

The Housing Boom and Bust: Model Meets Evidence

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Abstract

We build a model of the U.S. economy with multiple aggregate shocks (income, housing finance conditions, and beliefs about future housing demand) that generate fluctuations in equilibrium house prices. Through a series of counterfactual experiments, we study the housing boom and bust around the Great Recession and obtain three main results. First, we find that the main driver of movements in house prices and rents was a shift in beliefs. Shifts in credit conditions do not move house prices but are important for the dynamics of home ownership, leverage, and foreclosures. The role of housing rental markets and long-term mortgages in alleviating credit constraints is central to these findings. Second, our model suggests that the boom-bust in house prices explains half of the corresponding swings in non-durable expenditures and that the transmission mechanism is a wealth effect through household balance sheets. Third, we find that a large-scale debt forgiveness program would have done little to temper the collapse of house prices and expenditures, but would have dramatically reduced foreclosures and induced a small, but persistent, increase in consumption during the recovery.

Keywords: Consumption, Credit Conditions, Expectations, Foreclosures, Great Recession, Home Ownership, House Prices, Leverage.

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1 Introduction

A decade after the fact, it is now well accepted that the housing market was at the heart of the Great Recession. Propelled by the influential work of Atif Mian and Amir Sufi, a broadly shared interpretation of this time period has steadily evolved: after a sustained boom, house prices collapsed, triggering a financial crisis and fall in household expenditures which – paired with macroeconomic frictions – led to a slump in employment.¹

Yet, as demonstrated by the ever growing literature on the topic, many questions surrounding this narrative remain unanswered.² We address three of these. First, what were the sources of the boom and bust in the housing market? Second, to what extent, and through what channels, did the movements in house prices transmit to consumption expenditures? Third, was there a role for debt forgiveness policies at the height of the crisis?

Our answers hinge on the different implications of two potential driving forces for the boom and bust in house prices: credit conditions and expectations. The relative importance of these two forces has always been central to the study of house price fluctuations (for a discussion, see, e.g. Piazzesi and Schneider, 2016). In the context of the most recent episode, the empirical micro evidence is mixed, with reduced-form evidence supporting both views (see, e.g. Mian and Sufi, 2016a; Adelino, Schoar, and Severino, 2017).

Our contribution to this debate is to offer a structural equilibrium approach. We examine both cross-sectional micro data and macroeconomic time-series through the lens of an equilibrium overlapping-generations incomplete-markets model of the U.S. economy with a detailed housing finance sector and realistic household consumption behavior. Importantly, our model features three potential drivers of aggregate fluctuations that lead to stochastic equilibrium dynamics for housing investment, house prices, rents, and mortgage risk spreads: (i) changes in household income generated by shocks to aggregate productivity; (ii) changes in housing finance conditions generated by shocks to a subset of model parameters that determine mortgage debt limits and borrowing costs; and (iii) changes in beliefs about future housing demand. These shifts in beliefs are generated by stochastic fluctuations between two regimes that differ only in their likelihood of transiting to a third regime in which all households have a stronger preference for housing services. While this modeling approach shares the key features of a rational bubble, it is really a news shock about a fundamental parameter. We can thus employ standard techniques for computing equilibria in incomplete markets models with aggregate shocks.

After parameterizing the model to match salient life-cycle and cross-sectional dimensions

¹See, e.g., Mian and Sufi (2009), Mian, Rao, and Sufi (2013) and Mian and Sufi (2014).

²For a synthesis, see the Handbook chapters by Guerrieri and Uhlig (2016), on the macro side, and by Mian and Sufi (2016b) on the micro side.

of the micro data, we simulate the boom-bust episode. Our simulation corresponds to a ‘tail event’ (a history of shocks with low ex-ante probability) in which all three shocks simultaneously hit the economy: aggregate income increases, credit conditions relax and all agents come to believe that housing demand will likely increase in the near future. Subsequently, all three shocks are reversed: aggregate income falls, credit conditions tighten, and agents backtrack from their optimistic forecasts of future housing demand. Through a series of decompositions and counterfactuals, we infer which patterns of the boom-bust data are driven by each shock and use this information to answer our three questions.

First, we find that shifts in beliefs about future housing demand were the dominant force behind the observed swings in house prices and the rent-price ratio around the Great Recession. Changes in credit conditions had virtually no effect on prices and rents but were a key factor in the dynamics of leverage and home ownership. On its own, belief shifts lead to a counterfactual fall in leverage during the boom because they generate a sharp increase in house prices without a corresponding increase in debt. They also lead to a counterfactual decline in home ownership because expected future price appreciation depresses the rent-price ratio, pushing marginal households out of home ownership into renting. Looser credit conditions correct these forces by expanding borrowing capacity and pulling marginal buyers into home ownership, thus realigning the model with the data. The credit relaxation is also crucial for the model to match the spike in foreclosures observed at the start of the bust: households find themselves with high levels of mortgage debt at the peak and are then dragged into negative equity after the shift in beliefs depresses house prices.

Our quantitative theory of the housing boom and bust is also consistent with three recent cross-sectional observations: (i) the uniform expansion of mortgage debt during the boom across income levels (Foote, Loewenstein, and Willen, 2016); (ii) the increasing share of defaults during the bust attributable to prime borrowers (Albanesi, De Giorgi, Nosal, and Ploenzke, 2016); and (iii) the crucial role of young households in accounting for the dynamics of home ownership during this period (Hurst, 2017).

Second, we find that that the boom and bust in house prices directly accounts for roughly half of the corresponding boom and bust in non-durable expenditures, with the remaining half accounted for by the dynamics of labor income. A wealth effect is responsible for this finding; comparing across households, we find that the drop in consumption during the bust is proportional to the initial share of housing wealth in total (including human) wealth. This result is consistent with the emphasis placed by Mian et al. (2013) on heterogeneity in households’ balance sheets as a key factor in understanding consumption dynamics around the Great Recession. At the aggregate level, the wealth effect of a change in house prices is non-zero because of the shape of the life cycle profile of home-ownership in the model and

data. Homeowners who expect to downsize (the losers from the bust) control a larger share of aggregate consumption than those households who expect to increase their demand for housing (the winners from the bust). We find that substitution and collateral effects are not important for the transmission of house prices to consumption. These findings – obtained in a rich equilibrium model of housing – are consistent with the analytical decomposition and back-of-the-envelope calculations proposed by [Berger, Guerrieri, Lorenzoni, and Vavra \(2017\)](#).

Third, we investigate the potential role of debt forgiveness programs. In the midst of the housing crisis, the Obama administration enacted two programs – the Home Affordable Modification Program (HAMP) and the Home Affordable Refinance Program (HARP) – that were intended to cushion the collapse of house prices and aggregate demand. These programs had limited success ([Agarwal, Amromin, Ben-David, Chomsisengphet, Piskorski, and Seru, 2013](#)) and were criticized for their complex rules and narrow scope (see [Posner and Zingales, 2009](#), for a critical review of the proposals). Our model suggests that a debt forgiveness program would not have prevented the sharp drop in house prices and aggregate expenditures, even if it had been implemented in a timely manner (two years into the bust) and on a very large scale (affecting over 1/4 of homeowners with mortgages). This conclusion is driven by the very weak effects of changes in leverage on house prices in our model. However, we do find that the principal reduction program would have significantly dampened the spike in foreclosures by keeping many home owners above water.³ Moreover, because the program reduces households’ mortgage payments for the remaining life of the mortgage contract, we find that aggregate non-durable consumption would have been slightly higher throughout the whole post-bust recovery.

Overall, our results suggest that expectations about future house price appreciation played a central role in the macroeconomic dynamics around the Great Recession. Although in our benchmark model these expectations are over future housing demand, a version of our model where beliefs are over future availability of buildable land (as in [Nathanson and Zwick, 2017](#)) yields similar results.⁴ It is important that all agents in the economy share the same beliefs. For households to demand more housing, and hence push up prices, they must expect future house price growth that will generate expected capital gains. For the rent-price ratio to fall as in the data, the rental sector must also expect future price growth.

³It follows that, if foreclosure had very large externalities on house prices (which is not the case in our model), the principal reduction program might have a larger effect on prices. The empirical literature mostly estimates economically small and extremely localized effects ([Anenberg and Kung, 2014](#); [Gerardi, Rosenblatt, Willen, and Yao, 2015](#)). See, however, [Guren and McQuade \(2015\)](#) for an alternative view.

⁴In either case, it is essential that the shock is to *future* housing preferences or buildable land, rather than *current* housing preferences or buildable land. Otherwise, consumption or residential investment, respectively, would counterfactually fall during the boom and rise during the bust.

Finally, when lenders also believe that house prices are likely to increase, they rationally expect that borrowers are less likely to default and thus reduce spreads on mortgage rates, especially for risky borrowers – as observed during the boom (Demyanyk and Van Hemert, 2009). In this sense, shifts in beliefs generate endogenous shifts in credit supply in our model, i.e. expansions and contractions of cheap funds to sub-prime borrowers, using the language of Mian and Sufi (2016a) and Justiniano, Primiceri, and Tambalotti (2017).

Direct evidence on the role of expectations in the boom and bust is scarce, but evidence that does exist points convincingly towards beliefs being widely shared among households, investors, and lenders. Soo (2015) provides an index of sentiment in the housing market by measuring the tone of housing news in local newspapers and finds big swings, with a peak in 2004-05. The National Association of Home Builders creates a monthly sentiment index by asking its members to rate the prospective market conditions for the sale of new homes. This index was high throughout the 2000s and reached its peak in 2005. Cheng, Raina, and Xiong (2014) find that mid-level securitized finance managers did not sell off their personal housing assets during the boom. They interpret this result as evidence that lenders shared the same beliefs as the rest of the market about future house prices growth. Gerardi, Lehnert, Sherlund, and Willen (2008) argue that internal reports from major investment banks reveal that analysts were accurate in their forecasts of gains and losses, conditional on house price appreciation outcomes. However, they were ‘optimistic’ in that they assigned an extremely low probability to the possibility of a large-scale collapse of house prices.

In light of the existing studies of the housing crisis based on structural frameworks, especially Favilukis, Ludvigson, and Van Nieuwerburgh (2017) and Justiniano et al. (2017), our finding that house prices are almost completely decoupled from credit conditions is, arguably, the most surprising insight of our paper. Rental markets and long-term defaultable mortgages – two features of the U.S. housing market that are omitted in most of the literature – are behind this result. For credit conditions to affect house prices, it is necessary that many households are constrained in the quantity of housing services they desire to consume, and that changes in credit conditions loosen or tighten these constraints. In our model, as in the data, there are two reasons why this doesn’t happen.

First, because of the possibility to rent rather than own, too few households are constrained in this way. As in the data, households in our model who are unable to buy a house of their desired size choose to rent, rather than to buy an excessively small house. When credit conditions are relaxed, some renters become homeowners because they desire a different mix of housing equity and mortgage debt in their financial portfolio, not because they wish to substantially increase their consumption of housing services. In fact, these households buy similar sized houses to the ones they were previously renting. They thus

increase the home ownership rate, but not aggregate demand for housing or house prices. Instead, in our model, it is (largely unconstrained) existing owners, who drive the movements in house prices, in response to the shifts in beliefs. When expectations become optimistic, these homeowners choose to upsize in order to take advantage of the expected future house price growth, which pushes up house prices without increasing home ownership.

Second, the presence of long-term mortgages dampens another channel that links credit conditions to house prices in the existing literature. In models with only short-term debt, a sudden tightening of credit conditions forces all home owners to cut their consumption in order to meet the new credit limit. This risk factor generates a sizable and volatile housing risk premium that moves house prices (Favilukis et al., 2017). However, in models with long-term mortgages, constraints bind only at origination and then become irrelevant for the remainder of the mortgage contract. This reduces the strength of the risk-premium channel since credit tightenings do not force existing home owners into costly consumption fluctuations in order to quickly deleverage.

However, our insight is less surprising in light of the results of (Kiyotaki, Michaelides, and Nikolov, 2011), who also find that changes in financing constraints have limited effects on house prices, but that changes in fundamentals (land supply, productivity growth, and interest rates) can have a large effect on prices. Similarly to us, in their model a relaxation in credit leads to only a small increase in housing demand. They attribute this result to the fact that the potential beneficiaries of the credit relaxation (tenants and constrained owners) represent a small share of the total housing market, so only a limited amount of conversion between rental and owner-occupied units is needed to satisfy additional housing demand. But this intuition is incomplete. As we show, even in a version of our model with segmented housing stocks between rental and owner-occupied housing, a relaxation in credit only generates small movements in house prices. The presence of the rental market means that few households are constrained in the amount of housing they consume, which limits the increase in housing demand (for either conversions from rentals or new construction) when credit conditions are looser.

These results are not inconsistent with (Landvoigt, Piazzesi, and Schneider, 2015) who study the effect of a credit relaxation on house prices in a model where housing markets are segmented in many quality tiers. They find that prices increase more in segments of the housing market that contain a higher fraction of constrained households. But they have to abstract from long-term mortgages and the rental option in order to generate large movement in house prices in those markets at the bottom of the quality ladder.

The rest of the paper is organized as follows. In Section 2 we outline the model, equilibrium concept and computational strategy. In Section 3 we describe how we parameterize

the model and we compare its predictions with relevant empirical counterparts. In Section 4 we present findings from our numerical experiments on the boom-bust period. In Section 5 we solve several variants of the benchmark model to illustrate the key economic forces driving these findings. In Section 6 we analyze the debt forgiveness program. The Online Appendices include more detail about data sources, computation, and robustness.

2 Model

2.1 Overview

Our economy is populated by overlapping generations of households whose lifecycle is divided between work and retirement. During the working stage, they are subject to uninsurable idiosyncratic shocks to their efficiency units of labor, which are supplied inelastically to a competitive production sector that uses labor as its only input. Households can save in a non-contingent financial asset whose return is fixed exogenously. They consume non-durable consumption and housing services. Housing services can be obtained by either renting or buying houses. When bought and sold, housing is subject to transaction costs leading to lumpy adjustment dynamics. Home ownership requires overcoming certain financial constraints, such as maximum loan-to-value limits, that bind at origination. Housing can be used as collateral to establish a leveraged position with long-maturity defaultable mortgage debt priced competitively by financial intermediaries. Defaulting leads to foreclosure by the lender, which entails an exacerbated depreciation for the house and its immediate sale, as well as a utility loss for the borrower. Owning a house also allows the homeowner to refinance its mortgage or open an additional home equity line of credit (HELOC). On the supply side, a construction sector builds new additions to the residential stock, a competitive sector manages rental units, and financial intermediaries supply funds to households by pricing individual default risk into mortgage rates.

Many of these model elements are common to the large literature on housing (see Piazzesi and Schneider, 2016, for a survey). The life-cycle structure allows us to match data along the age dimension, which is a crucial determinant of housing, consumption, and wealth accumulation decisions. Uninsurable individual earnings risk, together with limits on unsecured borrowing, a risk-free liquid saving instrument and an illiquid savings instrument (housing), gives rise to precautionary saving and poor and wealthy hand-to-mouth households. These features generate realistic microeconomic consumption behavior (see Kaplan and Violante, 2014).

Our model differs from most of the literature in that we develop a fully stochastic model with aggregate shocks where house prices, rents and mortgage risk spreads are determined

in equilibrium, and in which there is also enough household heterogeneity to allow a tight mapping to the cross-sectional micro data on household earnings and asset portfolios.⁵ A notable exception is Favilukis et al. (2017), who also develop an equilibrium incomplete markets model with aggregate shocks. In Section 5.4 we provide a detailed explanation of how two key ingredients of our model, absent in theirs – rental market and long-term defaultable mortgages – account for our different conclusions about the importance of credit conditions in determining house prices.

Three types of exogenous aggregate shocks may hit the economy every period, generating fluctuations in aggregate quantities and prices: (i) labor productivity; (ii) credit conditions in the mortgage market; and (iii) beliefs about future demand for housing. It is convenient to postpone the definitions of these shocks to Section 2.6, after we have outlined the rest of the model in detail. Until then, we summarize the vector of exogenous and endogenous aggregate states as Ω .

We start by presenting the decision problem for households in Section 2.2. We then describe the financial intermediation sector, the rental sector, the production side of the economy and the process for the aggregate shocks in Sections 2.3 to 2.6. The recursive formulation of the household problem and the formal definition of equilibrium are contained in Appendix A and Appendix B, respectively.

2.2 Households

2.2.1 Household Environment

Demographics Time is discrete. The economy is populated by a measure-one continuum of finitely-lived households. Age is indexed by $j = 1, 2, \dots, J$. Households work from period 1 to $J^{ret} - 1$, and are retired from period J^{ret} to J . All households die with certainty after age J . In what follows, we omit the dependence of variables on age j except in cases where its omission may be misleading.

Preferences Expected lifetime utility of the household is given by

$$\mathbb{E}_0 \left[\sum_{j=1}^J \beta^{j-1} u_j(c_j, s_j) + \beta^J v(b) \right] \quad (1)$$

⁵Only a handful of papers on the crisis develops models with aggregate shocks that move equilibrium house prices, but they are environments with very limited heterogeneity (Iacoviello and Pavan, 2013; Justiniano et al., 2017; Greenwald, 2016). The rest of the literature either studies deterministic equilibrium transitions out of steady-state induced by measure-zero events (e.g., Garriga, Manuelli, and Peralta-Alva, 2017; Huo and Ríos-Rull, 2016; Kiyotaki et al., 2011), or assumes exogenous price shocks (e.g., Chen, Michaux, and Roussanov, 2013; Corbae and Quintin, 2015; Landvoigt, 2017).

where $\beta > 0$ is the discount factor, $c > 0$ is consumption of nondurables and $s > 0$ is the consumption of housing services. Nondurable consumption is the numeraire good in the economy. The expectation is taken over sequences of aggregate and idiosyncratic shocks that we specify below. The function v measures the felicity from leaving bequests $b > 0$.⁶

We assume that the utility function u_j is given by

$$u_j(c, s) = \frac{e_j [(1 - \phi) c^{1-\gamma} + \phi s^{1-\gamma}]^{\frac{1-\vartheta}{1-\gamma}} - 1}{1 - \vartheta}, \quad (2)$$

where ϕ measures the relative taste for housing services, $1/\gamma$ measures the elasticity of substitution between housing services and nondurables, and $1/\vartheta$ measures the intertemporal elasticity of substitution (IES). The exogenous equivalence scale $\{e_j\}$ captures deterministic changes in household size and composition over the life cycle and is the reason why the intra-period utility function u is indexed by j .

The warm-glow bequest motive at age J takes the functional form

$$v(b) = \psi \frac{(b + \underline{b})^{1-\vartheta} - 1}{1 - \vartheta}, \quad (3)$$

as in [De Nardi \(2004\)](#). The term ψ measures the strength of the bequest motive, while \underline{b} reflects the extent to which bequests are luxury goods.

Endowments Working-age households receive an idiosyncratic labor income endowment y_j^w given by

$$\log y_j^w = \Theta + \chi_j + \epsilon_j \quad (4)$$

where Θ is an index of aggregate labor productivity. Individual labor productivity has two components: (i) a deterministic age profile χ_j that is common to all households and (ii) an idiosyncratic component ϵ_j that follows a first-order Markov process. We denote the resulting age-dependent transition matrix for earnings by Υ_j , which does not depend on Θ , and we denote the unconditional earnings distribution at age j by Υ_j^* .

Households are born with an endowment of initial wealth that is drawn from an exogenous distribution that integrates up to the overall amount of wealth bequeathed in the economy by dying households. The draw is correlated with initial productivity y_1^w .

Liquid Saving Households can save in one-period bonds, b , at the exogenous price q_b determined by the net supply of safe financial assets from the rest of the world. For what

⁶This bequest motive prevents households from selling their house and dis-saving too much during retirement, which would be counterfactual.

follows, it is convenient to also define the associated interest rate on bonds $r_b := 1/q_b - 1$. Unsecured borrowing is not allowed.

Housing In order to consume housing services, households have the option of renting or owning a home. Houses are characterized by their sizes which belong to a finite set. For owner-occupied housing, house size belongs to the set $\mathcal{H} = \{h^0, \dots, h^N\}$, where $h^0 < h^1, \dots, h^{N-1} < h^N$. For rental housing, size belongs to the set $\tilde{\mathcal{H}} = \{\tilde{h}^0, \dots, \tilde{h}^N\}$. Markets for rental and owner-occupied housing are both frictionless and competitive, meaning that buying or selling does not take time and the law of one price holds. The rental rate of a unit of housing is denoted by $\rho(\Omega)$. The per-unit price of housing is denoted by $p_h(\Omega)$. Rental rates and house prices both depend on the exogenous and endogenous aggregate states Ω .

Renting generates housing services one-for-one with the size of the house, i.e. $s = h$. To capture the fact that there may be additional utility from home ownership, we assume that an owner-occupied house generates $s = \omega h$ units of housing services, with $\omega \geq 1$. Owner-occupied houses carry a per-period maintenance and tax cost of $(\delta_h + \tau_h)p_h(\Omega)h$, expressed in units of the numeraire good. Maintenance fully offsets physical depreciation of the dwelling δ_h . When a household sells its home, it incurs a transaction cost $\kappa_h p_h(\Omega)h$ that is linear in the house value. Renters can adjust the size of their house without any transaction costs.

Mortgages Purchases of housing can be financed by mortgages. All mortgages are (i) long-term, (ii) subject to a fixed origination cost κ^m , (iii) amortized over the remaining life of the buyer at the common real interest rate r_m , equal to r_b times an intermediation wedge $(1 + \iota)$, (iv) able to be refinanced subject to paying the origination cost, and (v) defaultable.

A household of age j that takes out a new mortgage with principal balance m' receives from the lender $q_j(\mathbf{x}', y; \Omega)m'$ units of the numeraire good in the period that the mortgage is originated. The mortgage pricing function $q < 1$ depends on the age j of the borrower, its choice of assets and liabilities for next period $\mathbf{x}' := (b', h', m')$, its current income state y and the current aggregate state vector Ω . These variables predict the household-specific probability of future default. The higher is this default probability, the lower is the price.⁷ It follows that the downpayment made at origination by a borrower of age j who takes out a mortgage of size m' to purchase a house of size h' is $p_h(\Omega)h' - q_j(\mathbf{x}', y; \Omega)m'$.

At the time of origination, borrowers must respect two constraints. First, a maximum loan-to-value (LTV) ratio limit: the initial mortgage balance m' must be less than a fraction

⁷Section 2.3 provides the exact expression for the equilibrium price q . One can interpret this gap between face-value of the mortgage m' and funds received $q_m m$ as so-called “points” or other up-front interest rate charges that households face when taking out loans.

λ^m of the collateral value of the house being purchased:

$$m' \leq \lambda^m p_h(\Omega) h'. \quad (5)$$

Second, a maximum payment to income (PTI) ratio limit: the minimum mortgage payment $\pi_j^{\min}(m')$ must be less than a fraction λ^π of income at the time of purchase:

$$\pi_j^{\min}(m') \leq \lambda^\pi y. \quad (6)$$

For any pair (j, m) , the minimum payment is determined by the constant amortization formula,

$$\pi_j^{\min}(m) = \frac{r_m(1+r_m)^{J-j}}{(1+r_m)^{J-j} - 1} m. \quad (7)$$

After origination, the borrower is required to make at most $J - j$ mortgage payments π that each exceed the minimum required payment (7) until the mortgage is repaid. The outstanding principal evolves according to $m' = m(1+r_m) - \pi$.⁸

Because mortgages are long-term, after origination there is no requirement that the principal outstanding on the mortgage be less than λ^m times the current value of the home. The only requirement for a borrower to not be in default is that it makes its minimum payment on the outstanding balance of the loan. If house prices decline, a home owner could end up with very small (or even negative) housing equity but, as long as it continues to meet its minimum payments, it is not forced to deleverage as it would be if debt was short-term and the constraint (5) held period by period.

Mortgage borrowers always have the option to refinance, by repaying the residual principal balance and originating a new mortgage. Since the interest rate is fixed, such refinancing should be interpreted as cash-out refi's whose only purpose is equity extraction. When a household sells its home, it is also required to pay off its remaining mortgage balance.

If a household defaults, mortgages are the subject of the primary lien on the house, imply-

⁸We impose the common amortization rate for tractability. Fixing q and allowing households to simultaneously choose the interest rate r_m and the principal m would be closer to reality, but such an alternative formulation would add a state variable (the individual amortization rate) to the homeowner problem. In our formulation, all the idiosyncratic elements are subsumed into q at origination. Note however that, even though all households pay the same interest rate r_m on the outstanding principal, the heterogeneity in mortgage amounts m and prices q results in heterogeneous effective interest rates. In simulations, we can compute the interest rate r_m^* that would yield a constant mortgage payment schedule $\pi_j^{\min}(m)$ on an outstanding balance of qm (the funds received at origination) using the relationship:

$$\frac{\pi_j^{\min}(m)}{q_j m} = \frac{r_m^*(1+r_m^*)^{J-j}}{(1+r_m^*)^{J-j} - 1}.$$

ing that the proceeds from the foreclosure are disbursed to the creditor. Foreclosing reduces the value of the house to the lender for two reasons: (i) it is the lender who must pay property taxes and maintenance, and (ii) foreclosed houses depreciate at a higher rate than regular houses, i.e. $\delta_h^d > \delta_h$. Thus, the lender recovers $\min \{ (1 - \delta_h^d - \tau_h) p_h(\Omega) h, (1 + r_m) m \}$. A household who defaults is not subject to recourse, but incurs a utility loss ξ and is excluded from buying a house in that period.⁹

HELOCs Home owners have access to home equity lines of credit (HELOCs). For tractability, we assume these are one-period non-defaultable contracts.¹⁰ Through HELOCs, households can borrow up to a fraction λ^b of the value of their house at an interest rate equal to $r_b(1 + \iota)$.¹¹ Note that, unlike mortgages, HELOCs are refinanced each period and thus are subject to the following period-by-period constraint on the balance relative to the current home value:

$$-b' \leq \lambda^b p_h(\Omega) h. \quad (8)$$

Government The government runs a PAYG social security system. Retirees receive social security benefits $y^{ret} = \rho_{ss} y_{j^{ret}}^w$, where ρ_{ss} is a replacement rate and the argument of the benefit function proxies for heterogeneity in lifetime earnings. We adopt the notation y for income, with the convention that if $j < J^{ret}$ then $y = y^w$, defined in (4), and $y = y^{ret}$ otherwise.

Government tax revenues come from the proportional property tax τ_h levied on house values, a flat payroll tax τ^{ss} and a progressive labor income tax $\tau^y(y)$. Households can deduct the interest paid on mortgages against their taxable income. We denote the combined income tax liability function $\mathcal{T}(y, m)$. In addition, the government gets revenue from the sale of new land permits for construction, which we describe in more detail in Section 2.5.

The residual differential between tax revenues and pension outlays, which is always positive, is spent on services $G(\Omega)$ that are not valued by households.

⁹We abstract from a direct effect of foreclosures on the aggregate house price through negative externalities running from distressed units to neighboring properties. The reason is that the empirical literature (Anenberg and Kung, 2014; Gerardi et al., 2015) finds economically small and extremely localized effects (a maximum of 2 pct for properties within 0.1 miles from the foreclosed unit) and over 80% of properties sell without a nearby foreclosed unit. Moreover, a component of this estimated effect is simply the consequence of more houses for sale, which is captured in the model.

