Do Credit Conditions Move House Prices?

Daniel L. Greenwald* and Adam Guren† ‡

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Abstract

To what extent did an expansion and contraction of credit drive the 2000s housing boom and bust? The existing literature lacks consensus, with findings ranging from credit having no effect to credit driving most of the house price cycle. We show that the key difference behind these disparate results is the extent to which credit insensitive agents such as landlords and unconstrained savers absorb credit-driven demand, which depends on the degree of segmentation in housing markets. We develop a model with frictional rental markets that allows us to consider cases in between the extremes of no segmentation and perfect segmentation typically assumed in the literature. We argue that the relative elasticities of the price-to-rent ratio and homeownership with respect to an identified credit shock is a sufficient statistic to measure the degree of segmentation. We estimate this moment using three different credit supply instruments and use it to calibrate our model. Our results reveal that rental markets are highly frictional and close to fully segmented, which implies large effects of credit on house prices. In particular, changing credit conditions can explain between 28% and 47% of the rise in price-rent ratios over the boom.

*MIT Sloan School of Management, dlg@mit.edu
†Boston University and NBER, guren@bu.edu
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1 Introduction

To what extent did an expansion and contraction of credit drive the 2000s housing boom and bust? This question is central to understanding the dramatic movements in housing markets that precipitated the Great Recession and to the effectiveness of macroprudential policy tools, yet a decade later there is no consensus on its answer. Some papers, such as Favilukis, Ludvigson, and Van Nieuwerburgh (2017), argue that changes in credit conditions can explain the majority of the movements in house prices in the 2000s.¹ In contrast, papers such as Kaplan, Mitman, and Violante (2020), argue that credit conditions explain none of the boom and bust in house prices. Credit plays an important role in these models for the dynamics of homeownership, leverage, and foreclosures, but does not affect not house prices or the price-to-rent ratio, which are instead driven by beliefs.

In this paper, we show that key difference behind these disparate findings is the degree to which credit insensitive agents such as landlords and unconstrained savers absorb credit-driven demand by constrained agents. This in turn depends on the degree of segmentation between credit insensitive and credit sensitive agents in housing markets. Many models assume either perfect segmentation or perfect integration for tractability, and this assumption plays a crucial role in determining the degree to which credit affects house prices.

The importance of segmentation is clearest between rental and owner-occupied housing. In models with complete integration, rental landlords step in to buy houses when credit contracts and sell houses when credit expands. If landlords are deep pocketed, their valuation of homes is equal to the present value of rents and insensitive to credit supply, so the prices they offer for homes is unaffected by credit. In this world, credit-induced shifts in demand for homes by constrained agents move the homeownership rate but have essentially no effect on the equilibrium price. This can be thought of as a

¹Favilukis et al. (2017) find that 60% of the rise in price to rent ratios can be explained by credit alone and all of the rise can be explained by a combination of credit and business cycle shocks. Landvoigt, Piazzesi, and Schneider (2015), Greenwald (2018), Guren, Krishnamurthy, and McQuade (2020), Garriga, Manuelli, and Peralta-Alva (2019), Garriga and Hedlund (2020), Garriga and Hedlund (2018), Justiniano, Primiceri, and Tambalotti (2019), and Liu, Wang, and Zha (2019) also analyze models in which credit conditions play a key role in the boom and bust. Conversely, Kiyotaki, Michaelides, and Nikolov (2011) study a model in which credit conditions play a limited role.
shift in borrower demand along a perfectly elastic landlord supply curve in price-to-rent ratio versus homeownership rate space. By contrast, in models with segmentation — for instance, because homes differ in their suitability for renting — landlords cannot step in to buy houses when credit conditions change. Shifts in credit supply then lead to strong responses of house prices. Intuitively, the shift in housing demand by constrained households leads to a shift along an inelastic supply curve, leading to adjustment along the price margin.

We quantify on the degree of segmentation using using a new empirical moment and a model that allows us to nest both the perfectly inelastic and perfectly elastic extremes in addition to considering intermediate cases. In particular, we argue that the size of the causal elasticity of the price-to-rent ratio with respect to credit supply relative to the causal elasticity of the homeownership rate with respect to credit supply is a highly informative moment that disciplines the degree of segmentation in housing markets and thus the response of house prices to credit. This ratio corresponds to the slope of the supply curve in price-to-rent ratio vs. homeownership rate space, which in turn determines the extent to which credit-induced shifts demand translate into movements in house prices. This slope consequently provides an important moment to be matched by any model seeking to study the influence of credit on house prices.

Rather than making modeling assumptions to pin down this slope, we treat it as an empirical object. To this end, the first part of our paper provides new empirical estimates of the causal effect of credit supply on prices, rents, and homeownership rates using three different off-the-shelf identification strategies. The first and most statistically-powerful empirical approach we pursue follows Loutskina and Strahan (2015) (LS) in instrumenting for local credit by using differential city-level exposure to changes in the conforming loan limit interacted with changes in the national conforming loan limit. The second empirical approach follows Di Maggio and Kermani (2017) (DM) by exploiting the 2004 preemption of state-level anti-predatory-lending laws for national banks by the Office of the Comptroller of the Currency. The third and final empirical approach follows Mian and Sufi (2019) (MS) in using differential city-level exposure to a sudden expansion in the private label securitization market.
While each of the three identification approaches we use has drawbacks, they all provide similar results and thus reinforce one another. All three sets of estimates indicate that shocks to credit supply increase prices, rents, and the price-to-rent ratio, but have a much smaller and rarely statistically significant effect on the homeownership rate. In terms of point estimates, all three approaches find that price-to-rent ratios respond at least four-to-five times as much as homeownership rates to a credit supply shock. We use a five-to-one ratio as the key empirical moment to pin down the level of frictions in the rental market.

With these estimates in hand, we construct a dynamic equilibrium model, building on Greenwald (2018), in which house prices, rents, and the homeownership rate are all endogenous. Our primary modeling contribution is to tractably incorporate heterogeneity in landlord and borrower preferences for ownership, which allows our model to reproduce a fractional and time-varying homeownership rate. Our framework nests both perfect segmentation and frictionless conversion between rental and owner-occupied housing, as well as a continuum of intermediate cases. We calibrate our model to match our key empirical moment, then use the model to compute the role of credit in driving the 2000s housing boom. We find that a relaxation of credit standards explains between 28% and 47% of the rise in the price-to-rent ratio observed in the boom, with the precise number depending on our assumptions about other forces in the model such as changes in interest rates and house price expectations.

Our results imply we are in a world with significant segmentation in housing markets. Our benchmark calibration generates house price dynamics that are closer to those under the extreme of full segmentation than under the assumption of a frictionless rental market. At the same time, our Benchmark model generates a sizable and realistic movement in the homeownership rate and significant rent-to-own conversion in the boom and own-to-rent conversion in the bust, which is consistent with the data (see, e.g., Guren and McQuade (2020) and Kaplan et al. (2020)) but would be impossible under full segmentation. The ability of our model to quantitatively capture both price and homeownership dynamics is an advantage of our approach.

Our baseline model assumes that landlords do not use credit and that the saver housing stock is entirely segmented from the borrower housing stock. We relax each of these
assumptions in turn. When landlords use credit, a credit supply expansion also shifts supply out. This leads to a larger price-to-rent ratio response and smaller homeownership rate response than under our baseline model. Next, as shown by Landvoigt et al. (2015), unconstrained savers can play a similar role to landlords since if their housing demand is not segmented from borrowers, they can exhibit a highly elastic demand schedule that also makes prices insensitive to credit. Nonetheless, we find this assumption is not important for our quantitative results. Because the saver and landlord margins jointly determine the slope of the supply schedule, relaxing the saver margin requires us to increase frictions on the landlord margin to hit our empirical targets, yielding similar sensitivities of house prices to credit.

In summary, the ability of owners who do not use credit, such as landlords or unconstrained households, to absorb credit-driven demand by constrained households, determines the extent to which shifts in credit supply influence house prices and the homeownership rate. Our empirical finding that price-to-rent ratios respond significantly more to a credit supply shock than homeownership rates implies that this margin is subject to substantial frictions, and that prices do respond to credit in a meaningful way. Mapped into our structural model, these frictions are sufficient for credit changes to have driven an important share of the rise in house prices during the 2000s housing boom.

Related Literature. Our paper relates to several literatures. Empirically, our analysis builds on prior analyses of the causal effect of credit and interest rates on house prices including Glaeser, Gottlieb, and Gyourko (2012), Adelino, Schoar, and Severino (2015), Favara and Imbs (2015), Loutskina and Strahan (2015), Di Maggio and Kermani (2017), Mian and Sufi (2019), and Gete and Reher (2018). These papers, however, cannot answer what fraction of the boom and bust can be explained by credit unless the quasi-random variation they use corresponds exactly to the shocks that drove the boom and bust. We build on this literature by showing that the ratio of the causal effect of credit on price-to-rent to the causal effect on the homeownership rate for any credit variation can be used as a moment to identify structural elasticities. These elasticities can be mapped into a structural model to assess the effect of credit on house prices for an arbitrary set of
shocks, including those that correspond to the 2000s boom and bust.

In terms of applied theory, our work relates to papers that study the effect of credit supply on house prices such as Favilukis et al. (2017), Kaplan et al. (2020), Kiyotaki et al. (2011), Greenwald (2018), Guren et al. (2020), Garriga et al. (2019), Garriga and Hedlund (2020), Garriga and Hedlund (2018), Justiniano et al. (2019), Liu et al. (2019), and Huo and Rios-Rull (2016). The most closely related paper is Landvoigt et al. (2015), who use an assignment model calibrated to micro data to study endogenous segmentation between constrained and unconstrained homeowners who sort into homes of different quality and find that credit is important in explaining the boom at the bottom of the quality distribution. We see our results as highly complementary to this work. While our model of borrower-saver segmentation is much more simplistic than that of Landvoigt et al. (2015), our tractable approach allows us to embed a similar set of frictions in a complete general equilibrium model of housing and mortgages that provides for a richer set of counterfactuals.

Our paper also relates to work on macroprudential policy. Because mortgage credit dominates household balance sheets, many macroprudential policies only work if credit affects house prices. Similarly, the effectiveness of ex-post debt reduction and foreclosure policies (Guren and McQuade (2020), Mitman (2016), Agarwal, Amromin, Ben-David, Chomsisengphet, Piskorski, and Seru (2017a), Agarwal, Amromin, Chomsisengphet, Landvoigt, Piskorski, Seru, and Yao (2017b), Hedlund (2016)) and mortgage design (Guren et al. (2020), Greenwald, Landvoigt, and Van Nieuwerburgh (2020), Campbell, Clara, and Cocco (2020), Piskorski and Tchistyi (2017)) is amplified to the extent that these policies affect house prices.

Overview. The rest of the paper is structured as follows. Section 2 presents the supply and demand model diagrammatically in order to generate intuition and to motivate our estimation of the causal effects of credit on the homeownership rate and price-to-rent ratio. Section 3 describes our data and empirical methodology. Section 4 presents our empirical results. Section 5 presents the model, Section 6 describes its calibration, and Section 7 presents our model results. Section 8 extends the model to include saver housing
Figure 1: Price-Rent Ratio vs. Homeownership Rate

Note: The figure displays national data at the quarterly frequency. The price-rent ratio is obtained from the Flow of Funds, as the ratio of the value of housing services to the value of residential housing owned by households. The homeownership rate is obtained from the census (FRED code: RHORUSQ156N).

demand and credit for landlords. Section 9 concludes.

2 Intuition: Supply and Demand

Before we turn to the empirics and model, this section explains the intuition for how the rental market influences transmission from credit into house prices. This intuition motivates the structure of our model as well as our empirical focus on the causal effects of credit supply on the price-rent ratio and homeownership rate as the crucial sufficient statistics for calibration.

For background, Figure 1 displays the evolution of the price-rent ratio and homeownership rate since 1965. Assuming that housing is either owned by households or by landlords/investors, each point on this plot represents an equilibrium between demand, the price the marginal renter is willing to pay to own a home, and supply, the price at which the marginal landlord is willing to sell that home.

