

The Housing Boom and Bust: Model Meets Evidence

Greg Kaplan

University of Chicago, Institute for Fiscal Studies, and National Bureau of Economic Research

Kurt Mitman

Institute for International Economic Studies, Stockholm University, Centre for Economic Policy Research, and Institute for Labor Economics

Giovanni L. Violante

Princeton University, Center for Economic Behavior and Inequality, Centre for Economic Policy Research, Institute for Fiscal Studies, Institute for Labor Economics, and National Bureau of Economic Research

We build a model of the US economy with multiple aggregate shocks that generate fluctuations in equilibrium house prices. Through counterfactual experiments, we study the housing boom-bust around the Great Recession, with three main results. First, the main driver of movements in house prices and rents was a shift in beliefs, not a change in credit conditions. Second, the boom-bust in house prices explains half of the corresponding swings in nondurable expenditures through a wealth effect. Third, 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.

Data are provided as supplementary material online.

Electronically published August 5, 2020

[*Journal of Political Economy*, 2020, vol. 128, no. 9]

© 2020 by The University of Chicago. All rights reserved. 0022-3808/2020/12809-0001\$10.00

I. 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 a fall in household expenditures that—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 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 US economy with a detailed housing finance sector and realistic household consumption behavior. Importantly, our model features three potential drivers of aggregate fluctuations in housing investment, house prices, rents, and mortgage risk spreads: (1) changes in household income generated by shocks to aggregate productivity, (2) changes in housing finance conditions generated by shocks to model parameters that determine mortgage debt limits and borrowing costs, and (3) 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.

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

² For 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.

After parameterizing the model to match salient life-cycle and cross-sectional dimensions 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 are the dominant force behind the observed swings in house prices and the rent-price ratio around the Great Recession. Changes in credit conditions have virtually no effect on prices and rents but are a key factor in the dynamics of leverage and homeownership. 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 homeownership because expected future price appreciation depresses the rent-price ratio, pushing marginal households out of homeownership into renting. Looser credit conditions correct these forces by expanding borrowing capacity and pulling marginal buyers into homeownership, 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: (1) the uniform expansion of mortgage debt during the boom across income levels (Foote, Loewenstein, and Willen 2016), (2) the increasing share of defaults during the bust attributable to prime borrowers (Albanesi et al. 2016), and (3) the crucial role of young households in accounting for the dynamics of homeownership during this period (Hurst 2017).

Second, we find that the boom and bust in house prices directly accounts for roughly half of the corresponding boom and bust in nondurable 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, Rao, and Sufi (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 nonzero 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 et al. (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 et al. 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 (2 years into the bust) and on a very large scale (affecting over one-quarter 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 homeowners above water. Moreover, because the program reduces households' mortgage payments for the remaining life of the mortgage contract, we find that aggregate nondurable consumption would have been slightly higher throughout the whole postbust 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. It is important that all types of 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. 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 2011). In this sense, shifts in beliefs generate endogenous shifts in credit supply in our model, that is, expansions and contractions

of cheap funds to subprime borrowers, using the language of Mian and Sufi (2016a) and Justiniano, Primiceri, and Tambalotti (2019).

Direct evidence on the role of expectations in the boom and bust is scarce, but evidence that does exist points convincingly toward 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 2004–5. 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 midlevel 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 et al. (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, Primiceri, and Tambalotti (2019), 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 US housing market that are omitted in most of the literature—account for this result. Credit conditions can affect house prices if many households are constrained in the quantity of housing services they desire to consume. Alternatively, credit conditions can affect house prices by making homeownership less risky and thereby changing the housing risk premium. However, for credit conditions to change the riskiness of housing, it is necessary that for a large fraction of homeowners, consumption is sensitive to the cost and availability of housing-related credit. In our model, as in the data, there are two reasons why this does not happen.

First, because of the possibility to rent rather than own, too few households are constrained in their consumption of housing services. 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 houses similar in size to the ones they were previously

renting. They thus increase the homeownership 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 homeownership.

Second, the presence of long-term mortgages dampens the link between credit conditions and the housing risk premium. In models with only short-term debt, a sudden tightening of credit conditions forces all homeowners 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, Ludvigson, and Van Nieuwerburgh 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 homeowners 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 our results, 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 housing stocks segmented between rental and owner-occupied housing, a relaxation in credit generates only 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 consistent with those of 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 II, we outline the model, equilibrium concept, and computational strategy. In section III, we describe how we parameterize the model, and we compare its predictions with relevant empirical counterparts. In section IV, we present findings from our numerical experiments on the boom-bust period. In section V, we solve several variants of the benchmark model to illustrate the key economic forces driving these findings. In section VI, we analyze the debt forgiveness program. The appendixes (available online) include more detail about data sources, computation, and robustness.

II. Model

A. Overview

Our economy is populated by overlapping generations of households whose life cycle 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. Households can save in a noncontingent financial asset whose return is fixed exogenously. They consume nondurable 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. Homeownership requires overcoming certain financial constraints, such as maximum loan-to-value (LTV) 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.³ A notable exception is the work of Favilukis, Ludvigson, and Van Nieuwerburgh (2017), who also develop an equilibrium incomplete-markets model with aggregate shocks. In section V.D, we provide a detailed explanation of how two key ingredients of our model absent in theirs—the 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 in every period, generating fluctuations in aggregate quantities and prices: (1) labor productivity, (2) credit conditions in the mortgage market, and (3) beliefs about future demand for housing. It is convenient to postpone the definitions of these shocks to section II.F, 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 II.B. 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 II.C–II.F. The recursive formulation of the household problem and the formal definition of equilibrium are contained in appendixes A and B, respectively.

B. Households

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 $J^{\text{ret}} - 1$, 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.

³ Only a handful of papers on the crisis develop models with aggregate shocks that move equilibrium house prices, but they study environments with very limited heterogeneity (Iacoviello and Pavan 2013; Greenwald 2016; Justiniano, Primiceri, and Tambalotti 2019). The rest of the literature either studies deterministic equilibrium transitions out of steady state induced by measure-zero events (e.g., Kiyotaki, Michaelides, and Nikolov 2011; Huo and Ríos-Rull 2016; Garriga, Manuelli, and Peralta-Alva 2017) or assumes exogenous price shocks (e.g., Chen, Michaux, and Roussanov 2013; Corbae and Quintin 2015; Landvoigt 2017).

Preferences.—Expected lifetime utility of the household is given by

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

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 $b > 0$.

We assume that the utility function u_j is given by

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

where ϕ measures the relative taste for housing services, $1/\gamma$ measures the elasticity of substitution between housing services and nondurables, and $1/\theta$ measures the intertemporal elasticity of substitution. 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

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

as in De Nardi (2004). The term ν 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

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

where Θ is an index of aggregate labor productivity. Individual labor productivity has two components: (1) a deterministic age profile χ_j that is common to all households and (2) an idiosyncratic component ϵ_j that follows a first-order Markov process.

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 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 $\tilde{\mathcal{H}} = \{\tilde{h}^0, \dots, \tilde{h}^{\tilde{N}}\}$. 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, that is, $s = h$. To capture the fact that there may be additional utility from homeownership, 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 (1) long-term, (2) subject to a fixed origination cost κ_m , (3) amortized over the remaining life of the buyer at the common real interest rate r_m , equal to r_b times an intermediation wedge $(1 + \iota)$, (4) able to be refinanced subject to paying the origination cost, and (5) defaultable.

A household of age j who 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, the borrower's choice of assets and liabilities for next period $\mathbf{x}' := (b', h', m')$ and 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.⁴ It follows that the down payment 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 LTV ratio limit: the initial mortgage balance m' must be less than a fraction λ_m of the collateral value of the house being purchased:

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

⁴ Section II.C. provides the exact expression for the equilibrium price q . One can interpret this gap between the 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.

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 $m' = m(1 + r_m) - \pi$.⁵

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 to make the minimum payment on the outstanding balance of the loan. If house prices decline, a homeowner could end up with very small (or even negative) housing equity, but, as long as they continue to meet their minimum payments, they are not forced to deleverage, as they 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 refinancings whose only purpose is equity extraction. When a household sells their home, they are also required to pay off the remaining mortgage balance.