¹⁰Allowing for multi-period HELOC contracts would effectively require keeping track of another asset as an endogenous state variable in the household problem. Allowing for default on HELOCs would require solving for an additional equilibrium pricing function akin to q . With this tractability comes a shortcoming: in the model HELOCs are a senior lien to mortgage debt, while in the data they are junior.

¹¹To lighten the exposition, with a slight abuse of notation, we continue to denote the interest rate on liquid assets as r_b , but it is implicit that it equals $r_b(1 + \iota)$ when $b < 0$. We use a similar convention for q_b .

2.2.2 Household Decisions

Here we provide an overview of households' decisions. Appendix A contains a full description of the household problem in recursive form.

A household who starts the period as a renter chooses between renting and buying a house. Those who remain as renters choose the size of house to rent, the quantity of nondurable goods to consume, and how much to save in the liquid asset. Since they do not own any collateral, they cannot borrow. Those who elect to become homeowners also choose the size of house to buy together with the value of the mortgage they wish to take out, and make an initial downpayment. This decision is made subject to the LTV constraint (5) and the PTI constraint (6).

The decision of whether to rent versus own is based on a comparison of the costs and gains of owning. The costs are due to the initial downpayment and maximum PTI requirements as well as to transaction fees upon selling. There are three advantages of owning over renting: (i) owning a house yields an extra utility flow; (ii) mortgage interest payments are tax deductible, whereas rents are not; (iii) housing can be used as a collateral for borrowing through HELOCs. In addition, owning insures households against fluctuations in rents, but exposes households to capital gains and losses from movements in house prices.

A household who starts the period as an owner has four options: (i) keep its current house and mortgage and make the minimum required payment; (ii) refinance its mortgage; (iii) sell its house; or (iv) default on its outstanding mortgage balance.

Households choosing to continue with their current mortgage, or to refinance, can borrow against their housing collateral through HELOCs. Since all mortgages amortize at the same rate r^m , refinancing is only useful as a means to extract equity (cash-out refinancing as opposed to interest rate refinancing). This could be optimal either when house prices rise so that the LTV constraint is relaxed, or when individual income grows so that the PTI constraint is loosened, depending on which constraint was binding at origination.¹²

Households choosing to sell their house start the period without owning any housing and with financial assets equal to those carried over from the previous period b_j plus the net-of-costs proceeds from the sale of the home, which are given by

$$(1 - \delta_h - \tau_h - \kappa_h) p_h(\Omega) h - (1 + r_m) m. \quad (9)$$

¹²There is a trade-off between the two means to extract equity in the model: HELOCs versus cash-out refinancing. Refinancing requires payment of a fixed cost and is subject to the pricing schedule q , which reflects the individual probability of default. This means that HELOCs are preferred over refinancing by households who wish to extract relatively small amounts of equity (since the fixed cost of refinancing would erode a sizable fraction of the loan) and by households with low income or high leverage (for whom mortgages are costly since they face a low q).

The household then chooses whether to rent or to buy a new house.

Finally, a household might choose to default if it has some residual mortgage debt and is ‘underwater’, meaning that, if it sold the house, the net proceeds from the sale in (9) would be negative.

2.3 Financial Intermediaries

There is a competitive financial intermediation sector that issues new mortgages m' subject to a mortgage origination wedge ζ_m per unit of consumption loaned out. We assume that these financial intermediaries are owned by risk-neutral foreign agents with deep pockets, and hence mortgage prices are determined by zero-profit conditions that hold in expectation loan by loan.¹³ Let $g_j^n(\mathbf{x}, y; \Omega)$, $g_j^f(\mathbf{x}, y; \Omega)$, and $g_j^d(\mathbf{x}, y; \Omega)$ denote (mutually exclusive) indicators for the decisions to sell, refinance and default, respectively. Each indicator is a function of age, portfolio $\mathbf{x} := (b, h, m)$, income y , and the aggregate state vector Ω , since all these variables predict default at age $j + 1$. Using this notation, we can express the unit price of a mortgage as

$$\begin{aligned} q_j(\mathbf{x}', y; \Omega) &= \frac{1 - \zeta^m}{(1 + r_m) m'} \cdot \mathbb{E}_{y, \Omega} \left\{ \left[g_j^n + g_j^f \right] (1 + r_m) m' \right. \\ &\quad + g_j^d (1 - \delta_h^d - \tau_h - \kappa_h) p_h(\Omega') h' \\ &\quad \left. + \left[1 - g_j^n - g_j^f - g_j^d \right] \langle \pi(\mathbf{x}', y'; \Omega') + q_{j+1}(\mathbf{x}'', y'; \Omega') [(1 + r_m) m' - \pi(\mathbf{x}', y'; \Omega')] \rangle \right\} \end{aligned} \quad (10)$$

where, to ease notation, we have suppressed dependence of the indicators g_j^i on $\mathbf{x}', y'; \Omega'$.

Intuitively, if the household sells ($g_j^n = 1$) or refinances ($g_j^f = 1$), it must repay the balance remaining on the mortgage, so the financial intermediary receives the full principal plus interest and hence $q = 1 - \zeta^m$. If the household defaults on the mortgage ($g_j^d = 1$), then the intermediary forecloses, sells the house and recovers the market value of the depreciated home. If the household continues with the existing mortgage by making a payment on the home ($g_j^n = g_j^f = g_j^d = 0$), then the value of the contract to the intermediary is the value of the mortgage payment π (itself a decision), plus the continuation value of the remaining mortgage balance going forward — which is compactly represented by the next period pricing function.¹⁴

¹³Because of the presence of aggregate risk, along the equilibrium path financial intermediaries make profits and losses. Despite these fluctuations in profits, the assumption that financial intermediaries are owned by risk-neutral foreign agents justifies discounting at rate r_m (equal to r_b times the lending wedge) in equation (10).

¹⁴Note that a lender who observes \mathbf{x}' can compute next-period decisions \mathbf{x}'' for each possible future realization y', Ω' . In other words, \mathbf{x}'' is a deterministic function of $(\mathbf{x}', y'; \Omega')$.

The equilibrium mortgage pricing function can be solved recursively as in the long-term sovereign debt default model of [Chatterjee and Eyigungor \(2012\)](#), adapted here to collateralized debt and finite lifetimes.¹⁵

2.4 Rental Sector

We assume that the rental rate is determined by a ‘Jorgensonian’ user-cost formula which relates the equilibrium rental rate to current and future equilibrium house prices:

$$\rho(\Omega) = \psi + p_h(\Omega) - (1 - \delta_h - \tau_h) \mathbb{E}_\Omega [\mathbf{m}(\Omega, \Omega') p_h(\Omega')]. \quad (11)$$

We show in [Appendix D.2](#) that this formula can be derived from the optimization problem of a competitive rental sector that owns housing units and rents them out to households. Rental companies can frictionlessly buy and sell housing units, on which they incur depreciation and pay property taxes, as well as a per-period operating cost ψ for each unit of housing rented out.

Rental companies discount use the stochastic discount factor \mathbf{m} , which we set equal to the risk-free rate $(1 + r_b)^{-1}$ in the baseline model. In [Section 5.3](#), we explore sensitivity of our results to alternative choices for \mathbf{m} , and we introduce various frictions into the rental sector which show up as time-varying wedges in [\(11\)](#).

2.5 Production

There are two production sectors in the economy: a final goods sector which produces nondurable consumption (the numeraire good of the economy) and a construction sector which produces new houses. Labor is perfectly mobile across sectors.

Final Good Sector The competitive final good sector operates a constant returns to scale technology

$$Y = \Theta N_c, \quad (12)$$

where Θ is the aggregate labor productivity level and N_c are units of labor services. The equilibrium wage per unit of labor services is thus $w = \Theta$.

Construction Sector The competitive construction sector operates the production technology $I_h = (\Theta N_h)^\alpha (\bar{L})^{1-\alpha}$, with $\alpha \in (0, 1)$, where N_h is the quantity of labor services

¹⁵Allowing lenders to condition on age (as, e.g., in [Corbae and Quintin, 2015](#)) simplifies the calculation of this equilibrium price schedule relative to the sovereign debt context because one can solve backwards from age J rather than iterating towards a fixed point.

employed and \bar{L} is the amount of new available buildable land. We assume that each period the government issues new permits equivalent to \bar{L} units of land, and we follow Favilukis et al. (2017) in assuming that these permits are sold at a competitive market price to developers. This implies that all rents from land ownership accrue to the government and the construction sector makes no profits in equilibrium.

A developer therefore solves the static problem:

$$\max_{N_h} p_h(\Omega) I_h - w N_h \quad \text{s.t.} \quad I_h = (\Theta N_h)^\alpha (\bar{L})^{1-\alpha}$$

which, after substituting the equilibrium condition $w = \Theta$, yields the following housing investment function:

$$I_h(\Omega) = [\alpha p_h(\Omega)]^{\frac{\alpha}{1-\alpha}} \bar{L} \tag{13}$$

implying an elasticity of aggregate housing supply to house prices equal to $\alpha/(1-\alpha)$.

2.6 Aggregate Risk and Computation of Equilibrium

We now describe the sources of aggregate risk in the economy and outline our strategy for computing the equilibrium. Appendix B contains the definition of a recursive competitive equilibrium and Appendix C provides more details on the numerical algorithm and its numerical accuracy.

Aggregate Shocks There are three types of mutually independent aggregate shocks in our economy, each following a stationary Markov process.

First, there are shocks to aggregate labor productivity Θ .

Second, there are a set of time-varying parameters that characterize credit conditions in mortgage markets: (i) the maximum loan-to-value ratio at origination λ^m ; (ii) the maximum payment-to-income level at origination λ^π ; (iii) the mortgage origination cost κ^m ; and (iv) the mortgage origination wedge ζ^m . We assume that these four parameters are perfectly correlated and combine them into an index of housing finance/credit conditions $F = (\lambda^m, \lambda^\pi, \kappa^m, \zeta^m)$. In Section 3.2 we explain the rationale behind modeling changes in housing finance conditions this way, and in Section 5.2 we consider alternative views of changes in credit condition that involve variation in other model parameters.

Third, we introduce aggregate uncertainty over future preferences for housing services, as captured by the share parameter ϕ in the utility function (2). We assume that ϕ follows a three state Markov process where the three states are denoted by $(\phi_L, \phi_L^*, \phi_H)$ with values

$\phi_H > \phi_L = \phi_L^*$. When the economy is in either of the two states ϕ_L, ϕ_L^* , the taste for housing is the same. However, these two states differ in terms of the likelihood of transitioning to the third state ϕ_H in which the taste for housing is greater. Therefore, a shift between ϕ_L and ϕ_L^* is a *news* or *belief shock* about future demand for housing, whereas a shift between ϕ_L (or ϕ_L^*) and ϕ_H is an actual preference shock. Formulating the stochastic process in this way allows us to construct equilibrium paths in which there are changes in beliefs about future preferences for housing, but those changes in the preferences themselves might not realize.

In what follows, we denote the vector of exogenous aggregate shocks (Θ, F, ϕ) as \mathcal{Z} . Our model features incomplete markets and aggregate risk, so the distribution of households across individual states μ is a state variable because it is needed to forecast future house prices and rents. Thus, the full vector of aggregate states is $\Omega = (\mathcal{Z}, \mu)$.

Numerical Computation of Equilibrium Our computation strategy follows the insight of [Krusell and Smith \(1998\)](#). Since it is not feasible to keep track of the entire distribution μ to compute its equilibrium law of motion, we replace it with a lower dimensional vector that, ideally, provides sufficient information for agents to make accurate price forecasts needed to solve their dynamic choice problems.

A crucial observation is that in every period there is only one price that households in our model need to know, and forecast, when making decisions: p_h , the price of owner-occupied housing. Knowing p_h this period and how to forecast p'_h next period conditional on the realization of the vector of exogenous states \mathcal{Z}' is sufficient to pin down both the full mortgage pricing schedule (see eq. 10) and the rental rate (see eq. 11).¹⁶ The assumptions of perfect competition and linear objectives in both the financial and rental sectors allow us to reduce the dimension of the price vector to be forecasted from three to one.

We consider an approximate equilibrium in which households use a conditional one-period ahead forecast rule for house prices that is a function of the current price, the current exogenous states and next period exogenous states. This strategy has promise because, as reflected in equation (13), housing investment is entirely pinned down by the price of housing. Specifically, we conjecture a law of motion for p_h of the form

$$\log p'_h(p_h, \mathcal{Z}, \mathcal{Z}') = a_0(\mathcal{Z}, \mathcal{Z}') + a_1(\mathcal{Z}, \mathcal{Z}') \log p_h, \quad (14)$$

and iterate, using actual market-clearing prices at each step, until we achieve convergence

¹⁶A key difference between our framework and [Krusell and Smith \(1998\)](#) is that the total stock of owner-occupied houses H is not predetermined, as is capital in their paper, but needs to be pinned down in equilibrium to clear the housing market every period. Thus our computational problem is closer to that of solving for equilibrium in a stochastic incomplete-markets economy with a risk-free bond or with endogenous labor supply. See [Krusell and Smith \(2006\)](#) for an overview of these different economies.

on the vector of coefficients $\{a_0(\mathcal{Z}, \mathcal{Z}'), a_1(\mathcal{Z}, \mathcal{Z}')\}$.

3 Parameterization

We parameterize the model to be consistent with key cross-sectional features of the U.S. economy in the late 1990s, before the start of the boom and bust in the housing market. When necessary to choose a specific year we use information from 1998, since it coincides with a wave of the Survey of Consumer Finances (SCF), which is the data source for many of our targets.

A subset of model parameters are assigned externally, without the need to solve for the model equilibrium. The remaining parameters are chosen to minimize the distance between a number of equilibrium moments from the stationary ergodic distribution implied by the model’s stochastic steady state and their data counterparts. The resulting parameter values are summarized in Table 1 and the targeted moments are in Table 2. We defer our description of the stochastic processes for the aggregate shocks $\mathcal{Z} = (\Theta, F, \phi)$ that generate this ergodic distribution until Section 3.2.

3.1 Model Parameters

Demographics The model period is equivalent to two years of life. Households enter the model at age 21, retire at age 65 (corresponding to $J^{ret} = 22$) and live until age 81 (corresponding to $J = 30$).

Preferences We set $1/\gamma$, the elasticity of substitution between nondurable consumption and housing in (2), to 1.25 based on the estimates in Piazzesi, Schneider, and Tuzel (2007). We set $\sigma = 2$ to give an elasticity of intertemporal substitution equal to 0.5. The consumption expenditures equivalence scale $\{e_j\}$ reproduces the McClements (1977) scale, a commonly used consumption equivalence measure. The discount factor β is chosen to replicate a ratio of aggregate net worth to annual labor income of 5.5 as in the 1998 SCF.¹⁷

The warm-glow bequest function (3) is indexed by two parameters. The strength of the bequest motive is governed by ν , while the extent to which bequests are a luxury good is governed by \underline{b} . These two parameters are chosen to match (i) the ratio of net worth at age 75 to net worth at age 50, which is an indicator of the importance of bequests as a saving motive; and (ii) the fraction of households in the bottom half of the wealth distribution that leave a positive bequest, which is an indicator of the luxuriousness of bequests.

¹⁷This is equivalent to an aggregate net worth to aggregate total income of 3.67. The model also generates a median net worth to labor income ratio around 1, close to its empirical counterpart from the 1998 SCF.

The additional utility from owner-occupied housing relative to rental housing, ω , is chosen to match the average home ownership rate in the US economy in 1998, which was 66% (Census Bureau). The calibrated value implies a consumption-equivalent gain from owning for the median home owner of around half a percentage point. The disutility from mortgage defaults ξ is chosen to target an equilibrium foreclosure rate of 0.5%, which was the average rate in the U.S. during the late 1990s. The calibrated value implies an average consumption-equivalent loss of roughly 30 percent in the period of default.

Endowments The deterministic component of earnings $\{\chi_j\}$ comes from [Kaplan and Violante \(2014\)](#). Average earnings grow by a factor of three from age 21 to its peak at age 50 and then decline slowly over the remainder of the working life. The stochastic component of earnings y_j is modeled as an AR(1) process in logs with annual persistence of 0.97, annual standard deviation of innovations of 0.20, and initial standard deviation of 0.42. This parameterization implies a rise in the variance of log earnings of 2.5 between the ages of 21 and 64, in line with [Heathcote, Perri, and Violante \(2010\)](#). We normalize earnings so that median annual household earnings (\$52,000 in the 1998 SCF) equal one in the model.

The mean and variance of the initial distribution of bequests, also from [Kaplan and Violante \(2014\)](#), are chosen to mimic the empirical distribution of financial assets and its correlation with earnings at age 21.

Housing To discipline the set of owner-occupied house sizes \mathcal{H} , we choose three parameters: the minimum size of owner-occupied units, the number of house sizes in that set, and the gap between house sizes. We target three moments of the distribution of the ratio of housing net worth to total net worth: the 10th percentile (0.11), median (0.50), and the 90th percentile (0.95). Similarly, to discipline the set $\tilde{\mathcal{H}}$ we choose two parameters: the minimum size of rental units, and the number of house sizes in that set (we restrict the gap between rental unit sizes to be the same as for owner-occupied houses). We target a ratio of the average house size of owners to renters of 1.5 ([Chatterjee and Eyigungor, 2015](#)) and a ratio of the average earnings of owners to renters of 2.1 (1998 SCF).

The proportional maintenance cost that fully offsets depreciation δ_h is set to replicate an annual depreciation rate of the housing stock of 1.5%.¹⁸ In the event of a mortgage default, the depreciation rate rises to 25%, consistent with the loss of value for foreclosed properties estimated in [Pennington-Cross \(2009\)](#). The transaction cost for selling a house κ_h equals 7% of the value of the house. Given this transaction cost, around 9.5% of all

¹⁸Bureau of Economic Analysis (BEA) Table 7.4.5, consumption of fixed capital of the housing sector divided by the stock of residential housing at market value, see [Appendix E](#).

houses are sold annually in the model, compared to 10% in the data (as estimated by [Ngai and Sheedy, 2017](#), from the American Housing Survey).¹⁹ The operating cost of the rental company ψ affects the relative cost of renting versus buying, a decision which is especially relevant for young households. Accordingly, we choose ψ to match the home ownership rate of households younger than 35, which was 39% in 1998 (Census Bureau). The calibrated value corresponds to an annual management cost for the rental companies of just under 1% of the value of the housing stock.

The construction technology parameter α is set to 0.6 so that the price elasticity of housing supply $\alpha/(1-\alpha)$ equals 1.5, which is the median value across MSAs estimated by [Saiz \(2010\)](#). The value of new land permits \bar{L} is set so that employment in the construction sector is 5% of total employment, consistent with Bureau of Labor Statistics data for 1998.

Financial Instruments We set the risk free rate r_b at 3% per annum. The origination cost for mortgages κ^m is set equal to the equivalent of \$2,000 in the model, corresponding to the sum of application, attorney, appraisal and inspection fees.²⁰ The proportional wedge ι is set to 0.33 (implying an amortization rate r_m of 4% p.a.) consistent with the gap between the average rate on 30-year fixed-term mortgages and the 10-year T-Bill rate in the late 1990s. The maximum HELOC limit as a fraction of the home value, λ^b , is set to 0.2 to replicate the 99th percentile of the combined LTV and HELOC limits distribution in the 1998 SCF.²¹

Government The property tax τ_h is set to 1% per annum, which is the median tax rate across US states (Tax Policy Center). For the income tax function $\mathcal{T}(\cdot)$, we adopt the functional form in [Heathcote, Storesletten, and Violante \(Forthcoming\)](#), i.e., $\mathcal{T}(y_j, m_j) = \tau_y^0 (y_j - r_m \min\{m_j, \bar{m}\})^{1-\tau_y^1}$. The parameter τ_y^0 , which measures the average level of taxation, is set so that aggregate tax revenues are 20% of output in the stochastic steady state of the model. The parameter τ_y^1 , which measures the degree of progressivity of the US tax and transfer system, is set to 0.15 based on the estimates of [Heathcote et al. \(Forthcoming\)](#). The argument of the function y_j is taxable income, which is defined as income net of the deductible portion of mortgage interest payments. Interest is only deductible for the first \$1,000,000 of mortgage debt.

To set the social security replacement rate ρ_{ss} , we proxy average individual lifetime

¹⁹This value of transaction costs is in line with common estimates of sales costs, including brokerage fees and local taxes ([Delcours and Miller, 2002](#)).

²⁰See <http://www.federalreserve.gov/pubs/refinancings/default.htm>

²¹This value is close to the 90th percentile of the HELOC limit distribution, roughly 30% of the home value.

Parameter	Interpretation	Internal	Value
Demographics			
J^w	Working life (years)	N	44
J	Length of life (years)	N	60
Preferences			
$1/\gamma$	Elasticity of substitution (c, s)	N	1.25
σ	Risk aversion	N	2.0
$\{e_j\}$	Equivalence scale	N	McClements scale
β	Discount factor	Y	0.964
ν	Strength of bequest motive	Y	100
\underline{b}	Extent of bequest as luxury	Y	7.7
ω	Additional utility from owning	Y	1.015
ξ	Utility cost of foreclosure	Y	0.8
Endowments			
$\{\chi_j\}$	Deterministic life-cycle profile	N	Kaplan and Violante (2014)
ρ_z	Autocorrelation of earnings	N	0.97
σ_z	S.D. of earnings shocks	N	0.20
σ_{z_0}	S.D. of initial earnings	N	0.42
$F(b_0, y_0)$	Initial distribution of bequest	N	Kaplan and Violante (2014)
Housing			
\mathcal{H}	Owner-occupied house sizes	Y	{1.50, 1.92, 2.46, 3.15, 4.03, 5.15}
$\tilde{\mathcal{H}}$	Rental house sizes	Y	{1.17, 1.50, 1.92}
κ_h	Transaction cost	Y	0.07
δ_h	Housing maintenance/depr. rate	N	0.015
δ_h^d	Loss from foreclosure	N	0.22
ψ	Operating cost of rental company	Y	0.008
$\alpha/(1-\alpha)$	Housing supply elasticity	N	1.5
\bar{L}	New land permits	Y	0.311
Financial Instruments			
r_b	Risk-free rate	N	0.03
ι	Mortgage and HELOC rate wedge	N	0.33
λ_L^b	Max HELOC	N	0.20
Government			
τ_h	Property tax	N	0.01
τ_y^0, τ_y^0	Income tax function	N	0.75, 0.151
\bar{m}	Mortg. interest deduction limit	N	19.2
ρ_{ss}	Social Security replacement rate	N	0.40

Table 1: Parameter values. The model period is two-years. All values for which the time period is relevant are reported here annualized. A unit of the final good in the model corresponds to \$52,000 (median annual household wage income from the 1998 SCF).

Moment	Empirical value	Model Value
Aggr. NW / Aggr. labor income (median ratio)	5.5 (1.2)	5.6 (0.9)
Median NW at age 75 / median NW at age 50	1.51	1.55
Fraction of bequests in bottom half of wealth dist.	0	0
Aggr. home-ownership rate	0.66	0.67
Foreclosure rate	0.005	0.001
P10 Housing NW / total NW for owners	0.11	0.12
P50 Housing NW / total NW for owners	0.50	0.38
P90 Housing NW / total NW for owners	0.95	0.80
Avg.-size owned house / rented house	1.5	1.5
Avg. earnings owners / renters	2.1	2.4
Annual fraction of houses sold	0.10	0.095
Home-ownership rate of < 35 y.o.	0.39	0.37
Relative size of construction sector	0.05	0.05
Belief Shock		
Average expenditure share on housing	0.16	0.16
Expected annual house price growth	0.06-0.15	0.06
Avg. duration of booms and busts	5.4 and 5.5 years	5 and 5 years
Avg. size of house price change in booms and busts	0.36 and 0.37	0.34 and 0.32

Table 2: Targeted moments in the calibration, corresponding to the 13 model parameters and to the 6 parameters of the belief shock process internally calibrated.

earnings with the last realization of earnings y_{Jret}^w . The distribution of these proxies is run through the same formula used in the U.S. social security system in 1998 to calculate the distribution of individual benefits. We then compute the ratio of average benefits to average lifetime earnings proxies, which gives an aggregate social security replacement rate of 0.4.

3.2 Aggregate Uncertainty and Boom-Bust Episode

As discussed in Section 2.6, the macroeconomy is subject to three aggregate shocks: labor income Θ , credit conditions $F = (\lambda^m, \lambda^\pi, \kappa^m, \zeta^m)$, and utility over housing services ϕ . We assume that each of these three shocks follow independent discrete-state Markov processes. We present our calibration below and summarize the parameter values in Table 3. We then describe how we simulate the boom and bust episode.

3.2.1 Aggregate Shocks

Aggregate Labor Income The aggregate labor income process Θ follows a two-point Markov chain that is obtained as a discrete approximation to an AR(1) process estimated from the linearly de-trended series for total labor productivity for the U.S.

Credit Conditions The shocks to credit conditions are intended to capture two important consequences of the transformation in housing finance that occurred in the early 2000s. At

the root of these changes in the nature of lending was the rise in securitization of private-label mortgages (Levitin and Wachter, 2011; Keys, Piskorski, Seru, and Vig, 2012a).²²

First, the ability to securitize private-label loans increased their appeal with investors and enhanced their liquidity, thereby reducing the origination costs of the underlying mortgages for lenders (e.g. Loutskina, 2011). We model this change as a reduction in both the fixed and the proportional components of the mortgage origination cost, κ^m and ζ^m . Based on the evidence in Favilukis et al. (2017), we assume that in times of normal credit conditions the fixed cost is \$2,000 and the wedge is 100 basis points and in times of relaxed credit the fixed cost falls to \$1,200 and the wedge to 60 basis points, corresponding to a 40% drop in both parameters.²³

Second, by offering insurance against local house price risk, securitization reduced originators' incentives to verify borrowers' documentation and led to a deterioration of lenders' screening practices (e.g. Keys, Seru, and Vig, 2012b). The consequent widespread relaxation of underwriting standards in the U.S. mortgage market allowed many buyers to purchase houses with virtually no downpayment and other buyers to borrow larger amounts than would have been previously possible, given their incomes.

Consistent with this body of work, we model these changes as variations in maximum LTV and PTI ratios at origination (λ^m, λ^π). A shift in maximum LTV ratio constitutes the main experiment in Iacoviello and Pavan (2013), Favilukis et al. (2017), Guerrieri and Lorenzoni (2015), Landvoigt et al. (2015) and Huo and Ríos-Rull (2016).²⁴ A shift in the maximum PTI ratio is the main experiment in Greenwald (2016).

We set $\lambda^m = 0.95$ in times of normal credit conditions, to replicate the 90th percentile of the LTV distribution in the late 1990s (1998 SCF), and set $\lambda^m = 1.1$ in times of relaxed credit conditions.²⁵ We set $\lambda^\pi = 0.25$ in normal times and set $\lambda^\pi = 0.50$ in times of relaxed credit conditions.²⁶

²²As explained, for example, by Levitin and Wachter (2011) securitization itself was not a new phenomenon. Prior to the early 2000s, however, securitization was mostly concentrated among amortizing fixed-interest conforming loans associated with Fannie Mae and Freddie Mac. Private-label mortgage-backed securities issuances accounted for less than 20% of all mortgage-backed securities in the mid 1990s, peaked at nearly 60% in 2006, and fell to around 5% after the crisis (see Levitin and Wachter, 2011, Figure 2).