The figure shows that these equilibria were fairly stable in the pre-boom era (1965-1997), with most observations clustered in the lower left portion of the figure. This pat-
tern changed dramatically during the 1997-2006 housing boom. During this period, the price-rent ratio and homeownership rate increased in tandem to unprecedented levels. Following the start of the bust in 2007, these variables reverse course, traveling nearly the same path downward that they ascended during the boom, and finally ending up close to the typical values from the pre-boom era.

To understand what forces could cause these patterns, we present a simple supply and demand treatment that illustrates the key forces in the equilibrium model we develop in Section 5. As in Figure 1, we use the price-rent ratio on the y-axis and the homeownership rate on the x-axis. We use the price-rent ratio instead of house prices and the homeownership rate instead of quantities of owned housing to ensure that changes are driven by the rent versus own margin rather than the construction margin.

Demand for owner-occupied housing comes from constrained households who require mortgages to own. As the price-rent ratio rises, more of these households prefer renting to owning, creating a downward slope. An expansion of credit supply shifts the demand curve rightward by allowing more favorable financing terms (either on interest rate or quantity of available credit) at a given price-rent ratio, inducing more households to choose ownership.

Supply comes from landlords who decide whether to convert units of rental housing to owner-occupied housing and sell it to households. The slope of the supply curve reflects the willingness of landlords to convert and sell more units as the price-rent ratio rises. The supply curve is shifted by anything that changes the landlords’ fundamental value of houses relative to rents.\(^2\)

Our supply-and-demand framework is displayed graphically in Figure 2. To begin, Figure 2a shows the case of perfect segmentation, in which units cannot be converted between owner-occupied and renter-occupied, and the homeownership rate is exogenously fixed. This example nests specifications such as Favilukis et al. (2017) and Justiniano, Primiceri, and Tambalotti (2015), in which households cannot rent housing, corresponding to a fixed homeownership rate of 100%. In our framework, this corresponds to a

\(^2\)If landlords require credit, a credit supply shock would also shift the supply curve upward. Although potentially important, we abstract from landlord credit for the time being and return to it in Section 8.
perfectly inelastic supply, indicated by the vertical line in Figure 2a. This curve intersects the downward sloping demand curve to generate an equilibrium in price-rent versus homeownership rate space.

From this starting point, we can consider the impact of a credit expansion. Assuming for now that only households use credit, the impact of this expansion is an outward shift in demand, as improved access to financing makes more households willing to purchase instead of renting at a given price. Under a perfectly inelastic (segmented) supply curve, this increased demand translates directly into an increase in house prices, while the homeownership rate remains fixed. Clearly, a credit expansion in this specification cannot reproduce the dual increases in both price-rent ratios and homeownership displayed in Figure 1.
Next, we can consider the alternative extreme case of a frictionless rental market in which identical risk-neutral and deep-pocketed landlords transact with households, similar to the baseline model of Kaplan et al. (2020). This specification leads to a perfectly elastic (horizontal) supply curve, since landlords are willing to buy or sell an unlimited amount of housing at a price equal to the present value of rents, which pins down prices. Since this present value does not depend on credit, an expansion of credit, corresponding to an outward shift of demand, increases the homeownership rate in this model, but cannot move the price-rent ratio.

Consequently, a credit expansion cannot explain the dual rise in price-rent ratios and homeownership. Instead, reproducing the empirical pattern requires a separate upward shift in the supply curve, indicated by the horizontal dashed line in Figure 2b. Since prices are equal to the present value of rents in this model, a shock to future rents is required to move prices relative to current rents. This analysis provides intuition for the finding in Kaplan et al. (2020) that a shock to housing beliefs (expected future rents) is responsible for the entire rise in price-rent ratios over the boom, while a credit expansion in their model affects the homeownership rate but not the price-rent ratio.

In this paper, we introduce a model that nests the extremes of perfect segmentation and frictionless rental markets and allows us to consider cases in between with an upward sloping supply curve. In this case, a credit expansion that shifts housing demand can simultaneously explain a rise in price-rent ratios and the homeownership rate because the equilibrium moves up the supply curve. As a result, this model can explain the empirical pattern observed during the housing boom with only a single shock.

At the same time, we could also combine a flatter supply curve with a shift in beliefs to obtain the same equilibrium as the single shock with a steeper supply curve, as shown in Figure 2d. In order to tell apart shifts in supply from movement along the supply curve – or equivalently tell apart the contribution of credit supply and beliefs – we need to know the slope of this supply curve.

As is typical in the simultaneous equations literature, the slope of the supply curve can

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3 A shift in risk premia for the same set of rental cash flows would also generate a rise in present values if we had not assumed risk neutrality.
be uncovered using a shock to the demand curve. In Section 3 we propose a credit supply shock that provides exactly this type of variation and use it to estimate the elasticity of supply.\textsuperscript{4} In the remainder of the paper, we estimate the slope of the supply curve and then write down a structural model that we calibrate to the estimated slope and use to decompose the role of credit in the recent housing boom and bust.

3 Empirical Approach

Our goal is to identify the effect of a local credit supply shock in city $i$ at time $t$ on house prices, rents, price-to-rent ratios, and homeownership rates in order to uncover the slope of the housing supply curve in price-to-rent versus homeownership rate space. Doing so using ordinary least squares (OLS) is problematic because credit is endogenous and because there is likely reverse causality with housing market conditions affecting credit supply. Furthermore, credit measures may be subject to measurement error. Consequently, we need an instrument for credit supply.

We use three different off-the-shelf identification approaches. While no approach is perfect and all three approaches are limited in their statistical power, particularly for homeownership rates, all three provide consistent results and thus reinforce one another. For each approach, the main text provides estimates of the impulse response to a credit supply shock and the impulse response of our key ratio. In the remainder of this section, we present our data construction, our basic regression frameworks, and then describe each empirical approach in detail. We relegate discussion of our instruments’ first stages, supplementary pooled regressions that estimate an average response rather than an impulse response, and other robustness checks to the Appendix.

\textsuperscript{4}In a simultaneous equations setting, one typically uses a demand shock to identify the slope of the supply curve. This is the approach we use, although the labeling is slightly confusing as our housing demand shock is a credit supply shock.
3.1 Data

We construct an annual panel at the core-based statistical area (CBSA) level that merges together data on house prices, rents, homeownership rates, credit, and controls. The data set is slightly different for each empirical approach we use, so we describe the common data sources here and describe these variations in Sections 3.2 - 3.4. Further details on our data construction can be found in the Appendix.

For house prices, we use the CoreLogic repeat sales house price index collapsed to an annual frequency. For credit we use the Home Mortgage Disclosure Act (HMDA) data, which we collapse to the CBSA level. Our main measure of credit is the dollar volume of loan originations; in the Appendix we test robustness to using the number of loans, and the loan-to-income ratio.

For rents, we use the CBRE Economic Advisors Torto-Wheaton Same-Store rent index (TW index), a high-quality repeat rent index for multi-unit apartment buildings.\textsuperscript{5} It is available quarterly for 53 CBSAs beginning in 1989 and 62 CBSAs beginning in 1994. Although using the TW index limits our sample sizes, it improves on rent measures typically used in the literature in two ways. First, its repeat sales methodology is preferable to median rent measures typically used in the literature, which are biased by changes in the composition of leased units. Second, while median rents tend to be sticky and slow moving due to contractual rigidities, the TW index uses asking rents on newly-leased apartments, which better reflect current market conditions. Since the price-to-rent ratio is meant to capture the rent a unit could command if leased instead of sold, these measures using newly-leased apartments are more appropriate for constructing this ratio.

Our homeownership data come from the Census’ Housing and Vacancy Survey. The Census provides annual estimates of the homeownership rate at the CBSA level from 1986 to 2017. This data is only available for an unbalanced panel of 82 CBSAs and is somewhat noisy. It is also plagued by decennial changes in CBSA definitions. In the baseline results

\textsuperscript{5}CBRE EA uses data on effective rents, which are asking rents for newly-rented units net of other leasing incentives. CBRE builds a historical rent series for each building and computes the index as the average change in rents for identical units in the same buildings. CBRE does not use the standard repeat sales methodology because rent data is available for most buildings continuously, so accounting for many periods of missing prices is unnecessary.
we do our best to harmonize the CBSA definitions and drop periods where they change and in the Appendix we pursue several strategies to ensure that changing definitions are not driving our results. For robustness, we supplement our data with alternative homeownership rates from the American Community Survey (ACS) 1-year estimates from the Census, and alternative house price indices from the FHFA. These data are available for more cities, but only starting in 2005.


Our first and most statistically powerful empirical approach uses a share-shift instrument from LS based on the conforming loan limit (CLL) — the maximum loan size eligible for securitization by Fannie Mae and Freddie Mac. Because mortgages backed by Fannie Mae and Freddie Mac received subsidized interest rates, an increase in the CLL represents an increase in the incidence of this subsidy, and a positive shock to the supply of mortgage credit for prime borrowers at the margin of receiving a mortgage backed by Fannie Mae and Freddie Mac relative to a jumbo loan.

The operating principle of the instrument is that the same nation-wide in the CLL should have stronger effects in cities where a larger fraction of loans are close to this threshold, since more new loans should shift from being unsubsidized to subsidized in these areas. For a concrete example, an average of 7.2% of loans originated in San Francisco over our sample fall within 5% of the next year’s conforming loan limit, compared to an average of only 0.4% in El Paso. Our instrument exploits the fact that a change in the CLL should therefore have a bigger average effect in San Francisco than in El Paso.

To construct an instrument that exploits this CLL variation, we follow LS and define

\[ Z_{i,t} = \text{ShareNearCLL}_{i,t} \times \% \text{ChangeInCLL}_t. \]

To measure the share of homes with loans near CLL, we follow LS in using the fraction of mortgage originations in the prior year that are within 5 percent of the current year’s CLL in the HMDA data. Since the CLL has occasionally varied by region, we use only

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6 Adelino et al. (2015) also use a similar empirical strategy.
We then estimate the impulse response of a change in credit $C_{i,t}$ on an outcome variable of interest $Y_{i,t}$ using a local projection instrumental variables (LP-IV) approach. This approach generalizes the Jordà (2005) local projection methods to use exogenous instrumental variables for identification as in Ramey (2016) and Ramey and Zubairy (2018). Stock and Watson (2018) formalize the identification conditions for LP-IV. We extend this to the panel context and add CBSA and time fixed effects following Chen (2018).

In particular, use two-stage least squares to estimate:

\[
\log(Y_{i,t+k}) = \xi_i + \psi_t + \beta_k \Delta \log(C_{i,t}) + \theta X_{i,t} + \epsilon_{i,t}. \tag{1}
\]

\[
\Delta \log(C_{i,t}) = \phi_i + \chi_t + \gamma Z_{i,t} + \omega X_{i,t} + \epsilon_{i,t}. \tag{2}
\]

for \( k = 0, ..., 5 \). \( \xi_i \) and \( \phi_i \) are location fixed effects in the second and first stages, respectively, \( \psi_t \) and \( \chi_t \) are time fixed effects, and \( X_{i,t} \) are controls. To graphically depict the impulse response, we plot the coefficients \( \beta_k \) along with their 95 percent confidence intervals against \( k \).

The formal identification conditions for the panel LP-IV specification following Stock and Watson (2018) are not only relevance and contemporaneous exogeneity but also exogeneity at all leads and lags. This requires that our instruments be independent of one another. To address the failure of this condition due to potential serial correlation, we follow Ramey (2016) and Ramey and Zubairy (2018) in including lags of our instrument \( Z \) as controls. Furthermore, to flexibly control for serial correlation and momentum in the outcome variable, we include \( \log(Y_{i,t-1}) \) and \( \log(Y_{i,t-2}) \) as controls, which helps to ensure that the lead and lag exogeneity conditions are satisfied.

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7 As part of the HERA legislation in 2008, Congress created more direct instructions for the national CLL. The legislation also allowed the CLL to rise by more in high-cost cities if their local house price index grew sufficiently quickly. This would violate an instrumental variable’s exclusion restriction because the change in the CLL would be mechanically correlated with lagged local outcomes. Consequently, in constructing the instrument we use the change in the national CLL regardless of the change in the local CLL in high-cost areas.

