 2007, for which the loan denial probability was 0.156.

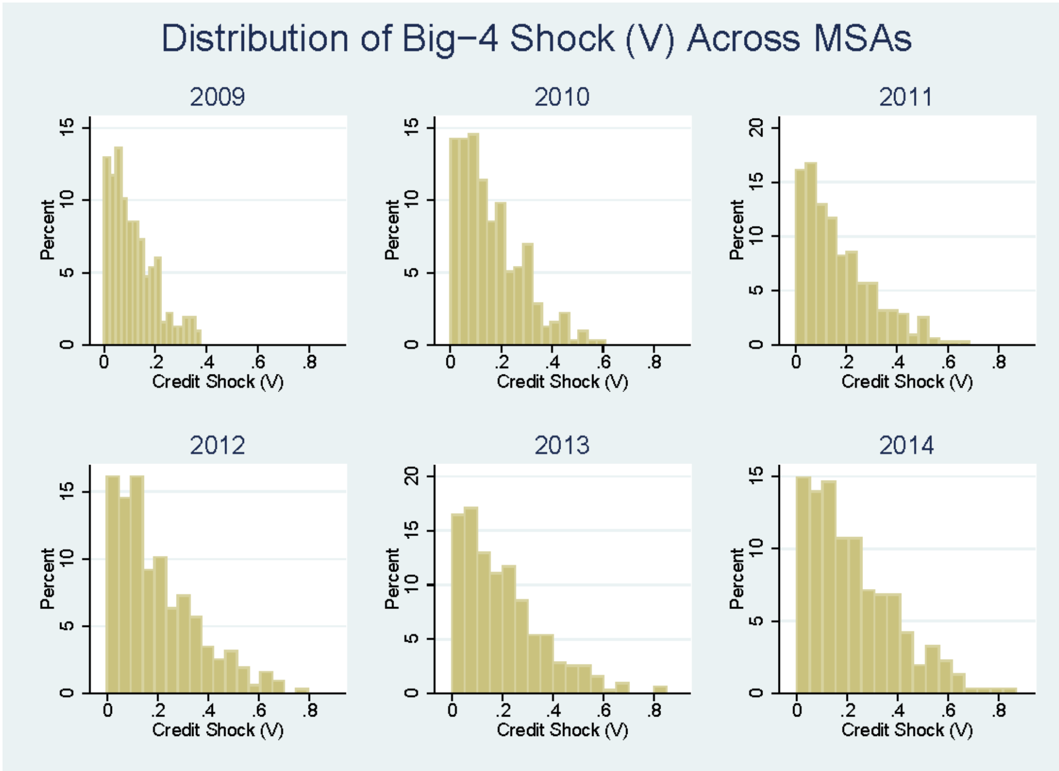

Figure 6. The Distribution of the Big-4 Bartik Shock ($V_{m,t}$). This figure plots a histogram of the Big-4 Bartik shock $V_{m,t}$ defined in equation (2). This shock is the product of the share of an MSA's mortgage applications to Big-4 banks in 2008 and the difference in the denial propensity of Big-4 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.