²³There is also direct evidence from other historical episodes that deregulation leads to a fall in intermediation costs. For example, Favara and Imbs (2015) study the effect of the passage of the Interstate Banking and Branching Efficiency Act (IBBEA) of 1994. Using balance sheet data, they show that these branching deregulations enabled banks to diversify deposit collection across locations, and to lower the cost of funds.

²⁴Like ours, none of these papers microfound the shift in downpayment constraints. See Guler (2015) for a model in which changes in screening technologies and screening incentives are the cause of such shifts.

²⁵This shift in λ^m is in line with Keys et al. (2012a) who report a rise in combined LTV ratios of roughly 15 percentage points between the mid-late 1990s and 2006. When we experimented with a lower value for λ^m of 0.80 in the tight state, our results were virtually unchanged.

²⁶These values are somewhat lower than the ones reported by Greenwald (2016) for front-end PTI limits, because they have been adjusted downward to account for the fact that the amortization period in our

Parameter	Interpretation	Internal	Value
Productivity Θ			
Θ_L	Earnings - Low state	N	0.965
Θ_H	Earnings - High state	N	1.035
$q_{LL}^\Theta = q_{HH}^\Theta$	Transition probability	N	0.90
Credit conditions F			
κ_L^m	Fixed Origination Cost - Low state	N	\$2000
κ_H^m	Fixed Origination Cost - High state	N	\$1200
ζ_L^m	Proportional Origination Cost - Low state	N	100 BP
ζ_H^m	Proportional Origination Cost - High state	N	60 BP
λ_L^m	Max LTV - Low state	N	0.95
λ_H^m	Max LTV - High state	N	1.1
λ_L^π	Max PTI - Low state	N	0.25
λ_H^π	Max PTI - High state	N	0.50
$q_{LL}^F = q_{HH}^F$	Transition probability	N	0.98
Beliefs about housing demand ϕ			
$\phi_L = \phi_L^*$	Taste for housing - Low state	Y	0.12
ϕ_H	Taste for housing - High state	Y	0.20
$q_{LL}^\phi = q_{HH}^\phi$	Transition probability	Y	0.95
$q_{LL}^\phi = q_{HL}^{\phi*}$	Transition probability	Y	0.04
$q_{L^*L^*}^\phi$	Transition probability	Y	0.12
$q_{L^*H}^\phi$	Transition probability	Y	0.80

Table 3: Parameters governing the Markov processes for the three aggregate shocks. Transition probabilities are biannual.

We assume that all four components of the index of credit conditions F are perfectly correlated and that the transition probabilities across the normal and relaxed states are such that a regime shift occurs on average once a generation. Regime shifts are thus perceived by households to be essentially permanent, given the lack of altruistic links.

Finally, it is useful to mention that the literature has emphasized the role of what it calls a *credit supply shock* (Mian and Sufi, 2009, 2016a; Di Maggio and Kermani, 2017), i.e. an expansion of cheap funds available to the low-quality borrowers (those who were traditionally denied loans) and a subsequent retraction of such credit after the bust. As illustrated by Justiniano et al. (2017), this shock is more consistent with the data than the collateral parameter shocks because it can simultaneously generate a rise in the quantity of credit and a fall in the mortgage spreads faced by low-quality borrowers during the boom. The components of our exogenous credit conditions that capture these features are the costs of mortgage origination κ^m and ζ^m . In Section 5.1.1 we show that our model is also able to endogenously generate these patterns in the stock of credit and in mortgage spreads as a direct consequence of changing beliefs of lenders.

model (remaining lifetime from date of purchase) is longer than in the data (typically 30 years from date of purchase). Greenwald reports smaller shifts between boom and bust in the distribution of PTI limits at origination, so ours is an upper bound for the role of this shock.

Expectations about Future Housing Demand We assume that the parameter governing the utility weight on housing services (which affects the demand for housing) follows a three state Markov process with values $(\phi_L, \phi_L^*, \phi_H)$ and a transition matrix with elements q_{ij}^ϕ for $i, j \in \{L, L^*, H\}$. We impose two symmetry restrictions on the transition matrix: $q_{LL}^\phi = q_{HH}^\phi$ and $q_{LL^*}^\phi = q_{HL^*}^\phi$. Together with the constraint that the rows of the transition matrix add to unity, this leaves a total of six parameters to calibrate: two preference parameters ϕ_L, ϕ_H and four transition probabilities.

We choose ϕ_L so that the average share of housing in total consumer expenditures is 0.16 (NIPA) in the stochastic steady state. We choose ϕ_H so that household expectations about house price appreciation during the boom are consistent with survey-based expectations. [Case and Shiller \(2003, Table 9\)](#) and [Case, Shiller, and Thompson \(2012, Table 3\)](#) report that during the booms of the 1980s and 2000s households located in four metropolitan areas and four counties with different local housing market conditions expected on average nominal house appreciation between 6 and 15 percent per year, over the next ten years. We target the middle of this range, i.e. 6% expected annual real house price growth (given an inflation rate of 2.5%) and obtain a value for ϕ_H corresponding to a housing expenditure share of 0.26.

We choose the four transition probabilities to match the average size and duration of house price boom and bust episodes. Using a long panel of OECD countries, [Burnside, Eichenbaum, and Rebelo \(2016\)](#) estimate that the average size of booms (busts) is 36% (37%) and that their median duration is 5.4 years (5.5 years).²⁷ The calibrated transition matrix (reported in [Table 3](#)) implies that a shift from ϕ_L to ϕ_L^* is rare, but when it happens it conveys news that a shift to the state where all households desire more housing (ϕ_H) is now much more likely to occur in the near future. It also implies that the high state, when it occurs, is very persistent.

3.2.2 Boom-Bust Episode

Our quantitative experiment is to simulate a particular joint realization of these stochastic processes in order to engineer a boom-bust episode that accurately describes the household earnings, housing finance and house price expectations conditions during the recent house price boom (1997-2007) and subsequent bust (2007-2015).

²⁷We compute model counterparts of these moments by simulating the stochastic steady-state of the model subject to *all* shocks (productivity, credit conditions and beliefs/preferences for housing). One can interpret our calibration of the belief shock as a residual to explain boom and bust episodes above and beyond what could be explained with income and credit conditions. Thus, ex-ante, credit shocks could have accounted for all the movements in house prices, in which case the calibrated belief shocks would have no residual effect on house prices.

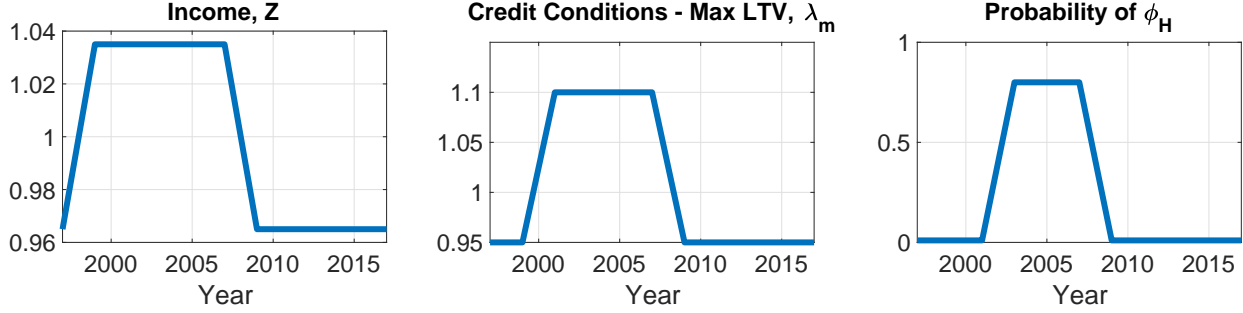


Figure 1: Boom-bust episode, realized path for shocks. Left panel: productivity. Middle panel: all components of financial deregulation (only max LTV showed). Right panel: probability of switching to the ϕ_H state.

In the pre-boom period, the economy is in a regime with low labor productivity, normal credit conditions, and utility for housing services equal to ϕ_L . We model the boom as a combined switch to high labor productivity, looser credit conditions, and housing utility state ϕ_L^* starting in 2001. The switch to ϕ_L^* means that all agents in the economy, not just households but also firms in the financial and rental sectors, rationally believe that a future increase in housing demand is now more likely (a point we return to in Section 5.1). We model the bust as a reversion of all three shocks to their pre-boom values in 2007.

Since we simulate a switch from ϕ_L to ϕ_L^* and vice-versa, at no point in our experiment is there any change in actual preferences for housing services; there is only a shift in the probability that such a change might occur in the future. We thus refer to this shift as a house price expectations/beliefs shock, since in equilibrium it generates an increase and subsequent decline in expectations of future house price growth. Figure F1 in the Appendix plots the realized path for expected house price growth generated by the switch, which is in line with the survey evidence discussed earlier.

Figure 1 plots the realized paths for the three components of the aggregate shocks over the boom-bust episode. The parameters of the combined shock process in Table 3 imply that the ex-ante probability (in 1997) that this particular history of shock realization occurs is very low, around 0.05%. Thus, through the lens of our model, the boom-bust episode of the 2000s is a tail event. As in every rational expectations equilibrium, all agents in the model always use correct conditional probability distributions to compute expectations, but the realized path of shocks in the boom-bust episode is very different from the paths that were most likely to occur ex-ante.

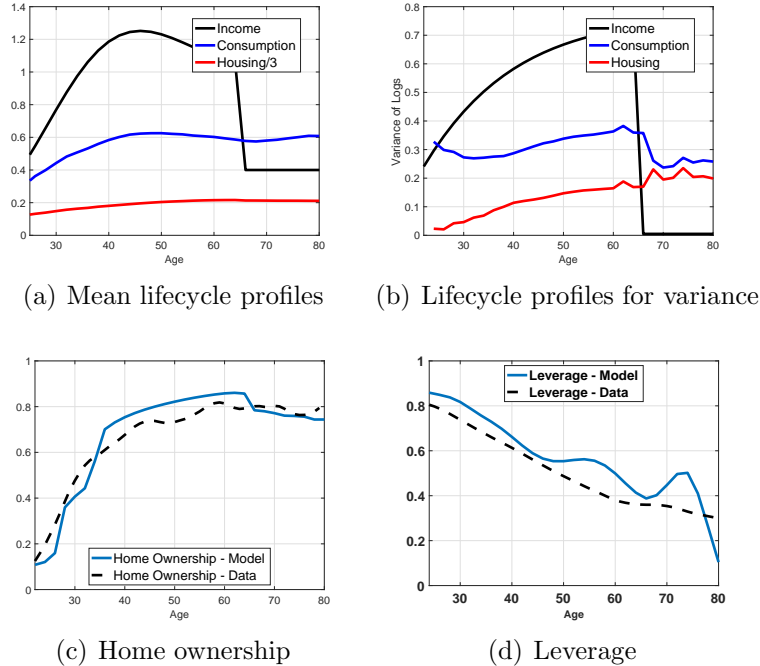


Figure 2: Top-left panel: Average earnings, nondurable and housing expenditures by age in the model. Top-right panel: Age profile of the variance of the logs for these same variables in the model. Bottom-left panel: home ownership in the model and in the data (source: SCF 1998). Bottom-right panel: leverage ratio among home-owners with mortgage debt in the model and in the data (source: SCF 1998).

3.3 Household Distributions in the Stochastic Steady State

Before examining the dynamics of the economy over the boom and bust period, we briefly present a set of predictions from the parameterized model in the stochastic steady-state that we did not explicitly target in the calibration.

Lifecycle Implications Figure 2 displays the lifecycle profiles for several key model variables. The mean lifecycle profiles for labor income, pension income, nondurable consumption and housing consumption are displayed in panel 2(a) and the corresponding lifecycle profiles for the variance of logs of these variables are displayed in panel 2(b). The shape of these profiles is typical of incomplete market models and broadly consistent with their empirical counterparts (Heathcote et al., 2010).

Figure 2(c) shows that the lifecycle profile of home ownership in the model rises steadily from 10% at age 25 to 80% at age 55 and then levels off, consistent with data. Home ownership rises with age in the model for two main reasons. First, it takes time for households to accumulate enough savings to overcome the downpayment and PTI constraints in order to

Size	< 35		35 – 49		50 – 64		≥ 64	
Class	Data	Model	Data	Model	Data	Model	Data	Model
1-2	42	63	30	52	32	41	34	37
3	28	24	24	19	24	19	25	18
4	15	12	18	10	18	16	18	18
5	8	1	10	17	11	15	9	16
6	5	0	11	2	9	9	8	9
7	3	0	6	0	6	1	5	2

Table 4: Distribution of owner-occupied housing sizes over the life-cycle (percentages). Data: AHS. Our segmentation assumption implies that the smallest house size cannot be owned, so in the table we grouped house sizes 1 and 2 together. In the data, on average only 9% of owners live in the smallest house size.

buy a house of desired size. Because of the income and wealth heterogeneity some households succeed earlier than others. Second, with CRRA utility the optimal portfolio allocation implies a roughly constant share of the risky asset. Since the only risky asset in our model is housing, as wealth grows over the lifecycle so does the amount of owner-occupied housing.

Figure 2(d) shows that, among home owners with mortgages, leverage (defined as the ratio of debt to house value) declines with age, which is also consistent with SCF data. Debt decreases steeply during the working life because of the retirement savings motive, and continues to decrease in retirement because the mortgage interest deduction becomes less valuable as income, and the relevant marginal tax rate, falls.

In Table 4 we report the distribution of house sizes over the life cycle for home owners in the data (American Housing Survey) and in the model. The model reproduces this distribution well, with the exception that it somewhat underestimates the ownership of large houses by young and middle-age households, a manifestation of the fact that it underestimates wealth concentration at the top, as we explain below.

Cross-sectional Implications Table 5 reports some additional cross-sectional moments of interest in the model and the data (1998 SCF). The model matches the distribution of house values for homeowners and the distribution of LTVs for mortgagors well.

Below the top decile, the wealth distribution in the model closely reproduces the wealth distribution in the SCF. The Gini coefficient for net worth is 0.69, compared with 0.80 in the data. As is common in this class of models, we miss the high degree of wealth concentration among the rich that is observed in the data. However, for the main questions of this paper this shortcoming is not too problematic: for households in the top 10% of the

Moment	Empirical value	Model Value
Fraction homeowners w/ mortgage	0.66	0.56
Fraction of homeowners with HELOC	0.06	0.03
Aggr. mortgage debt / housing value	0.42	0.34
P10 LTV ratio for mortgagors	0.15	0.14
P50 LTV ratio for mortgagors	0.57	0.58
P90 LTV ratio for mortgagors	0.92	0.89
Gini of NW distribution	0.80	0.69
Share of NW held by bottom quintile	0.00	0.00
Share of NW held by middle quintile	0.05	0.08
Share of NW held by top quintile	0.81	0.69
Share of NW held by top 10 pct	0.70	0.35
Share of NW held by top 1 pct	0.46	0.07
P10 house value / earnings	0.9	1.0
P50 house value / earnings	2.1	2.0
P90 house value / earnings	5.5	4.3
BPP consumption insurance coeff.	0.36	0.41

Table 5: Other implied cross-sectional moments not explicitly targeted in the model parameterization. Source: SCF 1998, except for the consumption insurance coefficient (Blundell et al., 2008).

wealth distribution, housing represents only one-quarter of their net worth, and thus one would expect these households not to play a major role in the dynamics of aggregate house prices and consumption.²⁸

We have also computed the aggregate marginal propensity to consume out of a small windfall of cash to be 39.5% over the two-year model period. This value is well in line with the empirical estimates discussed, for example, in Kaplan and Violante (2014). Matching this statistic is important since one of our goals is to quantify the transmission of house prices into consumption and, as shown by Berger et al. (2017), a change to house prices is akin to a transitory income shock. In addition, it provides independent evidence that our model does not misrepresent the share of constrained consumers.

Finally, in order to assess the plausibility of the degree of substitution between the rental and owner-occupied stocks implied by the segmentation in Table 1, we perform two additional comparisons between data and model. First, Table 6 compares the cross-sectional distribution of house sizes for renters and owners. This table shows that our partial segmentation assumption fits the data (American Housing Survey) quite well: in the data only 9% of home owners live in the smallest house size and 10% of renters live in the largest four house sizes. Second, we compare the average change in house size for households who switch house, conditional on their tenure status before and after the transition, in the data and in the model. The empirical counterparts of the model are estimated from the PSID for survey

²⁸In fact, the literature on the recent housing crisis singlehandedly emphasizes the role of the low- and middle-income homeowners (see Adelino, Schoar, and Severino, 2016; Foote et al., 2016; Mian and Sufi, 2016a).

Size Class	Owners		Renters	
	Data	Model	Data	Model
1	9	0	51	76
2	24	40	28	16
3	25	20	11	7
4	18	16	5	0
5	10	15	2	0
6	9	7	1	0
7	6	2	2	0

Table 6: House size distribution between owner-occupied and rentals in the data and in the model (percentages). Data AHS. Our segmentation assumption implies that the smallest house size cannot be owned and the largest four house sizes cannot be rented.

	$R \rightarrow O$	$R \rightarrow R$	$O \rightarrow R$	$O \rightarrow O$
Data	0.25 (0.01)	0.04 (0.01)	-0.29 (0.01)	0.04 (0.01)
Model	0.22	0.01	-0.10	0.06

Table 7: Average log-changes in house size (housing units in the model, number of rooms in the data) by type of transition. Standard errors in parenthesis. O: Owner, R: Renter. Data source: PSID 1968-1996. See Appendix E for details.

years 1968-1996, i.e. the pre-boom period corresponding to our stochastic steady state. Appendix E contains a detailed description of sample selection and methodology. Table 7 shows that the model is broadly consistent with the data, except for the fact that it under-predicts the average drop in house size for owner-rental transitions.

4 Results

We organize our quantitative findings around three questions:

1. What were the sources of the boom-bust in the housing market?
2. To what extent, and through what channels, did the changes in house prices transmit to consumption expenditures?
3. Are these mechanisms consistent with the cross-sectional patterns of mortgage debt expansion during the boom and mortgage defaults during the bust?

Throughout our analysis, we exploit the orthogonal nature of the shocks to decompose the dynamics of different aggregate time series into the effects of labor income, credit conditions

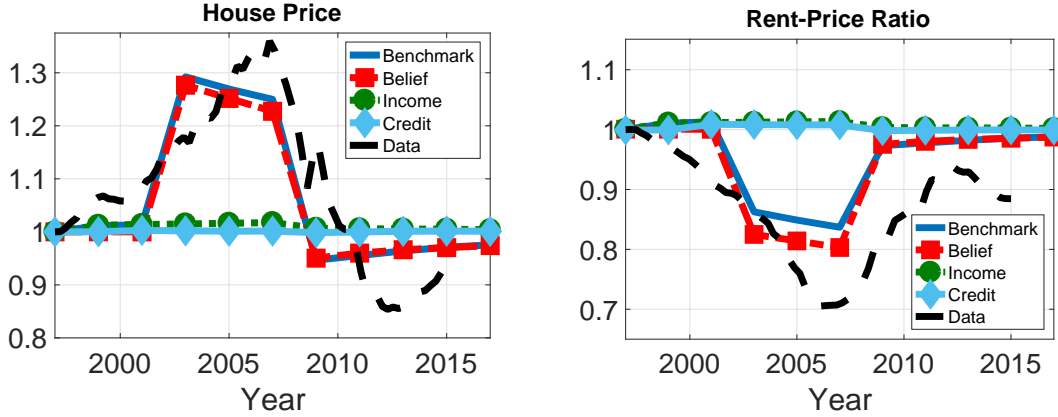


Figure 3: Left panel: house price. Right panel: rent-price ratio. Benchmark is the model’s simulation of the boom-bust episode with all shocks hitting the economy. The other lines correspond to counterfactuals where all shocks are turned off, except the one indicated in the legend. Model and data are normalized to 1 in 1997.

and beliefs. We do this by simulating the equilibrium dynamics that occur when each shock hits the economy in isolation. Although the shocks themselves are orthogonal, there are sometimes strong interactions in the economy’s response to the shocks so that, in general, the three components do not sum to the equilibrium dynamics that occur when all shocks hit the economy simultaneously (which we refer to as the benchmark economy).

4.1 Aggregate Boom-Bust Dynamics of the Housing Market

We start with the model’s implications for the dynamics of house prices and rent-price ratios. We then analyze the dynamics of home ownership, leverage, and foreclosures. In each case, we compare the model to its empirical time-series counterpart. See Appendix E for the relevant data sources.

House Prices and Rent-Price Ratio The benchmark model features a 30% increase in house prices followed by a similar-size decline (left panel of Figure 3). The decomposition reveals that the only shock that generates substantial fluctuations in house prices is the shift in beliefs about future house price appreciation. Changes in labor productivity lead to very small deviations in house prices – to the extent that housing is a normal good, housing demand responds to persistent income fluctuations – and changes in credit conditions have a trivial impact on house prices. The inability of changes in credit conditions to bring about significant movement in house prices is one of the main conclusions of our paper, and one to which we will return repeatedly. Our findings suggest that the boom and bust in house prices was due to a shift in expectations about future house price growth, not a shift in

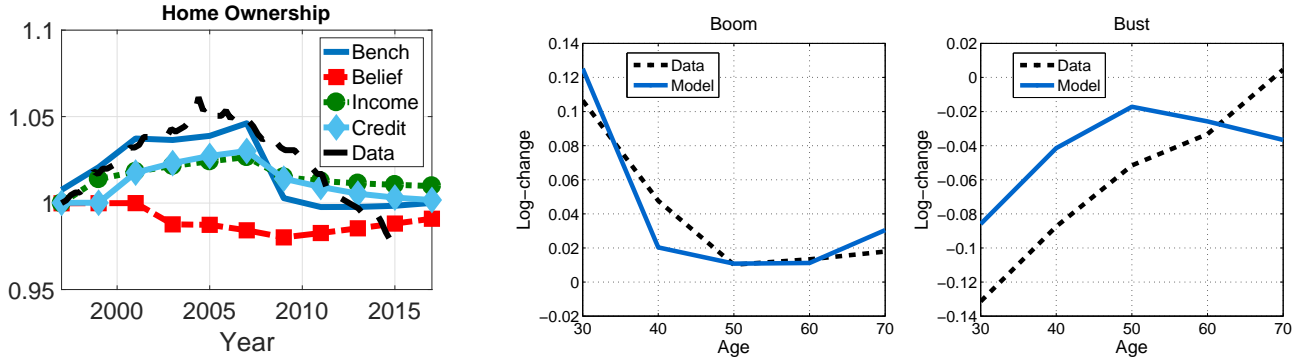


Figure 4: Change in home ownership over time (left panel) and across age groups (right panel) in the data and in the model. In the left panel, model and data are normalized to 1 in 1997.

credit conditions.

The model can generate more than half of the fall in the rent-price ratio observed in the data (right panel of Figure 3). The decomposition again demonstrates that this is almost entirely accounted for by the belief shock. To understand the dynamics of the rent-price ratio, it is useful to return to the equilibrium condition for the rental rate (11) (recall that, for now, we assume $\mathbf{m} = (1 + r_b)^{-1}$). This condition dictates that when current prices increase, rents increase too. So, without any change in beliefs, the rent-price ratio would remain roughly stable (or even go up, if the house price dynamics were mean-reverting). Under the belief shock, however, there is an increase in expected future house price growth, which pushes down rents and aligns the rent-price ratio in the model with its empirical counterpart.²⁹

Home Ownership Figure 4, which displays the model’s implication for home ownership, shows that the benchmark model matches the dynamics in the data well. By itself, the belief shock reduces home ownership during the boom by pushing down the rent-price ratio (dashed line in Figure 4) for two reasons. First, rents are cheaper relative to prices, which moves people at the margin towards renting. Second, the large increase in prices induced by the shift in beliefs makes the downpayment constraint binding for more households.

Both the productivity shock and the credit conditions shock, however, induce boom-bust dynamics in home ownership. The productivity shock results in a persistent rise in aggregate income, which relaxes the PTI constraint and pushes those renters for whom the constraint was binding toward buying a house. This force accounts for a 3% increase in home ownership. The relaxation of credit conditions has a similar size effect on home ownership that operates by relaxing the LTV constraint and lowering the cost of originating mortgages.

²⁹For this effect to be operational, it is important that rental companies share the same expectations as households. See Section 5.1 for a detailed discussion on the role of beliefs of different agents (households, financial intermediaries, and rental companies) in the economy.

Summing the individual effects of three shocks does not generate the home ownership dynamics in the benchmark model. The gap is due to an interaction between the belief shock and the relaxation of credit limits: taking advantage of looser PTI and LTV constraints requires sacrificing current consumption, which is more acceptable when house prices are expected to grow. In other words, the belief shock makes more households *want* to own more housing, while the credit conditions shocks makes more households *able* to buy a house.

The middle and right panels of Figure 4 show the change in home ownership for households of different ages. In both model and data, the rise and fall in home ownership is predominantly driven by young households. They dominate the movements in home ownership because these are the households for whom LTV and PTI constraints are most likely to bind and, as a result, those for whom credit relaxation and rise in income are most salient.

Decoupling of House Prices and Home Ownership We have shown that a relaxation of credit conditions has a strong effect on home ownership but not on house prices. What explains this surprising decoupling of house prices dynamics from home ownership dynamics following a credit shock?

For a credit boom to have a large effect on house prices, it is necessary for the economy to feature a large number of households who are constrained in the amount of housing services they consume. In this case, cheaper credit goes hand in hand with more housing demand. However in our model, as in the data, very few households are constrained in this way: rather than buying excessively small houses, they prefer the option to rent a house of the desired size. A credit relaxation induces renters to become owners, but these switchers buy similar sized houses to the ones they were previously renting. Therefore, home ownership increases without pushing up total housing services demanded and, hence, house prices.

Why, then, are renters buying when these constraints are relaxed if they are already consuming nearly the optimal amount of housing services? The answer lies in the fact that housing is both a consumption good and an asset, and the optimal asset portfolio allocation features a share of housing wealth. Thus credit limits, first and foremost, constrain households in their tenure status and thus their asset portfolio choice, not in the amount of housing services they demand.³⁰

In light of this discussion, it now becomes clear that the belief shock, instead, induces households (especially current home-owners who benefit from current appreciation) to buy bigger houses in order to take advantage of the expected future house price growth, which

³⁰As illustrated by [Landvoigt et al. \(2015\)](#), changes in credit conditions may have small effects on average house prices at the aggregate level, but they could have a larger impact on specific housing market segments populated by low-income borrowers for which constraints are more likely to bind.