8 The CLL does not adjust down and only adjusts up once prices pass their previous high watermark, so the LS instrument gives no variation in the bust.

9 In our empirical application, $C_{i,t}$ is the volume of new purchase loan origination in location $i$ at time $t$; we consider other measures of credit in the Appendix.
We include a number of additional control variables in our analysis to ensure that our estimates are based purely on the share-shift variation in our instrument. The CBSA effects absorb any average differences across areas, and the time fixed effects absorb aggregate conditions, including any average effects of the CLL on the national housing and mortgage markets. We also directly control for $\text{ShareNearCLL}_{i,t}$ and its lag as control variables so that time variation in this share is not identifying variation. To control for any links between our measure of exposure and local housing supply elasticity, we follow LS by including the interaction of $Z_{i,t}$ and the standardized (z-score) of the Saiz (2010) measure of local housing supply elasticity, as well as the lag of this interaction. Finally, as mentioned earlier, we control for two lags of the instrument $Z_{i,t}$ and the outcome variable $\log(Y_{i,t})$ to purge serial correlation.

The identifying assumption for this first empirical approach is that conditional on our controls there is no unobservable that varies with both the fraction of loans originated last year near the CLL and that varies with changes in the national CLL in the time series. If there were such an omitted variable, it would be picked up by our instrument, leading to biased results. In particular, one might be concerned that cities with higher prices tend to be more exposed to national business cycles. In the Appendix, we conduct a number of robustness checks to assuage some concerns, including adding city-level income shocks and time-varying controls for the industrial structure.

We use an unbalanced panel of 62 CBSAs with both rents and homeownership rates from 1992 to 2016 for our analysis, although most of the identifying variation is obtained over the period 1992 to 2006 because the national CLL is fixed through the bust and rebound.

Since we are also interested in estimating the slope of the supply curve directly, we also modify the LP-IV approach to directly estimate the impulse response of the slope. To do so, we use the homeownership rate as $Y_{i,t}$ and replace $\Delta \log(C_{i,t})$ with the price-to-rent ratio $\log(PRR_{i,t})$. The coefficients $\beta_k$ then represents the inverse of the slope of the supply curve. We estimate this inverse slope rather than the slope because in practice the instrument has a far stronger effect on price-to-rent ratios than homeownership rates, so the first stage is much stronger for estimating the inverse slope by IV than for estimating
the slope directly.

### 3.3 Second Empirical Approach: Di Maggio and Kermani (2017)

Our second approach follows DK by exploiting an expansion of credit that occurred due to the OCC’s 2004 preemption of state-level anti-predatory-lending laws (APLs) for national banks. States implemented APLs in 1999 to limit the terms of mortgages made to riskier borrowers. The preemption thus allowed national banks to expand credit more readily to riskier borrowers. The variation induced by this instrument thus provides a mortgage credit supply shock to a riskier segment of the population than the LS instrument.

DK identify credit supply shocks using within-state variation by comparing counties with different exposures to national banks that were regulated by the OCC before and after the change. We adapt their approach but do so at the CBSA level in order to use homeownership rate data that is only available for metropolitan areas.

The instrument is defined as:

\[ Z_i = APL_{2004} \times OCC_{2003} \]

where \( APL_{2004} \) is an indicator for whether the state that the majority of the CBSA resides in has an anti-predatory-lending law by 2004 and \( OCC_{2003} \) is the share of mortgage originated by OCC-regulated banks in 2003 from Home Mortgage Disclosure Act (HMDA) data. To ensure that only the interaction of \( APL_{2004} \) and \( OCC_{2003} \) is used for identification, we follow DK in controlling for both of these variables directly in addition to including year and CBSA fixed effects. We also control for the lag of the outcome variable and a number of controls that DK include in their analysis.\(^\text{10}\)

Because this instrument only induces variation across cities in response to a single credit supply shock, we use a reduced-form event study approach rather than the LP-IV approach we use for the LS instrument, which requires variation in the instrument

\(^{10}\)The only control variable that DK use that we do not use is a proprietary measure of the share of loans originated to subprime borrowers, which turns out to not be crucial to their results.
both across cities and over time. We follow much of the literature and focus on the reduced form regressing the outcome variables directly on the instrument. This is sufficient to obtain the slope of the supply curve, but implies that we cannot interpret coefficient magnitudes in units of credit. In particular, we estimate:

$$\log(Y_{i,t}) = \xi_i + \psi_t + \sum_{k \neq \tau} \beta_k Z_{i1}^{1-t=k} + \theta X_{i,t} + \epsilon_{i,t}$$

The coefficients $\beta_k$ represent the reduced form effect of the instrument at each date in time relative to a base period $\tau$ for which $\beta$ is normalized to zero. We again include CBSA and time fixed effects and controls, and plot the $\beta_t$'s as a function of calendar time $t$. Since this identification strategy is similar to a difference-in-difference with $Z_i$ measuring exposure, a natural placebo test is that $\beta$ is equal to zero prior to date $\tau$, which is a test of parallel trends.

The identifying assumptions are similar to a differences-in-differences approach: there must be parallel trends in the absence of treatment. DK provide extensive support for this identifying assumption in their paper and we replicate their finding of no pre-trends prior to 2003 in our empirical specifications.

We follow DK in estimating the equation using growth rates, so that the outcome variable is the log change in house prices or homeownership rates or the inverse slope. To create our figures, we then add up the coefficients of interest from the base period to each indicated period and compute standard errors by the delta method. This allows us to plot an IRF in levels while still estimating the equation in growth rates.

DK kindly provided us with their data set, and we use their data directly collapsed to the CBSA level to be as consistent with their paper as possible. We then merge in CBSA-level CoreLogic house price index and census homeownership rates. This gives us 262 CBSAs from 2001 to 2010 for house prices and 82 CBSAs from 2001 to 2010 for homeownership rates. Due to the limited power of a single event study, we focus on house prices rather than price-to-rent ratios. We follow DK by weighting our regressions by population, and by clustering standard errors by CBSA.

As with the LP-IV, we are also interested in estimating the inverse slope of the supply
curve. To do so, we again use two-stage least squares with the price-to-rent ratio as the endogenous regressor and the homeownership rate as the outcome. We estimate 3 letting the homeownership rate be \( Y \), replacing \( Z \) with \( \log(HPI_{i,t}) \), and instrumenting the endogenous regressors \( \beta Z_i 1_{t=k} \) for \( k \neq \tau \) with \( Z_i 1_{t=k} \). The \( \beta \)s are then the IRF of the inverse slope in calendar time.

### 3.4 Third Empirical Approach: Mian and Sufi (2019)

Our third approach is to use differential city-level exposure to the 2003 expansion in private label securitization (PLS) to identify the effect of credit supply on prices and homeownership rates based on MS. MS build on evidence from Justiniano, Primiceri, and Tambalotti (2017) of a sudden, sizable, and persistent expansion in PLS markets in late 2003 that persists until the crash. MS argue that the PLS expansion had a larger effect on lending by mortgage lenders that rely on non-core deposits to finance mortgages, so they define a bank-level measure of the ratio of non-core liabilities to total liabilities (NCL). High NCL banks, which are funded less by deposits, should have a greater exposure to the PLS expansion. They show that high NCL banks did in fact expand their lending more after following roughly parallel trends prior to 2002.

Because this instrument also induces variation across cities in response to a single shock, we use the reduced form event study approach from equation (3) that we use for the DK instrument. The instrument is defined as:

\[
Z_i = NCLShare_{2002}^i
\]

where \( NCLShare_{2002}^i \) is MS’s measure of CBSA-level exposure to high NCL lenders, which is equal to the origination-weighted average of lender-level NCLs in a CBSA based on 2002 originations. MS argue that the city-level NCL exposure satisfies an exclusion restriction and is a valid instrument for credit. We follow MS in weighting by the number of housing units and including year and CBSA fixed effects. While NCL exposure with limited controls is not a perfect instrument, it provides an additional exclusion restriction that can be used to corroborate our main results. It also isolates a non-prime credit supply.
shock like the DK instrument, while the LS instrument is a prime credit supply shock.

The MS instrument is underpowered using only the CBSAs for which we have Census HVS homeownership rates. Consequently, for this empirical approach we expand our data set by using ACS data for homeownership rates and FHFA data for house prices. This ACS-FHFA data sample covers 245 CBSAs from 1990 to 2017 for prices and 245 CBSAs from 2005 to 2017 for the homeownership rate. However, this means that we can only use prices as outcomes.\textsuperscript{11} Using this data sample also prevents us from setting the base year of 2002 used by MS because the ACS starts in 2005. We instead use 2013 as the base year, since our estimates of the impulse response for prices returns to its 2002 level in 2013. Our results are robust to using peak-to-trough changes rather than a particular base year.

Because the MS instrument, like the DK instrument, varies across geography but not time, we use the same econometric methodology described in Section 3.3 for our estimates using this instrument.

\section{Empirical Results}

\subsection{Loutskina-Strahan LP-IV Results}

Figure 3 shows the impulse responses using LP-IV and the LS instrument. As a reminder, the figures plot $\beta$ in equation (1). Panel A shows the response of the price-to-rent ratio, panel B shows the response of the homeownership rate, panel C shows the response of house prices, and panel D shows the inverse slope coefficient. The impulse response of rents can be found in the Appendix.

The price-to-rent ratio exhibits a hump-shaped response to credit shocks, peaking at three years at 0.46 before gradually mean reverting. Our estimates are significant at the 5\% level in years 2, 3, and 4. This type of short-run momentum and medium-run mean reversion is a classic finding for impulse responses of prices in housing markets.

\textsuperscript{11} We do not use the ACS homeownership rates for the LS instrument because the ACS begins in 2005 and most of the variation in the conforming loan limit comes before 2005. The ACS does have rents, but they are average rents and very sticky so a price-to-rent ratio constructed with ACS data looks like the same regression using prices as an outcome.
Figure 3: Loutskina-Strahan Instrument LP-IV Impulse Responses

Notes: 95% confidence interval shown in red bars. The figure shows panel local projection instrumental variables estimates of the response of the indicated outcomes to dollar credit volume. For panels A to C, the second stage is as indicated in equation (1) and the first stage is as indicated in equation (2). The instrument is $ShareNearCLL_{i,t} \times \%ChangeInCLL_{i,t}$, and control variables include $ShareNearCLL_{i,t-1}$, $ShareNearCLL_{i,t-1} \times \%ChangeInCLL_{i,t} \times Z(Saiz_{i})$, $ShareNearCLL_{i,t-2}$, $ShareNearCLL_{i,t-2} \times \%ChangeInCLL_{i,t-1}$, $ShareNearCLL_{i,t-2} \times \%ChangeInCLL_{t-1} \times Z(Saiz_{i})$, and two lags of the outcome variable. For panel D, we use the same controls but the outcome variable is the homeownership rate and the credit variable is replaced with the log price-to-rent ratio to obtain a coefficient for the inverse supply curve slope. All standard errors are robust.