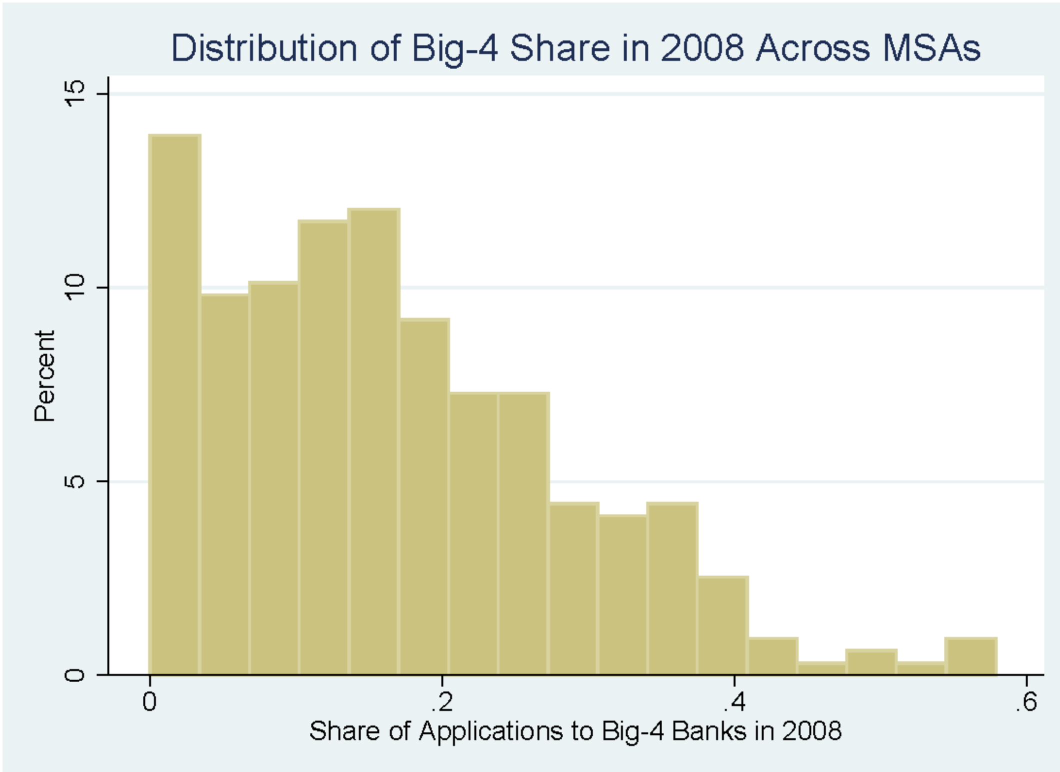

Figure 7. The Distribution of Big-4 Mortgage Application Shares. This figure plots the histogram of MSA-level mortgage application shares to Big-4 banks in 2008.

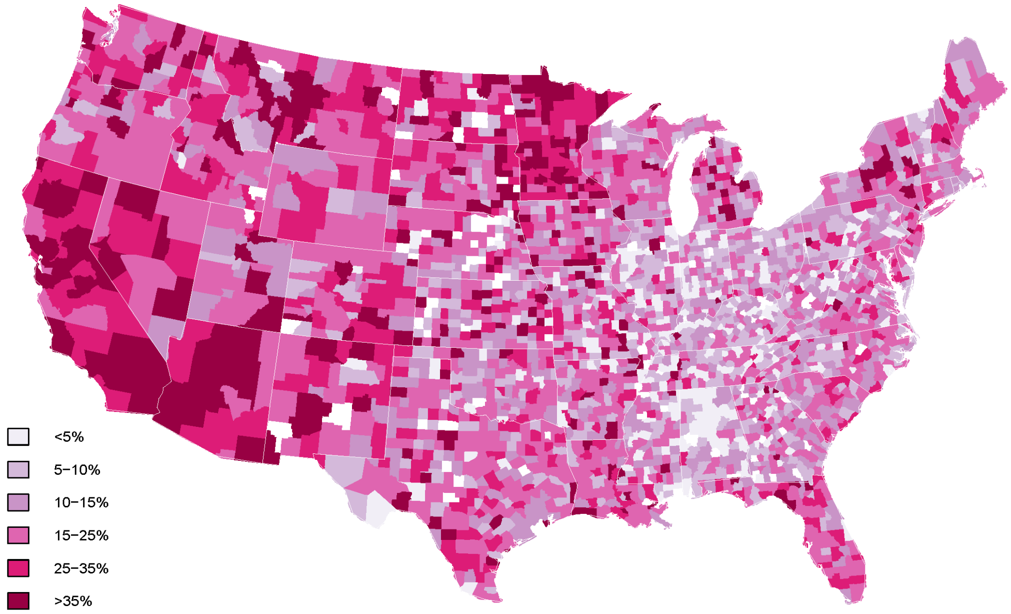

Figure 8. The Geography of Big-4 Mortgage Application Shares. This figure plots the share of mortgage applications by Big-4 lenders in each county in 2008.