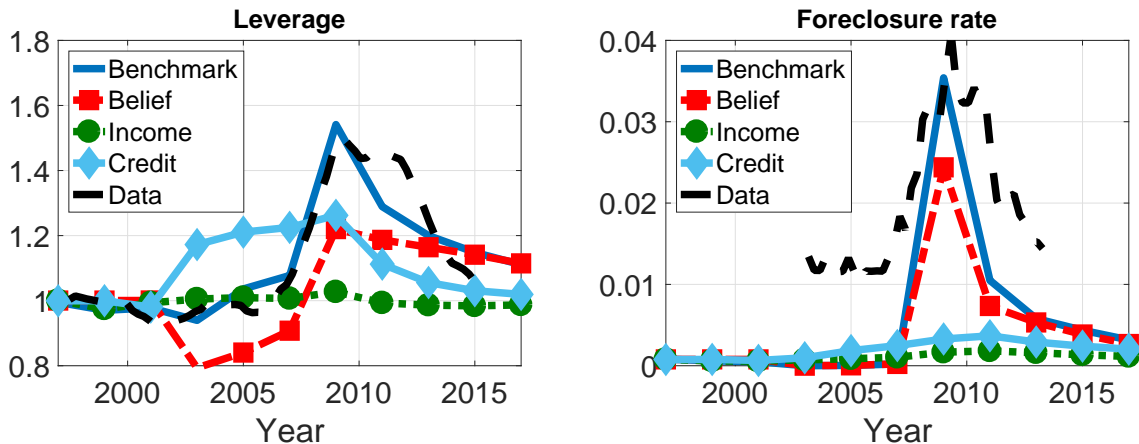


Figure 5: Left panel: leverage. Right panel: foreclosure rate. Benchmark is the model’s simulation of the boom-bust episode with all shocks hitting the economy. The other lines correspond to counterfactuals where all shocks are turned off, except the one indicated in the legend. Model and data are normalized to 1 in 1997.

pushes up house prices.

Leverage The left panel of Figure 5 displays the model’s implications for the dynamics of leverage, which is defined as aggregate mortgage debt divided by aggregate housing wealth. The model can generate a flat path for leverage during the boom, as in the data, because of two offsetting effects. The shift towards optimistic expectations pushes up house prices causing leverage to fall, while looser credit conditions lead to an expansion in mortgage debt causing leverage to rise.

During the bust, the belief shock then generates a sharp mechanical rise in leverage because of the large drop in house prices. Yet despite the drop in house prices, the stock of mortgage debt remains well above its pre-boom level for over a decade, implying that households delever slowly. Long-term mortgages play a crucial role in these dynamics: households who do not want to default can slowly reduce their debt burden by sticking to their existing amortization schedule, thus avoiding large swings in consumption. As explained in Section 2.2, if mortgages were short-term, then changes in house prices would induce nearly proportional changes in debt. In Section 5.4, we present an economy with only short-term debt where deleveraging behavior is much more abrupt.³¹

³¹In our model, only households who are near the maximum limit on HELOCs are forced to delever, but their effect on the aggregate economy is small because very few of them are in that situation when prices start to fall. This is consistent with the data: at the peak of the boom, only around 4% of home owners had an HELOC usage rate beyond 75% (SCF 2004 and 2007).

Foreclosures The spike in foreclosures in the model (right panel of Figure 5) is close in size to the spike in the data. In the model, the foreclosure crisis is driven by the collapse in house prices from the belief shock, which pushes many households underwater, not by the tightening of credit conditions. The tightening of credit conditions does not generate a spike in foreclosures for two reasons: (i) it does not move prices and (ii) in an environment with long-term debt, a tightening of LTV and PTI constraints is only relevant at origination. The figure shows that, as for home ownership, there is a strong interaction between credit conditions and beliefs. Credit relaxation amplifies the effect of belief shifts on foreclosures because, during the boom, it enables optimistic buyers to obtain larger and cheaper mortgages. When prices fall, it is then more likely that households find themselves underwater on their mortgages. As we explain in Section 5.1, it is important for these dynamics that lenders also experience the same shifts in their expectations.

4.2 Consumption

Figure 6 (left panel) shows that the model generates a similar size boom and bust in consumption as in the data.³² Because it does not affect prices, the credit conditions shock has virtually no effect on nondurable consumption. Around one-half of the movement in consumption is due to the labor income shock, with the remainder due to the belief shock. The belief shock affects consumption through its impact on house prices. We therefore conclude that around one-half of the boom-bust in consumption can be accounted for directly by changes in house prices.

What is the transmission mechanism for changes in house prices to consumption? The right-panel of Figure 6 shows that a wealth effect can go a long way in explaining the dynamics of consumption.³³ The panel plots the change in log consumption during the bust for households with different ratios of net housing wealth to total wealth at the peak of the boom.³⁴ The sharp negative slope indicates that the larger is the share of housing wealth in total wealth, the bigger is the impact of the fall in house prices on consumption. Quantitatively, the semi-elasticity of expenditures with respect to this ratio is not far from one.

Why does the negative wealth effect from the fall in house prices generate a fall in

³²The model also generates plausible movements in the current account, roughly 2-3% of output, over the boom-bust episode.

³³This effect is variously referred to as a wealth effect, an endowment income effect or an endowment effect. Berger et al. (2017) distinguish between this endowment income (wealth) effect and three other channels: an ordinary income effect, a substitution effect, and a collateral effect in the transmission of house prices to consumption.

³⁴Total wealth includes housing net worth, financial wealth and human wealth. Human wealth is computed as the expected future flows of earnings and social security benefits discounted at the risk-free rate.

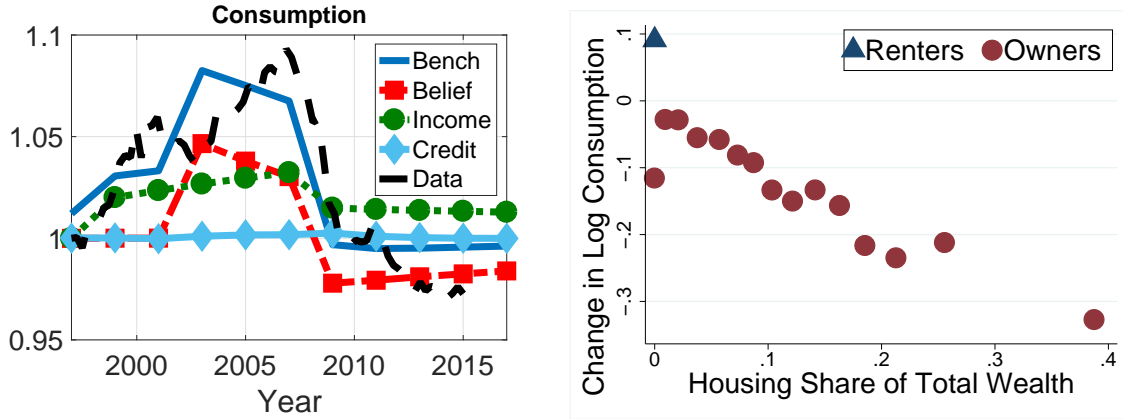


Figure 6: Left panel: consumption. Benchmark is the model’s simulation of the boom-bust episode with all shocks hitting the economy. The other lines correspond to counterfactuals where all shocks are turned off, except the one indicated in the legend. Model and data are normalized to 1 in 1997. Right panel: Log-change in consumption during the bust (2007-11) plotted against the housing net worth share of total wealth (including human wealth), from the model.

aggregate consumption? After all, there are counteracting forces that work in the opposite direction. For example, Figure 6 shows that the drop in house prices leads to a *positive* wealth effect for renters who plan to become homeowners in the future: since housing is cheaper, they don’t have to save as much for the down payment and can afford to consume more. It also generates a positive wealth effect for some existing homeowners who plan to upsize in the future – those who expect to upsize by more than the quantity of housing that they currently own.³⁵

The sign and size of the *aggregate* wealth effect on nondurable expenditures thus depends on the joint distribution across households of expected future changes in housing units and marginal propensities to consume (MPCs). The lifecycle dimension is crucial here and the age profiles in Figure 2 offer some valuable clues to the shape of this distribution. These figures show that by age 40-45, both the extensive margin (home ownership rate) and the intensive margin (housing units consumed) have effectively leveled off, meaning that the majority of households expect to climb down, rather than up, the housing ladder in the future. In our simulations, around 75% of households —accounting for around 80% of aggregate consumption— experience a negative wealth effect from the fall in house prices (that is they expect to either downsize, or upsize by less than the current stock of housing

³⁵A simple example that abstracts from leverage may help illustrate this point. Imagine a homeowner currently owns a house of size 1 and will upsize to a house of size 3 in the future. This household experiences a negative wealth effect on its existing stock (1), but it also receives a positive wealth effect on the amount that it wants to buy ($3 - 1 = 2 > 1$) such that, on net, that household has a positive wealth effect from the drop in prices.

they own).³⁶ Despite having slightly smaller MPCs on average than the remaining 25% of households, their abundance means that the aggregate effect is a fall in consumption.³⁷

The aggregate elasticity of consumption to house prices in our model is 0.20. This elasticity is broadly consistent with the rule-of-thumb advocated by [Berger et al. \(2017\)](#), in which only the wealth effect is operative. Applying their formula to the version of our model with only the belief shock (the version most comparable to their partial equilibrium model) yields an elasticity of 0.18.³⁸

4.3 Cross-Sectional Distribution of Debt and Foreclosures

In the last decade, a large empirical literature has developed that seeks to advance our understanding of the causes and consequences of the housing boom and bust by exploiting cross-sectional variation (across either households or regions) in house prices, balance sheets, housing market outcomes, financial conditions, consumer expenditures and labor market outcomes. A centerpiece of the early literature ([Mian and Sufi, 2009](#); [Mian et al., 2013](#); [Mian and Sufi, 2014](#)) was the emphasis on subprime borrowers – households who were excluded from mortgage markets before the credit relaxation of the early 2000’s opened the door for them to become home owners. This group of low-income, high-risk households was identified as the group most responsible for the expansion in mortgage debt during the boom, and for the consequent delinquencies and foreclosures during the bust.

As more and better data have become available (e.g. credit bureau data and loan-level data), the consensus on what these cross-sectional patterns reveal has evolved ([Adelino et al., 2016](#); [Albanesi et al., 2016](#); [Foote et al., 2016](#)). At least two challenges to the subprime view have been raised.

First, the left-panel of [Figure 7](#), reproduced from [Foote et al. \(2016\)](#), demonstrates that credit growth during the boom years was not concentrated among low-income households, but rather was uniformly distributed across the income distribution. The right-panel of [Figure 7](#) shows that our model is consistent with this observation. The shift in expectations about future house price growth is the key reason why the model generates an expansion

³⁶In their overlapping generations model, [Kiyotaki et al. \(2011\)](#) find that house price movements have negligible effects on aggregate consumption, but their calibration implies a much more pronounced hump in the home ownership profile and, as a consequence, positive and negative wealth effects offset each other more among the living generations.

³⁷The group of net upsizers is heavily weighted toward young, constrained households, whereas the group of net downsizers consists of both retired households (with high MPCs) and households in their prime retirement savings years (45-64) who have low MPCs.

³⁸For the reasons explained at length throughout the paper, the collateral channel is insignificant in our model. We verified that the substitution and income channels are also jointly unimportant by running experiments with a wide range of values for the elasticity of substitution between housing and nondurables. These all lead to similar size drops in consumption.

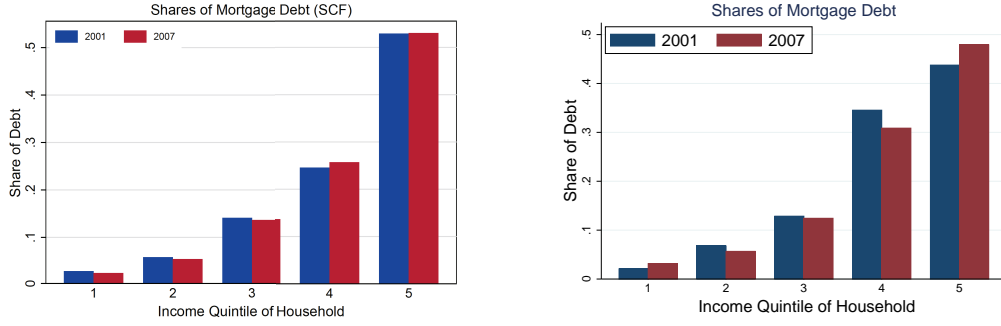


Figure 7: Left panel: Share of mortgage debt by income level in 2001 and 2006 from Foote et al. (2016). Right panel: Share of mortgage debt by income level in the model in 2001 and 2007.

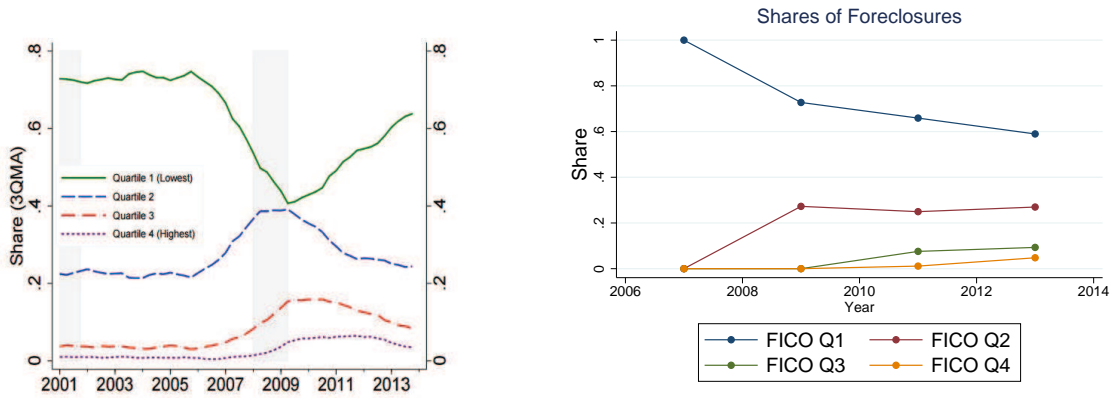


Figure 8: Left panel: Share of foreclosures by quartile of FICO score from Albanesi et al. (2016). Right panel: Share of foreclosures in the model by quartile of default probability, a proxy for FICO score.

of credit even for high-income households. All households expect large capital gains from holding housing, but high-income, low-risk households are those in the best position to take advantage of the optimistic beliefs, since they can access low-cost mortgages even in the absence of looser credit conditions.

Second, the left panel of Figure 8, reproduced from Albanesi et al. (2016), shows that the shares of foreclosures for households in the lowest quartile of the FICO score distribution at origination decreased during the bust. This observation suggests that prime borrowers contributed to the dynamics of the housing crisis at least as much as sub-prime ones. There is no explicit notion of credit score in our model, but we can proxy a household’s credit score by computing its default probability from the viewpoint of the financial institution, i.e. the value of the individual equilibrium mortgage rate spread at origination. The right panel uses this approach to construct the model counterpart of the left panel.

The model is consistent with a decline in the share of foreclosures among subprime borrowers (who, as in the data, always account for by far the largest share). Once again, the

reversal of expectations is key. A sizable fraction of prime borrowers, who levered up to buy more housing expecting to soon realize capital gains, find themselves with negative equity and choose to default.³⁹

5 Understanding our Results

Lying at the heart of all the results in Section 4 are differences in the way the economy responds to changes in beliefs about future housing demand, versus changes in credit conditions. In Sections 5.1 and 5.2 we show how alternative modeling choices for these two shocks would affect our findings. In Section 5.3 we show that our findings are robust to alternative modeling of the rental market. Finally, in Section 5.4 we demonstrate that if we suppress the two key model—and real world—ingredients (rental markets and long-term mortgages) that determine how the economy reacts to aggregate shocks, credit shocks can indeed lead to large fluctuations in house prices.

5.1 The Role of Beliefs

In our model we generate rational changes in beliefs about future house prices through exogenous stochastic changes in the conditional probability distribution over future preferences for housing services. Generating changes in expectations of future house price growth in this way implicitly entails three assumptions: (i) that all agents in the economy share these beliefs; (ii) that there is a change in beliefs about preferences, rather than a change in actual preferences; and (iii) that changes in beliefs are over a parameter that affects housing demand, rather than housing supply. We now assess these assumptions via counterfactual experiments where we modify some aspects of the belief shock. In all experiments, credit conditions and labor productivity shocks follow the same realized paths as in the benchmark economy.

5.1.1 Whose Beliefs Matter?

In our benchmark experiment, all agents in the economy (households, lenders, and rental companies) share the same beliefs about housing preferences. This means that when preferences switch from state $\phi = \phi_L$ to $\phi = \phi_{L^*}$ there are at least four channels through which the resulting shifts in beliefs could affect the economy.

³⁹In the data, credit growth is also uniform across FICO scores at origination (Adelino et al., 2017). When we use our same model-proxy for credit scores, we find that the model is also consistent with this observation.

(1) Own Beliefs vs (2) Other Households' Beliefs Individual households believe that in the future they themselves are likely to desire more housing services relative to nondurable consumption. Since housing adjustment is costly, they might increase their housing demand immediately, even in the absence of any current change in house prices (which we refer to as the direct effect). Moreover, individual households believe that all other households are likely to desire more housing services in the future, and thus rationally foresee that this future expansion in housing demand will lead to higher future house prices. A speculative motive may thus lead a household to increase its housing demand, even if its own preferences are unchanged.

To measure the relative strength of the speculative motive versus the direct effect, we compute the optimal decisions of households in two hypothetical economies. In the first experiment, which is designed to isolate the speculative motive, we consider a set of households whose preferences for housing services remain fixed at ϕ_L and who face the equilibrium price dynamics from the benchmark economy. In the second experiment, which is designed to isolate the direct effect, we consider a set of households whose preferences shift from ϕ_L to ϕ_{L^*} as in the benchmark, but who believe that all other households' preferences remain fixed at ϕ_L .⁴⁰

In Figure F2 in the appendix, we show that in both of these experiments the implied boom-bust in house prices is smaller than in the data, between 7% and 10%, or around 1/4 of the one in benchmark economy, suggesting that each motive on its own is relatively weak. Although neither the direct effect nor the speculative motive is very powerful on its own, there is a strong interaction between the two. Optimistic expectations about their own preferences lead households to want to purchase more housing in the future; optimistic beliefs about other households' preferences leads to optimistic beliefs about house price growth, which induces them to move those purchases to the present. This drives up house prices and rationalizes those beliefs.

(3) Lender's Beliefs Mortgage lenders understand both the direct and speculative effects of the shift in household beliefs on prices and thus rationally expect future house prices to rise. Expectations of rising house prices are accompanied by expectations of lower default rates, so lenders optimally offer more attractive mortgage contracts to households. These endogenous improvements in credit conditions may lead households to demand more housing.

To quantify the importance of lenders' beliefs in explaining the aggregate dynamics surrounding the boom-bust episode, we consider two counterfactual economies in which lenders

⁴⁰To compute the implied effects on house prices, we invert the aggregate housing supply function from the baseline economy at the level of housing demand implied by the aggregation of household decisions in the two experimental economies.

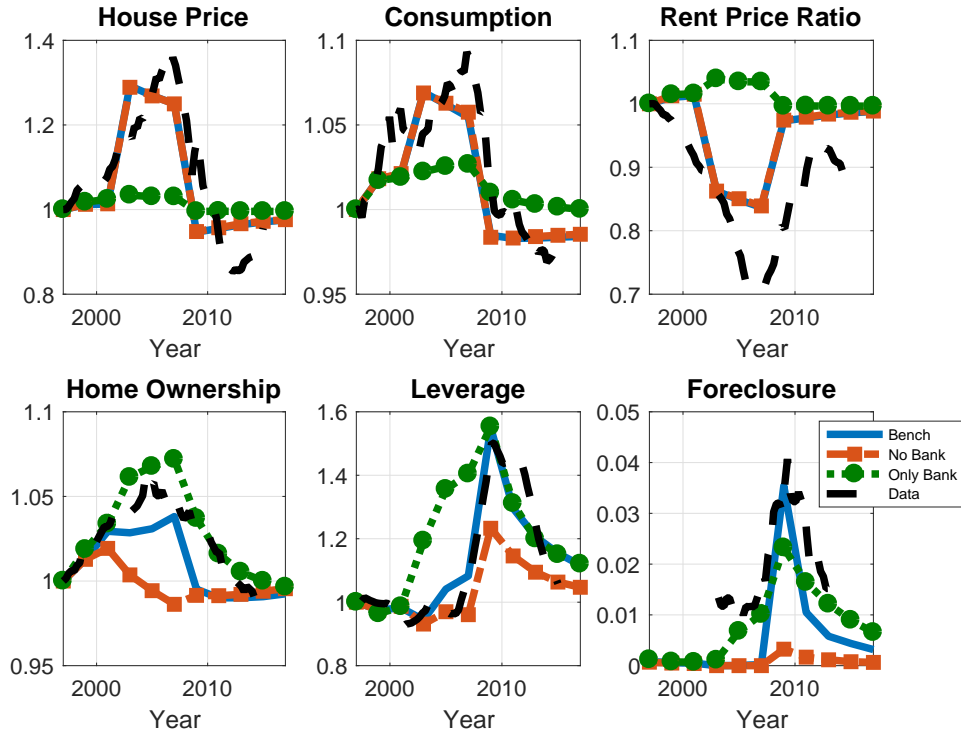


Figure 9: Only Bank: model where only lenders are subject to the belief shift (households and rental company are not). No Bank: model where the lenders are not subject to the belief shift (households and rental company are).

and households have different beliefs.

The lines labelled ‘Only Bank’ in Figure 9 reflect an economy where only mortgage lenders believe that the probability of transitioning to the high preference state ϕ_H rises and then falls, whereas households and the rental company remain pessimistic and believe that this probability is unchanged.⁴¹

When only lenders are optimistic, there is almost no boom-bust in house prices, and the movements in consumption are severely dampened relative to the benchmark. Because there is little growth in house prices, the pessimistic household economy does not generate a fall in the rent-price ratio and implies counterfactually high leverage during the boom.

The lines labelled ‘No Bank’ in Figure 9 reflect an economy where mortgage lenders are pessimistic in that believe that the probability of transitioning to the high preference ϕ_H is unchanged. Households and the rental company, instead, are subject to the shifts in

⁴¹To compute this equilibrium we assume that lenders price mortgages using the Markov transition matrix for ϕ as in the benchmark economy, whereas households make their optimal decisions using a modified Markov matrix in which transition probabilities in the ϕ_{L^*} state are the same as in the ϕ_L . In both states, households and rental companies use the same pricing forecast function as lenders do in the ϕ_L state. We compute the ‘No Bank’ equilibrium analogously.

expectations. This means that when the economy transitions from ϕ_L to ϕ_{L^*} in the boom, the default probabilities forecasted by the banks, and the implied offered mortgage rates, do not embed the impact of belief shifts on expected future house price growth.

The dynamics of house prices, consumption and the rent-price ratio are almost identical in the pessimistic lender economy and the benchmark. We thus conclude that lender beliefs are relatively unimportant for the boom-bust in house prices and consumption. However, the shifts in lenders' expectations are crucial for the dynamics of home ownership, leverage and foreclosure. In their absence, home ownership counterfactually falls when households become optimistic during the boom. Expansion of mortgage debt is 10% lower, which implies that this channel accounts nearly one-third of the total growth in debt during the boom. The effect on foreclosures is particularly stark – the foreclosure rate peaks at only 0.5% in the pessimistic lender economy, compared with 4% in the benchmark economy.

To better understand the role of lenders beliefs, it is useful to examine how the mortgage pricing schedule is affected by the optimistic beliefs of lenders during the boom. In Figure 10, we plot the endogenous mortgage borrowing rate, defined as the inverse of the price of a unit of mortgage debt $1/q_j(\mathbf{x}', y; \Omega)$ expressed as annual rate, as a function of the LTV at origination (see equation (10)).⁴² The solid line shows that, in normal times, the mortgage rate for this household increases from around 4.5% p.a. at low levels of leverage, where the default probability is close to zero, to nearly 7% p.a. at a LTV of 95%, which is the regulated maximum λ^m before the boom.

The dotted line in Figure 10 illustrates how the relaxation in credit conditions both lowers mortgage rates (approximately) uniformly across leverage and increases the range of feasible LTV ratios. The former effect is due to the reduction in the fixed and proportional origination costs, κ^m and ζ^m , and the latter effect is due to the increase in maximum LTV λ^m . Importantly, however, the relaxation in credit conditions leaves the *curvature* of the mortgage rate schedule unchanged.

The dashed line in Figure 10 shows that when lenders also believe that future house price growth will increase, and therefore expect lower default rates, the mortgage rate schedule flattens, leading to a fall in interest rates for highly-levered borrowers.⁴³ This is the sense in which our model generates an endogenous credit supply shock, i.e. an expansion of cheap funds to risky borrowers, using the language of Mian and Sufi (2009, 2016a) and Justiniano

⁴²This function depends on individual household characteristics that predict default. In the Figure we illustrate it for a 30 year-old household earning median income who is using all its savings for the downpayment to buy a \$150K house.

⁴³Demyanyk and Van Hemert (2009) document a decline in the subprime-prime spread between 50 and 100 basis points over the boom, once they control for LTV ratio. Figure 10 implies a similar reduction at the pre-boom maximum LTV ratio of 95%.

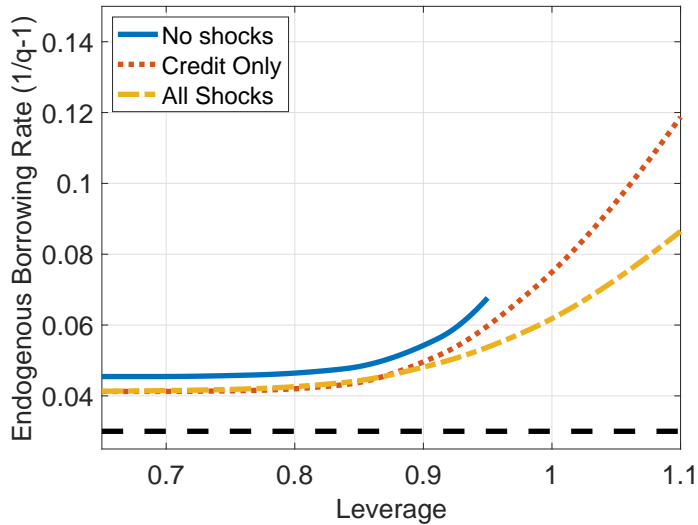


Figure 10: Mortgage interest rate as a function of leverage for a 30 year old household with median earnings who is using all its saving to buy a \$150K house. The switch to looser credit conditions induces a movement from the ‘No Shocks’ schedule to the ‘credit only’ schedule. The switch to optimistic beliefs (shared by all agents in the economy) induces a movement from the ‘Credit Only’ schedule to the ‘All Shocks’ schedule. The flat dashed line is the risk-free rate r_b .

et al. (2017).

In the absence of a shift in lender beliefs about expected future house price growth, high risk borrowers do not experience this endogenous fall in spreads. As a result, many of them either stay renters or, if they buy, take lower leveraged positions which are less prone to default in the bust. So while lenders’ beliefs have only a small effect on house prices, they are critical to match the joint dynamics of home ownership, leverage and foreclosure.

(4) Rental Company Beliefs In our benchmark experiment, during the boom rental companies also rationally expect an increase in future house prices, which lowers the user cost of housing and keeps the rental rate down (see equation (11)). As explained in Section 4, this force allows the model to match the sharp fall and subsequent rise in the rent-price ratio. If we had instead assumed that rental companies did not share these optimistic beliefs, then the model would imply counterfactual dynamics for the rent-price ratio and home ownership rate (see Figure F3 in the appendix). This finding highlights an important reason for the inclusion of rental markets in the analysis, as absent them one would infer that belief shocks lead to excessive rise in home ownership (Landvoigt, 2017).