Our results indicate that the behavior of the price-to-rent ratio is due to a hump-shaped response of house prices, which peak at around 0.70, and a quicker and more persistent response of rents, which jump by 0.22 rather quickly and remain high. Our results for the effect of credit on house prices are consistent with those found in the literature, such as Glaeser et al. (2012), Adelino et al. (2015), Favara and Imbs (2015), and Di Maggio and Kermani (2017). For instance, Favara and Imbs (2015) find an elasticity
of house prices to loan volumes over one year of 0.134; we find a response of 0.135 in the same year as the credit shock. We find a larger and quicker response of rents, likely because we are using the TW rent index, which provides the rent of a newly-rented multi-family unit using a repeat sales methodology, rather than stickier median rents as used by prior literature.\footnote{Our results are different from what Gete and Reher (2018) find about rents in the bust. Using the share of local loans originated by banks undergoing stress tests in the bust as an instrument for the loan denial rate, Gete and Reher find that loan denials cause an increase in rents, a decrease in homeownership rates, and a large decrease in the price-to-rent ratio. If one compares their coefficients on the price-to-rent ratio to the homeownership rate, one obtains a ratio of 85 to one, while we calibrate to a five-to-one ratio. Our results may differ for three reasons. First, Gete and Reher use denial rates as a measure of credit supply instead of credit quantities. Second, Gete and Reher use Zillow data on average rents rather than rents for newly-rented units. Third, while we focus on an instrument with significant variation in the boom, while Gete and Reher use an instrument for credit supply in the bust. In a robustness check, Gete and Reher use the Loutskina-Strahan instrument prior to the bust and find no significant effect of credit on rents. This is similar to what we find for measures of average rents rather than new rents.}

In contrast to our results on price-to-rent ratios and house prices, we find no significant response of homeownership rates to credit shocks. While some of this is due to low statistical power due to a small data set and noisy measures of the homeownership rate, the point estimates are consistently low, peaking at 0.08 in year 3 (they are larger in year 5, but the standard errors blow up). The top of the 95% confidence interval is around 0.3, which is significantly smaller than the response of house prices or price to rent ratios.

A back-of-the-envelope measure of the relative slope of the supply curve in price-to-rent versus homeownership rate space can be obtained by comparing the IRFs in panels A and B and observing that the peak point estimate of the price-to-rent impulse response is 5.6 times larger than the peak point estimate of the homeownership rate impulse response. We can be more precise econometrically by using the homeownership rate as the dependent variable and the price-to-rent ratio as the independent variable using the same instrument. As described in Section 3, we take this approach and estimate the inverse slope because we would have a weak first stage if the homeownership rate were the independent variable. Panel D shows that the inverse slope peaks at 0.2, indicating a slope of about 5, although it is lower in other periods. At the top of the 95% confidence interval, we have an inverse slope of 0.45, or a slope of 2.2.
4.2 Di Maggio-Keramani APL Preemption Results

Figure 4 shows the results for the reduced form event study using the of the DK instrument. As a reminder, we estimate equation (3) with house prices as the outcome in log changes and then cumulate the coefficient $\beta$ coefficients from the base period to the indicate period to obtain an IRF in levels.

Panel A shows the response of house prices for the full sample of CBSAs, which allows us to check our specification against DK’s results. Our results are very similar to theirs with house price growth as the outcome variable, although we find quicker mean reversion and a larger amount of overshooting in the bust, as shown in the Appendix. The impulse response in levels in panel A shows no significant pre-trends are evident prior to 2003, and after 2004 the results demonstrate a classic hump-shaped impulse response for house prices peaking at 0.76 in 2007, which is significant at the 5% level.

Panel B limits the sample to cities with homeownership rate data, which tend to be larger, more inelastic cities. Consequently, we obtain a larger response with a peak in 2006 of 1.8 that is significant at the 5% level.$^{13}$

Panel C shows the effect on homeownership rates, which tends to be much smaller and peak in 2006 at 0.53, although given the wide confidence bands we have on the homeownership rate this is not a statistically significant result. A naive division of the peak values thus yields a slope of the supply curve of 3.42. We can evaluate the slope more rigorously by using IV with homeownership rates as the outcome variable and house prices as the dependent variable; when we do so we obtain very wide confidence intervals and noisy coefficients that imply an inverse slope between 2 and 5.

4.3 Mian-Sufi PLS Expansion Results

Figure 5 shows the year $\beta_k$ coefficients for the Mian and Sufi NCL share instrument. As a reminder, the PLS market expansion is in 2002, and we have normalized 2013 to be the base year and use house prices as the outcome due to power concerns. Panel A shows

$^{13}$These coefficients correspond to a CBSA in an APL state with 100% OCC bank share and are thus not interpretable in terms of credit supply unlike the Loutskina-Strahan instrument; however we can still compare the responses of house price growth and homeownership growth to the same shock.
Notes: 95% confidence interval shown in red bars. Panels A to C show estimates of the cumulative sum from 2003 of $\beta_k$ for each indicated year estimated from equation (3), with the instrument being $Z_i = APL_{2004} \times OCC_{2003}$ and 2003 being the base year. The regression is weighted by population and standard errors are clustered by CBSA. The controls include median income growth, population growth, the Saiz (2010) elasticity interacted with a dummy for post-2004, the fraction of loans originated by HUD-regulated lenders interacted with a dummy for post-2004, and the fraction of HUD-regulated lenders interacted with a dummy for APLs. The controls are as Di Maggio and Kermani (2017) except our data is at the CBSA level and omits a control for the fraction of loans originated that are subprime (FICO under 620), which is based on proprietary data. For panel D, we use the same controls but the outcome variable is the homeownership rate and the credit variable is replaced with log house prices to obtain a coefficient for the inverse supply curve slope. All regressions are weighted by population and standard errors are clustered by CBSA as in the DK paper.

a zero effect on prices prior to 2002 and then a hump-shaped impulse response in line with our previous results with some overshooting in the bust. Panel B shows a positive
Notes: 95 % confidence interval shown in red bars. Panels A and B shows estimates of the effect of a city’s NCL share on each outcome based on estimating equation 3 with the instrument being $Z_i = NCLShare_{i2002}$ and 2013 being the base year. For panel C, we use the same controls but the outcome variable is the homeownership rate and the credit variable is replaced with log house prices to obtain a coefficient for the inverse supply curve slope All standard errors are robust.

and statistically-significant effect of the NCL share on homeownership rates beginning in 2005 that also mean reverts over time. Examining the coefficients reveals that the effect of house prices peaks at 1.19 while the effect on the homeownership rate peaks at 0.27. This implies a slope of approximately 4.4.

Again, we can estimate the inverse slope by IV. Panel C does this and shows results for 2005-2007; the other years have very wide standard errors and are omitted. One can see that the inverse slope coefficient is 0.28 in 2005 and 0.20 in 2006 and 2007. In these
later two years, the top of the 95% confidence interval is around 0.40. The MS instrument thus reveals a point estimate for the slope between 3.6 and 5, with a lower extreme value of 2.5.

4.4 Summary

All three of our empirical strategies are imperfect and have limited power. They also provide very different sources of variation in terms of what types of borrowers are affected by the credit expansion: the LS instrument expands credit to prime borrowers while DM and MS instruments expand credit to more risky borrowers. Despite these differences, all three identification strategies provide a similar story: the point estimates of the slope of the supply curve is at its lowest between 3.4 and 5, with higher values in other periods.\textsuperscript{14} Given these results, we use a slope of 5 as our primary calibration target for the slope of the supply curve when we turn to the model.

The fact that all three identification strategies are consistent provides us with significantly more confidence for this key moment than one would obtain with a single empirical strategy. We nonetheless see our efforts as an initial attempt to estimate this moment and hope that the literature continues to make progress on precisely estimating this key relative causal effect in the future.

5 Model

This section develops an equilibrium model that we use to quantitatively evaluate the role of credit in driving house prices, with a particular focus on the recent boom-bust cycle.

Demographics. There is a representative borrower, landlord, and saver. Each are infinitely lived, permanent types, with perfect risk sharing within the members of each type.

\textsuperscript{14}We view the LS instrument as the most informative data point given its power and given that we can use the price-to-rent ratio rather than just prices
Housing Technology. Housing is produced by construction firms (described subsequently) whose supply at the end of period $t$ is denoted $\bar{H}_t$. Housing can be owned either by borrowers or by landlords, who in turn rent the housing they own to borrowers. We denote borrower-owned housing as $H_{B,t}$ and landlord-owned rental housing as $H_{L,t}$. Housing produces a service flow proportional to the stock, and is sold ex-dividend (i.e., after the service flow is consumed).

Preferences. Borrowers and savers both have log preferences over a Cobb-Douglas aggregator of nondurable consumption and housing services:

$$U_B = \sum_{t=0}^{\infty} \beta_B^t \log \left( \hat{c}_{B,t}^{1-\xi} \hat{h}_{B,t}^{\xi} \right)$$

$$U_S = \sum_{t=0}^{\infty} \beta_B^t \log \left( \hat{c}_{S,t}^{1-\xi} \hat{h}_{S,t}^{\xi} \right)$$

where $c$ represents nondurable consumption, $h$ represents housing services, and hats indicate that variables have been put in per-capita terms by dividing through by the population share $\chi_j$ for $j \in \{B, S\}$. Importantly, however, savers are restricted to always demand the fixed quantity of housing $\bar{H}_S$. This is equivalent to assuming a completely segmented housing market, in which savers and borrowers consume different types of housing (e.g., live in different neighborhoods, occupy different quality tiers). This restrictive and important assumption shuts down any margin for borrowers and savers to transact housing, equivalent to fully segmented housing markets between these two groups. The implications of this choice are discussed in detail in Section 6. For landlords, we use risk neutral preferences

$$U_L = \sum_{t=0}^{\infty} \beta_L^t \hat{c}_{L,t}$$

which correspond to the interpretation of landlords as a foreign-owned, profit-maximizing firm, as in e.g., Kaplan et al. (2020).

Asset Technology. Borrowers and landlords can trade long-term mortgage debt with savers at equilibrium, with the mortgage technology following Greenwald (2018). Bor-
rower debt is denoted $M_{B,t}$ while landlord debt is denoted $M_{L,t}$. Debt is issued in the form of fixed-rate nominal perpetuities with coupons that geometrically decay at rate $\nu$. This means that a mortgage that is issued with balance $M^*$ and rate $r^*$ will have payment stream of $(r^* + \nu)M^*$, $(1 - \nu)(r^* + \nu)M^*$, $(1 - \nu)^2(r^* + \nu)M^*$, .... Mortgage loans are prepayable, with fraction $\rho_{j,t}$ of agents of type $j$ choosing to prepay their loans in a given period. As in Greenwald (2018), the average size of new loans for agents $i$ of type $j$ (denoted $M^*_{i,j,t}$) is subject to both loan-to-value (LTV) and payment-to-income (PTI) limits at origination, of the form:

$$M^*_{i,j,t} \leq \theta^\text{LTV}_{j,t} p_t H^*_{i,j,t}$$

$$M^*_{i,j,t} \leq \left(\theta^\text{PTI}_{j,t} - \omega_j\right) \text{income}_{i,j,t}$$

where $p_t$ is the price of housing, $H^*_{i,j,t}$ is the borrower’s new house size, and $\omega_j$ and $\alpha_j$ are offsets used in calibration to account for non-housing debts, and taxes and insurance, respectively.

In addition to the mortgage contract, there is a one-period bond $B_t$ in zero net supply. Agents cannot take a short position in this bond, so it is traded by the savers only at equilibrium. All financial contracts are nominal, meaning that real payoffs from both one-period bonds and mortgages decay each period at the constant rate of inflation $\pi$.

Finally, there is a divisible housing good, whose holdings by the borrower and landlord are denoted $H_B$ and $H_L$, respectively. Only borrowers who are currently prepaying their existing loans are eligible to purchase new housing (i.e., borrowers face a constant probability of receiving a moving shock). This good produces a flow of housing services equal to its stock, and requires a per-period maintenance cost of fraction $\delta$ of the current value of housing.

Ownership Benefit Heterogeneity. Without additional heterogeneity, the model would be unable to generate a fractional and time-varying homeownership rate. If all borrowers have the same valuation for housing and all landlords have the same valuation for housing, then whichever group has the higher valuation will own all the housing, leading to
a homeownership rate of either 0% or 100%. In order to generate a fractional homeownership rate, we need to impose further heterogeneity in how agents value housing within at least one of these types. Our key modeling contribution in this paper is to explicitly allow for this within-type heterogeneity.