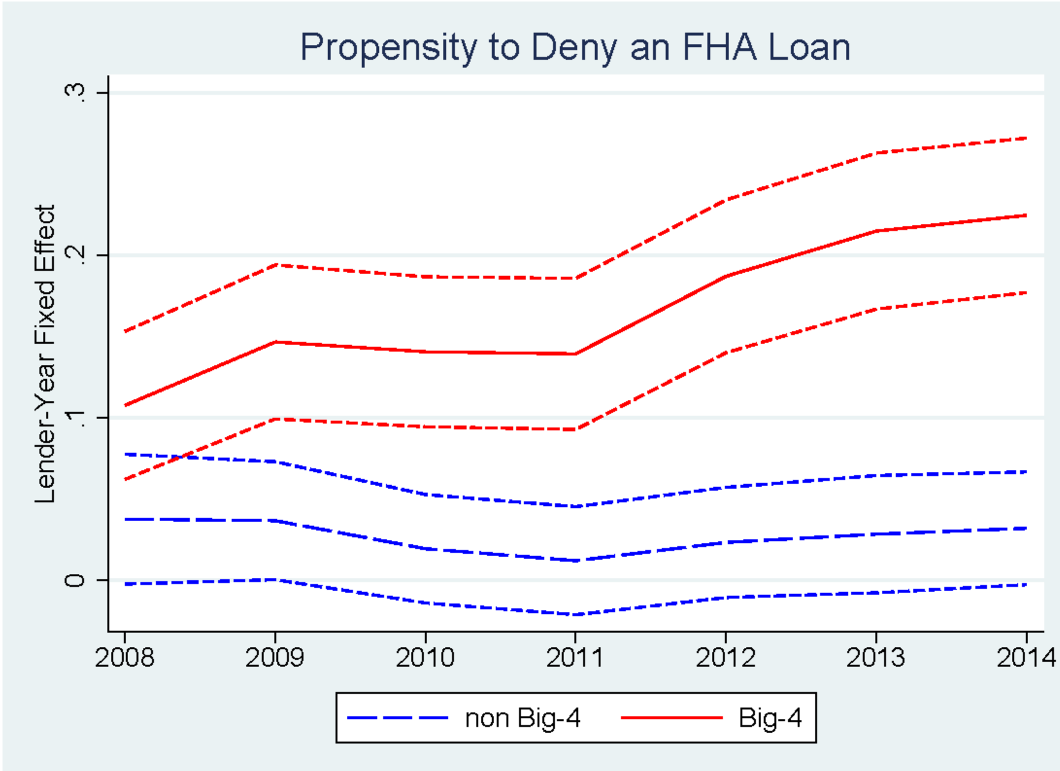

Figure 9. Propensity to Deny of Big-4 Banks and Other Lenders in FHA Mortgages. This figure plots the lenders' fixed effects estimated in equation (1) for FHA loans. The dashed lines correspond to a 95% confidence interval, computed with heteroskedasticity robust standard errors. The reference lender-year category is non Big-4 lenders in 2007, for which the denial probability for FHA loans was 0.148.

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
$\Delta \log(\text{Age}_{m,t})$	2137	0.005	0.021	-0.158	0.17
Δ Denial $\text{Rate}_{m,t}$	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	-.272	1.305	-5.862	4.533
$\Delta \text{Vacancy Rate}_{m,t}$	494	-.004	.037	-.163	.15
$\Delta \text{Foreclosure Rate}_{m,t}$	666	0	.006	-.021	.053
Elasticity_m	1682	2.605	1.436	0.627	12.148
Big-4 $\text{Share}_{m,08}$	2204	0.168	0.12	0	0.579

Note: This table displays summary statistics of the key variables in our sample. The subscripts t and m denote years and MSAs, respectively. Rent is measured by the Zillow Rent 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: Credit Shock and Housing Rents in Bartik-type Regressions

Outcome:	$\Delta\log(\text{Rent}_{m,t})$	$\Delta\log(\text{Rent}_{m,t})$
$V_{m,t-1}$	1.373^{***}	1.373^{***}
	(0.471)	(0.526)
MSA-Year Controls	No	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.019	0.108
Number Observations	1380	1380

Note: 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 mortage 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, measured by the Zillow Rent Index. All specifications include MSA and year fixed effects. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value < 0.10; *p-value < 0.05; ***p-value < 0.01).