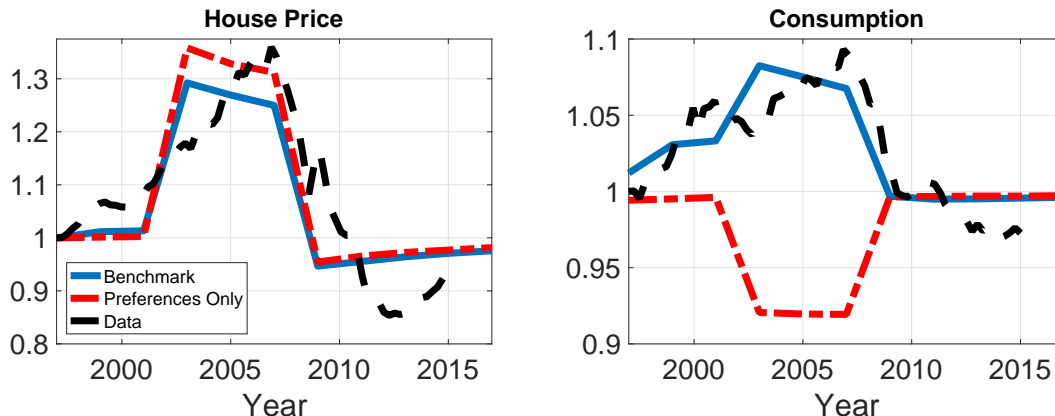


Figure 11: House prices and aggregate consumption. Benchmark is the model’s simulation with the shift in beliefs about taste for housing hitting the economy. Preferences Only is the model’s simulation with an actual shift in taste for housing ($\phi_L \rightarrow \phi_H \rightarrow \phi_L$) hitting the economy.

5.1.2 Belief Shifts or Preference Shifts?

Figure 11 shows the house price and consumption dynamics in the baseline economy, in which there is a shock to beliefs about future preferences (ϕ_L to ϕ_{L^*}), alongside a version of the model in which instead there is a shock to actual preferences (ϕ_L to ϕ_H).

Both shocks induce a similar boom-bust in prices. However, when actual preferences change (dashed line), the consumption dynamics are counterfactual. Since utility from housing services increases relative to nondurable consumption, households substitute away from consumption, causing it to drop sharply in the boom and to rise in the bust – the opposite of what was observed in the data. The joint dynamics of consumption and house prices are hence strong evidence against an *actual shift* in housing demand and are, instead, consistent with a *shift in beliefs* about future housing demand.⁴⁴

5.1.3 Beliefs about Housing Demand or Supply?

In our benchmark experiments, we generate growth in future house price expectations through an increase in beliefs about future utility from housing services. This mechanism has large effects because, if that change in preference were actually to occur, it would indeed generate an increase in equilibrium house prices (see left panel of Figure 11). In fact, it is possible to induce a boom-bust in house prices through a change in beliefs over *any* structural parameter, provided that were that change to actually occur, equilibrium house

⁴⁴With strong enough complementarity between housing and nondurable consumption in the utility function, it would be possible to generate an increase in nondurable expenditures in response to a positive preference shock for housing services. However, such a high degree of complementarity would imply vastly counterfactual changes over time (both at low and high frequencies) in the aggregate share of housing services in total consumption.

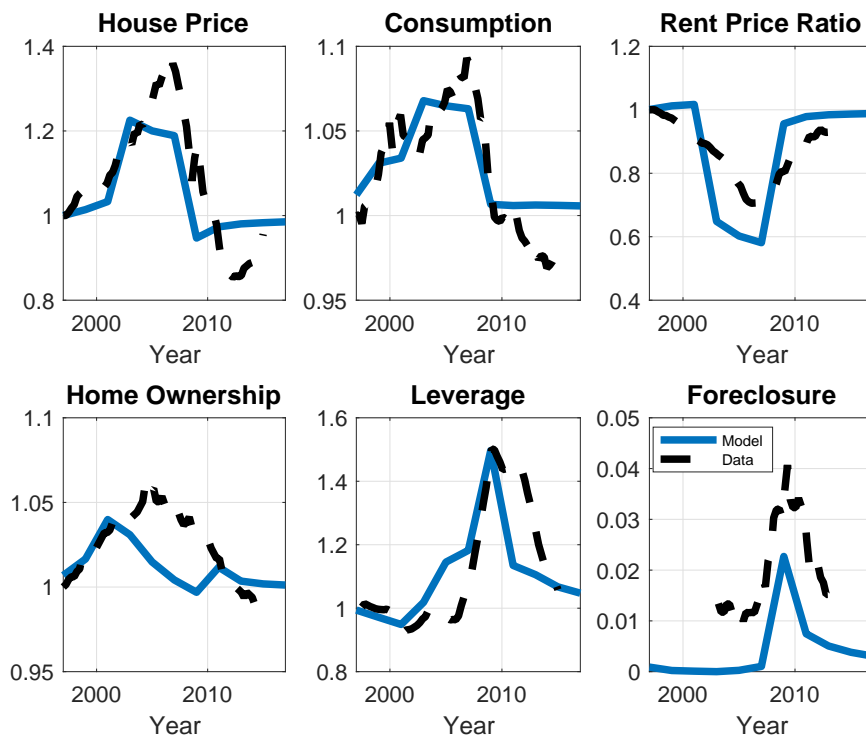


Figure 12: Model where beliefs are over the supply of future land permits compared to the data.

prices would qualitatively move significantly. In particular, it is not essential that the swing in beliefs affects housing demand rather than housing supply.

To illustrate this alternative, we consider a version of the model in which the ergodic distribution of ϕ is degenerate at ϕ_L , but in which there is stochastic variation in the number of new land permits \bar{L} that are made available by the government for construction. We use a similar three state belief structure, in which there are two states with loose land supply, \bar{L}_H and \bar{L}_{H^*} , and one state with tight land supply \bar{L}_L . The number of available permits is the same in the two loose states, $\bar{L}_H = \bar{L}_{H^*}$, but under \bar{L}_{H^*} the probability of transitioning to the tight state is high. We generate an increase in expected future house price growth by assuming that households come to believe that *fewer* land permits will be available in the future, i.e. a shift from \bar{L}_H to \bar{L}_{H^*} . The bust is obtained through a switch back to \bar{L}_H .⁴⁵ We assume that in the tight land supply state the number of new permits issued is two-third of that in the loose states.

The aggregate dynamics associated with this experiment, displayed in Figure 12, are similar to those in the baseline. House prices rise by around 20%, which is more than

⁴⁵Nathanson and Zwick (2017) argue the city of Las Vegas provides a stark example of how the perception of future availability of buildable land can affect residential investment and house prices.

half of the observed increase. As with the preference shock in the baseline economy, it is important that what changes are beliefs about future land supply, rather than land supply itself. Although a fall in the actual number of available land permits would lead to an increase in prices, it would also lead to a counterfactual drop in housing investment (analogously to the counterfactual drop in consumption in the right panel of Figure 11).

This finding illustrates a more general force suggesting that shifts in beliefs about preferences or technology parameters, rather than actual shifts in these structural parameters, account for the boom-bust in house prices.

5.2 Alternative Models of Credit Relaxation

A central finding in Section 4 was that a relaxation and subsequent tightening of credit conditions has very little power to generate a boom-bust in house prices and consumption. We now show that this finding is not a consequence of the particular way that we model credit relaxation by considering three alternatives that have been proposed in the literature and showing that in all cases this finding is unaffected.

5.2.1 Houses as ATMs

One aspect of the rise in securitization of private label mortgages that we have not so far considered, is the rise in approval rates for second liens and looser limits on HELOCs, which allowed both new and existing homeowners to extract a larger fraction of their home equity. In our model, we capture these effects, which are commonly referred to as “houses as ATMs” (Chen et al., 2013), through an increase in the maximum HELOC limit λ_b .

Figure 13 shows the equilibrium house price (top left panel) and consumption dynamics (top right panel) in response to a loosening and subsequent tightening of HELOC limits, from 0.2 to 0.3 and back again (line labelled “ATM”).⁴⁶ As with the baseline model of credit conditions, changes in HELOC limits have almost no effect on house prices and consumption. This finding is a consequence of matching the distribution of HELOC take-up and usage rates in the data, which suggest that only a minority of households were close to their limit at the time of the relaxation, so the looser constraint barely affects their consumption or housing demand. Figure 13 shows also that the equilibrium dynamics for home ownership (bottom left panel) and leverage (bottom right panel) are also barely affected by the change in HELOC limits.⁴⁷

⁴⁶The value of 0.3 corresponds to the 90th percentile of the HELOC limit distribution for households in the SCF who originated mortgages within the previous two years during the boom.

⁴⁷Figure F4 in the Appendix shows foreclosures for all alternative representations of the credit shock. In all of them, as in the benchmark, the shift in credit conditions alone has virtually no impact on foreclosures.

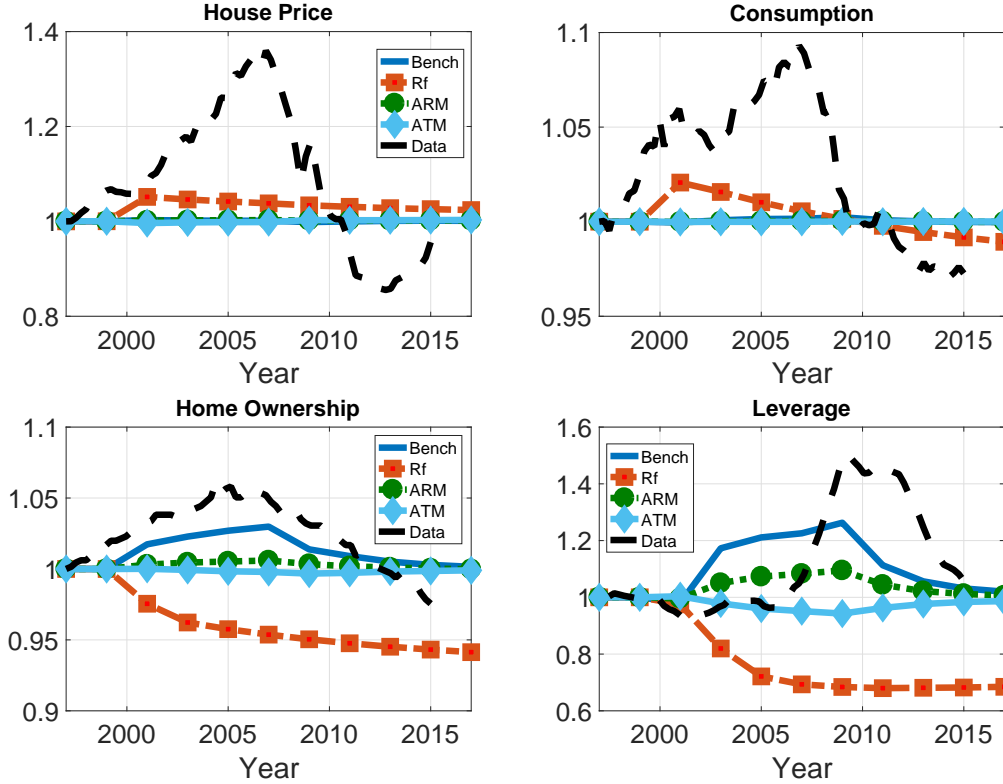


Figure 13: House price, consumption, home ownership and leverage dynamics under alternative models of credit relaxation. Bench: benchmark credit shock. ATM: shifts in the maximum HELOC limit. ARM: shifts in the amortization rate. Risk free: decline in the risk free rate. All series are normalized to 1 in 1997.

5.2.2 Adjustable Rate Mortgages

Another aspect of the mortgage market environment of the early 2000's that we have not so far considered was the proliferation of adjustable rate and low teaser-rate mortgages. These had the effect of lowering monthly mortgage payments and thus simultaneously making home ownership more attractive while freeing up funds for nondurable consumption. From the perspective of households in our model, a simple way to capture these effects is through changes in the amortization rate r^m , which determines the minimum required mortgage payment in equation (7). The lines labelled 'ARM' in Figure 13 show the results of an experiment where the relaxation in credit conditions is modeled as a fall in r^m (engineered through a lower wedge ι) from 4% p.a. to 3.75%. This reduction is chosen to match the decline in the average spread between private-label mortgage-backed securities and maturity-matched Treasuries (see Levitin and Wachter, 2011, Figure 5). The fall in r^m translates into a 7% average reduction in minimum mortgage payments.

Figure 13 shows that the change in required mortgage payments has almost no effect on

either house prices of consumption, and that the equilibrium dynamics for home ownership and leverage are qualitatively similar, but more muted, than in the benchmark model.

5.2.3 Movements in the Risk-free Rate

One further candidate explanation for the boom in house prices was the dramatic decline in the risk-free rate experienced in the U.S. in the 2000s. We did not include movements in the risk-free rate as part of our benchmark experiments because, while lower risk-free rates have the potential to explain the housing and consumption boom, the absence of a corresponding rise to pre-2000 levels in the data makes it impossible to explain the subsequent bust.

To evaluate the potential strength of changes in the risk-free rate, we consider a version of the economy with a stochastic risk-free rate r_b , and model the relaxation in credit conditions as a fall in r_b from 3% p.a. to 2% p.a. in 2001, which persists until 2020.⁴⁸ Figure 13 shows that the drop in r^b does generate an increase in house prices and consumption, followed by a gradual decline, but the movements are much smaller than in the data.⁴⁹ House prices rise because the return on housing increases relative to the return from saving in bonds, pushing up housing demand. The fall in rents, due to the fact that the expected capital gain component is exacerbated by the decline in the risk-free rate (see equation 11), pulls down home ownership. Finally, since the marginal buyers with high LTV now opt to rent, the rise in aggregate mortgage debt is much weaker and so leverage declines.

5.3 Alternative Models of the Rental Market

In this section we show that our conclusions about the role of belief shifts and credit conditions are robust to how we model the rental market. We explore four extensions: different degrees of segmentation between rental and property markets, the introduction of various frictions in the problem of the rental company, a model with fixed rents, and a model where rental units are owned by individual household-landlords. In what follows we briefly describe our findings. Appendix D contains more details on these economies.

5.3.1 Segmentation of Rental and Owner-Occupied Housing Markets

As described in Section 3, our model has seven house sizes with partial segmentation between rental and owner-occupied units. The first row of Table 8 illustrates which size houses

⁴⁸Ideally, we would model the dynamics of the risk-free rate as a long-term trend, rather than a sudden changes. However, this would require computational complexity that our model can not handle.

⁴⁹The semi-elasticity of house prices to interest rates implied by this simulation is around 5.5, not far from the value estimated by Glaeser, Gottlieb, and Gyourko (2012), which is between 7 and 8.

		Smallest \rightarrow Largest						
		1	2	3	4	5	6	7
Baseline	O		•	•	•	•	•	•
	R	•	•	•				
No Segmentation	O	•	•	•	•	•	•	•
	R	•	•	•	•	•	•	•
Partial Segmentation 1	O		•	•	•	•	•	•
	R	•	•					
Partial Segmentation 2	O			•	•	•	•	•
	R	•	•	•				
Full Segmentation	O				•	•	•	•
	R	•	•	•				

Table 8: Overlap of owner-occupied and rental house sizes in various versions of the model. O means that house size can be owned, R means that house size can be rented. These seven classes correspond, respectively, to 1.17, 1.50, 1.92, 2.46, 3.15, 4.03, 5.15 units of housing.

can be rented and owned in the baseline. Appendix F contains four figures showing aggregate dynamics in the model under alternative assumptions about the extent of market segmentation, as illustrated in the remaining four rows of Table 8.

All cases give results that are virtually indistinguishable from the baseline. The only exception is that, in response to the belief shock, home ownership rises by a smaller amount in the full segmentation case, which confirms that in our model renters are not constrained in the amount of housing services they consume. Thus, if in order to buy they are forced to increase their house size a lot, they opt to remain renters.

One might worry that our assumption of a rental sector that faces no frictions in purchasing, operating or converting housing units is an important reason why we find that credit conditions have a very weak effect on house prices regardless of the degree of segmentation between rental and owner-occupied markets. In the next section we relax the assumption of a frictionless rental sector and show that this conclusion is not affected. Even so, our baseline assumption that stocks of rental and owner-occupied housing are highly substitutable is also supported by the data. For example, after the crisis, conversion of single family houses from owner-occupied to rentals was widespread. From 2007 to 2011, roughly 3M units were converted ([Joint Center for Housing Studies, 2013](#)) and over the same period, 4.5M households switched status from owners to renters.⁵⁰ Thus conversions account for the bulk of these transitions during the bust.

⁵⁰Over this period, home ownership fell by 5 pct points and in 2007 there were about 93M homeowners.

5.3.2 A Rental Sector with Financial and Convertibility Frictions

So far we have assumed that the rent-price ratio is determined by the frictionless user-cost formula (11) that relates rents to current and expected future house prices under risk-neutrality, i.e. $\mathbf{m} = (1 + r_b)^{-1}$. Based on this formula, in Section 5.1.1 we argued that belief shocks to the rental companies are crucial in order to match the dynamics of the rent-price ratio over the boom and bust.

Is this conclusion driven by the assumption that the owners of rental units face no credit or other frictions and discount at the risk-free rate? In Appendix D.2 we derive the following more general version of equation (11) that accounts for stochastic discounting, costly conversion between owner-occupied units and rental units, and financing constraints for the rental company that may affect its ability to purchase, operate, and convert units:

$$\rho(\Omega) = \psi + p_h(\Omega) - (1 - \delta_h - \tau_h) \mathbb{E}_\Omega[\mathbf{m}(\Omega, \Omega') p_h(\Omega')] + p_h(\Omega) \eta(\Omega) + \zeta(\Omega). \quad (15)$$

There are three differences between equation (15) and its baseline version (11). First, the stream of future profits of the rental company is discounted with a general aggregate stochastic discount factor $\mathbf{m}(\Omega, \Omega')$ reflecting preferences of the investors, rather than at the risk-free rate. Second, movements in the leverage constraint of the rental company introduce the stochastic wedge $\eta(\Omega)$. Third, fluctuations in the cost of conversion between owner-occupied and rental units introduce another stochastic wedge $\zeta(\Omega)$. In the absence of financial and convertibility frictions ($\eta = \zeta = 0$) and under risk-neutral discounting ($\mathbf{m} = (1 + r_b)^{-1}$), equation (15) reduces to (11), our baseline. However, in its general formulation, it allows for several additional sources of fluctuations in the rent-price ratio beyond shifts in expectations.

Leverage Constraints and Costly Conversion The relaxation and tightening of credit conditions experienced by home-buyers might have also impacted access to credit by rental companies, leading to movements in η . Moreover, as the boom developed and more and more units were converted into owner-occupied ones, it is likely that the marginal cost of conversion rose as well, leading to movements in ζ .

Can these financial and conversion frictions explain the boom-bust in house prices? We investigate this conjecture by shutting down the belief shock and reverse-engineering time series for the leverage wedge η and the convertibility wedge ζ so that the model generates the same dynamics for the rent-price ratio as in the data. One can think of movements in these wedges as being directly caused by the changing credit conditions. For example, our derivations in Appendix D.2 show that fluctuations in the borrowing constraint of the rental

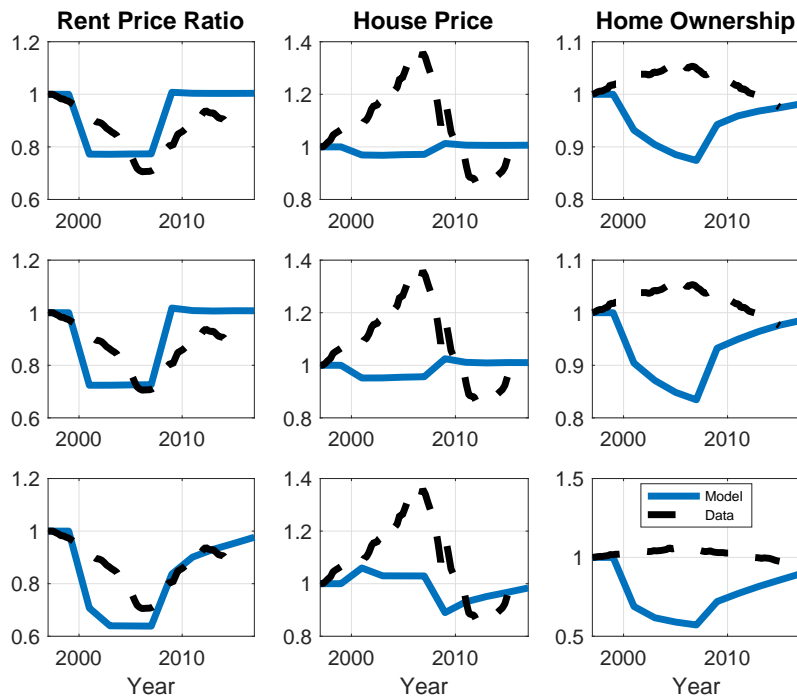


Figure 14: Rent-price ratio, house price, and home ownership dynamics with frictions in rental sector. Top row: shock to leverage constraint. Middle row: shock to convertibility between rental and owner-occupied units. Bottom row: shock to the stochastic discount factor of investors.

sector map directly into movements in η . This experiment gives the credit shock its best chance at explaining the boom-bust in house prices since we are not restricting the shock based on movements in the underlying constraint; rather, we are treating them as a residual much like we treat beliefs in the baseline.

Figure 14 shows that both leverage shocks (η , top row) and convertibility shocks (ζ , middle row) can generate a drop and recovery in the rent-price ratio of the same magnitude as in the data. However, in both cases, this adjustment occurs through a fall and rise in rents rather than through movements in prices. Consequently, neither type of shock generates a boom-bust in house prices, and both shocks induce a counterfactual decline in home ownership during the boom. The reason is that a fall in the user cost of rental units during the boom due, for example, to easier access to credit for the rental sector makes renting more attractive than owning without changing the overall demand for housing by households.

Investors' Discounting The assumption that the discount factor \mathbf{m} in (15) is equal to the inverse of the risk-free rate would be valid if, for example, all rental properties were owned by deep-pocketed investors who are not affected by changes in cost of or access to credit.

However, if rental properties are owned by households facing credit constraints, changes in credit conditions might lead to movements in the rent-price ratio by changing the discount factor \mathbf{m} of the marginal investor. To evaluate this possibility, we adopt the same strategy as for leverage and convertibility shocks: we reverse engineer a time path for the discount factor \mathbf{m} so that the model generates the same dynamics for the rent-price ratio as in the data.

The results shown in the bottom row of Figure 14 mimic those in the previous cases. A shock to the stochastic discount factor of the marginal investor can induce realistic rent-price ratio dynamics. However, as for the other experiments, it generates a fall in rents and no change in prices because the aggregate demand for owner-occupied housing does not increase enough to counteract the steep decline in rents.⁵¹

5.3.3 A Version with Fixed Rents

An alternative to our model of the rental sector that is often used in the literature is one in which the rental rate is exogenous: a linear technology converts labor into rental services.⁵² In this economy, house prices are determined only by the stock of owner-occupied housing and rents are always equal to the marginal cost, a constant. In Appendix F we report results under this alternative model of the rental market. Our basic finding that credit conditions barely move house prices, while the belief shock has a large effect, is unchanged. However, unlike our baseline, this version generates a large counterfactual fall in home ownership during the boom.⁵³

The reason why the model with fixed rents only generates a small movement in house prices when credit is relaxed is due to the fact that the fraction of households that are constrained in being able to purchase a home is small (a few percentage points). At the margin, those households buy small homes. Moreover, since the rental price is fixed, as house prices increase the mass of households that prefer owning to renting under the credit relaxation shrinks—rentals get comparatively more attractive. Thus, the total increase in demand for owner occupied housing is modest, leading to a small move up the housing supply curve.

⁵¹Our general model also allows for a non-negativity constraint on the dividend payment of the rental sector to its investors. Appendix D.2 shows that in periods when this constraint binds (e.g., in the bust, when the rental company is potentially making losses and would benefit from an equity injection) both \mathbf{m} and η would be affected, and thus this shock is a combination of the others we already analyzed.

⁵²See, for example, Garriga and Hedlund (2017) and Guren, Krishnamurthy, and McQuade (2018).

⁵³The decline in home ownership is driven by retired households. When the belief shock hits, these households experience a large capital gain, but now face the chance that house prices will fall. These households have a short horizon, so they realize their capital gains on housing and move into rentals to hedge the future house price risk. This force is absent in the benchmark analysis because of the endogenous movements in rents.

5.3.4 A Version with Household-Landlords

According to the [Joint Center for Housing Studies \(2017\)](#), one half of all rental units in the U.S. are owned by individuals, while the other half are owned by corporations, small businesses, and pass-through entities which are owned by individuals. Thus individual households have a major ownership stake in the rental market, and thus one may worry that our model of the rental sector (which we assume is owned by risk-neutral unconstrained corporations) is misguided.

To the extent that corporations compete with individuals in local rental markets, one might expect the equilibrium rental rate to satisfy the user-cost condition for the large companies (since presumably they face lower borrowing and operating costs). In that case, our baseline model would be a good approximation. But even though corporations are active in all segments of the rental market, they are more present in some segments than in others. For example, for multi-family properties with more than five units, corporations own the vast majority of the rental stock, but for single- or small multi-family units, corporations own only around 15-20% nationally. Thus, in certain segments, the rental market might be better approximated by a model of household-landlords, who rent out some of the housing units that they own.

To investigate whether this difference in rental ownership is important for our findings, we have also solved a version of the model where we allow home-owners to rent out a fraction of their housing stock. Instead of the equilibrium rental rate being determined by rental companies' user-cost condition, it is determined by supply and demand for rental properties.

In this version of the model, credit conditions may affect the demand for housing, and house prices, through the behavior of these household-landlords: households may take advantage of cheaper credit to buy additional housing units, which they can then rent out to other households, and vice-versa. However, once again, our simulations do not show any significant effect of the credit relaxation on house prices, by itself (see [Figure F10](#)). The reason is that, when credit gets cheaper, in absence of beliefs of future capital gains, the expected return on the additional housing units is not large enough to induce a major shift in household portfolios away from bonds and towards housing.

In conclusion, the result that credit shocks are not an important driver of house price dynamics, and belief shocks can lead to house price changes, is robust to the details of how the rental market is modeled. What is key is the fact that by introducing an option for households in the model to rent, and by matching the home-ownership rate and the distribution of leverage in the data, one does not overstate the share of constrained households whose housing demand is sensitive to the availability of cheap credit. We articulate this point further in the next section.

5.4 Models Where Credit Conditions Affect House Prices

Several existing papers have argued that changes in credit conditions can indeed explain a substantial fraction of the recent boom and bust in house prices (e.g. Favilukis et al., 2017; Garriga et al., 2017; Greenwald, 2016; He, Wright, and Zhu, 2015; Justiniano et al., 2017). Why do we reach a different conclusion? Models in which house prices are sensitive to credit conditions are typically models in which either (i) housing commands a large collateral value (because of a binding collateral constraint), and in which changes in credit conditions affect the ability to collateralize the asset; or (ii) housing commands a large risk premium, and in which changes in credit conditions have a large impact on the size of the premium.

Within this last class of models, Favilukis et al. (2017) find that house prices respond strongly to changes in the maximum LTV. Three features of their model, all which differ from ours, combine to yield a large housing risk premium that is sensitive to LTV limits: (i) the absence of a rental market; (ii) short-term non-defaultable mortgages; and (iii) higher risk aversion.⁵⁴ The absence of a rental market means that all households are home owners, including a large fraction of households who would prefer to consume more housing but are constrained by the maximum LTV limit. Because they are constrained, when the LTV limit is loosened, these households optimally raise their demand for housing and so house prices increase. In addition, they increase their LTV ratio, generating a counterfactual increase in aggregate leverage.