We impose this heterogeneity in a simple way, by assuming that agents receive an additional service flow (either positive or negative) from owning housing. For parsimony, we assume that if borrower $i$ owns one unit of housing, he or she receives surplus equivalent to $\omega_{i,t}$ of the numeraire, where $\omega_{i,t}^B \sim \Gamma_{\omega,B}$ is drawn i.i.d. across borrowers and time. Symmetrically, if landlord $i$ owns one unit of housing, he or she receives surplus equivalent to $\omega_{i,t}^L \sim \Gamma_{\omega,L}$ of the numeraire. Since we perceive these costs as likely non-financial, we rebate them lump-sum to households, making them equivalent to utility benefits or costs.\(^{15}\)

There are several forms of heterogeneity that would map intuitively into this framework. On the borrower side, heterogeneity in the value of ownership likely stands in for household age, family composition, ability to make a down payment, and true personal preference for ownership. On the landlord side, we suspect that the biggest source of heterogeneity is on the suitability of different properties for rental. For example, while urban multifamily units can be efficiently monitored and maintained in a rental state, the depreciation and moral hazard concerns for renting a detached suburban or rural house may be much higher. Under this interpretation, at high homeownership rates, the marginal converted property is easy to convert and maintain, and is valued highly by landlords relative to the rent it produces. At low homeownership rates, by contrast, the marginal converted property is relatively costly to maintain as a rental property, and landlords are willing to part with it at a lower price-to-rent ratio.

The degree of dispersion of the distributions $\Gamma_{\omega,B}$ and $\Gamma_{\omega,L}$ map into the slopes of the demand and supply curves, respectively, in Section 2. Specifically, the more dispersed are the ownership benefits, the steeper the slope, as the marginal valuation changes rapidly as

\(^{15}\)For timing, we assume that agents must pick out their target house size prior to drawing $\omega_{i,t}$, but can then choose whether to proceed with the transaction or back out. This ensures that a single landlord with the highest benefit cannot buy up the entire stock of rental housing, undoing the effects of heterogeneity at equilibrium.
we move along the distribution. In contrast, a distribution with low dispersion will yield a flatter, more elastic curve, as agents share highly similar valuations, implying that prices move little as the homeownership rate, and the identities of the marginal owner/renter and landlord vary.

Borrower’s Problem. The borrower’s budget constraint is:

$$\begin{align*}
\underline{c}_{B,t} & \leq \frac{(1 - \tau)y_{B,t}}{	ext{after-tax income}} + \rho_{B,t} \left( M_{B,t}^* - \pi^{-1}(1 - \nu_B)M_{B,t-1} \right) - \pi^{-1}(1 - \tau)X_{B,t-1} - \nu_B \pi^{-1}M_{B,t-1} \\
& \quad - \rho_{B,t} \left( H_{B,t}^* - H_{B,t-1} \right) - \delta p_t H_{B,t-1} - q_t (H_{B,t} - H_{B,t-1}) + \left( \int_{\tilde{\omega}_{B,t-1}} \omega d\Gamma_{\omega,B} \right) \tilde{H}_{t-1} \\
& \quad - \left( \int_{\Gamma_{\kappa}^{-1}(\rho_{B,t})} \kappa d\Gamma_{\kappa}(\kappa) - \bar{\Psi}_t \right) M_{B,t}^* + T_{B,t} \\
& \quad - \text{net housing purchases} \quad - \text{maintenance} \quad - \text{rent} \quad \text{owner surplus} \quad \text{refi cost (rebated)} \quad \text{other rebates}
\end{align*}$$

where $y_{B,t}$ is exogenous outside income and $q_t$ is the rental rate (i.e., the price of housing services). The optimal policy is for all borrowers with owner utility shock $\omega_{i,t} > \tilde{\omega}_t$ to choose to buy housing. By market clearing, $\tilde{\omega}_{B,t} = \Gamma_{\omega,B}^{-1}(1 - H_{B,t}/\tilde{H}_t)$, which ensures that the fraction of borrowers choosing to own is equal to the fraction of borrower-owned housing. Income is taxed at rate $\tau$, while interest payments on the mortgage are tax deductible. For refinancing, borrowers draw heterogeneous costs $\kappa_{i,t}$ so that the borrowers with the lowest draws refinance following Greenwald (2018).

The laws of motion for mortgage balance $M_{B,t}$, interest payment $X_{B,t}$, and owned housing $H_{B,t}$ are:

$$\begin{align*}
M_{B,t} & = \rho_{B,t} M_{B,t}^* + (1 - \rho_{B,t})(1 - \nu_B) \pi^{-1} M_{B,t-1} \\
X_{B,t} & = \rho_{B,t} r_{B,t}^* M_{B,t}^* + (1 - \rho_{B,t})(1 - \nu_B) \pi^{-1} X_{B,t-1} \\
H_{B,t} & = \rho_{B,t} H_{B,t}^* + (1 - \rho_{B,t}) H_{B,t-1}
\end{align*}$$
Landlord’s Problem. The landlord’s problem is similar to that of the borrower, with the key exception that the landlord only sells housing services to the borrower instead of consuming them. The landlord’s budget constraint is:

\[
c_{L,t} \leq \frac{(1 - \tau)y_{L,t}}{\text{after-tax income}} + \rho_{L,t} \left( M_{L,t}^* - \pi^{-1}(1 - \nu_L)M_{L,t-1} \right) - \pi^{-1}(1 - \tau)X_{L,t-1} - \nu_L \pi^{-1}M_{L,t-1}
\]

where the wedge \( \Delta \) allows for time variation in mortgage spreads. A value of \( \Delta > 0 \) implies that mortgage rates exceed the rates on risk-free bonds implied by the expectations hypothesis (or in other words, that mortgage bonds trade at a discount). In addition to the budget constraint, the saver must also satisfy the fixed housing demand constraint (friction) \( H_{S,t} = H_S \) at all times.

Saver’s Problem. The saver’s budget constraint is:

\[
c_{S,t} \leq \frac{(1 - \tau)y_{S,t}}{\text{after-tax income}} - \frac{(B_t - R_{L-1}B_{t-1})}{\text{net bond purchases}} - \frac{p_t \left( H_{S,t}^* - H_{S,t-1} \right)}{\text{net housing purchases}} - \frac{\delta p_t H_{S,t-1}}{\text{maintenance}} + \sum_{j \in \{B,L\}} \left\{ \frac{- \rho_{j,t} \exp(\Delta_{j,t})M_{j,t}^* - \pi^{-1}(1 - \nu_j)M_{j,t-1}}{\text{net mortgage iss.}} \right\}
\]

while the landlord’s laws of motion are

\[
M_{L,t} = \rho_{L,t} M_{L,t}^* + (1 - \rho_{L,t})(1 - \nu_L) \pi^{-1} M_{L,t-1}
\]

\[
X_{L,t} = \rho_{L,t} r_{L,t}^* M_{L,t}^* + (1 - \rho_{L,t})(1 - \nu_L) \pi^{-1} X_{L,t-1}
\]

\[
H_{L,t} = \rho_{L,t} H_{L,t}^* + (1 - \rho_{L,t}) H_{L,t-1}
\]
**Construction Firm’s Problem.** New housing is produced by a continuum of competitive construction firms. Similar to Favilukis et al. (2017) and Kaplan et al. (2020), we assume that new housing is produced using nondurable goods $Z$ and land $L_t$ according to the technology:

$$I_t = L_t^{\varphi} Z_t^{1-\varphi}$$
$$\bar{H}_t = (1 - \delta) \bar{H}_{t-1} + I_t$$

where $L$ units of land permits are auctioned off by the government each period, with the proceeds returned pro-rata to the households. Each construction firm therefore solves:

$$\max_{L_t, Z_t} p_t L_t^{\varphi} Z_t^{1-\varphi} - p_{\text{Land},t} L_t - Z_t$$

where $p_{\text{Land},t}$ is the equilibrium price of land permits, and the price of nondurables is normalized to unity.

**Equilibrium.** A competitive equilibrium economy consists of endogenous states $(H_{B,t-1}, M_{B,t-1}, X_{B,t-1}, M_{L,t-1}, X_{L,t-1}, \bar{H}_{t-1})$, borrower controls $(c_{B,t}, h_{B,t}, \rho_{B,t}, M^*_B, H^*_B)$, landlord controls $(c_{L,t}, \rho_{B,t}, M^*_L, H^*_L)$, saver controls $(c_{S,t}, B_t)$, construction firm controls $(L_t, Z_t)$, and prices $(p_t, q_t, r^*_B, r^*_L)$ that jointly solve the borrower, landlord, saver, and construction firm problems, as well as the market clearing conditions.

- **Housing:** $\bar{H}_t = H_{B,t} + H_{L,t}$
- **Housing Services:** $\bar{H}_t = h_{B,t}$
- **Resources:** $Y_t = c_{B,t} + c_{L,t} + c_{S,t} + Z_t + \delta p_t \bar{H}_t$
- **Housing Permits:** $L = L_t$.

### 5.1 Model Solution

We now present the key equilibrium conditions of the model, while reserving the full set of equilibrium conditions to Appendix A. These key equations are the optimality condi-
tions for borrower and landlord housing, which correspond to the inverted demand and supply curves:

\[
p_{t}^{\text{Demand}}(H_{B,t}) = \mathbb{E}_{t}\left\{ \Lambda_{B,t+1}\left[ \bar{\omega}_{B,t} + q_{t+1} + \left(1 - \delta - (1 - \rho_{B,t+1})C_{B,t+1}\right)p_{t+1} \right]\right\} \frac{1 - C_{B,t}}{1 - C_{B,t}}
\]

\[
p_{t}^{\text{Supply}}(H_{B,t}) = \mathbb{E}_{t}\left\{ \Lambda_{L,t+1}\left[ \bar{\omega}_{L,t} + q_{t+1} + \left(1 - \delta - (1 - \rho_{L,t+1})C_{L,t+1}\right)p_{t+1} \right]\right\} \frac{1 - C_{L,t}}{1 - C_{L,t}}.
\]

\(p_{t}^{\text{Demand}}\) is the price at which borrowers are willing to purchase quantity \(H_{B,t}\), and \(p_{t}^{\text{Supply}}\) is the price at which landlords are willing to provide quantity \(H_{B,t}\) to the market, which by market clearing is equivalent to landlords choosing quantity \(H_{L,t} = \bar{H}_{t} - H_{B,t}\) of housing.

These equations map directly into the supply and demand framework of Section 2, where the slopes of the supply and demand schedules are pinned down by the \(\bar{\omega}_{j,t}\) terms. Recall that these terms are defined by \(\bar{\omega}_{B,t} = \Gamma_{\omega,B}(1 - H_{B,t}/\bar{H})\) and \(\bar{\omega}_{L,t} = \Gamma_{\omega,L}(H_{B,t}/\bar{H})\).

As \(H_{B,t}\) increases, so does the fraction of owner-occupied housing. This pushes down \(\bar{\omega}_{B,t}\), as the houses obtained become increasingly less suitable for owner-occupation, generating a downward sloping demand curve. At the same time, \(\bar{\omega}_{L,t}\) rises as the marginal unit becomes more and more favorable for rental, generating an upward sloping supply curve. In equilibrium, the level of owner-occupied housing \(H_{B,t}\) adjusts so that \(p_{t}^{\text{Demand}} = p_{t}^{\text{Supply}}\), and the market clears. The degree of dispersion in the \(\Gamma_{\omega,B}\) and \(\Gamma_{\omega,L}\) distributions determine how much the \(\bar{\omega}_{j,t}\) terms change with the homeownership rate, which governs the slopes of the demand and supply curves, respectively.

6 Model Quantification

We calibrate our model at quarterly frequency to match several external targets from the literature together with our key empirical moment. Our calibration proceeds in two steps: we first calibrate a number of parameters externally or to external targets. We then match our key empirical moment in the data with the remaining model parameters.
6.1 External Targets and Parameters

The baseline model turns off landlord credit, so that $M_{L,t} = X_{L,t} = \rho_{L,t} = 0$ for all $t$. We additionally fix the refinancing rate to be equal to $\rho_t = \bar{\rho} = 0.034$, the steady state refinancing rate from Greenwald (2018). The remaining parameters and functional forms are described below and summarized in Table 1.