Table 3: Denial Rates and Big-4 Credit Shock (IV Stage 1).

Outcome:	ΔDenial Rate$_{m,t}$	ΔDenial Rate$_{m,t}$	ΔDenial Rate$_{m,t}$
$V_{m,t-1}$	0.586***	0.590***	0.599**
	(0.203)	(0.220)	(0.277)
$V_{m,t-1} \times$ Elasticity$_m$			-0.005
			(0.045)
MSA-Year Controls	No	Yes	Yes
MSA FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R-squared	0.119	0.127	0.127
Number Observations	1380	1380	1380

Note: This table estimates equation (4). 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 credit shock $V_{m,t}$ is defined in equation (2). This shock is the product of the share of an MSA's mortage 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. Elasticity denotes the elasticity of housing supply as estimated by Saiz (2010). All specifications include MSA and year fixed effects. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value $<$ 0.10; *p-value $<$ 0.05; ***p-value $<$ 0.01).

Table 4: Denial Rates and Rent Growth based on IV Estimation (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$_{m,t}$	2.342***	2.329**	3.056	3.789***
	(0.845)	(0.940)	(1.999)	(1.352)
ΔDenial Rate$_{m,t}$ $\times$ Elasticity$_m$			-0.333	
			(0.420)	
ΔDenial Rate$_{m,t}$ $\times$ Rent Control$_m$				-2.479
				(1.923)
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: 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 mortage 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. 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 in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value $<$ 0.10; *p-value $<$ 0.05; ***p-value $<$ 0.01). The underidentification test is based on Kleibergen and Paap (2006).

Table 5: Determinants of Big-4 Share in 2008.

Outcome:	$\text{Share}_{m,08}$
$\Delta\log(\text{Rent})_{m,07\text{-}08}$	0.028
	(0.110)
$\Delta\log(\text{Income})_{m,07\text{-}08}$	0.189
	(0.151)
$\Delta\log(\text{Population})_{m,07\text{-}08}$	0.091
	(0.685)
$\Delta\log(\text{Age})_{m,07\text{-}08}$	0.450
	(0.446)
$\Delta\text{Unempl Rate}_{m,07\text{-}08}$	1.845***
	(0.510)
$\Delta\log(\text{Rent})_{m,00\text{-}08}$	1.116***
	(0.393)
$\Delta\log(\text{Income})_{m,00\text{-}08}$	-2.283***
	(0.554)
$\Delta\log(\text{Population})_{m,00\text{-}08}$	-0.122**
	(0.055)
$\Delta\log(\text{Age})_{m,00\text{-}08}$	-3.200***
	(1.023)
$\Delta\text{Unempl Rate}_{m,00\text{-}08}$	-14.404***
	(2.849)
Big-4 Headquarter_m	0.118***
	(0.020)
R-squared	0.302
Number of Observations	299

Note: This table regresses MSA-level share of mortgage applications to the Big-4 banks in 2008 on MSA-level controls. 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, and log rents, measured by the Zillow Rent Index, as well as the 2007-2008 change in each of these variables. Big-4 Headquarter denotes whether the MSA is located in a state close to or near where a Big-4 bank has its headquarters. 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 in parentheses and are heteroskedasticity robust (*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$).

Table 6: Robustness Check: Bartik Regression, and First and Second Stage IV Estimation

Outcome:	ΔDenial Rate$_{m,t}$	$\Delta\log(\text{Rent}_{m,t})$	$\Delta\log(\text{Rent}_{m,t})$
$W_{m,t-1}$	0.559**	1.245***	
	(0.217)	(0.397)	
ΔDenial Rate$_{m,t}$			2.226**
			(0.901)
MSA-Year Controls	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R-squared	0.128	0.109	
Underidentification test (p-value)			0.159
Number of Observations	1368	1368	1368

Note: This table estimates equations (4), (3), and (5) in columns one, two, and three, respectively, using the idiosyncratic credit shock $W_{m,t}$ defined in equation (6) as opposed to the baseline Big-4 credit shock $V_{m,t}$ used to estimate Tables 2-4. 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. Column three uses $W_{m,t}$ as an instrument for denial rates. The MSA-Year controls are those described in Table 2. All specifications include MSA and year fixed effects. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value $<$ 0.10; *p-value $<$ 0.05; ***p-value $<$ 0.01). The underidentification test is based on Kleibergen and Paap (2006).