Moreover, since all mortgage debt is short-term and non-defaultable, housing is a very risky asset for these households – any fall in house prices requires them to cut consumption in order to rollover their housing debt. And because of the high risk aversion, they require a large risk premium to hold an asset (i.e. housing) that exposes them to so much consumption risk. The size of the required risk premium responds endogenously to changes in the maximum LTV limit. When the limit is loosened, household consumption is less sensitive to those price fluctuations, so the risk premium falls which also leads to an increase in house prices.

When we modify our model to incorporate the three features above, we are able to generate a large effect of credit conditions on house prices just like in Favilukis et al. (2017).⁵⁵ With parameters chosen to mimic their economy, we show in Figure F11 in the Appendix that a relaxation and subsequent tightening of credit conditions can, on its own, generate a 20-25% boom-bust in house prices, but at the cost of a large, counterfactual increase in

⁵⁴These are not all the dimensions among which the two models differ, i.e. our model does not nest theirs. For example, their model is more general in that it features equity (claims on risky physical capital) and an endogenously determined risk-free rate.

⁵⁵See Appendix D.5 for details of the calibration of this economy.

leverage over the boom, and fast deleveraging in the bust.

Of the three features, it is the short-term non-defaultable debt and the absence of rental markets that are the key ingredients required for credit conditions to move house prices.⁵⁶ Without these two ingredients, the risk premium on housing is much smaller and less sensitive to credit conditions. When housing is financed with long-term defaultable mortgages, consumption is less exposed to movements in house prices. Moreover, as explained in Section 4.1, the presence of a rental market means that very few households are constrained in the quantity of housing that they consume and home-ownership dynamics are disconnected from house price dynamics. Therefore, movements in constraints do not move house prices. House price volatility in our model arises from volatility of beliefs, rather than volatility of risk premia.⁵⁷

Which set of assumptions (and hence which view of the transmission from credit conditions to house prices) is more convincing? Since around one-third of U.S. households are renters, we think that the existence of a rental market is a more realistic assumption than the absence of one. Section 5.3 demonstrated that the details of how the rental market is modeled are not crucial.

We also think that the assumption of long-term defaultable mortgages is a better description of the U.S. housing market than the assumption that housing is financed by one-period non-defaultable debt. Long-term debt is nearly universal in the U.S.; in 2015, the median mortgagor had a 30 year mortgage contract, and only 2.6 percent of mortgagors had contracts less than 13 years in duration (American Housing Survey 2015). Finally, roughly half the population live in states where they can default on mortgages with no additional financial liability (no-recourse states) and in the remainder their liability is further limited by the option to declare personal bankruptcy (Mitman, 2016).

In conclusion, we have confirmed that credit constraints can matter for house prices in an economy with a large housing risk premium that varies significantly in response to fluctuations in credit conditions. However, we have argued that the assumptions needed to achieve a tight connection between credit conditions and the housing risk premium are discordant with the structure of US housing and mortgage markets.

⁵⁶In our benchmark economy with long-term defaultable debt and a rental market, increasing the coefficient of relative risk aversion does, on its own, lead to a larger effect of credit conditions on house prices. However, even with a coefficient of 8 (the value in Favilukis et al. (2017)), the credit relaxation alone can generate a boom-bust in house prices of at most 5% (compared with 35% in the data), and then only if the economy is also subject to belief shocks in the stochastic steady state. See Appendix D for details of the calibration of this economy.

⁵⁷This is perhaps not surprising, as it is well known in asset pricing that changes to beliefs can be isomorphic to changes in risk premia.

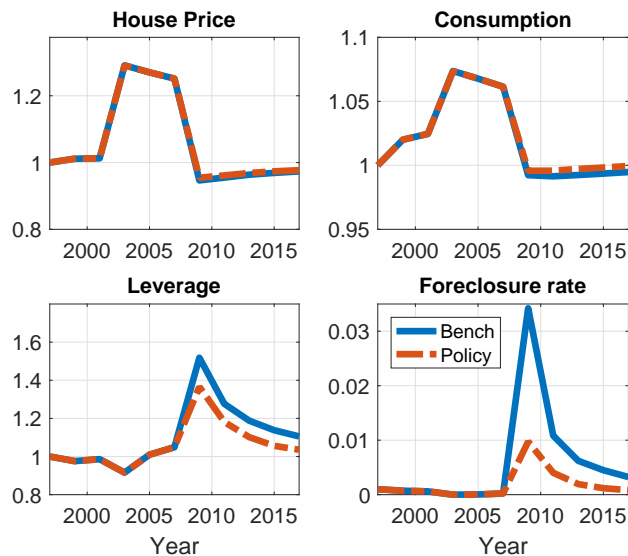


Figure 15: Principal forgiveness program where all mortgages with more than 95% LTV ratio reset to 95% in 2009.

6 Policy Experiment: A Debt Forgiveness Program

In early 2009, at the height of the housing crisis, the Obama administration implemented two mortgage modification programs: the Home Affordable Modification Program (HAMP) and the Home Affordable Refinance Program (HARP). These interventions were intended both to provide relief to heavily indebted borrowers and to slow the collapse in house prices and spike in delinquencies. At the time, these policies were widely criticized for being too timid – it was argued that a more aggressive debt relief program for underwater borrowers could have cushioned the housing crash and accelerated the recovery in aggregate expenditures.⁵⁸ Our model provides a useful laboratory for evaluating this conjecture.

We design a policy intervention in which all homeowners with LTV ratios above 95 percent in 2009 have a fraction of their mortgage debt forgiven so that their LTV ratio is brought down to 95%. Households then repay the residual mortgage debt according to the baseline amortization formula.⁵⁹ In our model, this program affects around one-quarter of all homeowners with mortgages. As such, it displays a much larger scale and degree of generosity than either HARP or HAMP and (presumably, unlike in reality) its financing does not induce additional distortions or fall in disposable income from higher taxes.

Figure 15 shows the macroeconomic implications of the policy. By reducing the number of

⁵⁸See, e.g., Posner and Zingales (2009) for a critical discussion of different proposals.

⁵⁹We assume that the government reimburses the financial intermediaries for the losses they incur as a result of the intervention, and finances these reimbursements through a cut in non-valued expenditures. We also assume that the debt forgiveness program is not expected by households, and that households do not believe that such a program will ever be implemented again.

underwater households, the intervention is successful at reducing foreclosures. Thus, to the extent that foreclosures lead to utility losses and higher depreciation, there are welfare gains for the affected households and for the corresponding banks whose assets are more valuable. Because of the debt relief, the increase in aggregate leverage is mechanically smaller.

Neither the decline in house prices nor the decline in consumption are affected by the policy. As explained, credit and house prices are disconnected, and house prices are the key driver of consumption dynamics in the model.⁶⁰ Moreover, foreclosure is itself a vehicle for consumption smoothing. So by limiting foreclosures, the program induces households who would have otherwise defaulted to consume less (because they have to continue to make mortgage payments, which they happily do to avoid the utility cost of default). These results are qualitatively consistent with the empirical findings in [Agarwal et al. \(2013\)](#), who show that regions where HAMP was used most intensively experienced virtually no change in nondurable consumption but did experience a reduction in foreclosures.

Although the intervention has a trivial impact on the fall in consumption during the housing bust, a closer look at the top-right panel of [Figure 15](#) reveals that it does have a small, but very persistent, positive effect on consumption during the subsequent recovery (around 0.3% per year for at least a decade). Forgiving some debt for a large number of households results in lower future mortgage payments. Since many of these households are nearly hand-to-mouth, they increase consumption slowly as the lower payments are realized, rather than immediately when the policy is enacted. This result is in line with the findings of [Ganong and Noel \(2017\)](#) who compare households who only get a payment reduction under HAMP with those who also get a principal reduction. They find a significant effect on expenditures for the former group of households but no additional effect for the latter group.⁶¹

7 Conclusions

Viewed through the lens of our model, the housing boom and bust of the 2000s was caused by shifts in expectations about future house price growth. These beliefs were shared by households, investors and lenders. In particular, the wave of optimistic beliefs during the boom induced lenders to endogenously expand cheaper credit to risky borrowers. At the

⁶⁰Only large foreclosure externalities on house prices —not present in our model— might change this result. Earlier in the paper ([Section 2](#)) we argued that the micro estimates of the size of such local externality indicate that, by abstracting from this channel, the model misses very small feedback effects of foreclosures on aggregate house prices.

⁶¹Studying the HARP program, [Mitman \(2016\)](#) finds quantitatively similar effects on consumption for high LTV households but much smaller effects on foreclosure. Since HARP only affected payments but not principal, this suggests that the reduction in payments most directly effects consumption, whereas principal reduction mitigates foreclosures (and our experiment is a combination of both).

same time, our model also suggests that an exogenous relaxation of credit conditions was essential for explaining the dynamics of leverage, home ownership and foreclosures, despite it having a negligible impact on house prices and consumption. Together, these two findings epitomize how difficult it can be to separately identify the effects of credit supply shocks and shifts in expectations from micro data, without firm guidance from theory.

Methodologically, our analysis is based on a state-of-the-art heterogeneous-agent incomplete-markets overlapping-generations model with endogenous house prices, rents and mortgage rate schedules, and multiple sources of aggregate shocks. We are able to feasibly compute the equilibrium of this seemingly intractable model by assuming that housing, rental and credit markets are competitive and that housing is homogeneous – this allows us to iterate over laws of motion for one house and rental price. However, because of this computational complexity, we refrained from exploring some promising research directions. We conclude by mentioning three of them.

In our model, belief shifts are exogenous. It is conceivable that during the boom, optimistic beliefs emerged because of a primitive change in some fundamental, such as the low interest rate environment or the change in lenders' behavior caused by securitization. Learning models (e.g., [Adam, Marcet, and Beutel, 2017](#)) provide a way to formalize the idea that fundamental shocks can lead to the formation of optimistic expectations. Clearly, any such fundamental shock must be one that has the potential to move house prices. In this sense, the low risk-free rate environment seems a more promising candidate.

Our model does not feature strong internal propagation of exogenous shocks to house prices and thus cannot generate house price momentum (although it does generate propagation for home ownership, consumption and leverage). A more gradual unraveling of the initial shocks could occur in a version where beliefs diffuse slowly in the population, as in the theoretical framework of [Burnside et al. \(2016\)](#), or in a version where belief shifts hit all households simultaneously but they respond slowly because of frictions either in the housing markets or in the conversion between rental units and owner-occupied units (see [Hedlund, 2016](#); [Guren, Forthcoming](#)).

We also assumed that there is no feedback from house prices to earnings. In richer models with nominal rigidities (as in [Midrigan and Philippon, 2016](#)) or demand externalities (as in [Huo and Ríos-Rull, 2016](#)), the collapse in house prices could cause a decline in aggregate labor demand that leads to a drop in earnings. In that case, part of the fall in expenditures that we attributed to labor income would actually be attributed to house prices. In this respect, our calculation of how much of the dynamics in consumption are attributable to house prices should be interpreted as a lower bound.

References

- ADAM, K., A. MARCET, AND J. BEUTEL (2017): “Stock Price Booms and Expected Capital Gains,” *American Economic Review*, 107, 2352–2408.
- ADELINO, M., A. SCHOAR, AND F. SEVERINO (2016): “Loan Originations and Defaults in the Mortgage Crisis: The Role of the Middle Class,” *Review of Financial Studies*, 1635–1670.
- (2017): “Dynamics of Housing Debt in the Recent Boom and Bust,” in *NBER Macroeconomics Annual 2017, volume 32*, University of Chicago Press.
- AGARWAL, S., G. AMROMIN, I. BEN-DAVID, S. CHOMSISENGPHET, T. PISKORSKI, AND A. SERU (2013): “Policy Intervention in Debt Renegotiation: Evidence from the Home Affordable Modification Program,” Working Paper, Federal Reserve Bank of Chicago.
- ALBANESI, S., G. DE GIORGI, J. NOSAL, AND M. PLOENZKE (2016): “Credit Growth and the Financial Crisis: A New Narrative,” Mimeo, Ohio State University.
- ANENBERG, E. AND E. KUNG (2014): “Estimates of the Size and Source of Price Declines due to Nearby Foreclosures,” *American Economic Review*, 104, 2527–2551.
- BERGER, D., V. GUERRIERI, G. LORENZONI, AND J. VAVRA (2017): “House Prices and Consumer Spending,” Working Paper, National Bureau of Economic Research.
- BLUNDELL, R., L. PISTAFERRI, AND I. PRESTON (2008): “Consumption Inequality and Partial Insurance,” *American Economic Review*, 98, 1887–1921.
- BURNSIDE, C., M. EICHENBAUM, AND S. REBELO (2016): “Understanding Booms and Busts in Housing Markets,” *Journal of Political Economy*, 124, 1088–1147.
- CASE, K. E. AND R. J. SHILLER (2003): “Is There a Bubble in the Housing Market?” *Brookings Papers of Economic Activity*, 2, 299–362.
- CASE, K. E., R. J. SHILLER, AND A. K. THOMPSON (2012): “What Have They Been Thinking? Homebuyer Behavior in Hot and Cold Markets,” *Brookings Papers of Economic Activity*, 2, 265–298.
- CHATTERJEE, S. AND B. EYIGUNGOR (2012): “Maturity, Indebtedness, and Default Risk,” *American Economic Review*, 102, 2674–2699.
- (2015): “A Quantitative Analysis of the U.S. Housing and Mortgage Markets and the Foreclosure Crisis,” *Review of Economic Dynamics*, 18, 165–184.
- CHEN, H., M. MICHAUX, AND N. ROUSSANOV (2013): “Houses as ATMs? Mortgage Refinancing and Macroeconomic Uncertainty,” Working Paper, National Bureau of Economic Research.
- CHENG, I.-H., S. RAINA, AND W. XIONG (2014): “Wall Street and the Housing Bubble,” *American Economic Review*, 104, 2797–2829.
- CORBAE, D. AND E. QUINTIN (2015): “Leverage and the Foreclosure Crisis,” *Journal of Political Economy*, 123, 1–65.
- DE NARDI, M. (2004): “Wealth Inequality and Intergenerational Links,” *Review of Economic Studies*, 71, 743–768.
- DELCOURE, N. AND N. G. MILLER (2002): “International Residential Real Estate Brokerage Fees and Implications for the US Brokerage Industry,” *International Real Estate Review*, 5, 12–39.
- DEMYANYK, Y. AND O. VAN HEMERT (2009): “Understanding the Subprime Mortgage Crisis,” *Review of Financial Studies*, 24, 1848–1880.
- DEN HAAN, W. J. (2010): “Assessing the Accuracy of the Aggregate Law of Motion in Models with Heterogeneous Agents,” *Journal of Economic Dynamics and Control*, 34, 79–99.
- DI MAGGIO, M. AND A. KERMANI (2017): “Credit-Induced Boom and Bust,” *Review of Financial Studies*.

- FAVARA, G. AND J. IMBS (2015): “Credit Supply and the Price of Housing,” *American Economic Review*, 105, 958–992.
- FAVILUKIS, J., S. C. LUDVIGSON, AND S. VAN NIEUWERBURGH (2017): “The Macroeconomic Effects of Housing Wealth, Housing Finance, and Limited Risk Sharing in General Equilibrium,” *Journal of Political Economy*, 125, 140–223.
- FOOTE, C. L., L. LOEWENSTEIN, AND P. WILLEN (2016): “Cross-Sectional Patterns of Mortgage Debt during the Housing Boom: Evidence and Implications,” Working Paper, National Bureau of Economic Research.
- GANONG, P. AND P. NOEL (2017): “The Effect of Debt on Default and Consumption: Evidence from Housing Policy in the Great Recession,” Mimeo, Harvard University.
- GARRIGA, C. AND A. HEDLUND (2017): “Mortgage Debt, Consumption, and Illiquid Housing Markets in the Great Recession,” Working Paper, University of Missouri.
- GARRIGA, C., R. MANUELLI, AND A. PERALTA-ALVA (2017): “A Macroeconomic Model of Price Swings in the Housing Market,” *Federal Reserve Bank of Saint Louis Working Paper*.
- GERARDI, K., A. LEHNERT, S. M. SHERLUND, AND P. WILLEN (2008): “Making Sense of the Subprime Crisis,” *Brookings Papers on Economic Activity*, 2008, 69–159.
- GERARDI, K., E. ROSENBLATT, P. WILLEN, AND V. YAO (2015): “Foreclosure Externalities: New Evidence,” *Journal of Urban Economics*, 87, 42–56.
- GLAESER, E. L., J. D. GOTTLIEB, AND J. GYOURKO (2012): “Can Cheap Credit Explain the Housing Boom?” in *Housing and the Financial Crisis*, University of Chicago Press, 301–359.
- GREENWALD, D. L. (2016): “The Mortgage Credit Channel of Macroeconomic Transmission,” Working Paper, MIT Sloan.
- GUERRIERI, V. AND G. LORENZONI (2015): “Credit Crises, Precautionary Savings, and the Liquidity Trap,” Mimeo, University of Chicago.
- GUERRIERI, V. AND H. UHLIG (2016): “Housing and Credit Markets: Booms and Busts,” *Handbook of Macroeconomics*, 2, 1427–1496.
- GULER, B. (2015): “Innovations in Information Technology and the Mortgage Market,” *Review of Economic Dynamics*, 18, 456–483.
- GUREN, A. (Forthcoming): “House Price Momentum and Strategic Complementarity,” *Journal Political Economy*.
- GUREN, A. AND T. MCQUADE (2015): “How Do Foreclosures Exacerbate Housing Downturns?” Mimeo, Boston University.
- GUREN, A. M., A. KRISHNAMURTHY, AND T. J. MCQUADE (2018): “Mortgage Design in an Equilibrium Model of the Housing Market,” .
- HE, C., R. WRIGHT, AND Y. ZHU (2015): “Housing and Liquidity,” *Review of Economic Dynamics*, 18, 435–455.
- HEATHCOTE, J., F. PERRI, AND G. L. VIOLANTE (2010): “Unequal We Stand: An Empirical Analysis of Economic Inequality in the United States, 1967–2006,” *Review of Economic Dynamics*, 13, 15–51.
- HEATHCOTE, J., K. STORESLETTEN, AND G. L. VIOLANTE (Forthcoming): “Optimal Tax Progressivity: An Analytical Framework,” *Quarterly Journal of Economics*.
- HEDLUND, A. (2016): “The Cyclical Dynamics of Illiquid Housing, Debt, and Foreclosures,” *Quantitative Economics*, 7, 289–328.

- HUO, Z. AND J.-V. RÍOS-RULL (2016): “Financial Frictions, Asset Prices, and the Great Recession,” Working Paper, Federal Reserve Bank of Minneapolis.
- HURST, E. (2017): “Comment on “Dynamics of Housing Debt in the Recent Boom and Bust,” by Adelino et al.” *NBER Macroeconomics Annual*, 32.
- IACOVIELLO, M. AND M. PAVAN (2013): “Housing and Debt over the Life Cycle and over the Business Cycle,” *Journal of Monetary Economics*, 60, 221–238.
- JESKE, K., D. KRUEGER, AND K. MITMAN (2013): “Housing, mortgage bailout guarantees and the macro economy,” *Journal of Monetary Economics*, 60, 917–935.
- JOINT CENTER FOR HOUSING STUDIES (2013): “America’s Rental Housing,” Mimeo, Harvard University.
- (2017): “America’s Rental Housing,” Mimeo, Harvard University.
- JUSTINIANO, A., G. E. PRIMICERI, AND A. TAMBALOTTI (2017): “Credit Supply and the Housing Boom,” Mimeo, Federal Reserve Banks of Chicago.
- KAPLAN, G. AND G. L. VIOLANTE (2014): “A Model of the Consumption Response to Fiscal Stimulus Payments,” *Econometrica*, 82, 1199–1239.
- KEYS, B. J., T. PISKORSKI, A. SERU, AND V. VIG (2012a): “Mortgage Financing in the Housing Boom and Bust,” in *Housing and the Financial Crisis*, University of Chicago Press, 143–204.
- KEYS, B. J., A. SERU, AND V. VIG (2012b): “Lender Screening and the Role of Securitization: Evidence from Prime and Subprime Mortgage Markets,” *Review of Financial Studies*, 2071–2108.
- KIYOTAKI, N., A. MICHAELIDES, AND K. NIKOLOV (2011): “Winners and Losers in Housing Markets,” *Journal of Money, Credit and Banking*, 43, 255–296.
- KRUSELL, P. AND A. A. SMITH (1998): “Income and Wealth Heterogeneity in the Macroeconomy,” *Journal of Political Economy*, 106, 867–896.
- (2006): “Quantitative Macroeconomic Models with Heterogeneous Agents,” *Econometric Society Monographs*, 41, 298.
- LANDVOIGT, T. (2017): “Housing Demand During the Boom: The Role of Expectations and Credit Constraints,” *Review of Financial Studies*, 30, 1865–1902.
- LANDVOIGT, T., M. PIAZZESI, AND M. SCHNEIDER (2015): “The Housing Market(s) of San Diego,” *American Economic Review*, 105, 1371–1407.
- LEVITIN, A. J. AND S. M. WACHTER (2011): “Explaining the Housing Bubble,” *Georgetown Law Journal*, 100, 1177.
- LOUTSKINA, E. (2011): “The Role of Securitization in Bank Liquidity and Funding Management,” *Journal of Financial Economics*, 100, 663–684.
- MCCLEMENTS, L. (1977): “Equivalence Scales for Children,” *Journal of Public Economics*, 8, 191–210.
- MIAN, A., K. RAO, AND A. SUFI (2013): “Household Balance Sheets, Consumption, and the Economic Slump,” *Quarterly Journal of Economics*, 128, 1687–1726.
- MIAN, A. AND A. SUFI (2009): “The Consequences of Mortgage Credit Expansion: Evidence from the US Mortgage Default Crisis,” *Quarterly Journal of Economics*, 124, 1449–1496.
- (2014): “What Explains the 2007–2009 Drop in Employment?” *Econometrica*, 82, 2197–2223.
- (2016a): “Household Debt and Defaults from 2000 to 2010: The Credit Supply View,” Mimeo, Princeton University.
- (2016b): “Who Bears the Cost of Recessions? The Role of House Prices and Household Debt,” *Handbook of Macroeconomics*, 2, 255–296.

- MIDRIGAN, V. AND T. PHILIPPON (2016): “Household Leverage and the Recession,” Working Paper, CEPR Discussion Papers.
- MITMAN, K. (2016): “Macroeconomy Effects of Bankruptcy and Foreclosure Policies,” *American Economic Review*, 106, 2219–2255.
- NATHANSON, C. G. AND E. ZWICK (2017): “Arrested Development: Theory and Evidence of Supply-Side Speculation in the Housing Market,” Working Paper, National Bureau of Economic Research.
- NGAI, L. R. AND K. D. SHEEDY (2017): “The Decision to Move House and Aggregate Housing-Market Dynamics,” Mimeo, London School of Economics.
- PENNINGTON-CROSS, A. (2009): “The Value of Foreclosed Property,” *Journal of Real Estate Research*.
- PIAZZESI, M. AND M. SCHNEIDER (2016): “Housing and Macroeconomics,” *Handbook of Macroeconomics*, 2, 1547–1640.
- PIAZZESI, M., M. SCHNEIDER, AND S. TUZEL (2007): “Housing, Consumption and Asset Pricing,” *Journal of Financial Economics*, 83, 531–569.
- POSNER, E. A. AND L. ZINGALES (2009): “A Loan Modification Approach to the Housing Crisis,” *American Law and Economics Review*, 11, 575–607.
- SAIZ, A. (2010): “The Geographic Determinants of Housing Supply,” *Quarterly Journal of Economics*, 125, 1253–1296.
- SOO, C. K. (2015): “Quantifying Animal Spirits: News Media and Sentiment in the Housing Market,” Working Paper, University of Michigan.

APPENDIX FOR ONLINE PUBLICATION

This Appendix is organized as follows. Section **A** describes all the household problems in their recursive formulation. Section **B** defines a recursive competitive equilibrium for our economy. Section **C** outlines the algorithms for the computation of the equilibrium. Section **D** provides more details on the models we solved in our robustness analysis. Section **E** describes the various data sources used in the paper. Section **F** contains some additional plots.

A Household Problems

Let \mathcal{Z} be the vector of exogenous states and μ denote the measure of households. Let $\Gamma_{\mathcal{Z}}$ denote the conditional distribution of the exogenous aggregate states and $\Gamma_{\mu}(\mu; \mathcal{Z}, \mathcal{Z}')$ be the equilibrium law of motion of the measure. Recall that we denote the full vector of aggregate states as $\Omega = (\mathcal{Z}, \mu)$. We begin by stating the problem of non-homeowners (renters and buyers). Next we state the problem of home-owners (sellers, keepers who repay, keepers who refinance, and households who default). Finally, we describe the problem of the retiree in its last period of life when the warm-glow bequest motive is active.

Renters and Buyers: Let \mathbf{V}_j^n denote the value function of households who start the period without owning any housing. These households choose between being a renter and buying a house to become an owner by solving:

$$\mathbf{V}_j^n(b, y; \Omega) = \max \{V_j^r(b, y; \Omega), V_j^o(b, y; \Omega)\}, \quad (\text{A1})$$

where we let $g_j^o(b, y; \Omega) \in \{0, 1\}$ denote the decision to own a house.

Those who choose to rent solve:

$$V_j^r(b, y; \Omega) = \max_{c, \tilde{h}', b'} u_j(c, s) + \beta \mathbb{E}_{y, \mathcal{Z}} [\mathbf{V}_{j+1}^n(b', y'; \Omega')] \quad (\text{A2})$$

s.t.

$$c + \rho(\Omega) \tilde{h}' + q_b b' \leq b + y - \mathcal{T}(y, 0)$$

$$b' \geq 0$$

$$s = \tilde{h}' \in \tilde{\mathcal{H}}$$

$$y' \sim \Upsilon_j(y), \quad \mathcal{Z}' \sim \Gamma_{\mathcal{Z}}(\mathcal{Z})$$

$$\mu' = \Gamma_{\mu}(\mu; \mathcal{Z}, \mathcal{Z}')$$

Let $\mathbf{x} \equiv (b, h, m)$ denote the household portfolio of assets and liabilities. Those who choose to buy and become owners solve:

$$V_j^o(b, y; \Omega) = \max_{c, b', h', m'} u_j(c, s) + \beta \mathbb{E}_{y, \mathcal{Z}} [\mathbf{V}_{j+1}^h(\mathbf{x}', y'; \Omega')] \quad (\text{A3})$$

s.t.

$$c + q_b b' + p_h(\Omega) h' + \kappa^m \leq b + y - \mathcal{T}(y, 0) + q_j(\mathbf{x}', y; \Omega) m'$$

$$m' \leq \lambda^m p_h(\Omega) h'$$

$$\pi_j^{\min}(m') \leq \lambda^\pi$$

$$b' \geq 0$$

$$h' \in \mathcal{H}, \quad s = \omega h'$$

$$y' \sim \Upsilon_j(y), \quad \mathcal{Z}' \sim \Gamma_{\mathcal{Z}}(\mathcal{Z})$$

$$\mu' = \Gamma_\mu(\mu; \mathcal{Z}, \mathcal{Z}')$$

where $\mathbf{V}^h(\cdot)$ is the value function of a household that starts off the next period as a homeowner which we describe below. The expression for the minimum required mortgage payment is in equation (7) in the main text.