Table 1: Parameter Values: Baseline Calibration (Quarterly)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Name</th>
<th>Value</th>
<th>Internal</th>
<th>Target/Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Demographics and Preferences</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Borrower pop. share</td>
<td>$\chi_B$</td>
<td>0.626</td>
<td>N</td>
<td>1998 SCF</td>
</tr>
<tr>
<td>Borrower inc. share</td>
<td>$s_B$</td>
<td>0.525</td>
<td>N</td>
<td>1998 SCF</td>
</tr>
<tr>
<td>Landlord pop. share</td>
<td>$\chi_L$</td>
<td>0.000</td>
<td>N</td>
<td>Normalization</td>
</tr>
<tr>
<td>Borr. discount factor</td>
<td>$\beta_B$</td>
<td>0.974</td>
<td>Y</td>
<td>PMI Rate (see text)</td>
</tr>
<tr>
<td>Saver discount factor</td>
<td>$\beta_S$</td>
<td>0.992</td>
<td>Y</td>
<td>Nom. interest rate = 6.46%</td>
</tr>
<tr>
<td>Landlord discount factor</td>
<td>$\beta_L$</td>
<td>0.974</td>
<td>Y</td>
<td>Equal to $\beta_B$</td>
</tr>
<tr>
<td>Housing utility weight</td>
<td>$\xi$</td>
<td>0.200</td>
<td>N</td>
<td>Davis and Ortalo-Magné (2011)</td>
</tr>
<tr>
<td>Saver housing demand</td>
<td>$\bar{H}_S$</td>
<td>5.299</td>
<td>Y</td>
<td>Steady state optimum</td>
</tr>
<tr>
<td><strong>Ownership Benefit Heterogeneity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Landlord het. (location)</td>
<td>$\mu_{\omega,L}$</td>
<td>-0.002</td>
<td>Y</td>
<td>Avg. homeownership rate</td>
</tr>
<tr>
<td>Landlord het. (scale)</td>
<td>$\sigma_{\omega,L}$</td>
<td>0.020</td>
<td>Y</td>
<td>Empirical elasticities (Section 6)</td>
</tr>
<tr>
<td>Borr. het. (location)</td>
<td>$\mu_{\omega,B}$</td>
<td>0.004</td>
<td>Y</td>
<td>Borr. VTI (1998 SCF)</td>
</tr>
<tr>
<td>Borr. het. (scale)</td>
<td>$\sigma_{\omega,B}$</td>
<td>0.008</td>
<td>Y</td>
<td>Implied subsidy (see text)</td>
</tr>
<tr>
<td><strong>Technology and Government</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New land per period</td>
<td>$L$</td>
<td>0.090</td>
<td>Y</td>
<td>Residential inv = 5% of GDP</td>
</tr>
<tr>
<td>Land share of construction</td>
<td>$\varphi$</td>
<td>0.371</td>
<td>N</td>
<td>Res inv. elasticity in boom</td>
</tr>
<tr>
<td>Housing depreciation</td>
<td>$\delta$</td>
<td>0.005</td>
<td>N</td>
<td>Standard</td>
</tr>
<tr>
<td>Inflation</td>
<td>$\bar{\pi}$</td>
<td>1.008</td>
<td>N</td>
<td>3.22% Annualized</td>
</tr>
<tr>
<td>Tax rate</td>
<td>$\tau$</td>
<td>0.204</td>
<td>N</td>
<td>Standard</td>
</tr>
<tr>
<td><strong>Mortgage Contracts</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Refinancing rate</td>
<td>$\bar{\rho}$</td>
<td>0.034</td>
<td>N</td>
<td>Greenwald (2018)</td>
</tr>
<tr>
<td>Loan amortization</td>
<td>$\nu$</td>
<td>0.45%</td>
<td>N</td>
<td>Greenwald (2018)</td>
</tr>
<tr>
<td>Borr. LTV Limit</td>
<td>$\theta_B^{LTV}$</td>
<td>0.850</td>
<td>N</td>
<td>Greenwald (2018)</td>
</tr>
<tr>
<td>Borr. PTI Limit</td>
<td>$\theta_B^{PTI}$</td>
<td>0.360</td>
<td>N</td>
<td>Greenwald (2018)</td>
</tr>
<tr>
<td>Borr. PTI offset (taxes etc.)</td>
<td>$\alpha_B$</td>
<td>0.09%</td>
<td>N</td>
<td>Greenwald (2018)</td>
</tr>
<tr>
<td>Landlord LTV Limit</td>
<td>$\theta_L^{LTV}$</td>
<td>0.000</td>
<td>N</td>
<td>No landlord credit</td>
</tr>
</tbody>
</table>

**Demographics and Preferences** To determine the borrower population share, we use the 1998 Survey of Consumer Finances. In the model, borrowers are constrained house-
holds whose choice of rental vs. ownership is influenced by credit conditions. Correspondingly, we identify a household as a “borrower” if it either (i) owns a home, and whose mortgage balance net of liquid assets is greater than 30% of the home’s value, or (ii) does not own a home. We believe both of these groups would likely find it very difficult to purchase a home without credit. This procedure yields a population share of $\chi_B = 0.626$ and an income share of $s_B = 0.525$. For landlord demographics, we consider the limit $\chi_L \to 0$ and assume that landlords do not receive labor income, instead subsisting entirely on their rental earnings.

For preferences, the key parameter is the borrower’s discount factor, $\beta_B$, which determines how much latent demand for credit there is in the economy, and in turn, how much a relaxation of credit will influence house prices. We infer this parameter from the pricing on private mortgage insurance (PMI) — the additional fees and interest rates that a borrower must pay in order to obtain a high-LTV loan. This approach is motivated by the fact that many borrowers choose to pay for PMI, while many do not, meaning that the typical borrower should be close to indifferent.\footnote{For example, 37.7% of Fannie Mae purchase loans required PMI over the 1999-2008 boom period (source Fannie Mae Single Family Dataset).} We choose $\beta_B$ so that the typical borrower would be indifferent between receiving a loan at 80% LTV, and paying the exact FHA insurance scheme for a loan at 95% LTV: an up front fee of 1.75% of the loan, plus a spread of 80bp.\footnote{We choose the FHA scheme because it is much simpler to implement in the model than the GSE insurance scheme, where pricing is less transparent, and insurance premia are only paid until the borrower’s LTV drops below 80%. However, the overall costs of the two forms of insurance are similar, as can be seen in e.g., Goodman and Kaul (2017).}

For the other preference parameters, we assume a standard consumption weight parameter of $\xi = 0.200$ on housing, following the evidence in Davis and Ortalo-Magné (2011). We set the saver discount factor to target a nominal interest rate of 6.46%, equal to the average rate on 10-year treasury bills in the immediate pre-boom era (1993 - 1997). We set the saver’s fixed level of demand $\bar{H}_S$ equal to the level they would choose in steady state at prevailing prices. This implies that while saver demand is fixed in the short run, it is at the correct “long run” equilibrium value.

Lastly, we set the landlord discount rate $\beta_L$ to be equal to $\beta_B$. This calibration is con-
venient for experiments involving overoptimistic house price expectations, which we im-
pose as news about high expected future rents. When borrowers and landlords have
different discount factors, the more patient group values future rental services or cash
flows more and accumulates housing, affecting the homeownership rate. To avoid taking
a stand on how overoptimism influenced homeownership during the boom, we choose
as our baseline the symmetric case where expectations influence both borrower and land-
lord valuations equally.

Ownership Cost Heterogeneity. The paper’s most novel modeling mechanism relates
to heterogeneity in the benefits to borrower and landlord ownership, represented by the
distributions \( \Gamma_{\omega,B} \) and \( \Gamma_{\omega,L} \). We specify each of these as a logistic distribution, so that each
c.d.f. is defined by:

\[
\Gamma_{\omega,j}(\omega) = \left[ 1 + \exp \left\{ - \left( \frac{\omega - \mu_{\omega,j}}{\sigma_{\omega,j}} \right) \right\} \right]^{-1} \quad j \in \{B, L\}.
\]

For the borrower distribution, we set \( \mu_{\omega,B} \), the typical ownership utility for borrowers, to
target the average ratio of home value to income among “borrowers” who own homes
in the 1998 SCF, equal to 8.81 (quarterly). The ownership benefit dispersion parameter
\( \sigma_{\omega,B} \) difficult to pin down in the data, but this parameter plays little role in our results.
To provide a sense of scale, we set \( \sigma_{\omega,B} \) so that 5% of borrowers (10% of borrowers who
own) would instead prefer to rent at steady state if given a 15% rental subsidy. For the
landlord, we set \( \mu_{\omega,L} \) to attain the correct homeownership rate among “borrowers” in the
1998 SCF (49.64%). Since all savers own, this ensures an overall homeownership rate of
68.50% at steady state, matching the 1998 SCF. The landlord dispersion term \( \sigma_{\omega,L} \) — the
key parameter in the model — is calibrated to match our empirical estimates from Section
4. This calibration procedure is described in detail in Section 6.2.

Technology and Government. For the construction technology, we set the amount of
new land permits issued per period to generate residential investment \( Z_t \) equal to 5% of
total output in the steady state. For the land weight in the construction function \( \varphi \), we
note that $\alpha / (1 - \alpha)$ is the elasticity of residential investment to house prices, and choose 0.371 so that this elasticity is equal to the ratio of the peak log increase in the residential investment share of output to the peak log increase in prices over the boom. We set housing depreciation and the tax rate to standard values, and set inflation to be equal to the average 10-year inflation expectation in the pre-boom era (1993-1997) following Greenwald (2018).

**Mortgage Contracts.** For the mortgage contract parameters, we follow Greenwald (2018), who provides a detailed calibration for this mortgage structure.

### 6.2 Calibration of Landlord Heterogeneity to Our Empirical Results

The key parameter governing the model’s quantitative behavior is the dispersion in the cost of landlord ownership, which determines the slope of the housing supply curve. We calibrate this parameter so that the model is able to reproduce our empirical findings on the relative sensitivity of the price-to-rent ratio and homeownership rate to a credit supply shock. Doing so requires that we take a stance on what the variation induced by our instruments looks like in the model. Because the LS instrument is the most powerful instrument, we replicate the CLL instrument which changes the price of mortgage credit in the model by considering the impulse response with respect to the mortgage spread $\Delta B_t$. As a change in the conforming loan limit is expected to persist indefinitely, we use a near permanent shock with quarterly persistence 0.995.

Figure 6 shows this impulse response for three possible calibrations of our dispersion parameter, $\sigma_{\omega,L}$. Our benchmark calibration of $\sigma_{\omega,L} = 0.020$ is chosen to match our target of a five-to-one ratio between the elasticities of the price-to-rent ratio and the homeownership rate, with 20Q growth in these variables of 3.37 and 0.67, respectively. The other two series show paths for alternative calibration choices: the “Higher Dispersion” series doubles the dispersion to $\sigma_{\omega,L} = 0.030$, while the “Lower Dispersion” series halves the dispersion to $\sigma_{\omega,L} = 0.007$. The figure shows that these alternative calibrations lead to substantially different ratios for these elasticities, largely due to the high sensitivity of the homeownership rate elasticity to this parameter. In particular, the “Higher Disper-
Figure 6: Model Response to our Identified Credit (CLL) Shock by $\sigma_{\omega,L}$

Figure 7: Model Response to our Identified Credit Shock, Benchmark vs. Polar Cases

The “Higher Dispersion” series generates a ratio after 20 quarters of 9.3 (3.80 vs. 0.41, respectively) while the “Lower Dispersion” series generates a ratio after 20 quarters of 2.8 (2.77 vs. 0.99, respectively). Overall, this comparison illustrates that $\sigma_{\omega,L}$ can be identified using this procedure.

### 6.3 The Role of Credit in Our Calibrated Model

Before we examine the role of credit in the boom and bust of the 2000s, it is instructive to consider to consider where our calibrated response to this credit shock compares to the extremes explored in the literature: full segmentation ($\sigma_{\omega,L} \to \infty$) and frictionless rental markets ($\sigma_{\omega,L} \to 0$).

To this end, Figure 7 compares the same impulse response (a near-permanent shock to mortgage spreads, $\Delta B_{t}$) For comparison, the path labeled “No Landlord Het.” displays
the same impulse response in an alternative economy with no landlord heterogeneity ($\sigma_{\omega,L} \to 0$). Contrasting these two series shows that our benchmark calibration implies a substantial departure, generating large positive increase in price-to-rent ratios compared to the no heterogeneity world, and displaying less than half of the increase in the homeownership rate (0.69\% vs. 2.09\%), in line with the intuition of Section 2.