Table 7: Robustness Check: FHA Credit Shock and Housing Rents in Bartik-type Regressions

Outcome:	$\Delta\log(\text{Rent}_{m,t})$	$\Delta\log(\text{Rent}_{m,t})$
$Y_{m,t-1}$	0.904^{***}	0.931^{***}
	(0.336)	(0.354)
MSA-Year Controls	No	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.020	0.110
Number Observations	1380	1380

Note: This table estimates equation (3) using the credit shock based on FHA denial propensity, $Y_{m,t}$. The subscripts t and m denote years and MSAs, respectively. The sample period is 2008-2014. The credit shock $Y_{m,t}$ is defined in equation (9). It is the product of the share of an MSA's mortage applications to Big-4 banks in 2008 and the difference in the denial propensity of Big-4 and non Big-4 lenders for FHA loans 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, measured by the Zillow Rent Index. All specifications include MSA and year fixed effects. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value $<$ 0.10; *p-value $<$ 0.05; ***p-value $<$ 0.01).

Table 8: Robustness Check: Denial Rates, Rents, and FHA Denial Propensity based on IV Estimation (Stage 2).

Outcome:	$\Delta\log(\text{Rent}_{m,t})$	$\Delta\log(\text{Rent}_{m,t})$
ΔDenial Rate$_{m,t}$	2.091***	2.096**
	(0.780)	(0.868)
MSA-Year Controls	No	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
Underidentification test (p-value)	0.130	0.130
Number of Observations	1380	1380

Note: This table estimates equation (5) using the credit shock based on FHA denial propensity, $Y_{m,t}$, as an instrument for Denial Rate. 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 credit shock $Y_{m,t}$ is defined in equation (9). This shock is the product of the share of an MSA's mortage applications to Big-4 banks in 2008 and the difference in the denial propensity of Big-4 and non Big-4 lenders for FHA loans in a given year. The MSA-Year controls are those described in Table 7. All specifications include MSA and year fixed effects. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value < 0.10; *p-value < 0.05; ***p-value < 0.01). The underidentification test is based on Kleibergen and Paap (2006).

Table 9: Robustness Check: 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 $\text{Rate}_{m,t}$	2.762***	2.384***	3.505***	2.622***
	(0.703)	(0.788)	(1.168)	(0.973)
CLL Instruments	Yes	Yes	Yes	Yes
$V_{m,t-1}$ as an Instrument	No	Yes	No	Yes
MSA-Year Controls	No	No	Yes	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: 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 estimator is 2SLS, and the instruments for ΔDenial $\text{Rate}_{m,t}$ 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 the credit shock $V_{m,t-1}$ defined in equation (2). Columns (2) and (4) include $V_{m,t-1}$ in the instrument set, and columns (1) and (3) exclude it. The MSA-Year controls are those described in Table 2. All specifications include MSA and year fixed effects. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value $<$ 0.10; *p-value $<$ 0.05; ***p-value $<$ 0.01). The C-statistic corresponds to the difference-in-Sargan test that $V_{m,t-1}$ is a valid instrument.

Table 10: Robustness Check: Credit Shock, Housing Rents, and Foreclosures

Outcome:	$\Delta\log(\text{Rent}_{m,t})$	$\Delta\log(\text{Rent}_{m,t})$
$V_{m,t-1}$	0.951***	0.944***
	(0.271)	(0.285)
ΔForeclosure $\text{Rate}_{m,t}$		-0.124
		(0.477)
MSA-Year Controls	Yes	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.099	0.099
Number of Observations	484	484

Note: This table estimates equation (3) on the subsample of MSAs with data on foreclosure rates. The subscripts t and m denote years and MSAs, respectively. The sample period is 2008-2014. Foreclosure Rate denotes the fraction of homes foreclosed in MSA m and year t. The credit shock $V_{m,t}$ is defined in equation (2). It is the product of the share of an MSA's mortage 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, measured by the Zillow Rent Index. All specifications include MSA and year fixed effects. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value $<$ 0.10; *p-value $<$ 0.05; ***p-value $<$ 0.01).