If a household defaults, mortgages are the subject of the primary lien on the house, implying that the proceeds from the foreclosure are disbursed to the creditor. Foreclosing reduces the value of the house to the lender for two reasons: (1) it is the lender who must pay property taxes and maintenance, and (2) foreclosed houses depreciate at a higher

⁵ We 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 $\pi_j^{\min}(m)/q_j m = r_m^*(1 + r_m^*)^{J-j}/[(1 + r_m^*)^{J-j} - 1]$.

rate than regular houses, that is, $\delta_h^d > \delta_h$. 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.⁶

HELOCs.—Homeowners have access to HELOCs. For tractability, we assume these are one-period nondefaultable contracts.⁷ Through HELOCs, households can borrow up to a fraction λ_b of the value of their house at an interest rate equal to $r_b(1 + \iota)$.⁸ 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 pay-as-you-go social security system. Retirees receive social security benefits $y^{\text{ret}} = \rho_{ss} y_j^w(\bar{\Theta})$, where ρ_{ss} is a replacement rate, the argument of the benefit function proxies for heterogeneity in lifetime earnings, and $\bar{\Theta}$ is average value of aggregate productivity (we thus abstract from aggregate uncertainty in pension income). We adopt the notation y for income, with the convention that if $j < J^{\text{ret}}$ then $y = y^w$, defined in equation (4), and $y = y^{\text{ret}}$ otherwise.

Government tax revenues come from the proportional property tax τ_h levied on house values and a progressive labor income tax schedule. 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 II.E.

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.

⁶ We 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% 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.

⁷ Allowing for multiperiod 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.

⁸ To 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. Household Decisions

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

Households who start the period as renters choose 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 down payment. 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 down-payment and maximum PTI requirements as well as to transaction fees upon selling. There are three advantages of owning over renting: (1) owning a house yields an extra utility flow, (2) mortgage interest payments are tax deductible, whereas rents are not, and (3) housing can be used as 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: (1) keep the current house and mortgage and make the minimum required payment, (2) refinance the mortgage, (3) sell the house, or (4) default on the 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 useful only 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.

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_t plus the net-of-costs proceeds from the sale of the home, which are given by

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

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

Finally, a household might choose to default if they have some residual mortgage debt and is "underwater," meaning that the net proceeds from the sale of the house in (9) would be negative.

C. 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 that mortgage prices are determined by zero-profit conditions that hold in expectation loan by loan.⁹ 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 household 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

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

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 ($g_j^f = 1$), they 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.

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.

⁹ Because 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).

D. Rental Sector

We assume that the rental rate is determined by a “Jorgensonian” user-cost formula that 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 using 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 V.C, 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 equation (11).

E. Production

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

1. 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 $w = \Theta$.

2. Construction Sector

The competitive construction sector operates the production technology $I_h = (\Theta N_h)^\alpha (\bar{L})^{1-\alpha} c$, with $\alpha \in (0, 1)$, where N_h is the quantity of labor services employed and $\bar{L}$ is the amount of new available, buildable land. We assume that in each period the government issues new permits equivalent to $\bar{L}$ units of land, and we follow Favilukis, Ludvigson, and Van Nieuwerburgh (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

$$\max_{N_h} p_h(\Omega) I_h - w N_h, \quad \text{subject to} \quad I_h = (\Theta N_h)^\alpha (\bar{L})^{1-\alpha},$$

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

$$I_h(\Omega) = (\alpha p_h(\Omega))^{\alpha/(1-\alpha)} \bar{L}, \quad (13)$$

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

F. 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.

1. 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: (1) the maximum LTV ratio at origination λ_m , (2) the maximum PTI level at origination λ_π , (3) the mortgage origination cost κ_m , and (4) 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 III.B, we explain the rationale behind modeling changes in housing finance conditions this way, and in section V.B, 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 materialize.

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 $\Omega = (\mathcal{Z}, \mu)$.

2. 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]).¹⁰ The assumptions of perfect competition and linear objectives in both the financial and rental sectors allow us to reduce the dimensions 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 the 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 on the vector of coefficients $\{a_0(\mathcal{Z}, \mathcal{Z}'), a_1(\mathcal{Z}, \mathcal{Z}')\}$.

¹⁰ A key difference between our framework and that of Krusell and Smith (1998) is that the total stock of owner-occupied houses H is not predetermined, as is capital in their paper, but has 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.

III. Parameterization

We parameterize the model to be consistent with key cross-sectional features of the US 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 III.B.

A. Model Parameters

1. Demographics

The model period is equivalent to 2 years of life. Households enter the model at age 21, retire at age 65 (corresponding to $J^{\text{ret}} = 23$), and die at age 81 (ages 79–80 correspond to $J = 30$).

2. Preferences

We set $1/\gamma$, the elasticity of substitution between nondurable consumption and housing in equation (2), to 1.25 on the basis of estimates in Piazzesi, Schneider, and Tuzel (2007). We set $\vartheta = 2$ 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, which is equivalent to a ratio of aggregate net worth to aggregate total income of 3.67. The model generates a median net-worth-to-labor-income ratio around 1, close to its empirical counterpart from the 1998 SCF.

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 (1) 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 (2) the fraction of households in the bottom half

TABLE 1
PARAMETER VALUES

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
ϑ	Risk aversion	N	2.0
$\{e_j\}$	Equivalence scale	N	McClements scale
β	Discount factor	Y	.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	.8
Endowments:			
$\{\chi_j\}$	Deterministic life-cycle profile	N	Kaplan and Violante 2014
ρ_ϵ	Autocorrelation of earnings	N	.97
σ_ϵ	Standard deviation of earnings shocks	N	.20
σ_{e0}	Standard deviation of initial earnings	N	.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	.07
δ_h	Housing maintenance/ depreciation rate	N	.015
δ_h^d	Loss from foreclosure	N	.22
ψ	Operating cost of rental company	Y	.008
$\alpha/(1 - \alpha)$	Housing supply elasticity	N	1.5
$\bar{L}$	New land permits	Y	.311
Financial instruments:			
r_b	Risk-free rate	N	.03
ι	Mortgage and HELOC rate wedge	N	.33
λ_b	Maximum HELOC	N	.20
Government:			
τ_h	Property tax	N	.01
τ_y^0, τ_y^1	Income tax function	N	.75, .151
$\bar{m}$	Mortgage interest deduction limit	N	19.2
ρ_{ss}	Social Security replacement rate	N	.40

NOTE.—The model period is 2 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).

TABLE 2
TARGETED MOMENTS IN THE CALIBRATION

Moment	Empirical Value	Model Value
Aggregate NW/aggregate labor income (median ratio)	5.5 (1.2)	5.6 (.9)
Median NW at age 75/median NW at age 50	1.51	1.55
Fraction of bequests in bottom half of wealth distribution	0	0
Aggregate homeownership rate	.66	.67
Foreclosure rate	.005	.001
10th percentile housing NW/total NW for owners	.11	.12
50th percentile housing NW/total NW for owners	.50	.38
90th percentile housing NW/total NW for owners	.95	.80
Average-size owned house/rented house	1.5	1.5
Average earnings owners/renters	2.1	2.4
Annual fraction of houses sold	.10	.095
Homeownership rate of <35-year-olds	.39	.37
Relative size of construction sector	.05	.05
Belief shock:		
Average expenditure share on housing	.16	.16
Expected annual house price growth	.06–.15	.06
Average duration of booms, busts (years)	5.4, 5.5	5, 5
Average size of house price change in booms, busts	.36, .37	.34, .32

NOTE.—Moments correspond to the 13 model parameters and the six parameters of the belief shock process internally calibrated. NW = net worth.

of the wealth distribution that leave a positive bequest, which is an indicator of the luxuriousness of bequests.

The additional utility from owner-occupied housing relative to rental housing, ω , is chosen to match the average homeownership 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 homeowner 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 United States during the late 1990s. The calibrated value implies an average consumption-equivalent loss of roughly 30% in the period of default.

3. Endowments

The deterministic component of earnings $\{\chi_t\}$ comes from Kaplan and Violante (2014). Average earnings grow by a factor of 3 from age 21 to their peak at age 50 and then decline slowly over the remainder of the working life. The stochastic component of earnings ϵ_t is modeled as an AR(1) (first-order autoregressive) 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.

4. 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 (a value of 0.11), the 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 owners' average house size to renters' of 1.5 (Chatterjee and Eyigungor 2015) and a ratio of owners' average earnings 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%.¹¹ 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 (2006). 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 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).¹² The operating cost of the rental company ψ affects the relative cost of renting versus buying, a decision that is especially relevant for young households. Accordingly, we choose ψ to match the homeownership 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 metropolitan statistical areas 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.

¹¹ Bureau of Economic Analysis table 7.4.5, consumption of fixed capital of the housing sector divided by the stock of residential housing at market value; see app. E.