Importantly, the benchmark economy also generates much higher credit growth, as shown in the third panel of Figure 7. This is a direct consequence of the increased price response due to the steeper housing supply curve under landlord heterogeneity. Although the “No Landlord Het.” economy sees more renters become mortgage-holding owners following this shock, generating a larger increase in credit at the extensive margin, this effect is overwhelmed by the increase in house value in the benchmark economy, whose more valuable collateral boosts the size of new loans. Overall, the ratio of mortgage debt to total borrower income grows by roughly twice as much in the Benchmark vs. No Landlord Heterogeneity economy (3.11\% vs. 1.47\%), implying that models without heterogeneity may seriously understate the impact of credit shocks on household leverage.

In contrast, the benchmark model is much closer to the other extreme case, labeled “Full Segmentation,” which has a fixed homeownership rate ($\sigma_{\omega,L} \to \infty$). In fact, the benchmark model generates 83\% of the 20Q rise in both price-to-rent and loan-to-income found under full segmentation. These results demonstrate that matching our empirical findings requires substantial frictions, with house price and credit dynamics that are more similar to full segmentation than to a frictionless rental market. Of course, the benchmark model does deliver meaningful movements in the homeownership rate that are precluded in the “Full Segmentation” model, implying that a departure from this extreme is still essential to match the full set of dynamics.

As an additional check against our empirical results and the existing literature, we consider the effects on prices and rents separately in Appendix Figure B.1. These results indicate that our benchmark price-rent response is driven by a large increase in house prices, with an elasticity around 3.4, and a much smaller increase in rents, consistent (up to scale) with our empirical findings. This elasticity of house prices to interest rates is consistent with estimates in the literature, for instance Adelino et al. (2015) who find that
Figure 8: Credit Relaxation Experiment

this elasticity measured from a similar shock to the conforming loan limit lies in the interval $[1.2, 9.1]$. The full segmentation model also delivers an elasticity in this range, while a model with no heterogeneity implies a house price elasticity close to zero, consistent with our theory in Section 2 but at odds with this empirical finding.

7 Model Results

Now that the model has been calibrated to match our empirical results, we can ask the core quantitative question of our paper: What role did credit play in the housing boom? To answer this question, we simulate a realistic relaxation of credit standards and evaluate the model’s implications for the evolution of debt and house prices. Our baseline experiment follows KMV in relaxing LTV limits from 85% to 99% PTI limits from 36% to 65% unexpectedly and permanently in 1998 Q1. The new standards are left in place until 2007 Q1, at which time they unexpectedly and permanently revert to their original values. The model responses are then computed as nonlinear perfect foresight paths.

The results of this experiment are shown in Figure 8. To highlight the role of landlord heterogeneity, we again plot the responses in our Benchmark model against those of alternative models with no landlord heterogeneity and full segmentation (infinite heterogeneity). The results show that our calibrated level of heterogeneity is large enough to deliver a large price response in the Benchmark model, accounting for 28% of the peak rise in price-to-rent ratios observed in the boom. This stands in sharp contrast to the
model without landlord heterogeneity, where the same credit relaxation explains 0% of the peak growth in price-to-rent ratios, as landlords are able to completely satisfy the increase in demand, preventing a rise in prices. As before, the house price dynamics in the Benchmark model are much closer to the “Full Segmentation” model, where this credit relaxation would account for 38% of the observed rise in price-to-rent ratios. Overall, these results indicate that a realistically calibrated rental market still delivers an economically important response of house prices to a relaxation of credit conditions similar to that observed in the 2000s boom.

This finding for house prices also has important implications for credit growth. While credit standards are loosened equally along both paths of Figure 8, credit growth over the boom is much larger in the Benchmark economy relative to the No Heterogeneity economy, explaining 52% relative to 33% of the observed rise. This additional credit growth is a direct consequence of the larger house price appreciation in the Benchmark economy, which increases the value of housing collateral, and allows larger loans for a given maximum LTV ratio. As a result, the same credit loosening leads to much more levered households in the Benchmark economy when credit conditions return to baseline. Again, the Benchmark path very close to the Full Segmentation path, which also exhibits a large house price rise.

Although our Benchmark model indicates that a credit expansion played an important role in driving the boom, it clearly leaves room for other factors to play important roles. To explore what our results indicate in a more comprehensive simulation of the boom,
we first incorporate a 2ppt fall in mortgage spreads, assumed to be permanent. Like our credit expansion, this causes an outward shift of housing demand, which, given our estimated rental frictions generates a large additional increase in house prices. Specifically, combining our credit relaxation and the fall in rates, shown in Appendix Figure B.2 can explain 60% of the rise in price-to-rent ratios and 80% of the rise in loan-to-income ratios.

To complete our explanation of the boom, we add overoptimistic house price expectations to generate a rise in price-to-rent ratios equal to that observed in the data. Unlike the credit experiments, this shift in expectations shifts the supply curve instead of moving along it. We find that matching the overall rise in house prices requires that agents believe in a future increase in $\xi$, the expenditure share on housing services, of 30%. Given the size of this required expected growth, we note that part if not all of this supply shift required to fit the data could alternatively be generated by shifts in landlord access to credit, which we discuss in Section 8.

To match the bust, we impose a further 3ppt fall in interest rates, which is also reflected in a 3ppt fall in the landlord discount rate, consistent with the entry of yield-seeking financial firms into the single family rental market, as well as a 10% decline in LTV and PTI limits, consistent with tightening credit standards. Overall, these assumptions generate a reasonably good fit of the dynamics of the boom and bust, with two main exceptions: (i) house prices adjust much less sluggishly in our model than in the data, as is typically found in models lacking frictions (see, e.g.,) Guren (2018)); and (ii) our model “bust” is much more gradual in the model relative to the data, as we lack the foreclosures and financial market features that transformed the housing crash into a global financial crisis.

To isolate the role of credit conditions in this simulated boom-bust, we then remove the simulated credit expansion, while leaving all the other factors in place, to generate the series labeled “Tight Credit” These results indicate that removing the credit expan-

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18Overoptimistic house price expectations are modeled as expected increases in the housing utility parameter $\xi$. Agents believe this parameter will increase in 2007Q1, but at that time it is instead revealed to stay at its original level.

19A change in landlord risk premia, similar to the results in Favilukis et al. (2017), could also contribute to this shift.

20This is best interpreted as increasing standards for credit scores preventing a fraction of the population from obtaining credit at the extensive margin, rather than a decline in maximum LTV and PTI ratios at the intensive margin.
sion from the rest of the boom would have reduced the overall rise in price-to-rent ratios by 47% and in loan-to-income ratios by 75% relative to our Benchmark scenario. These figures, which provide the upper bound for our estimated role of credit during the boom-bust, are larger than the shares explained by relaxing credit in isolation (Figure 8), because in the Benchmark model, loose credit also amplifies the other components of the boom, particularly the role of house price expectations. The simple intuition, discussed at length in Greenwald (2018), is that even if households are very optimistic about future cash flows from housing, binding PTI limits limit households’ ability to finance these properties in the absence of a corresponding rise in income, dampening prices and credit growth when credit remains tight.

To summarize our results, our calibrated model implies an important role for credit conditions in explaining the housing and credit cycles observed in the 2000s boom-bust, with a relaxation of credit standards explaining roughly half the rise in price-to-rent ratios, with house price dynamics that are closer to the extreme of full segmentation than to a frictionless model with no landlord heterogeneity.

8 Model Extensions

In the model as presented so far, the only credit insensitive agents who could enter the owner-occupied market are deep-pocketed landlords who face heterogenous costs in converting properties between owner-occupied and renter-occupied. While this makes the economics of the model clear, it may not be realistic. In particular, it may be that these landlords also face financial constraints. Furthermore, it may also be the case that unconstrained savers can trade housing with borrowers and landlords. In this section, we extend the model to include each of these two forces in turn.

8.1 Landlord Credit

In practice, landlords are not deep-pocketed, and nearly every investor-owned property is purchased with a mortgage. We consequently first allow landlords to purchase properties
with mortgage credit that is affected by credit supply.

**Supply and Demand Intuition.** We begin by reassessing the intuition developed in Section 2. Recall we developed a supply-and-demand model in homeownership rate versus price-to-rent ratio space. The demand curve represents demand by constrained homeowners, while the supply curve represents supply from landlords who convert renter housing to owner-occupied housing and sell it to households. A credit relaxation shifts the demand curve, which leads to movement in the price-to-rent ratio with no homeownership rate movement if rental and ownership are perfectly segmented (Figure 2a) and movement in the homeownership rate with no price-to-rent ratio movement if conversion is perfectly frictionless and (Figure 2b). With upward sloping supply, credit supply causes movement in both the homeownership rate and the price-to-rent ratio (Figure 2c).

Introducing credit for landlords implies that a relaxation in credit not only shifts the demand curve upward but also shifts the supply curve upward as in Figure 2d. The degree of the supply curve shift is endogenous and depends on the model’s parameters. Due to this shift, adding landlord credit to the baseline model while holding the parameters fixed would lead to a smaller change in the homeownership rate (and potentially a negative change if the supply curve shifts enough) and a larger change in the price-to-rent ratio, as represented by a shift from the solid supply curve to the dashed supply curve in Figure 2d.

To illustrate this intuition quantitatively (while still holding parameters fixed), we implement a version of the model with landlord credit. Specifically, we assume that landlords face an LTV limit of 65%, – the standard constraint for multi-family construction loans – and do not face a PTI limit.\(^{21}\) Figure 10 compares the responses to our same credit shock of this model with our benchmark calibration with no landlord credit assuming that the shock causes mortgage spreads for households and landlords fall equally. In terms of magnitudes, the shift in the supply curve due to landlord credit modestly increases the response of the price-rent ratio (3.44% to 4.07%) at the 20Q horizon, while cutting the rise in the homeownership rate close to zero (0.69% to 0.15%) over the same period.

\(^{21}\)These assumptions correspond to the parameter values \(\theta_L^{LTV} = 0.65\) and \(\theta_L^{PTI} = \infty\), and imply \(F_{L,t}^{LTV} = 1\).
There are three important takeaways from this plot. The first is that the presence of landlord credit can act as a quantitatively important substitute for rental frictions, with the Landlord Credit line in Figure 10 looking very similar to the Full Segmentation response in Figure 7, despite having the same rental friction as the Benchmark model. Second, landlord reliance of credit can potentially generate a zero or nonpositive response of homeownership to credit shocks, which cannot be rejected by our empirical estimates, and may explain our finding of nonpositive point estimates in Figure 3. Finally, to transparently show the effect of the supply shift, we have not recalibrated the model to model to match our target moments when we added landlord credit. Matching target price-rent relative to homeownership causal effect would imply a lower level of rental frictions in the landlord credit model, leading to highly similar dynamics across the two specifications.

8.2 Saver Housing Demand

We also assume that housing demand by unconstrained households (“savers”) is perfectly segmented in our baseline model. Because these savers have a relatively constant marginal utility and are not credit constrained at the margin, if their housing is not segmented from that of the borrowers then they will make the supply curve very elastic. Intuitively, they absorb or supply housing to the constrained borrower households as credit supply fluctuates. Examples of models with this feature include Justiniano et al.
However, even if the slope of the housing supply curve is influenced by savers, this slope is still a sufficient statistic for the effect of credit supply expansions on the price-to-rent ratio and homeownership rate; it just now controls the degree of seller segmentation as well. The fact that we find that the price-to-rent ratio responds more than the homeownership rate implies that saver housing demand must also be highly segmented. This may be the case for several reasons. First, constrained agents purchase lower-quality housing (Landvoigt et al. (2015)) and often buy “starter homes” (Ortalo-Magné and Rady (2006)). Second, housing is non-divisible; it is hard for a rich household to add to its large house by purchasing several smaller homes from constrained agents when credit contracts and to sell off portions of its large house when credit expands, which is what is needed for the saver margin to be strong. A more realistic margin is a second home, but these tend to be segmented in areas where people vacation, not in areas where constrained households purchase.