Table 11: Robustness Check: Denial Rates, Rent Growth, and Foreclosures. (IV Stage 2).

Outcome:	$\Delta\log(\text{Rent}_{m,t})$	$\Delta\log(\text{Rent}_{m,t})$
ΔDenial $\text{Rate}_{m,t}$	1.361***	1.345***
	(0.466)	(0.463)
ΔForeclosure $\text{Rate}_{m,t}$		-0.226
		(0.813)
MSA-Year Controls	Yes	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
Underidentification test (p-value)	0.147	0.146
Number of Observations	484	484

Note: This table estimates equation (5) on the subsample of MSAs with data on foreclosure rates. The subscripts t and m denote years and MSAs, respectively. The sample period is 2008-2014. Foreclosure Rate denotes the fraction of homes foreclosed in MSA m and year t. 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 mortage 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. 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 in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value $<$ 0.10; *p-value $<$ 0.05; ***p-value $<$ 0.01). The underidentification test is based on Kleibergen and Paap (2006).

Table 12: New Building Permits and Big-4 Credit Shock in Bartik-type Regressions

Outcome:	Δlog(Multifamily Permits)$_{m,t}$	Δlog(Multifamily Permits)$_{m,t}$
$V_{m,t-1}$	24.534**	29.796***
	(12.273)	(8.899)
MSA-Year Controls	No	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.331	0.430
Number of Observations	1223	1223

Note: This table estimates equation (11). 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 the product of (i) the share of mortgage applications from MSA m sent to the Big-4 banks in 2008 and (ii) the difference between the Big-4 and other lenders' propensity to deny an application, as estimated from (1). 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. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value < 0.10; *p-value < 0.05; ***p-value < 0.01).

Table 13: Denial Rates and New Building Permits Based on IV Estimation (Stage 2)

Outcome:	Δlog(Multifamily Permits)$_{m,t}$	Δlog(Multifamily Permits)$_{m,t}$
ΔDenial Rate$_{m,t}$	41.671***	49.529***
	(15.264)	(9.546)
MSA-Year Controls	No	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
Underidentification test (p-value)	0.139	0.142
Number of Observations	1223	1223

Note: This table estimates equation (12). 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 the product of (i) the share of mortgage applications from MSA m sent to the Big-4 banks in 2008 and (ii) the difference between the Big-4 and other lenders' propensity to deny an application, as estimated from (1). All specifications include MSA and year fixed effects. The MSA-year controls are the same as those in Table 12. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value < 0.10; *p-value $<$ 0.05; ***p-value < 0.01).

Table 14: Rental Vacancies and Big-4 Credit Shock in Bartik-type Regressions

Outcome:	ΔVacancy Rate$_{m,t}$	ΔVacancy Rate$_{m,t}$
$V_{m,t-1}$	-0.593	-0.923*
	(0.641)	(0.523)
MSA-Year Controls	No	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.052	0.290
Number of Observations	348	348

Note: This table estimates equation (13). 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 the product of (i) the share of mortgage applications from MSA m sent to the Big-4 banks in 2008 and (ii) the difference between the Big-4 and other lenders' propensity to deny an application, as estimated from (1). 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. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value $<$ 0.10; *p-value $<$ 0.05; ***p-value $<$ 0.01).

Table 15: Denial Rates and Rental Vacancies Based on IV Estimation (Stage 2)

Outcome:	ΔVacancy Rate$_{m,t}$	ΔVacancy Rate$_{m,t}$
ΔDenial Rate$_{m,t}$	-1.256	-2.501
	(1.399)	(2.051)
MSA-Year Controls	No	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
Underidentification test (p-value)	0.139	0.186
Number of Observations	348	348

Note: This table estimates equation (14). 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 the product of (i) the share of mortgage applications from MSA m sent to the Big-4 banks in 2008 and (ii) the difference between the Big-4 and other lenders' propensity to deny an application, as estimated from (1). All specifications include MSA and year fixed effects. The MSA-year controls are the same as those in Table 14. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value < 0.10; *p-value < 0.05; ***p-value < 0.01).