¹² This value of transaction costs is in line with common estimates of sales costs, including brokerage fees and local taxes (Delcours and Miller 2002).

5. 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.¹³ The proportional wedge ι is set to 0.33 (implying an amortization rate r_m of 4% per annum), 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.¹⁴

6. 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 (2017), $\mathcal{T}(y_j, m_j) = \tau_y^0 (y_j - r_m \min\{m_j, \bar{m}\})^{1-\tau_y^1}$. 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 on the basis of estimates by Heathcote, Storesletten, and Violante (2017). 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 deductible for only the first \$1,000,000 of mortgage debt.

To set the Social Security replacement rate ρ_{ss} , we proxy average individual lifetime earnings with the last realization of earnings y_{ret}^w . The distribution of these proxies is run through the same formula used in the US 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.

B. Aggregate Uncertainty and Boom-Bust Episode

As discussed in section II.F, 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 follows independent discrete-state Markov processes. We present our

¹³ See <http://www.federalreserve.gov/pubs/refinancings/default.htm>.

¹⁴ This value is close to the 90th percentile of the HELOC limit distribution, roughly 30% of the home value.

TABLE 3
PARAMETERS GOVERNING THE MARKOV PROCESSES FOR THE THREE AGGREGATE SHOCKS

Parameter	Interpretation	Internal	Value
Productivity Θ :			
Θ_L	Earnings: low state	N	.965
Θ_H	Earnings: high state	N	1.035
$q_{LL}^\Theta = q_{HH}^\Theta$	Transition probability	N	.90
Credit conditions F:			
κ_L^m	Fixed origination cost: low state	N	\$2,000
κ_H^m	Fixed origination cost: high state	N	\$1,200
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	Maximum LTV: low state	N	.95
λ_H^m	Maximum LTV: high state	N	1.1
λ_L^π	Maximum PTI: low state	N	.25
λ_H^π	Maximum PTI: high state	N	.50
$q_{LL}^F = q_{HH}^F$	Transition probability	N	.98
Beliefs about housing demand ϕ :			
$\phi_L = \phi_L^*$	Taste for housing: low state	Y	.12
ϕ_H	Taste for housing: high state	Y	.20
$q_{LL}^\phi = q_{HH}^\phi$	Transition probability	Y	.95
$q_{LL}^{\phi*} = q_{HH}^{\phi*}$	Transition probability	Y	.04
q_{L*L}^ϕ	Transition probability	Y	.12
q_{L*H}^ϕ	Transition probability	Y	.80

NOTE.—Transition probabilities are biannual. BP = basis points.

calibration below and summarize the parameter values in table 3. We then describe how we simulate the boom-and-bust episode.

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 detrended series of total labor productivity for the United States.

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 was the rise in securitization of private-label mortgages (Levitin and Wachter 2011; Keys et al. 2013).¹⁵

¹⁵ As explained by, e.g., Levitin and Wachter (2011), securitization itself was not a new phenomenon. Before 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 fig. 2 in Levitin and Wachter 2011).

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 . On the basis of the evidence in Favilukis, Ludvigson, and Van Nieuwerburgh (2017), we assume that in times of normal credit conditions the fixed cost is \$2,000 and the wedge is 100 basis points and that 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.¹⁶

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 2012). The consequent widespread relaxation of underwriting standards in the US mortgage market allowed many buyers to purchase houses with virtually no down payment 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), Guerrieri and Lorenzoni (2015), Landvoigt, Piazzesi, and Schneider (2015), Huo and Ríos-Rull (2016), and Favilukis, Ludvigson, and Van Nieuwerburgh (2017). 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.¹⁷ In the stochastic steady state, 4% of households originate new mortgages exactly at the LTV constraint, and 40% of households originate mortgages with an LTV of 80% or higher. In comparison, in 1999, 48% of US households had a combined LTV of 80% or higher, and 8% had mortgages with combined LTV of 95% or higher. We set $\lambda_\pi = 0.25$ in normal times and set $\lambda_\pi = 0.50$ in times of relaxed credit conditions.¹⁸ In the stochastic steady

¹⁶ There 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 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.

¹⁷ This shift in λ_m is in line with Keys et al. (2013), 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.

¹⁸ These 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 model (remaining lifetime from date of purchase) is longer than that in the data (typically 30 years from date of purchase). Greenwald reports

state, 10% of households that originate new mortgages are within 5 percentage points of the PTI constraint. In comparison, in 1999, 9% of US households were within 5 percentage points of a 50% PTI, which was the most commonly prevailing PTI limit. Our model thus generates a fraction of potentially constrained households that is in line with the data.¹⁹

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), that is, 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, Primiceri, and Tambalotti (2019), 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 V.A.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.

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 $q_{LL}^{\phi*} = q_{HH}^{\phi*}$. 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 and ϕ_H , and four transition probabilities.

We choose ϕ_L so that the average share of housing in total consumer expenditures is 0.16 (National Income and Product Accounts) 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

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.

¹⁹ These statistics come from the Freddie Mac Single Family Loan-Level Dataset, available at http://www.freddiemac.com/research/datasets/sf_loanlevel_dataset.page, as of February 10, 2015; 1999 is the earliest year for which data are available.

(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% per year over the next 10 years. We target the middle of this range, that is, 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 (Organisation for Economic Co-operation and Development) 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 (5.5) years.²⁰ 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.

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 (2007–15).

In the preboom 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 sec. V.A). We model the bust as a reversion of all three shocks to their preboom 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

²⁰ We 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.

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 (figs. F1–F11, G1, G2, and H1 are available online) plots the realized path for expected house price growth generated by the switch, which is in line with the survey evidence discussed above.

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.

C. 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.

1. Life-Cycle Implications

Figure 2 displays the life-cycle profiles for several key model variables. The mean life-cycle profiles for labor income, pension income, nondurable consumption, and housing consumption are displayed in panel *A*, and the corresponding life-cycle profiles for the variance of logs of these variables are displayed in panel *B*. The shape of these profiles is typical of incomplete-market models and broadly consistent with their empirical counterparts (Heathcote, Perri, and Violante 2010).

Figure 2*C* shows that the life-cycle profile of homeownership in the model rises steadily from 10% at age 25 to 80% at age 55 and then levels off, consistent with data. Homeownership rises with age in the model for two main reasons. First, it takes time for households to accumulate enough savings to overcome the down-payment and PTI constraints in order to buy a house of desired size. Because of the income and wealth heterogeneity, some households succeed earlier than others. Second, with constant relative risk aversion 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 life cycle so does the amount of owner-occupied housing.

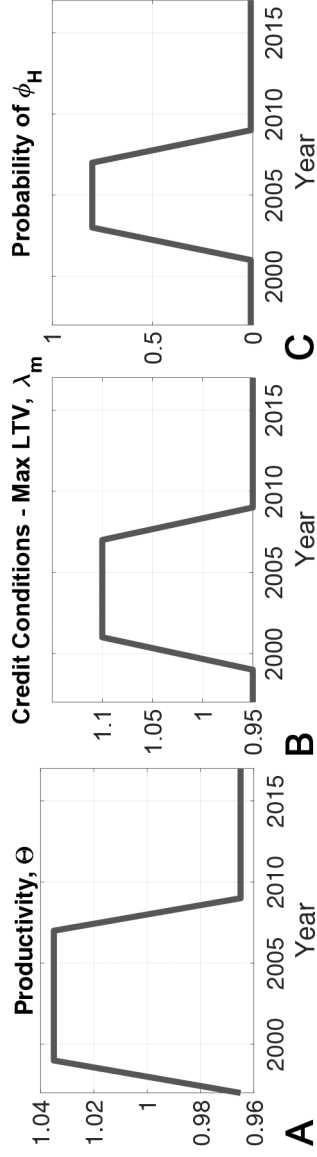


FIG. 1.— Boom-bust episode, realized path for shocks. *A*, Productivity, Θ . *B*, All components of financial deregulation (only max LTV shown). *C*, Probability of switching to the ϕ_H state. A color version of this figure is available online.