We once again demonstrate the intuitive we develop above with a quantitative example. We extend the baseline model to allow the saver households to flexibly transact with borrowers and landlords in the housing market. This implies the additional optimality condition from the saver first order condition:

\[ p_{Saver}^t = \mathbb{E}_t \left\{ \Lambda_{t+1}^{S} \left[ \frac{u_{S,h}^S}{u_{S,c}^S} + \left( 1 - \delta \right) p_{t+1} \right] \right\}, \]

where \( p_{Saver}^t \) must equal the market house price at equilibrium. To clear this market, the savers adjust their housing stock \( H_{S,t} = \tilde{H}_t - H_{B,t} - H_{L,t} \) by transacting in housing, which in turn adjusts the marginal rate of substitution \( u_{S,h}^S / u_{S,c}^S \).

Figure 11 shows the response to our credit shock in this extension, denoted “Saver Demand,” alongside our Benchmark results. As can be seen, adding a flexible saver margin substantially decreases the response of the price-rent ratio by nearly half (3.96% to 2.01% at the 20Q horizon) while leaving the homeownership rate unchanged (0.69% vs. 0.74%). The dampening effect of saver demand on prices is quantitatively large, and could be
even stronger for saver preferences with less curvature.\textsuperscript{22} By contrast, saver demand matters little for the homeownership rate because model savers always own and never rent, with their transactions affecting the intensive margin of house size. As a result, these transactions have little effect on the overall homeownership rate.

Since we are skeptical that unconstrained households buying and selling second homes was an important factor during the boom-bust, we shut down this margin in our benchmark model. Nonetheless, if this margin were active, our calibration procedure would capture this margin. Intuitively, adding unconstrained savers dampens the house price response to credit while leaving the homeownership rate response unchanged, which would reduce our empirical moment and lead us to increase the amount of rental market frictions to match our key moment. This would offset the elastic demand created by adding unconstrained savers and lead to similar overall results.

9 Conclusion

More than a decade after the Great Recession there is still a lack of consensus about the role of credit supply in explaining house prices and price-to-rent ratios in the boom and bust. In this paper, we argue that this is because most of the literature has fo-

\textsuperscript{22}The degree of dampening is determined by how strongly the marginal rate of substitution term $u^S_{h,t}/u^S_{c,t}$ varies with $H_{S,t}$. For example, with linear saver preferences $u^S(c, h) = c + \xi h$, we would obtain the constant value $u^S_{h,t}/u^S_{c,t} = \xi$, implying that house prices would be completely invariant to a credit shock.
cised on two polar cases with regards to the segmentation in housing markets between credit-insensitive agents such as landlords and unconstrained savers and credit-sensitive agents. In the first, landlords are unable to convert homes from owner-occupied to renter-occupied and savers cannot step in to purchase (sell) more housing when constrained households cut (raise) their housing demand. This means that all changes in housing demand show up in house prices and homeownership rates are stable. At the other extreme, models feature either deep-pocketed landlords who can frictionlessly convert between owner-occupied and rental housing, or unconstrained savers with elastic demand for housing, who completely absorb changes in borrower housing demand due to credit conditions. These features imply that changes in credit supply lead to large changes in homeownership rates but no movement in price-to-rent ratios.

We generalize these polar cases to examine intermediate levels of rental frictions, which we view as realistic. We argue that a key sufficient statistic for determining where reality falls on the spectrum between these two extremes is the causal effect of credit on the price-to-rent ratio relative to the homeownership rate. We show in a new data set using instrumental variables methods that credit supply shocks cause a significant increase in price-to-rent ratios and a more muted and statistically insignificant homeownership response. Our empirical findings suggest that five-to-one is a conservative estimate of the ratio of the two casual effects. When we calibrate a model to match this ratio, we find that credit supply can explain roughly half of the boom and bust in house prices and price-to-rent ratios. Relative to our polar cases, the calibrated model displays house price dynamics that are close to those under perfect segmentation, implying large frictions in rental markets.

Our work highlights the importance of assumptions about rental markets and the elasticity of saver demand for macro models of the housing market. These model features are often overlooked but are critical for many important results. We hope that our findings motivate future work to use and develop intermediate models in place of either polar assumption. We also highlight the use of identified credit supply shocks and a novel empirical moment for calibrating macroeconomic models of the housing market. We hope that future work will improve on our estimates of the relative causal effect of credit sup-
ply on price-to-rent ratios and homeownership rates and use these identified moments to improve the calibration of macro-housing models.
References


A Equilibrium Conditions

This section presents the full set of equilibrium conditions of the model.

**Borrower’s Problem.** The borrower’s optimality conditions are:

\[(h_{B,t}) : \quad q_t = (u_{B,t}^B / u_{B,t}^C)\]  
\[(H_{B,t}^*) : \quad p_t = \mathbb{E}_t \left\{ \Lambda_{B,t+1} \left[ \bar{\omega}_{B,t} + q_{t+1} + (1 - \delta - (1 - \rho_{B,t+1}) C_{B,t+1}) p_{t+1} \right] \right\} \]  
\[(M_{B,t}^*) : \quad 1 = \Omega_{M,t}^B + r^*_{B,t} \Omega_{X,t}^B + \mu_{B,t} \]  
\[(\rho_{B,t}) : \quad \rho_{B,t} = \Gamma_\kappa \left\{ (1 - \Omega_{M,t}^B - \Omega_{X,t}^B \bar{r}_{B,t-1}) \left( 1 - \frac{(1 - \nu) \pi_t^{-1} M_{B,t-1}}{M_{B,t}} \right) \right\} \]  
\[\text{new debt incentive} \]  
\[\text{interest rate incentive} \]  

where

\[C_{B,t} = \mu_{B,t} F_{B,t}^{LT} \theta_{B,t}^{LT}.\]

\(\mu_{B,t}\) is the multiplier on the borrowing constraint, \(F_{B,t}^{LT}\) is the fraction of borrowers who are LTV-constrained, \(\bar{r}_{B,t-1} = X_{B,t-1}/M_{B,t-1}\) is the average rate on existing debt, and the marginal continuation cost of principal balance \(\Omega_{M,t}^B\) and of interest payments \(\Omega_{X,t}^B\) satisfy:

\[\Omega_{M,t}^B = \mathbb{E}_t \left\{ \Lambda_{B,t+1} \pi_t^{-1} \left[ v_B + (1 - v_B) \left( \rho_{B,t+1} + (1 - \rho_{B,t+1}) \Omega_{M,t+1}^B \right) \right] \right\} \]  
\[\Omega_{X,t}^B = \mathbb{E}_t \left\{ \Lambda_{B,t+1} \pi_t^{-1} \left[ (1 - \tau) + (1 - v_B)(1 - \rho_{B,t+1}) \Omega_{X,t+1}^B \right] \right\}.\]

Equation (4) sets the rent equal to the marginal rate of substitution between housing services and consumption. Equation (5) specifies that at an interior solution, the price of housing must be equal to the present value of next period’s service flow (the rent combined with the owner’s utility bonus) plus the continuation value. Note that since \(p_t\) is the price of newly purchased housing that is about to be borrowed against, \(p_t\) includes
the value of collateral services, which the borrower does not receive in periods when she does not refinance. Therefore, the continuation value is equal to the market value of housing net of maintenance costs, \((1 - \delta)p_{t+1}\), minus the value of collateral services \(\mu_{B,t+1}\theta_B\) in states of the world when the borrower does not refinance, which occurs with probability \((1 - \rho_{B,t+1})\). Equation (6) sets the marginal benefit of one unit of face value debt ($1 today) against the marginal cost (the continuation cost of the debt plus the shadow cost of tightening the borrowing constraint). Equation (7) sets the transaction cost for the marginal refinancer equal to the net marginal benefit of refinancing, making this borrower indifferent.

**Landlord’s Problem.** The landlord’s optimality conditions are:

\[
(H^*_{B,t}) : \quad p_t = \frac{\mathbb{E}_t \left\{ \Lambda_{L,t+1} \left[ \bar{\omega}_{L,t} + q_{t+1} + (1 - \delta - (1 - \rho_{L,t+1})\bar{C}_{L,t+1})p_{t+1} \right] \right\}}{1 - \bar{C}_{L,t}}
\]

\[
(M^*_{L,t}) : \quad 1 = \Omega_{M,t}^L + r_{j,t}^* \Omega_{X,t}^L + \mu_{L,t}
\]

\[
(\rho_{L,t}) : \quad \rho_{L,t} = \Gamma_{x} \left\{ (1 - \Omega_{M,t}^L - \Omega_{X,t}^L r_{L,t-1}) \left( 1 - \frac{(1 - \nu)\pi t^{-1}M_{L,t-1}}{M^*_{L,t}} \right) - \Omega_{X,t}^L (r_{L,t}^* - \bar{r}_{L,t-1}) \right\},
\]

where \(C_{L,t} = \mu_{L,t}^{\text{LTV}}\theta_{L,t}^{\text{LTV}}\) is defined analogously to the borrower case. The fixed point conditions that pin down the marginal continuation costs of debt are defined by

\[
\Omega_{M,t}^L = \mathbb{E}_t \left\{ \Lambda_{L,t+1} \pi^{-1} [\nu L + (1 - \nu L)\rho_{L,t+1} + (1 - \rho_{L,t+1})\Omega_{M,t+1}^L] \right\}
\]

\[
\Omega_{X,t}^L = \mathbb{E}_t \left\{ \Lambda_{L,t+1} \pi^{-1} [(1 - \tau) + (1 - \nu L)(1 - \rho_{L,t+1})\Omega_{X,t+1}^L] \right\}.
\]

symmetric to the borrower case.

**Saver’s Problem.** The saver’s optimality conditions are:

\[
(B_t) : \quad 1 = R_t \mathbb{E}_t \left[ \pi^{-1} \Lambda_{S,t+1} \right]
\]

\[
(M^*_{j,t}) : \quad 1 = Q_{M,t}^S + r_{j,t}^* Q_{X,t}^S
\]

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where the marginal continuation values of principal balance and promised interest payments are given by

\[
Q^S_{M,t} = \mathbb{E}_t \left\{ \Lambda_{S,t+1} \pi^{-1} \left[ \nu_B + (1 - \nu_B) \left( \rho_{B,t+1} + (1 - \rho_{B,t+1})Q^S_{M,t+1} \right) \right] \right\}
\]

\[
Q^S_{X,t} = \mathbb{E}_t \left\{ \Lambda_{S,t+1} \pi^{-1} \left[ (1 - \tau) + (1 - \nu_B)(1 - \rho_{B,t+1})Q^S_{X,t+1} \right] \right\}.
\]

**Construction Firm’s Problem.** The construction firm’s optimality conditions are

\[
p_{\text{Land},t} = p_t \varphi L_t^{\varphi - 1} Z_t^{1 - \varphi} = p_t (1 - \varphi) L_t^{\varphi} Z_t^{-\varphi}.
\]

### B Additional Figures

![Graphs showing model response to identified credit (CLL) shock by \( \sigma_{\omega,L} \)](image)

**Figure B.1:** Model Response to our Identified Credit (CLL) Shock by \( \sigma_{\omega,L} \)

### C Empirical Appendix

This section describes our data construction and presents additional empirical results and robustness checks.

#### C.1 Data Construction

ADD
C.2 LS Instrument Details and Robustness

C.2.1 First Stage

C.2.2 Pooled Regressions With Average Response

C.2.3 Additional Results Not In Main Text

Rent IRF

C.2.4 Robustness

Other measures of credit.

State-level results.

AHS results.

City-level income shocks, time-varying controls for industrial structure, other controls.

C.3 DK Instrument Details and Robustness

C.3.1 Replicating DK’s Exact Specification
C.3.2 Pooled Regressions With Average Response

C.3.3 Robustness

C.4 MS Instrument Details and Robustness

C.4.1 Pooled Regressions With Average Response

C.4.2 Robustness