Table 16: Credit Shock and Homeownership Rate in Bartik-type Regressions

Outcome:	$\Delta \text{HR}_{m,t}$	$\Delta \text{HR}_{m,t}$
$V_{m,t-1}$	-0.983***	-1.003***
	(0.277)	(0.135)
MSA-Year Controls	No	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.015	0.082
Number of Observations	358	358

Note: This table estimates equation (15). 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). This shock is the product of the share of an MSA's mortage 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 homeownership rate. All specifications include MSA and year fixed effects. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value < 0.10; *p-value < 0.05; ***p-value < 0.01).

Table 17: Denial Rates and Homeownership Rate based on IV Estimation (Stage 2)

Outcome:	$\Delta \mathrm{HR}_{m,t}$	$\Delta \mathrm{HR}_{m,t}$
ΔDenial $\mathrm{Rate}_{m,t}$	-2.014*	-2.367**
	(1.128)	(0.933)
MSA-Year Controls	No	Yes
MSA FE	Yes	Yes
Year FE	Yes	Yes
Underidentification test (p-value)	0.141	0.189
Number of Observations	358	358

Note: This table estimates equation (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. Denial Rate is the fraction of mortgage applications from MSA m in year t denied by lenders. The estimator is 2SLS, with the credit supply shock $V_{m,t-1}$ as an instrument for ΔDenial $\mathrm{Rate}_{m,t}$. The credit shock $V_{m,t}$ is the product of (i) the share of mortgage applications from MSA m sent to the Big-4 banks in 2008 and (ii) the difference between the Big-4 and other lenders' propensity to deny an application, as estimated from (1). The MSA-Year controls are the change in log of median household income, the log of population, the log of median inhabitant age, and the unemployment rate; the once-lagged change in each of these four variables; and the once-lagged change in homeownership rate. All specifications include MSA and year fixed effects. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value $<$ 0.10; *p-value $<$ 0.05; ***p-value $<$ 0.01). The underidentification test is based on Kleibergen and Paap (2006).

Table 18: Credit Shock and Homeownership Rate by Internet Access

Outcome:	$\Delta HR_{m,t}$	$\Delta HR_{m,t}$	$\Delta HR_{m,t}$	$\Delta HR_{m,t}$
$V_{m,t-1}$	-1.620***	-0.293	-1.336***	0.238
	(0.220)	(0.279)	(0.359)	(0.152)
$V_{m,t-1} \times \text{Older}_m$	-0.510***		-0.509***	
	(0.168)		(0.173)	
$V_{m,t-1} \times \text{LowInternet}_m$		-0.941***		-1.136***
		(0.360)		(0.307)
$V_{m,t-1} \times \text{WRLURI}_m$			-0.398	-0.538*
			(0.309)	(0.281)
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: This table estimates equations (17) and (18). 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). This shock is the product of the share of an MSA's mortage 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. Older is the standardized ratio of an MSA's ratio of inhabitants aged $\geq$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 16. All specifications include MSA and year fixed effects. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value $<$ 0.10; *p-value $<$ 0.05; ***p-value $<$ 0.01).

Table 19: Credit Shock and Homeownership Rate by Broker and Lender Competition

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***
	(0.248)	(1.027)	(0.527)	(0.976)
$V_{m,t-1} \times \text{License}_m$	-0.223		-0.381	
	(0.208)		(0.318)	
$V_{m,t-1} \times \text{HHI}_m$		-2.583**		-2.769**
		(1.135)		(1.176)
$V_{m,t-1} \times \text{WRLURI}_m$			-0.438	-0.690**
			(0.341)	(0.339)
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: This table estimates equations (19) and (20). 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). This shock is the product of the share of an MSA's mortage 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. 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 et al. (2008). The MSA-Year controls are those used in Table 16. All specifications include MSA and year fixed effects. Standard errors are in parentheses, and are computed according to Driscoll and Kraay (1998) allowing for spatial correlation and autocorrelation of up to two periods (*p-value $<$ 0.10; *p-value $<$ 0.05; ***p-value $<$ 0.01).