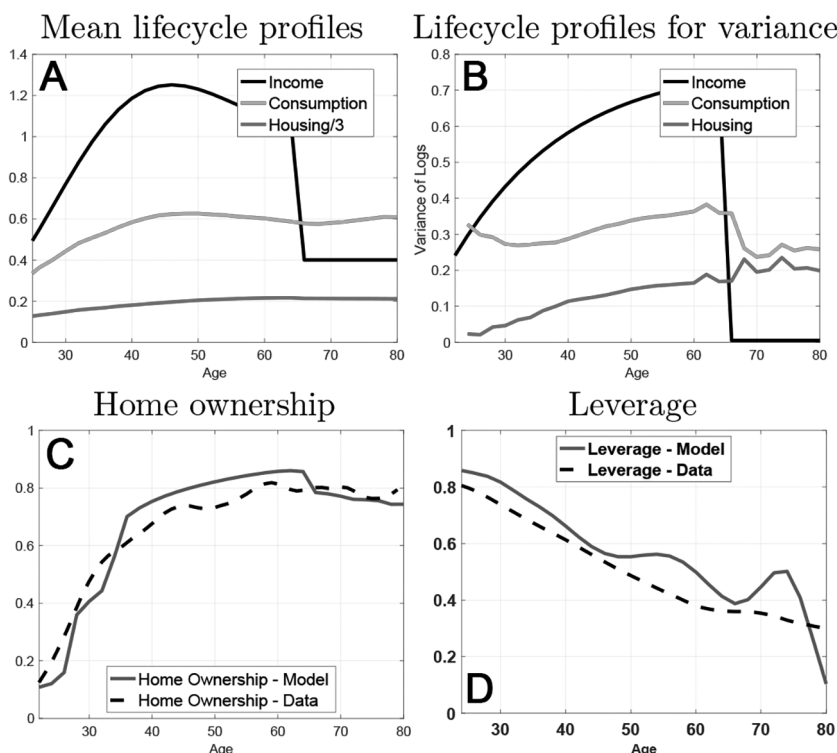


FIG. 2.—A, Average earnings, nondurable consumption, and housing expenditures by age in the model. B, Age profile of the variance of the logs for these same variables in the model. C, Homeownership in the model and in the data (source: 1998 SCF). D, Leverage ratio among homeowners with mortgage debt in the model and in the data (source: 1998 SCF). A color version of this figure is available online.

Figure 2D shows that, among homeowners 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 F1 (tables D1 and F1 are available online), we report the distribution of house sizes over the life cycle for homeowners 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-aged households, a manifestation of the fact that it underestimates wealth concentration at the top, as we explain below.

2. Cross-Sectional Implications

Table 4 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 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.

We have also computed the aggregate marginal propensity to consume out of a small windfall of cash to be 39.5% over the 2-year model period. This value is well in line with the empirical estimates discussed in, for example, 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.

TABLE 4
OTHER IMPLIED CROSS-SECTIONAL MOMENTS NOT EXPLICITLY TARGETED
IN THE MODEL PARAMETERIZATION

Moment	Empirical Value	Model Value
Fraction of homeowners with mortgage	.66	.56
Fraction of homeowners with HELOC	.06	.03
Aggregate mortgage debt/housing value	.42	.34
10th percentile LTV ratio for mortgagors	.15	.14
50th percentile LTV ratio for mortgagors	.57	.58
90th percentile LTV ratio for mortgagors	.92	.89
Gini of net worth distribution	.80	.69
Share of net worth held by bottom quintile	.00	.00
Share of net worth held by middle quintile	.05	.08
Share of net worth held by top quintile	.81	.69
Share of net worth held by top 10%	.70	.35
Share of net worth held by top 1%	.46	.07
10th percentile house value/earnings	.9	1.0
50th percentile house value/earnings	2.1	2.0
90th percentile house value/earnings	5.5	4.3
BPP consumption insurance coefficient	.36	.41

SOURCE.—1998 SCF, except for the consumption insurance coefficient (Blundell, Pistaferri, and Preston [BPP] 2008).

TABLE 5
HOUSE SIZE DISTRIBUTION BETWEEN OWNER-OCCUPIED AND RENTAL
IN THE DATA AND IN THE MODEL (%)

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

NOTE.—Data are from the American Housing Survey. Our segmentation assumption implies that the smallest house size cannot be owned and the largest four house sizes cannot be rented.

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 5 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 homeowners 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 (Panel Study of Income Dynamics) for survey years 1968–96, that is, the preboom period corresponding to our stochastic steady state. Appendix E contains a detailed description of sample selection and methodology. Table 6 shows that the model is broadly consistent with the data, except for the fact that it underpredicts the average drop in house size for owner-rental transitions.

IV. Boom-Bust Dynamics in the Housing Market

In this section, we present our main quantitative findings on the sources of the boom-bust in the housing market and the extent and channels

TABLE 6
AVERAGE LOG CHANGES IN HOUSE SIZE BY TYPE OF TRANSITION

	R→O	R→R	O→R	O→O
Data	.25 (.01)	.04 (.01)	−.29 (.01)	.04 (.01)
Model	.22	.01	−.10	.06

NOTE.—House size refers to housing units in the model and number of rooms in the data. Standard errors are in parentheses. O = owner; R = renter. Data source is PSID 1968–96. See app. E for details.

through which the changes in house prices transmitted to consumption expenditures.

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, 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).

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

A. House Prices and Rent-Price Ratio

The benchmark model features a 30% increase in house prices followed by a similar-sized decline (fig. 3A). 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

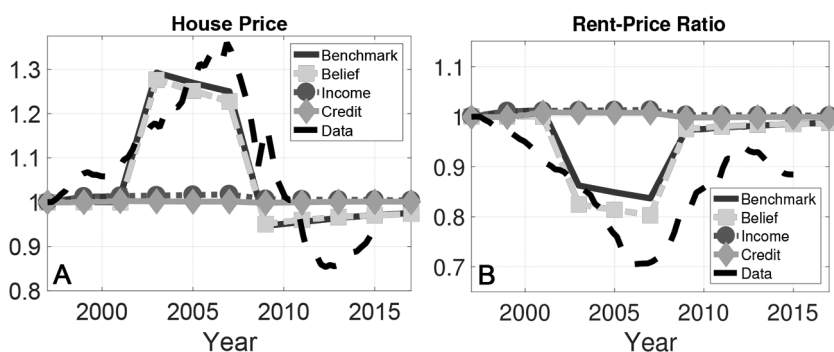


FIG. 3.—A, House price. B, Rent-price ratio. “Benchmark” represents the model’s simulation of the boom-bust episode with all shocks hitting the economy. The other lines correspond to counterfactuals where all shocks are turned off except the one indicated in the legend. Model and data are normalized to 1 in 1997. A color version of this figure is available online.

about significant movement in house prices is one of the main conclusions of our paper and one to which we return repeatedly. Our findings suggest that the boom-bust in house prices was due to a shift in expectations about future house price growth, not a shift in credit conditions.

The model can generate more than half of the fall in the rent-price ratio observed in the data (fig. 3*B*). 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 (eq. [11]; recall that, for now, we assume $m = (1 + r_b)^{-1}$). This condition dictates that when current prices increase, rents increase too. 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.

B. Homeownership

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

Both the productivity shock and the credit conditions shock, however, induce boom-bust dynamics in homeownership. 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 homeownership. The relaxation of credit conditions has a similar-sized effect on homeownership that operates by relaxing the LTV constraint and lowering the cost of originating mortgages.

Summing the individual effects of three shocks does not generate the homeownership 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.

Figures 4*B* and 4*C* show the change in homeownership for households of different ages. In both model and data, the rise and fall in

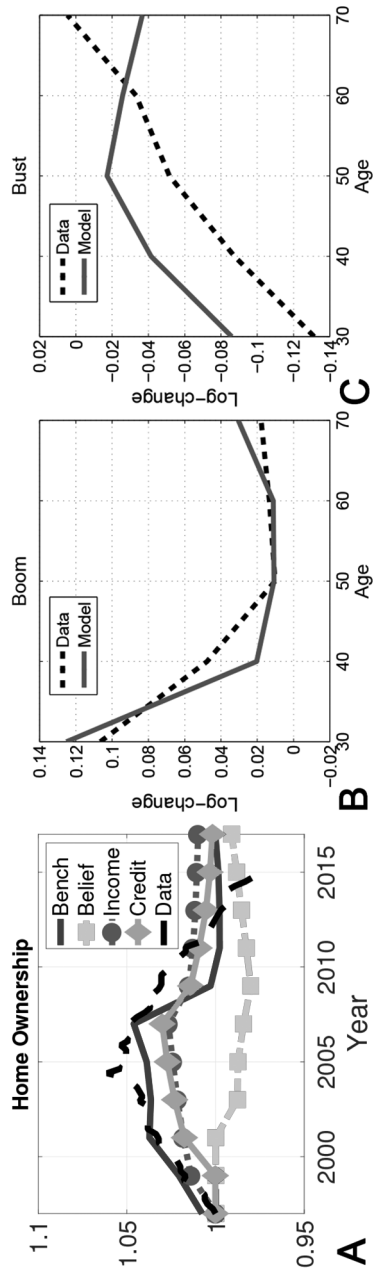


FIG. 4.—Change in homeownership over time (*A*) and across age groups (*B*, *C*) in the data and in the model. In *A*, model and data are normalized to 1 in 1997. “Bench” represents the model’s simulation of the boom-bust episode with all shocks hitting the economy (i.e., benchmark). A color version of this figure is available online.

homeownership are predominantly driven by young households. They dominate the movements in homeownership 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.