Homeowners: A homeowner has the option to keep the house and make its mortgage payment, refinance the house, sell the house, or default (obviously, this latter option can be optimal only if the household has some residual mortgage debt).

$$\mathbf{V}_j^h(\mathbf{x}, y; \Omega) = \max \left\{ \begin{array}{ll} \text{Pay:} & V_j^p(\mathbf{x}, y; \Omega) \\ \text{Refinance:} & V_j^f(\mathbf{x}, y; \Omega) \\ \text{Sell:} & \mathbf{V}_j^n(b^n, y; \Omega) \\ \text{Default:} & V_j^d(b, y; \Omega) \end{array} \right\}$$

It is convenient to denote the refinance decision by $g_j^f(\mathbf{x}, y; \Omega)$, the selling decision by $g_j^n(\mathbf{x}, y; \Omega)$, and the mortgage default decision by $g_j^d(\mathbf{x}, y; \Omega)$. All these decisions are dummy variables in $\{0, 1\}$ and it is implicit that, when they are all zeros, the homeowner chooses to make a payment on its mortgage during that period. We now describe all these four options one by one.

A household that chooses to make a mortgage payment solves:

$$\begin{aligned}
V_j^p(\mathbf{x}, y; \Omega) &= \max_{c, b', \pi} u_j(c, s) + \beta \mathbb{E}_{y, \mathcal{Z}} [\mathbf{V}_{j+1}^h(\mathbf{x}', y'; \Omega')] & (\text{A4}) \\
&\text{s.t.} \\
c + q_b b' + (\delta_h + \tau_h) p_h(\Omega) h + \pi &\leq b + y - \mathcal{T}(y, m) \\
\pi &\geq \pi_j^{\min}(m) \\
m' &= (1 + r_m) m - \pi \\
b' &\geq -\lambda^b p_h(\Omega) h \\
s &= \omega h, \quad h' = h \\
y' &\sim \Upsilon_j(y), \quad \mathcal{Z}' \sim \Gamma_{\mathcal{Z}}(\mathcal{Z}) \\
\mu' &= \Gamma_{\mu}(\mu; \mathcal{Z}, \mathcal{Z}')
\end{aligned}$$

An homeowner who chooses to refinance its mortgage solves the following problem:

$$\begin{aligned}
V_j^f(\mathbf{x}, y; \Omega) &= \max_{c, b', m'} u_j(c, s) + \beta \mathbb{E}_{y, \mathcal{Z}} [\mathbf{V}_{j+1}^h(\mathbf{x}', y'; \Omega')] & (\text{A5}) \\
&\text{s.t.} \\
c_j + q_b b' + (\delta_h + \tau_h) p_h(\Omega) h + (1 + r_m) m + \kappa^m & \\
\leq b + y - \mathcal{T}(y, m) + q_j(\mathbf{x}', y; \Omega) m' & \\
m' &\leq \lambda^m p_h(\Omega) h \\
\pi_j^{\min}(m') &\leq \lambda^{\pi} y \\
b' &\geq -\lambda^b p_h(\Omega) h \\
s &= \omega h, \quad h' = h \\
y' &\sim \Upsilon_j(y), \quad \mathcal{Z}' \sim \Gamma_{\mathcal{Z}}(\mathcal{Z}) \\
\mu' &= \Gamma_{\mu}(\mu; \mathcal{Z}, \mathcal{Z}')
\end{aligned}$$

A homeowner that chooses to sell its home solves the problem as if it started the period without any housing, i.e., with value function \mathbf{V}_j^n given by (A1) with financial assets equal to its previous holdings b plus the net-of-costs proceeds from the sale of the home, i.e.

$$b^n = b + (1 - \delta_h - \tau_h - \kappa_h) p_h(\Omega) h - (1 + r_m) m \quad (\text{A6})$$

The timing ensures that a household can sell and buy a new home within the period.

Finally, a household that defaults on its mortgage incurs a utility penalty ξ and must rent for a period, thus solving (A2). Only in the following period the household can become

a home-owner again.

Bequest: In the last period of life, $j = J$, the warm-glow inheritance motive, apparent from the preference specification in (1), induces households to leave a bequest. For example, a retired homeowner of age J (who does not sell its house in this last period) would solve:

$$\begin{aligned}
 V_J^p(\mathbf{x}, y; \Omega) &= \max_{c, b'} u_J(c, s) + \beta v(b) & (\text{A7}) \\
 & \text{s.t.} \\
 & c + q_b b' + (1 + r_m) m \leq b + y - \mathcal{T}(y, 0) \\
 & b = b' + (1 - \delta_h - \tau_h - \kappa_h) \mathbb{E}_{\mathcal{Z}} [p_h(\Omega')] h \\
 & b' \geq 0 \\
 & s = \omega h \\
 & \mathcal{Z}' \sim \Gamma_{\mathcal{Z}}(\mathcal{Z}) \\
 & \mu' = \Gamma_{\mu}(\mu; \mathcal{Z}, \mathcal{Z}')
 \end{aligned}$$

In other words, in the last period of life households pay off their residual mortgage and HELOC and orders the house to be liquidated at the beginning of next period. Therefore, bequeathers take into account that their residual housing wealth contributes to bequests only as the expected net-of-costs proceedings from the sale.

B Equilibrium

To ease notation, in the definition of equilibrium we denote the vector of individual states for homeowners and non-homeowners as $\mathbf{x}^h := (b, h, m, y) \in \mathbb{X}^h$ and $\mathbf{x}^n := (b, y) \in \mathbb{X}^n$. Also, let μ_j^h and μ_j^n be the measure of these two types of households at age j , with $\sum_{j=1}^J (\mu_j^h + \mu_j^n) = 1$. As before, we denote compactly $\Omega = (\mathcal{Z}, \mu)$.

A *recursive competitive equilibrium* consists of value functions $\{\mathbf{V}_j^n(\mathbf{x}^n; \Omega), V_j^r(\mathbf{x}^n; \Omega), V_j^o(\mathbf{x}^n; \Omega), \mathbf{V}_j^h(\mathbf{x}^h; \Omega), V_j^p(\mathbf{x}^h; \Omega), V_j^f(\mathbf{x}^h; \Omega), V_j^d(\mathbf{x}^h; \Omega)\}$, decision rules $\{g_j^o(\mathbf{x}^n; \Omega), g_j^n(\mathbf{x}^h; \Omega), g_j^f(\mathbf{x}^h; \Omega), g_j^d(\mathbf{x}^h; \Omega), c_j^h(\mathbf{x}^h; \Omega), c_j^n(\mathbf{x}^n; \Omega), b_{j+1}^h(\mathbf{x}^h; \Omega), b_{j+1}^n(\mathbf{x}^n; \Omega), \tilde{h}_j(\mathbf{x}^n; \Omega), h_{j+1}(\mathbf{x}^n; \Omega), m_{j+1}(\mathbf{x}^n; \Omega), m_{j+1}^f(\mathbf{x}^h; \Omega)\}$, a rental function $\rho(\Omega)$, house price function $p_h(\Omega)$, mortgage price function $q_j(\mathbf{x}_{j+1}^h; \Omega)$, aggregate functions for construction labor, rental units stock, property housing stock, housing investment, and government expenditures $\{N_h(\Omega), \tilde{H}(\Omega), H(\Omega), I_h(\Omega), G(\Omega)\}$, and a law of motion for the aggregate states Γ such that:

1. Household optimize, by solving problems (A1)-(A7), with associated value functions $\{\mathbf{V}_j^n, V_j^r, V_j^o, \mathbf{V}_j^h, V_j^p, V_j^f, V_j^d\}$ and decision rules $\{g_j^o, g_j^n, g_j^f, g_j^d, c_j^h, c_j^n, b_{j+1}^h, b_{j+1}^n, \tilde{h}_j, h_{j+1}, m_{j+1}, m_{j+1}^f\}$.
2. Firms in the construction sector maximize profits, by solving (13), with associated labor demand and housing investment functions $\{N_h(\Omega), I_h(\Omega)\}$.
3. The labor market clears at the wage rate $w = \Theta$, and labor demand in the final good sector is determined residually as $N_c(\Omega) = 1 - N_h(\Omega)$.
4. The financial intermediation market clears loan-by-loan with pricing function $q_j(\mathbf{x}_{j+1}^h; \Omega)$ determined by condition (10).
5. The rental market clears at price $\rho(\Omega)$ given by (11), and the equilibrium quantity of rental units satisfies:

$$\begin{aligned} \tilde{H}'(\Omega) &= \sum_{j=1}^J \left[\int_{\mathbb{X}^h} \tilde{h}_j(b_j^n(\mathbf{x}^h; \Omega), y; \Omega) [1 - g_j^o(b_j^n(\mathbf{x}^h; \Omega), y; \Omega)] g_j^n(\mathbf{x}^h; \Omega) d\mu_j^h \right. \\ &\quad \left. + \int_{\mathbb{X}^h} \tilde{h}_j(\mathbf{x}^n; \Omega) g_j^d(\mathbf{x}^h; \Omega) d\mu_j^h + \int_{\mathbb{X}^n} \tilde{h}_j(\mathbf{x}^n; \Omega) [1 - g_j^o(\mathbf{x}^n; \Omega)] d\mu_j^n \right] \end{aligned}$$

where the LHS is the total supply of rental units and the RHS is the demand of rental units by households who sell and become renters, households who default on

their mortgage and must rent in that period, plus renters who stay renters. The function $b_j^n(\mathbf{x}^h; \Omega)$ represents the financial wealth of the seller, after the transaction, see equation (A6).

6. The housing market clears at price $p_h(\Omega)$ and the equilibrium quantity of housing, measured at the end of the period after all decisions are made, satisfies:

$$\begin{aligned} I_h(\Omega) - \delta_h H(\Omega) + \sum_{j=1}^J \left[\int_{\mathbb{X}^h} h_j [g_j^n(\mathbf{x}^h; \Omega) + (1 - (\delta_h^d - \delta_h)) g_j^d(\mathbf{x}^h; \Omega)] d\mu_j^h \right] \\ + \int_{\mathbb{X}^h} h_{J+1}(\mathbf{x}^h; \Omega) d\mu_J^h \\ = \left[\tilde{H}'(\Omega) - (1 - \delta_h) \tilde{H}(\Omega) \right] + \sum_{j=1}^J \int_{\mathbb{X}^n} h_{j+1}(\mathbf{x}^n; \Omega) g_j^o(\mathbf{x}^n; \Omega) d\mu_j^n \end{aligned}$$

The left-hand side represents the inflow of houses on the owner occupied market, equal to the addition to the housing stock from the construction sector net of depreciation, plus sales of houses by owners and sales of foreclosed properties by financial intermediaries and houses sold on the market when the wills of the deceased are executed. The right-hand side combines outflows, equal to the owner-occupied houses purchased by the rental company and by new buyers.

7. The final good market clears:

$$\begin{aligned} Y(\Omega) = & \sum_{j=1}^J \left\{ \int_{\mathbb{X}^h} c_j^h(\mathbf{x}^h; \Omega) d\mu_j^h + \int_{\mathbb{X}^n} c_j^n(\mathbf{x}^n; \Omega) d\mu_j^n \right. \\ & + \kappa_h p_h(\Omega) \int_{\mathbb{X}^h} h_j [g_j^n(\mathbf{x}^h; \Omega) + g_j^d(\mathbf{x}^h; \Omega)] d\mu_j^h \\ & + (\zeta^m + \kappa^m) \left[\int_{\mathbb{X}^n} m_{j+1}(\mathbf{x}^n; \Omega) g_j^o(\mathbf{x}^n; \Omega) d\mu_j^n + \int_{\mathbb{X}^h} m_{j+1}^f(\mathbf{x}^h; \Omega) g_j^f(\mathbf{x}^h; \Omega) d\mu_j^h \right] \\ & \left. + \nu r^b \int_{\mathbb{X}^h} (m_j + b_j \cdot \mathbb{I}_{\{b < 0\}}) d\mu_j^h \right\} \\ & + \kappa_h h_{J+1}(\mathbf{x}^h; \Omega) d\mu_J^h + \psi \tilde{H}'(\Omega) + G(\Omega) + NX \end{aligned} \quad (\text{B1})$$

where the first two terms on the RHS are expenditures in nondurable consumption of owners and renters, the terms in the second line are transaction fees on sales (including foreclosures), the terms on the third line are mortgage origination and refinancing costs, the fourth line represents flow intermediation costs on all mortgage and HELOC credit, and the last line includes transaction fees on sales from executed wills, operating costs of

the rental company, government expenditures on the numeraire good, and net exports NX that are the counterpart of outflows of profits/losses of the financial and rental sector to their foreign owners.

8. The government budget constraint holds, with expenditures $G(\Omega)$ adjusting residually to absorb shocks:

$$G(\Omega) + \left(\frac{J - J^{ret} + 1}{J} \right) \int_{\mathbb{Y}^{ret}} y^{ret}(\epsilon_{J^{ret}}) d\Upsilon_{J^{ret}}^* = [p_h(\Omega) I_h(\Omega) - wN_h(\Omega)] \quad (\text{B2})$$

$$+ \sum_{j=1}^J \left[\int_{\mathbb{X}^h} \mathcal{T}(y, m) d\mu_j^h + \int_{\mathbb{X}^n} \mathcal{T}(y, 0) d\mu_j^n \right]$$

$$+ \tau_h p_h H(\Omega)$$

where expenditures on goods and pension payments (the LHS) are financed by revenues from selling new licences to developers, income taxes net of mortgage interest deductions (second line), and property taxes (third line).

9. The aggregate law of motion of the measure Γ_μ is induced by the exogenous stochastic processes for idiosyncratic and aggregate risk as well as all the decision rules and, as a result, it is consistent with individual behavior.

C Numerical Computation

This section is organized as follows. We start by outlining the computation strategy to approximate the stochastic equilibrium. Next, we provide some measures of accuracy. Finally, we describe how we run the specific simulation corresponding to the boom-bust.

C.1 Strategy to Approximate the Stochastic Equilibrium

Reducing the state space To understand how we simplify the problem, consider for example the dynamic problem of renters which we rewrite here as

$$\begin{aligned}
 V_j^r(b, y; \mu, \mathcal{Z}) &= \max_{c, \tilde{h}', b'} u_j(c, s) + \beta \mathbb{E}_{y, \mathcal{Z}} [\mathbf{V}_{j+1}^n(b', y'; \mu', \mathcal{Z}')] & (C1) \\
 & \text{s.t.} \\
 & c + \rho(\Omega) \tilde{h}' + q_b b' \leq b + y - \mathcal{T}(y, 0) \\
 & b' \geq 0 \\
 & s = \tilde{h}' \in \tilde{\mathcal{H}} \\
 & y' \sim \Upsilon_j(y), \quad \mathcal{Z}' \sim \Gamma_{\mathcal{Z}}(\mathcal{Z}) \\
 & \mu' = \Gamma_{\mu}(\mu; \mathcal{Z}, \mathcal{Z}')
 \end{aligned}$$

to make the dependence of the value function on μ explicit. This is an infinite dimensional problem because of the presence of μ as an argument of values and is not solvable. The approximate problem we solve is

$$\begin{aligned}
 V_j^r(b, y; p_h, \mathcal{Z}) &= \max_{c, \tilde{h}', b'} u_j(c, s) + \beta \mathbb{E}_{y, \mathcal{Z}} [\mathbf{V}_{j+1}^n(b', y'; p_h', \mathcal{Z}')] & (C2) \\
 & \text{s.t.} \\
 & c + \rho(p_h, \mathcal{Z}) \tilde{h}' + q_b b' \leq b + y - \mathcal{T}(y, 0) \\
 & b' \geq 0 \\
 & s = \tilde{h}' \in \tilde{\mathcal{H}} \\
 & y' \sim \Upsilon_j(y), \quad \mathcal{Z}' \sim \Gamma_{\mathcal{Z}}(\mathcal{Z}) \\
 & p_h' = \Gamma_{p_h}(p_h; \mathcal{Z}, \mathcal{Z}')
 \end{aligned}$$

which differs from (C1) because, instead of keeping track of the distribution μ , we keep track of the variable p_h , with conditional law of motion Γ_{p_h} specified as in (14). Given Γ_{p_h} , one can compute the rental ρ from the optimality condition of the rental company, which we can

restate as:

$$\rho(p_h, \mathcal{Z}) = \psi + p_h - \left(\frac{1 - \delta_h - \tau_h}{1 + r_b} \right) \mathbb{E}_{\mathcal{Z}} [\Gamma_{p_h}(p_h; \mathcal{Z}, \mathcal{Z}')]]$$

The other household problems are simplified in a similar way.

Solving the household problems The household value and policy functions are solved via backward induction starting with the final period of life. In order to solve the model, we discretize \mathbb{X}^h and \mathbb{X}^n by fixing grids on income Y (7 points), house sizes \mathcal{H} (6 points), mortgages \mathcal{M} (21 points) and liquid assets \mathcal{B} (26 points). We also set a grid for the house price p_h (13 points). Household mortgage choice when purchasing or refinancing a mortgage is restricted to be on \mathcal{M} . However, when following the amortization schedule, the next period mortgage balance is computed via linear interpolation between grid points. Conditional on the mortgage and housing choice, we eliminate consumption via the budget constraint and then solve for the optimal level of liquid assets where we linearly interpolate to allow for choices off the grid.⁶²

Updating the law of motion With the policy functions in hand, in order to simulate the model we fix distributions of owners $\mu_0^h \in \hat{\mathcal{B}} \times \mathcal{H} \times \hat{\mathcal{M}} \times Y \times J$ and $\mu_0^n \in \hat{\mathcal{B}} \times Y \times J$ space. We allow the ‘hat’ distribution over mortgages and liquid assets to be finer (by a factor of 3) than the grids over which we solved for the policy functions. We fix a long time series for the realization of the aggregate shocks, \mathcal{Z} . Using the realization \mathcal{Z}_t and μ_t^h, μ_t^n , we can compute the excess demand for housing for each value in the grid over p_h . We linearly interpolate the excess demand function to solve for $p_{h,t}$ that clears the housing market within the period. To compute the update to the distributions, μ_{t+1}^h, μ_{t+1}^n we interpolate the intermediate value functions [A2-A5](#) to determine the optimal discrete choice, and then interpolate the associated policy function.⁶³ We then apply the policy functions and the Markov transition matrix for y to the measures at date t .

We assume that the law of motion for the house price, $\Gamma_{p_h}(p_h; \mathcal{Z}, \mathcal{Z}')$, takes the following form:

$$\log(\bar{p}_{h,t+1}) = a_0(\mathcal{Z}_t, \mathcal{Z}_{t+1}) + a_1(\mathcal{Z}_t, \mathcal{Z}_{t+1}) \log(\bar{p}_{h,t}).$$

Since $\#\mathcal{Z}=12$ (2 values for aggregate productivity, 2 for credit conditions, and 3 for beliefs), we effectively have $(\#\mathcal{Z})^2 = 144$ forecasting equations that need to be estimated. We start

⁶²For the case where a household is making a mortgage payment we use bilinear interpolation over the mortgage balance and liquid asset position.

⁶³In the case the household buys a home we explicitly solve for the optimal house size constrained to be in \mathcal{H} .

off with initial guesses for the coefficients a_0 and a_1 , solve the household problem, then simulate the economy. This generates a time series $\{p_{h,t}, \mathcal{Z}_t\}_{t=0}^T$. We update our forecasting equation by computing the associated regression on the model generated time series and check whether the regression coefficients are consistent with our guesses, a_0, a_1 . If they are, we have found the law of motion; if not, we update our guesses and repeat until convergence.

C.2 Numerical Accuracy

Despite only using the house price and exogenous aggregate states to forecast the aggregate law of motion the R^2 for the forecasting regressions are in excess of 0.9997. While reassuring, as [Den Haan \(2010\)](#) has pointed out, the accuracy of the numerical solution could still be poor, despite having large R^2 values for the forecasting regressions. He suggests simulation of the aggregate endogenous state under the forecast rule and comparing it with the aggregate endogenous state that is calculated by aggregating across the distribution. We run many simulations for 1,000 time periods. The average one-period ahead forecast error between the implied law of motion from the forecast equations and the computed law of motion 0.08% with a maximal error of 0.71%. Even very long forecasts are very accurate: the average error 1,000 periods (2,000 years) ahead is 0.2%, with a maximum error of 1.9%.

C.3 Simulation of Boom-Bust

For the simulation of the Boom-Bust we start off by running the economy for 100 periods where we keep the credit conditions in the low state and the belief shock at ϕ_L , but allow for productivity to fluctuate. We save the pre-boom distribution (when all shocks are in the low state). Then, we simulate the boom-bust by first changing from the low productivity to the high productivity state. In the subsequent model period, we switch from the low credit condition to the high credit condition state. Then, in the subsequent model period we switch from ϕ_L to ϕ_L^* . After three periods all shocks then revert to the low state and remain there for five periods (10 years). For each of the decompositions we initialize the economy with the pre-boom distribution and then turn on the relevant shock with the same timing as in the benchmark experiment.

D Alternative Models

In this Appendix we provide more details on some of the experiments with the alternative models described in Sections 5.3 and 5.4.

D.1 Segmentation of Rental and Property Housing Markets

In section 5.3.1 we discussed our results under various assumptions about the degree of overlap between types (sizes) of rental and owner-occupied units. We note here that the home ownership rate changes slightly in these experiments, it changes to 69% under No Segmentation, 68% under Partial Segmentation 1 and 63% under Partial Segmentation 2. Under Full Segmentation, absent recalibration, the home ownership rate would fall to 55%. As such, we introduce an additive utility benefit of home ownership to the model to match the benchmark ownership rate of 67%.

D.2 Generalizing the Problem of the Rental Sector

In this appendix we derive the user-cost formulas for the rent-price ratio in equations (11) and (15). We lay out a general problem for the rental company of which the baseline model of Section 2.4 is a special case. We write the problem in recursive form, as for the rest of the model. Recall that Ω summarizes the vector of exogenous and endogenous aggregate states.

The rental company is owned by individual households and its decisions are based on an aggregate stochastic discount factor $m(\Omega, \Omega')$ determined by some assignment of property rights across households. We maintain generality and do not specify such assignment or how it evolves over time. Let H be the total stock of housing units owned by the rental company and let h is the number of new units purchased. Let X be the number of housing units owned by the rental company that are rented out and let x be the number of new rental housing units that are added/subtracted to the stock. We assume that the rental company faces a linear operation cost on rental units as well as quadratic adjustment costs $\kappa(x) = \frac{\kappa_x}{2}x^2$ in converting housing units to rent-ready units and vice-versa. We allow κ to vary over time, and thus to be part of Ω . The rental company can borrow to finance purchases of housing subject to a net worth constraint. Let B be the amount of one-period non-defaultable debt owed by the company that must be repaid at gross interest rate $R = 1 + r$ in the following period.⁶⁴ Finally, the rental company faces a non-negative dividend constraint, i.e. it cannot receive equity injection from its shareholders. Combining these assumptions, the problem of

⁶⁴We allow for B to be negative in which case the rental company would be saving possibly to overcome future collateral constraints. Thus $r = r_b$ when $B < 0$ and $r = r_b(1 + \iota) > r_b$ when $B > 0$. In what follows, we ignore the case where $B = 0$ is optimal, but none of our conclusions depend on it.

the rental company becomes:

$$\begin{aligned}
J(H, X, B; \Omega) &= \max_{d, h, x, B'} d + \mathbb{E}_{\Omega} [m(\Omega, \Omega') J(H', X', B'; \Omega')] \\
&\text{subject to} \\
d &= [\rho(\Omega) - \psi] X' + B' - p_h(\Omega) h - \tau_h p_h(\Omega) H - \kappa_x(x) - RB \geq 0 \\
H' &= (1 - \delta_h) H + h \\
X' &= (1 - \delta_h) X + x \\
B' &\leq \lambda^{\rho} p_h(\Omega) H' \\
X' &\leq H'
\end{aligned}$$

The individual state variables are the total number of housing units owned by the company H , the number of rent-ready housing units X and the amount of debt outstanding B . As usual, Ω summarizes the vector of aggregate states.

The first equation is the definition of dividends, i.e. revenues which include net rental income $(\rho(\Omega) - \psi) X'$ and new debt issuance B' minus costs which include purchases of new houses $p_h(\Omega) h$ (sales if $h < 0$), property taxes $\tau_h p_h(\Omega) H$, costs of conversion to/from rental properties $\kappa(x)$, and repayment of outstanding debt RB . This equation states dividends cannot be negative. The second constraint is the accumulation equation for housing units, which says that next period housing units owned by rental company, H' , are the units from last period net of depreciation plus new purchases. The third constraint is the accumulation equation for rental units, which says that next period rent-ready units, X' , equals rental units from last period net of depreciation plus new conversions. The fourth constraint is the borrowing constraint, which says that new debt issuances must be less than a fraction λ^{ρ} —possibly varying stochastically together with the other credit condition parameters—of the value of the rental company's assets $p(\Omega) H$. The fifth constraint is the rental conversion constraint, which says that the number of units rented out to households cannot be larger than the number of housing units owned by the rental company.

Substituting the laws of motion for H and X in the value function and attaching Lagrange

multipliers (μ_d, μ_b, μ_x) to the three constraints, the problem of the rental company becomes:

$$\begin{aligned}
J(H, X, B; \Omega) &= \max_{H', X', B'} [\rho(\Omega) - \psi] X' + B' - p(\Omega) [H' - (1 - \delta_h) H] - \tau_h p_h(\Omega) H \\
&\quad - \frac{\kappa_x}{2} [X' - (1 - \delta_h) X]^2 - RB + \mathbb{E}_\Omega [m(\Omega, \Omega') J(H', X', B'; \Omega')] \\
&\quad + \mu_d \left\{ [\rho(\Omega) - \psi] X' + B' - p_h(\Omega) [H' - (1 - \delta_h) H] - \tau_h p_h(\Omega) H - \frac{\kappa_x}{2} [X' - (1 - \delta) X]^2 - RB \right\} \\
&\quad + \mu_b [\lambda^\rho p_h(\Omega) H' - B'] \\
&\quad + \mu_x [H' - X']
\end{aligned}$$

Rearranging the first-order and envelope conditions of this Lagrangian, we arrive at the following two optimality conditions for the rental company:

$$R\mathbb{E}_\Omega \left[m(\Omega, \Omega') \left(\frac{1 + \mu'_d}{1 + \mu_d} \right) \right] = 1 - \frac{\mu_b}{1 + \mu_d} \quad (\text{D1})$$

$$\begin{aligned}
\rho(\Omega) &= \psi + p_h(\Omega) - p_h(\Omega) \left(\frac{\lambda^\rho \mu_b}{1 + \mu_d} \right) - (1 - \delta_h - \tau_h) \mathbb{E}_\Omega \left[m(\Omega, \Omega') \left(\frac{1 + \mu'_d}{1 + \mu_d} \right) p_h(\Omega') \right] \\
&\quad - (1 - \delta_h) \mathbb{E}_\Omega \left[m(\Omega, \Omega') \left(\frac{1 + \mu'_d}{1 + \mu_d} \right) \kappa'_x x' \right] + \kappa_x x
\end{aligned} \quad (\text{D2})$$

The first condition links the rental company stochastic discount factor to the multipliers on the dividend and collateral constraints. If neither one binds ($\mu_d = \mu_b = 0$), we obtain the standard asset price equation linking the risky asset (shares of the rental company) to the risk free rate.