C. Decoupling of House Prices and Homeownership

We have shown that a relaxation of credit conditions has a strong effect on homeownership but not on house prices. What explains this surprising decoupling of house prices from homeownership dynamics following a credit shock?

Households in the model choose to own rather than rent for one of three reasons: (1) in order to live in a house larger than the ones available in the rental market, (2) in order to take advantage of the utility benefit of owning, or (3) in order to capture the expected capital gain from owning a house. 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—they would like to own a home for the first of these reasons but cannot because of credit constraints. 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 to rent a house of their desired size. A credit relaxation induces these renters to become owners, for the second and third reasons. But these switchers buy houses similar in size to the ones they were previously renting. Homeownership increases without pushing up total demand for housing services and, hence, without pushing up house prices. The age profile of homeownership shifts to the left—households who would have become owners in the future buy houses today in order to take advantage of the utility benefit and capital gains—but the life-cycle profile of consumption of housing services remains virtually unchanged.²¹

In contrast, the belief shock induces existing homeowners to buy bigger houses so that they can take advantage of expected future house price growth, which pushes up house prices.

D. Leverage

Figure 5A displays the model's implications for the dynamics of leverage, which is defined as aggregate mortgage debt divided by aggregate housing

²¹ As illustrated by Landvoigt, Piazzesi, and Schneider (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.

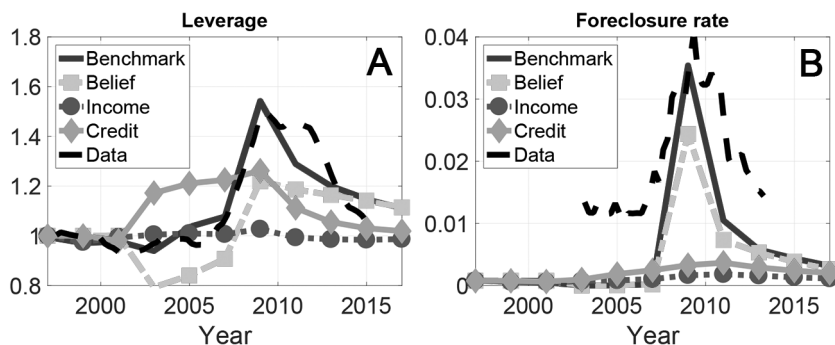


FIG. 5.—*A*, Leverage. *B*, Foreclosure rate. “Benchmark” represents the model’s simulation of the boom-bust episode with all shocks hitting the economy. The other lines correspond to counterfactuals where all shocks are turned off except the one indicated in the legend. Model and data are normalized to 1 in 1997. A color version of this figure is available online.

wealth. The model can generate a flat path for leverage during the boom, as in the data, because of two offsetting effects. The shift toward 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 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 II.B, if mortgages were short-term, changes in house prices would induce nearly proportional changes in debt. In section V.D, we present an economy with short-term debt where deleveraging behavior is much more abrupt.²²

E. Foreclosures

The spike in foreclosures in the model (fig. 5*B*) is close in size to the spike in the data. In the model, the foreclosure crisis is driven by the

²² In 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 homeowners had a HELOC usage rate beyond 75% (2004 and 2007 SCF).

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: (1) it does not move prices, and (2) in an environment with long-term debt, a tightening of LTV and PTI constraints is relevant only at origination. The figure shows that, as for homeownership, 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 V.A, it is important for these dynamics that lenders also experience the same shifts in their expectations.

F. Cross-Sectional Distribution of Debt and Foreclosures

In appendix G, we show that our model is consistent with two key features of the cross-sectional distribution of housing debt and distress. First, we show that the model reproduces the level and change in the share of outstanding mortgage debt owed by different parts of the household income distribution. Second, we show that the model tracks the relative shares of foreclosures accounted for by different quartiles of the credit score distribution (which we proxy in the model with probability of default) during the bust.

G. Consumption

Figure 6A shows that the model generates a boom-bust in consumption similar in size to that in the data. The credit conditions shock has virtually no effect on nondurable consumption because it does not affect house prices. 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 from changes in house prices to consumption? Figure 6B shows that a wealth effect can go a long way in explaining the dynamics of consumption.²³ The panel plots the change in log consumption during the bust for households with different ratios

²³ This 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.

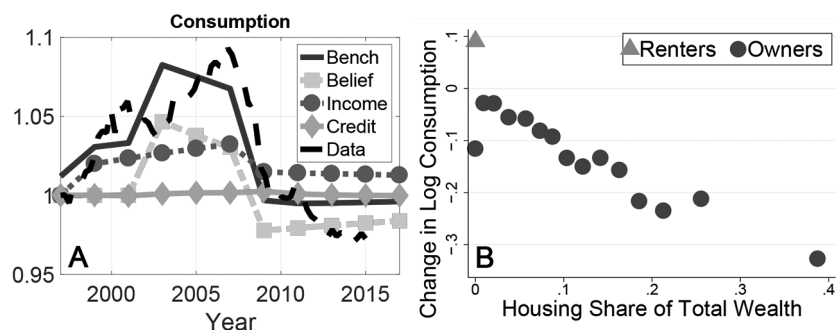


FIG. 6.—A, Consumption. “Bench” represents the model’s simulation of the boom-bust episode with all shocks hitting the economy (i.e., benchmark). The other lines correspond to counterfactuals where all shocks are turned off except the one indicated in the legend. Model and data are normalized to 1 in 1997. B, 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. A color version of this figure is available online.

of net housing wealth to total wealth at the peak of the boom.²⁴ 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 semielasticity 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 aggregate consumption? After all, there are counteracting forces that work in the opposite direction. For example, figure 6B 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 do not 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.²⁵

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 life-cycle dimension is crucial here, and the age

²⁴ Total 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.

²⁵ A simple example that abstracts from leverage may help illustrate this point. Imagine that 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.

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 (homeownership 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 (i.e., they expect to either downsize or upsize by less than the current stock of housing they own).²⁶ 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.

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 0.18.²⁷

V. Understanding Our Results

Lying at the heart of all the results in section IV are differences in the way the economy responds to changes in beliefs about future housing demand, versus changes in credit conditions. In sections V.A and V.B, we show how alternative modeling choices for these two shocks would affect our findings. In section V.C, we show that our findings are robust to alternative modeling of the rental market. Finally, in section V.D, 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.

A. *The Role of Beliefs*

In our model we generate rational shifts in beliefs about future house prices through exogenous stochastic changes in the conditional probability

²⁶ In their overlapping-generations model, Kiyotaki, Michaelides, and Nikolov (2011) find that house price movements have negligible effects on aggregate consumption, but their calibration implies a much more pronounced hump in the homeownership profile, and, as a consequence, positive and negative wealth effects offset each other more among the living generations.

²⁷ For 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-sized drops in consumption.

distribution over future preferences for housing services. This mechanism is built on three assumptions: (1) that all agents in the economy share these beliefs, (2) that there is a change in beliefs about preferences, rather than a change in actual preferences, and (3) 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.

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.

1, 2. Own beliefs (1) versus other households' beliefs (2).—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 .²⁸

In figure F2, we show that in both of these experiments the implied boom-bust in house prices is smaller than that in the data, between 7% and 10%, or around one-fourth of the one in the benchmark economy,

²⁸ To 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.

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 lead 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. *Lenders' beliefs.*—Mortgage lenders understand both the direct and the speculative effects 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 and households have different beliefs.

The lines labeled "Only Bank" in figure 7 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.²⁹

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 labeled "No Bank" in figure 7 reflect an economy where mortgage lenders are pessimistic, in that they 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 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.

²⁹ To 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 those 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.

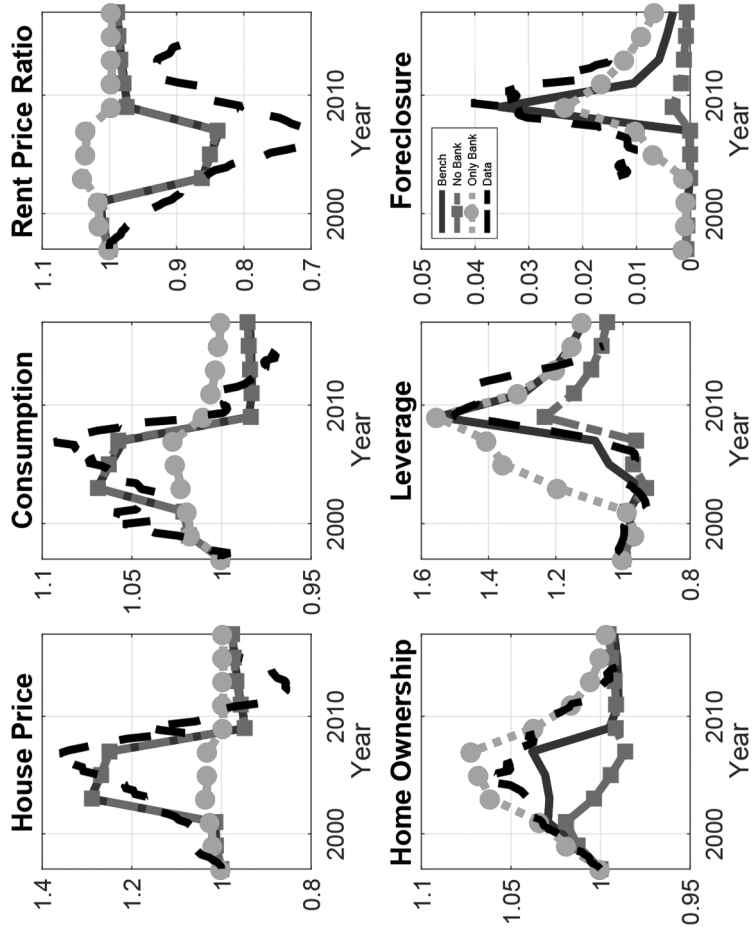


FIG. 7.—“Only Bank” represents the model where only lenders are subject to the belief shift (households and rental company are not). “No Bank” represents the model where the lenders are not subject to the belief shift (households and rental company are). “Bench” has the same meaning as in figure 6. A color version of this figure is available online.

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 homeownership, leverage, and foreclosure. In their absence, homeownership counterfactually falls when households become optimistic during the boom. Expansion of mortgage debt is 10% lower, which implies that this channel accounts for 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 endogenous mortgage pricing schedule is affected by the optimistic beliefs of lenders during the boom. In figure 8, we show an example of this schedule for particular type of household. We plot the

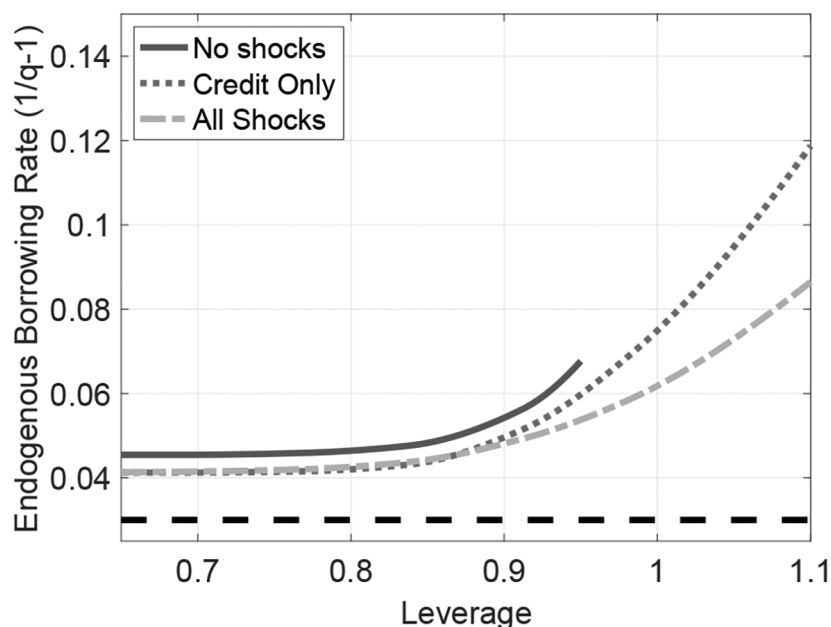


FIG. 8.—Mortgage interest rate as a function of leverage for a 30-year-old household with median earnings using all their savings to buy a \$150K house. The switch to looser credit conditions induces a movement from the “No Shocks” schedule to the “Credit Only” schedule. The switch to optimistic beliefs (shared by all agents in the economy) induces a movement from the “Credit Only” schedule to the “All Shocks” schedule. The flat dashed line represents the risk-free rate r_f . A color version of this figure is available online.

mortgage rate, defined as the inverse of the price of a unit of mortgage debt $1/q_j(\mathbf{x}', y; \Omega)$ and expressed annually, against the LTV at origination (see eq. [10]). The solid line shows that, in normal times, the mortgage rate for this household increases from around 4.5% per annum at low levels of leverage, where the default probability is close to zero, to nearly 7% per annum at an LTV of 95%, which is the regulated maximum λ_m before the boom.

The dotted line in figure 8 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 8 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.³⁰ This is the sense in which our model generates an endogenous credit supply shock, that is, an expansion of cheap funds to risky borrowers, using the language of Mian and Sufi (2009, 2016a) and Justiniano, Primiceri, and Tambalotti (2019).

In the absence of a shift in lenders' 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 less 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 homeownership, 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 eq. [11]). As explained in section IV, 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 homeownership rate (see fig. F3). 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 an excessive rise in homeownership (Landvoigt 2017).

³⁰ Demyanyk and Van Hemert (2011) document a decline in the subprime-prime spread of between 50 and 100 basis points over the boom, once they control for LTV ratio. Figure 8 implies a similar reduction at the preboom maximum LTV ratio of 95%.



FIG. 9.—House prices and aggregate consumption. “Benchmark” represents the model’s simulation with the shift in beliefs about taste for housing hitting the economy. “Preferences Only” represents the model’s simulation with an actual shift in taste for housing ($\phi_L \rightarrow \phi_H \rightarrow \phi_L$) hitting the economy. A color version of this figure is available online.

2. Belief Shifts or Preference Shifts?

Figure 9 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 that from 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 thus strong evidence against an actual shift in housing demand and are, instead, consistent with a shift in beliefs about future housing demand.³¹

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

³¹ With 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 (at both low and high frequencies) in the aggregate share of housing services in total consumption.

change in preference were actually to occur, it would generate an increase in equilibrium house prices (see fig. 9A). 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 prices would 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, that is, a shift from $\bar{L}_H$ to $\bar{L}_H^*$. The bust is obtained through a switch back to $\bar{L}_H$.³² We assume that in the tight-land-supply state the number of new permits issued is two-thirds of that in the loose states.

The aggregate dynamics associated with this experiment, displayed in figure 10, are similar to those in the baseline. House prices rise by around 20%, which is more than 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: a fall in the actual number of available land permits would lead to an increase in prices, but it would also lead to a counterfactual drop in housing investment (analogously to the counterfactual drop in consumption in fig. 9B).

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

B. Alternative Models of Credit Relaxation

A central finding in section IV was that a relaxation and subsequent tightening of credit conditions has very little power to generate a boom-bust in house prices and consumption. In appendix H, we show that this finding is not a consequence of the particular way that we have modeled credit relaxation. We consider three alternatives that have been proposed in the literature.

³² Nathanson and Zwick (2017) argue that 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.