The second condition can be rearranged as:

$$\rho(\Omega) = \psi + p_h(\Omega) - (1 - \delta_h - \tau_h) \mathbb{E}_\Omega [\mathbf{m}(\Omega, \Omega') \cdot p_h(\Omega')] - p_h(\Omega) \eta(\Omega) + \zeta(\Omega), \quad (\text{D3})$$

where we have defined

$$\mathbf{m}(\Omega, \Omega') = m(\Omega, \Omega') \left(\frac{1 + \mu'_d}{1 + \mu_d} \right) \quad (\text{D4})$$

$$\eta(\Omega) = \frac{\lambda^\rho \mu_b}{1 + \mu_d} \quad (\text{D5})$$

$$\zeta(\Omega) = \kappa_x x - (1 - \delta_h) \mathbb{E}_\Omega [\mathbf{m}(\Omega, \Omega') \cdot \kappa'_x x'] \quad (\text{D6})$$

Equation (D3) —or equation (15) in the main text— establishes a standard ‘Jorgensonian’ relationship between equilibrium rent and current and future equilibrium house prices. Consider first the case where there is no financial friction ($\mu_d = \mu_b = 0$) and no convertibility cost ($\kappa_x = 0$). If we also assume that the owners of the rental company are deep-pocketed and hence effectively risk neutral individuals, then combining (D3) with (D4) and (D1), we

obtain $\mathbf{m}(\Omega, \Omega') = \frac{1}{1+r_b}$. In this case, the rent-price user cost condition becomes the one in the baseline, equation (11).

More in general, equation (D3) illustrates that a number of factors, besides shifts in expectations, can cause fluctuations in the rent-price ratio. The first is movements in the households' stochastic discount factor aggregator m due to changes in aggregate economic conditions, including tighter or looser household credit. For example, tighter household credit would strengthen the negative covariance between m and p'_h and increase the rent-price ratio. The second is shocks to the collateral parameter λ^ρ that directly affect the problem of the rental company. Tighter credit conditions for the rental company impede its ability to convert owner-occupied into rental units when households desire to switch from owning to renting and thus, increase the rent-price ratio. Third, and similarly, a negative shocks to convertibility which raises the value of κ_x can affect the rent-price ratio. Finally, endogenous fluctuations in the multipliers μ_d and μ_b on the dividend and collateral constraints induced by each of the aggregate shocks in the economy have the ability of moving the rent-price ratio. In Section 5.3, we examine these possibilities one at the time.

D.3 Model with Fixed Rents

In the model described in Section 5.3.3 a linear technology to produce rental services pins down the rent to a constant. Now the aggregate housing stock consists only of owner occupied housing, so when a renter becomes a homeowner that necessarily would increase the housing stock and the house price. We set the fixed rental rate in this version of the model to match the same average rent-price ratio from the benchmark in the stochastic steady state of 5% annually.

D.4 Model with Household-Landlords

In the model described in Section 5.3.4, all of the housing stock is owned by households who can freely trade the housing services generated by the housing that they own.

In this version of the model we treat housing as a pure asset that pays a tradable dividend in housing services as in [Jeske, Krueger, and Mitman \(2013\)](#). We assume that households can continuously choose the rental services they want to consume, but for owning the housing asset we assume that it comes in the same six house sizes as in the benchmark economy. We keep this formulation as opposed to a continuous housing choice to try to maintain a meaningful home ownership characterization⁶⁵. In this version of the model, both the house price and rental price become aggregate state variables which clear the market for housing

⁶⁵If we allowed a truly continuous choice of owned housing stock we would generate a counterfactual home ownership rate as essentially all unconstrained households would own some small fraction of a house.

investment and housing services, such that all housing services are generated by houses owned by households and all housing services are consumed by households (no vacancies).

Unlike in the benchmark economy, the rental price is now explicitly a state variable. We approximate the law of motion for the rental price similarly to how we approximate the law of motion for the house price:

$$\log \rho' = b_0(\mathcal{Z}, \mathcal{Z}') + b_1(\mathcal{Z}, \mathcal{Z}') \log \rho. \quad (\text{D7})$$

When we simulate the model, we clear the housing market by using bilinear interpolation of the excess demand functions for the housing stock and housing services. We then iterate on the laws of motion for the house prices and the rental price until we achieve convergence on the vector of coefficients $\{a_0(\mathcal{Z}, \mathcal{Z}'), a_1(\mathcal{Z}, \mathcal{Z}'), b_0(\mathcal{Z}, \mathcal{Z}'), b_1(\mathcal{Z}, \mathcal{Z}')\}$. To keep the model tractable, and as we are mainly interested in studying the effects of credit relaxation under alternative formulations of the housing market, we solve this version of the model without the belief shock and only consider the income and credit relaxation shocks.

Now the aggregate housing stock consists only of household-owned housing, so when a household becomes a homeowner-landlord that necessarily would increase the housing stock and the house price. We calibrate the utility benefit of owning housing to match the same home ownership rate as in the benchmark. We replace the multiplicative utility benefit of home ownership with an additive utility benefit, as now we have a distinction between the size of the owned house and the services consumed.

D.5 Economy Where Credit Conditions Affect House Prices

For the model of Section 5.4, we move our economy closer to the one studied in Favilukis et al. (2017). Specifically, we set the risk aversion parameter γ to 8, and adjust the discount factor β to match the same aggregate net worth as in our benchmark, yielding $\beta = 0.938$. We eliminate the rental sector so that all households must now own homes (we allow the smallest house size, which previously could only be rented to now be owned). On the mortgage side, we increase the cost of default to eliminate foreclosure except in case of an empty budget set. We eliminate the fixed cost κ^m and the intermediation wedge ι , set the HELOC limit, λ^b , to 0 and eliminate the PTI limit, λ^π . We set the mortgage amortization horizon to one period. In the low credit state the max LTV, λ_L^m is set to 0.75 and in the relaxed credit state λ_H^m equals 1.1, as in our benchmark. We adjust the proportional origination cost in the low credit state, ζ_L^m , to be 5% of the value of the loan and in the high credit state (λ_H^b) relax it to 3% (so a 40% reduction as in our benchmark). This configuration of cost and constraint parameters are chosen to mimic the credit relaxation experiment in Favilukis et al. (2017).

In order to calibrate the high-risk-aversion version of our benchmark economy, we first set $\gamma = 8$. Next, we calibrate the discount factor to match the same aggregate net worth as in the benchmark, which yields a value $\beta = 0.941$. In addition, we want to ensure that along the home ownership dimension the high-risk-aversion model is comparable to the benchmark, so we lower the additional utility value of home ownership until we have a comparable home-ownership rate in the steady state.

E Data Sources

E.1 Aggregate Data

- **Consumption:** Nominal nondurable consumption expenditures (line 8 of NIPA Table 2.3.5. Personal Consumption Expenditures by Major Type of Product) divided by the price index for nondurable consumption (line 8 of NIPA Table 2.3.4. Price Indexes for Personal Consumption Expenditures by Major Type of Product).
- **Home Ownership:** Census Bureau Homeownership rate for the U.S. (Table 14) and by age of the householder (Table 19). Housing Vacancies and Homeownership (CPS/HVS) - Historical Tables.
- **House Prices:** House Price Index for the entire U.S. (Source: Federal Housing Finance Agency) divided by the price index for nondurable consumption (line 6 of NIPA Table 2.3.4. Price Indexes for Personal Consumption Expenditures by Major Type of Product).
- **House Rent-Price Ratio:** Rents (Bureau of Labor Statistics Consumer Price Index for All Urban Consumers: Rent of primary residence) divided by nominal house prices.
- **Foreclosures:** Number of Consumers with New Foreclosures and Bankruptcies from the Federal Reserve Bank of New York Quarterly Report on Household Debt and Credit divided by Population (FRED-St. Louis Fed series CNP16OV, Civilian Noninstitutional Population).
- **Leverage:** Home Mortgage Liabilities divided by Owner Occupied Housing Real Estate at Market Value. Source: Flow of Funds B.101 Balance Sheet of Households and Nonprofit Organizations.
- **Labor Productivity:** FRED-St. Louis Fed series ULQELP01USQ661S (Total Labor Productivity for the United States).
- **Mortgage and Treasury Interest Rates:** FRED-St. Louis Fed series MORTGAGE30US (30-Year Fixed Rate Mortgage Average in the United States) and GS10 (10-Year Treasury Constant Maturity Rate).

The data for real consumption expenditures and real house prices used in all plots in the paper are detrended through a linear trend estimated over the pre-boom period 1975-1996.

E.2 Measurement of House-Size Changes from PSID

The objective of this exercise is to estimate the change in house sizes for households that transition across different houses and, possibly, at the same time switch their tenure status from renters to owners or viceversa. These moments are helpful to assess the plausibility of the degree of substitutability between the rental and owner-occupied stock implied by our segmentation described in Section 3.

The PSID is the only survey that allows to track over a long period of time a representative sample of the U.S. population and that has information on house sizes and tenure status. The PSID questions we use for this purpose are the following:

- *How many rooms do you have here for your family (not counting bathrooms)?* (e.g., variables V102 for 1968 and V592 for 1969). This is the measure of house size we use, as it is the only one available.
- *Do you (FU [family unit]) own this home or pay rent or what?* (e.g., variables V103 for 1968 and V593 for 1969). The potential answers here are own, rent, or neither. This variable is used to identify house ownership status and how it changes from a survey to the next, i.e. the four type of transitions: owner-to-renter (O-R), renter-to-owner (R-O), owner-to-owner (O-O) and renter-to-renter (R-R).
- *Have you (HEAD) moved since last spring?* (e.g., V603 for 1969). This variable is useful to identify people who move between different houses.

We collect responses for all heads of households over the survey years 1968-1996, i.e. the pre-boom period corresponding to the stochastic steady state of our model. The total sample size includes 13,782 individuals and 105,774 observations. However, for a number of heads of households it is impossible to identify whether they underwent a transition for a number of reasons: (i) it is their first or last year in the PSID sample as heads; (ii) in some cases the heads temporarily disappear from the sample only to reappear later; (iii) the head is present in adjacent years but her/his answers to these specific questions are missing (for example, in 1994, there is a significantly higher fraction of missing variables, nearly 7%, compared to the other years). Overall, we are left with 9,283 individuals for which we can identify tenure status and house size. 5,301 of these individuals move at least once, totaling 15,235 transitions.

We aim at comparing house-size changes upon moving in the data and in the model. In the data, we have information on number of rooms (excluding bathrooms). In the model changes are measured in housing units. The two would exactly coincide under the following scenario. Imagine every house is composed of bedrooms, one living room and one kitchen

(plus bathrooms). Normalize the size of a bedroom to 1 and assume that the area including living room plus kitchen is always double the size of a bedroom, i.e. 2. Also assume that the bathroom space is always proportional to the rest of the space in the house, e.g. 10%. Then, the percentage change in rooms (excluding bathrooms) exactly corresponds to the percentage change in housing units. For example, moving from a 1 to a 2 bedroom house implies an increase of rooms (excluding bathrooms, so only bedrooms, the living room and the kitchen) from 3 to 4 and it implies exactly an increase in housing units from 3.3 to 4.4, corresponding to a percentage change of 33%. Moving from a 2 to a 3 bedroom house implies an increase in the number of rooms from 4 to 5 and an increase in housing units from 4.4 to 5.5 (or a change of 25%), etc. Under these assumptions, data and model calculations are comparable.

Our findings are shown in Table 7 in the main text.

F Additional Figures



Figure F1: Expected annual house appreciation in the model along the realized history of the boom-bust episode.

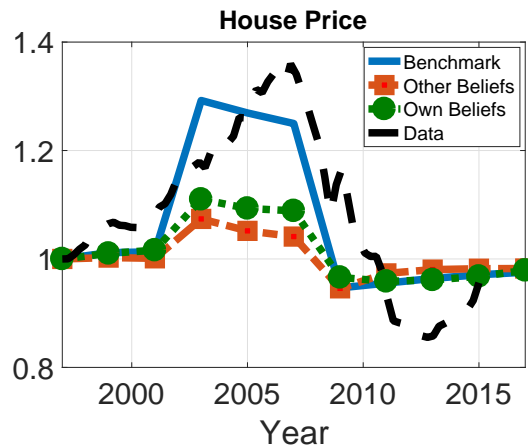


Figure F2: Implied house price dynamics under own vs. other households' shifts in beliefs. Other beliefs: the economy where households think that only other households (but not themselves) experience the belief shock. Own beliefs: the economy where you believe that only your own preferences for housing (but not those of other households) may possibly change. Benchmark: both own and others' shift in beliefs active. All series are normalized to 1 in 1997.

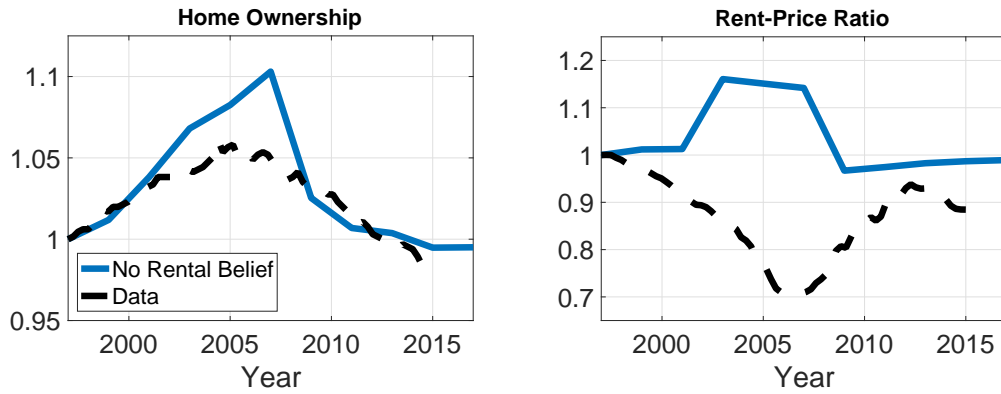


Figure F3: House price and rent-price ratio dynamics in an economy where the rental company does not have optimistic beliefs. Both series are normalized to 1 in 1997.

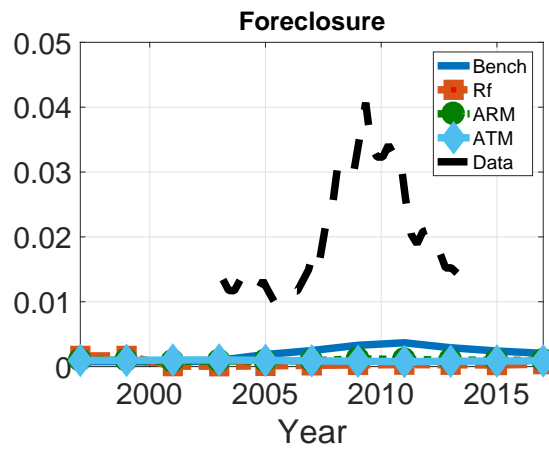


Figure F4: Foreclosure dynamics under alternative models of credit relaxation. ATM: shifts in the maximum HELOC limit. ARM: shifts in the amortization rate. Risk free: decline in the risk free rate. Bench: benchmark shock to credit conditions. All series are normalized to 1 in 1997.

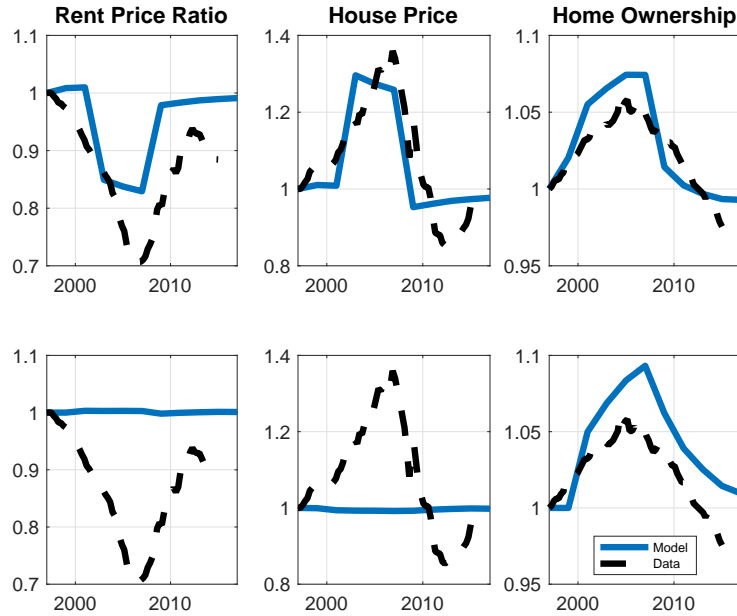


Figure F5: Implied dynamics of rent-price ratio, house prices and home ownership in the ‘No Segmentation’ model with complete overlap of rental and housing house sizes in response to the three benchmark shocks (top row) and only credit relaxation (bottom row). Dashed line: data. Solid line: model.

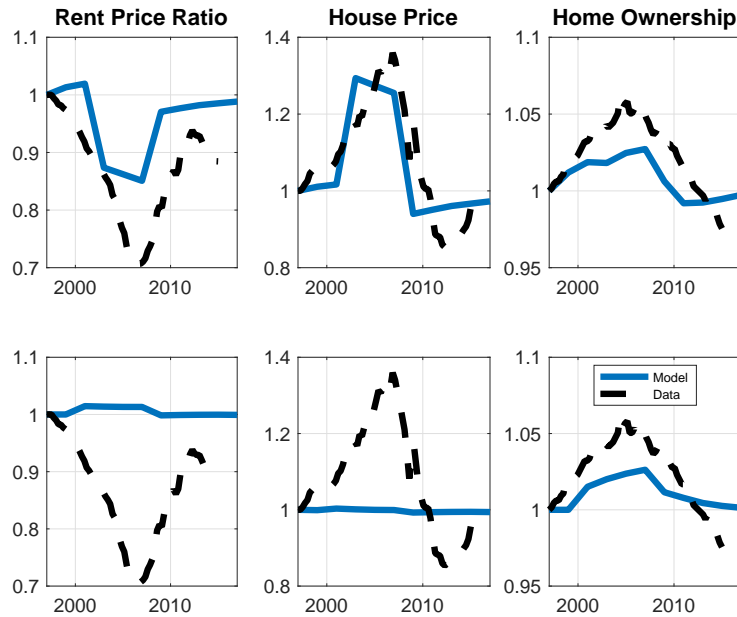


Figure F6: Implied dynamics of rent-price ratio, house prices and home ownership in the ‘Partial Segmentation 1’ model with two rental house sizes (and an overlap of 1) in response to the three benchmark shocks (top row) and only credit relaxation (bottom row). Dashed line: data. Solid line: model.

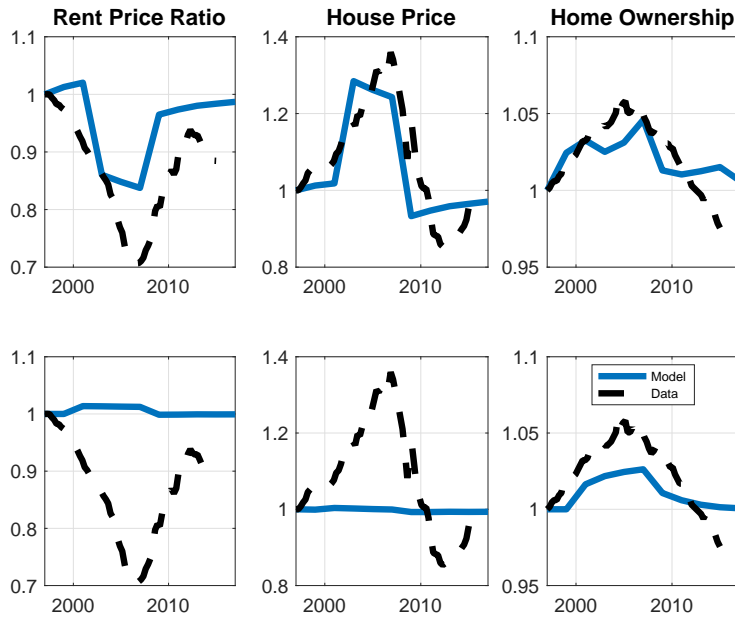


Figure F7: Implied dynamics of rent-price ratio, house prices and home ownership in the ‘Partial Segmentation 2’ model with three rental house sizes (and an overlap of 1) in response to the three benchmark shocks (top row) and only credit relaxation (bottom row). Dashed line: data. Solid line: model.

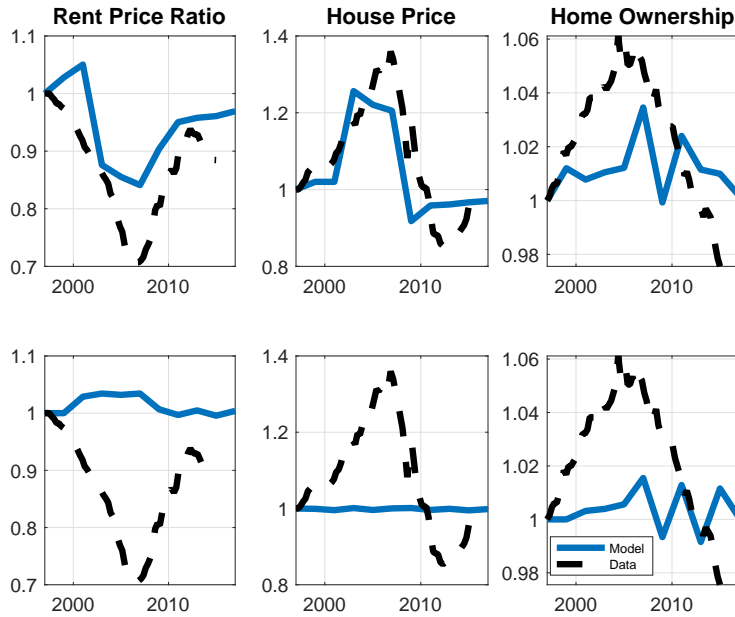


Figure F8: Implied dynamics of rent-price ratio, house prices and home ownership in the ‘Full Segmentation ’ model with no overlap of rental and housing house sizes in response to the three benchmark shocks (top row) and only credit relaxation (bottom row). Dashed line: data. Solid line: model.

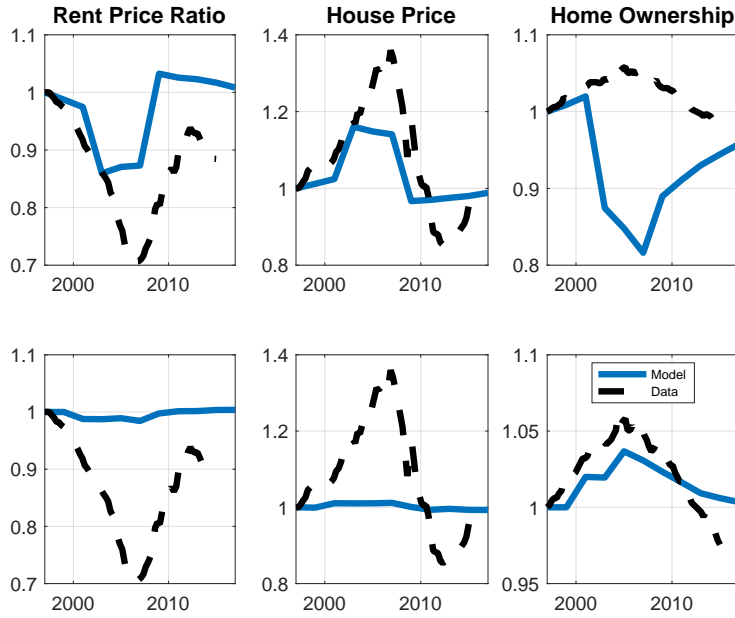


Figure F9: Implied dynamics of rent-price ratio, house prices and home ownership in the fixed-rent model in response to the three benchmark shocks (top row) and only credit relaxation (bottom row).

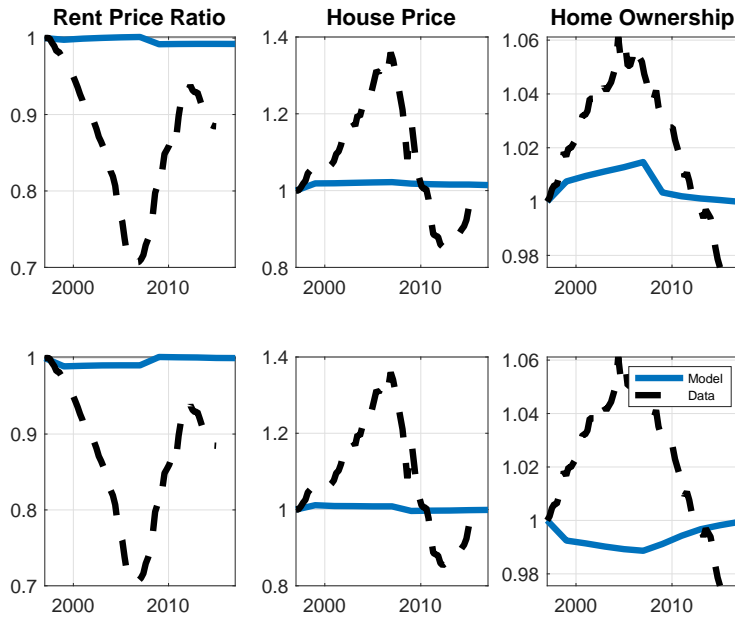


Figure F10: Implied dynamics of rent-price ratio, house prices and home ownership in the household-landlord model in response to the income and credit relaxation shocks (top row) and only credit relaxation (bottom row).

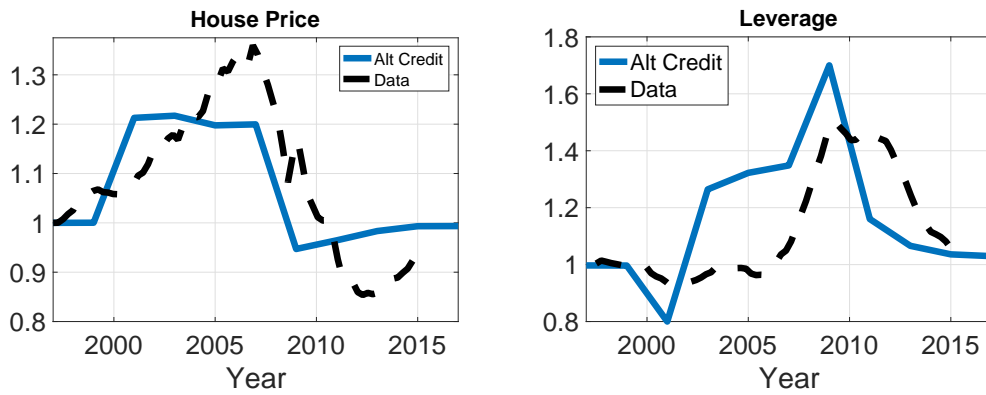


Figure F11: House price and leverage dynamics in the economy of Section 5.4 where credit conditions have a large effect on prices. Both series are normalized to 1 in 1997.