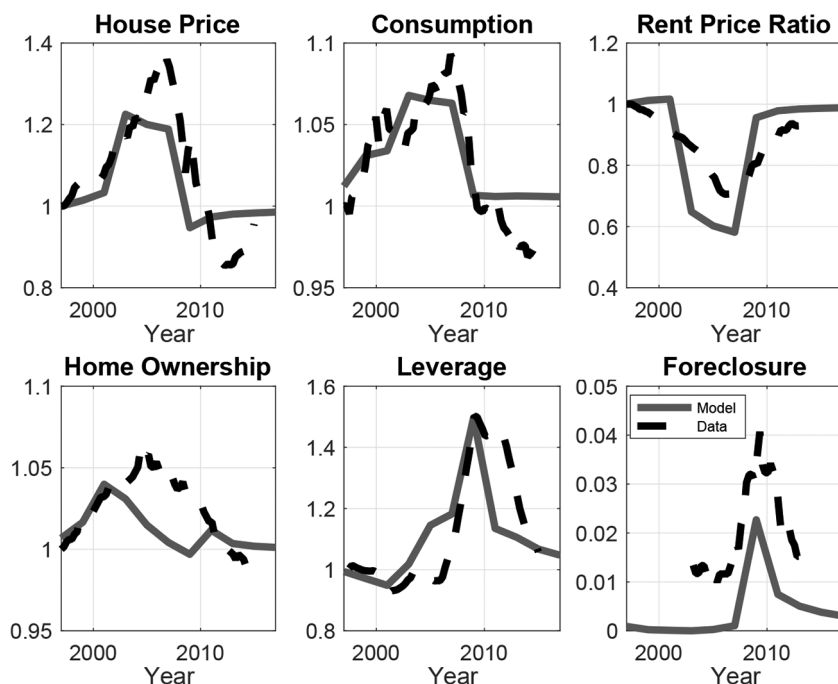


FIG. 10.—Model where beliefs are over the supply of future land permits compared to the data. A color version of this figure is available online.

First, we consider the “houses-as-ATMs” view (Chen, Michaux, and Roussanov 2013): the rise in approval rates for second liens and the looser limits on HELOCs allowed homeowners to extract a larger fraction of their home equity. We capture these effects through an increase in the maximum HELOC limit λ_b . Second, we consider the effects of adjustable-rate and low-teaser-rate mortgages, which lowered monthly mortgage payments. We capture these effects through a reduction in the amortization rate r_m , which determines the minimum required mortgage payment in equation (7). Third, we consider a reduction in the risk-free rate r_b .

Each of these alternate ways of modeling credit relaxation has different implications for leverage, foreclosures, homeownership, and refinancing, but none of them generates a substantial boom-bust in house prices.

C. 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.

1. Segmentation of Rental and Owner-Occupied Housing Markets

As described in section III, our model has seven house sizes, with partial segmentation between rental and owner-occupied units. The first row of table D1 illustrates which size houses can be rented and owned in the baseline. Appendix F also 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 D1.

All cases give results that are virtually indistinguishable from the baseline. The only exception is that, in response to the belief shock, homeownership rises by a smaller amount in the case where there is complete segmentation between rental and owner-occupied units. This confirms that in our model renters are not constrained in the amount of housing services they consume: if in order to buy they are forced to increase their house size a lot, they opt to remain renters.

2. A Rental Sector with Financial and Convertibility Frictions

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.

First of all, our baseline assumption that stocks of rental and owner-occupied housing are highly substitutable is 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 3 million units were converted (Joint Center for Housing Studies 2013), and over the same period, 4.5 million households switched status from owners to renters. Thus, conversions account for the bulk of these transitions during the bust. Second, as we show in this section, when we relax the assumption of a frictionless rental sector our conclusions are not affected.

So far we have assumed that the rent-price ratio is determined by the frictionless user-cost formula (eq. [11]) that relates rents to current and expected future house prices under risk neutrality, that is, $m = (1 + r_b)^{-1}$. On the basis of this formula, in section V.A.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 D2, we generalize equation (11), which 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:

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

There are three differences between equation (15) and its baseline version, equation (11). First, the stream of future profits of the rental company is discounted with a general aggregate stochastic discount factor $\mathfrak{m}(\Omega, \Omega')$ 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 ($\mathfrak{m} = (1 + r_b)^{-1}$), equation (15) reduces to equation (11), our baseline. However, in its general formulation, it allows for several additional sources of fluctuation 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 affected 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 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 on the basis of movements in the underlying constraint; rather, we are treating them as a residual, much as we treat beliefs in the baseline.

Figure 11 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 homeownership 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 m in equation (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,



FIG. 11.—Rent-price ratio, house price, and homeownership dynamics with frictions in rental sector. *Top*, shock to leverage constraint. *Middle*, shock to convertibility between rental and owner-occupied units. *Bottom*, shock to the stochastic discount factor of investors. A color version of this figure is available online.

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 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 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 11 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.³³

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.³⁴ 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 homeownership during the boom.³⁵

The reason why the model with fixed rents generates only a small movement in house prices when credit is relaxed is 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

³³ Our general model also allows for a nonnegativity 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 m and η would be affected, and thus this shock is a combination of the others we already analyzed.

³⁴ See, e.g., Garriga and Hedlund (2017) and Guren, Krishnamurthy, and McQuade (2018).

³⁵ The decline in homeownership 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.

increase in demand for owner-occupied housing is modest, leading to a small move up the housing supply curve.

4. A Version with Household-Landlords

According to the Joint Center for Housing Studies (2017), one-half of all rental units in the United States are owned by individuals, while the other half are owned by corporations, small businesses, and pass-through entities that are owned by individuals. Thus, individual households have a major ownership stake in the rental market, and 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 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 multifamily properties with more than five units, corporations own the vast majority of the rental stock, but for single-family or small multifamily 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 homeowners 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 fig. F10).

The reason is that when credit gets cheaper, in the 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 toward housing. In this version of the model without belief shocks, the annualized expected excess return on housing is around 2%, which is much lower than the 5%–6% average excess returns on US housing estimated by Giglio et al. (2015). With belief shocks, the excess return in the model is 3%, higher but still below the estimated value. This is a limitation of our framework and poses a challenge for the literature.

As we elaborate on in the next section, existing models that generate a high expected return on housing without belief shocks do so by preventing unconstrained households from arbitraging away those returns, typically by shutting down rental markets.

In conclusion, the result that credit shocks are not an important driver of house price dynamics and that 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 homeownership 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.

D. Models Where Credit Conditions Affect House Prices

Several 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., He, Wright, and Zhu 2015; Greenwald 2016; Favilukis, Ludvigson, and Van Nieuwerburgh 2017; Garriga, Manuelli, and Peralta-Alva 2017; Justiniano, Primiceri, and Tambalotti 2019). Why do we reach a different conclusion? Models in which house prices are sensitive to credit conditions are typically models in which either (1) housing commands a large collateral value (because of a binding collateral constraint) and changes in credit conditions affect the ability to collateralize the asset, or (2) housing commands a large risk premium and changes in credit conditions have a large impact on the size of the premium.

Within this last class of models, Favilukis, Ludvigson, and Van Nieuwerburgh (2017) find that house prices respond strongly to changes in the maximum LTV. Three features of their model, all of which differ from ours, combine to yield a large housing risk premium that is sensitive to LTV limits: (1) the absence of a rental market, (2) short-term nondefaultable mortgages, and (3) higher risk aversion.³⁶ The absence of a rental market means that all households are homeowners, 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.

³⁶ These 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.

Moreover, since all mortgage debt is short-term and nondefaultable, housing is a very risky asset for these households—any fall in house prices requires them to cut consumption in order to roll over 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 Favilukis, Ludvigson, and Van Nieuwerburgh (2017; see app. D.5 for details). With parameters chosen to mimic their economy, we show in figure F11 that a relaxation and subsequent tightening of credit conditions can, on its own, generate a 20%–25% boom-bust in house prices. However, just as with the credit shock in our baseline model, this comes at the cost of a large increase in leverage during the boom, unlike in the US data, in which leverage remained flat during the boom (see fig. 5).

Of the three features, the short-term nondefaultable debt and the absence of a rental market are the key ingredients required for credit conditions to move house prices.³⁷ 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. When rental markets are present, few households are constrained in the quantity of housing that they consume and homeownership 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.

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 US households are renters, we think that the existence of a rental market is a more realistic assumption than the absence of one. Section V.C 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 US housing market than the assumption that housing is financed by one-period nondefaultable debt. Long-term

³⁷ In 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, Ludvigson, and Van Nieuwerburgh 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 app. D for details of the calibration of this economy.

debt is nearly universal in the United States; in 2015, the median mortgagor had a 30-year mortgage contract, and only 2.6% 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.

VI. Policy Experiment: A Debt Forgiveness Program

In early 2009, at the height of the housing crisis, the Obama administration implemented two mortgage modification programs: HAMP and HARP. These interventions were intended both to provide relief to heavily indebted borrowers and to slow the collapse in house prices and the 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.³⁸ Our model provides a useful laboratory for evaluating this conjecture.

We design a policy intervention in which all homeowners with LTV ratios above 95% 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.³⁹ In our model, this program affects around one-quarter of all homeowners with mortgages. As a result, 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 a fall in disposable income from higher taxes.

Figure 12 shows the macroeconomic implications of the policy. By reducing the number of 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

³⁸ See, e.g., Posner and Zingales (2009) for a critical discussion of different proposals.

³⁹ We 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 nonvalued 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.

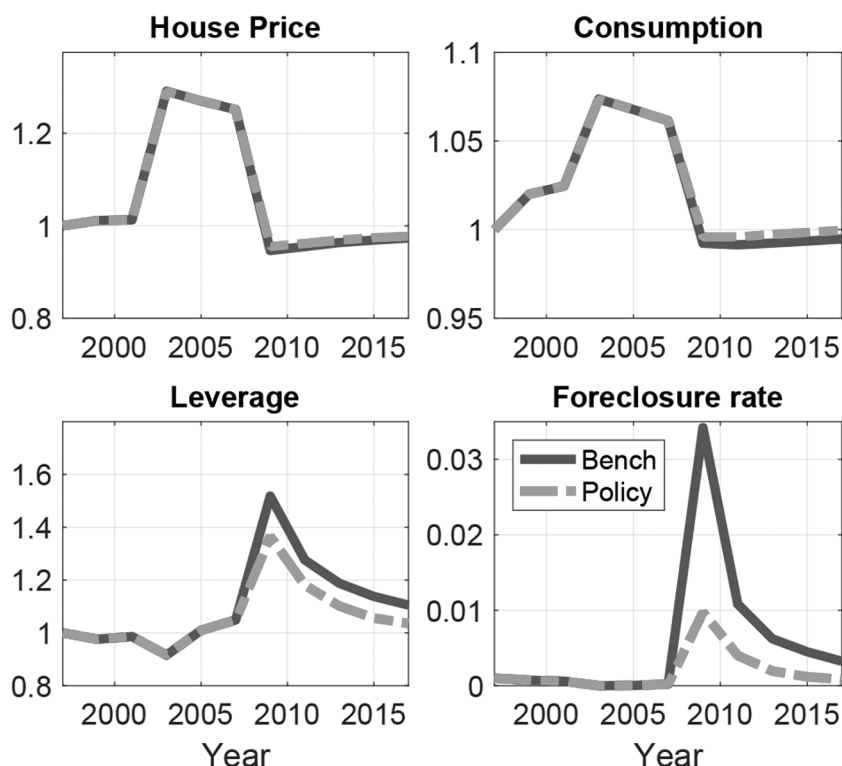


FIG. 12.—Principal forgiveness program where all mortgages with more than 95% LTV ratio reset to 95% in 2009. “Bench” represents the model’s simulation of the boom-bust episode with all shocks hitting the economy (i.e., benchmark). A color version of this figure is available online.

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 is affected by the policy. As explained above, credit and house prices are disconnected, and house prices are the key driver of consumption dynamics in the model.⁴⁰ 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

⁴⁰ Only large foreclosure externalities on house prices—not present in our model—might change this result. Earlier in the paper (sec. II), we argued that the micro estimates of the size of such local externalities indicate that, by abstracting from this channel, the model misses very small feedback effects of foreclosures on aggregate house prices.

the empirical findings of Agarwal et al. (2013), who show that regions where HAMP was used most intensively experienced virtually no change in non-durable 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 12 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 get only 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.⁴¹

VII. Conclusions

Viewed through the lens of our model, the housing boom-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 same time, our model also suggests that an exogenous relaxation of credit conditions was essential for explaining the dynamics of leverage, homeownership, 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 model by assuming that housing, rental, and credit markets are competitive and that housing is homogeneous—as explained, this allows us to iterate only over the law of motion for house price. However, because of this

⁴¹ Studying HARP, Mitman (2016) finds quantitatively similar effects on consumption for high-LTV households but much smaller effects on foreclosure. Since HARP affected only payments but not principal, this suggests that the reduction in payments most directly affects consumption, whereas principal reduction mitigates foreclosures (and our experiment is a combination of both).

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 homeownership, 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, Eichenbaum, and Rebelo (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 2018).

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, Klaus, Albert Marcet, and Johannes Beutel. 2017. "Stock Price Booms and Expected Capital Gains." *A.E.R.* 107:2352–408.
- Adelino, Manuel, Antoinette Schoar, and Felipe Severino. 2017. "Dynamics of Housing Debt in the Recent Boom and Great Recession." *NBER Macroeconomics Ann.* 32:265–311.
- Agarwal, Sumit, Gene Amromin, Itzhak Ben-David, Souphala Chomsisengphet, Tomasz Piskorski, and Amit Seru. 2013. "Policy Intervention in Debt Renegotiation: Evidence from the Home Affordable Modification Program." Working Paper no. 2013-27, Fed. Reserve Bank Chicago.
- Albanesi, Stefania, Giacomo De Giorgi, Jaromir Nosal, and Matthew Ploenzke. 2016. "Credit Growth and the Financial Crisis: A New Narrative." Manuscript, Ohio State Univ.

- Anenberg, Elliot, and Edward Kung. 2014. "Estimates of the Size and Source of Price Declines Due to Nearby Foreclosures." *A.E.R.* 104:2527–51.
- Berger, David, Veronica Guerrieri, Guido Lorenzoni, and Joseph Vavra. 2017. "House Prices and Consumer Spending." Working Paper no. 21667 (August), NBER, Cambridge, MA.
- Blundell, Richard, Luigi Pistaferri, and Ian Preston. 2008. "Consumption Inequality and Partial Insurance." *A.E.R.* 98:1887–921.
- Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo. 2016. "Understanding Booms and Busts in Housing Markets." *J.P.E.* 124:1088–147.
- Case, Karl E., and Robert J. Shiller. 2003. "Is There a Bubble in the Housing Market?" *Brookings Papers Econ. Activity* 2003 (2): 299–362.
- Case, Karl E., Robert J. Shiller, and Anne K. Thompson. 2012. "What Have They Been Thinking? Homebuyer Behavior in Hot and Cold Markets." *Brookings Papers Econ. Activity* 2012 (2): 265–98.
- Chatterjee, Satyajit, and Burcu Eyigungor. 2012. "Maturity, Indebtedness, and Default Risk." *A.E.R.* 102:2674–99.
- . 2015. "A Quantitative Analysis of the U.S. Housing and Mortgage Markets and the Foreclosure Crisis." *Rev. Econ. Dynamics* 18:165–84.
- Chen, Hui, Michael Michaux, and Nikolai Roussanov. 2013. "Houses as ATMs? Mortgage Refinancing and Macroeconomic Uncertainty." Working Paper no. 19421 (September), NBER, Cambridge, MA.
- Cheng, Ing-Haw, Sahil Raina, and Wei Xiong. 2014. "Wall Street and the Housing Bubble." *A.E.R.* 104:2797–829.
- Corbae, Dean, and Erwan Quintin. 2015. "Leverage and the Foreclosure Crisis." *J.P.E.* 123:1–65.
- Delcours, Natalya, and Norm G. Miller. 2002. "International Residential Real Estate Brokerage Fees and Implications for the US Brokerage Industry." *Internat. Real Estate Rev.* 5:12–39.
- Demyanyk, Yuliya, and Otto Van Hemert. 2011. "Understanding the Subprime Mortgage Crisis." *Rev. Financial Studies* 24:1848–80.
- De Nardi, Mariacristina. 2004. "Wealth Inequality and Intergenerational Links." *Rev. Econ. Studies* 71:743–68.
- Di Maggio, Marco, and Amir Kermani. 2017. "Credit-Induced Boom and Bust." *Rev. Financial Studies* 30:3711–58.
- Favara, Giovanni, and Jean Imbs. 2015. "Credit Supply and the Price of Housing." *A.E.R.* 105:958–92.
- Favilukis, Jack, Sydney C. Ludvigson, and Stijn Van Nieuwerburgh. 2017. "The Macroeconomic Effects of Housing Wealth, Housing Finance, and Limited Risk Sharing in General Equilibrium." *J.P.E.* 125:140–223.
- Foote, Christopher L., Lara Loewenstein, and Paul S. Willen. 2016. "Cross-Sectional Patterns of Mortgage Debt during the Housing Boom: Evidence and Implications." Working Paper no. 22985 (December), NBER, Cambridge, MA.
- Ganong, Peter, and Pascal Noel. 2017. "The Effect of Debt on Default and Consumption: Evidence from Housing Policy in the Great Recession." Manuscript, Harvard Univ.
- Garriga, Carlos, and Aaron Hedlund. 2017. "Mortgage Debt, Consumption, and Illiquid Housing Markets in the Great Recession." Working Paper, Univ. Missouri.
- Garriga, Carlos, Rodolfo Manuelli, and Adrian Peralta-Alva. 2017. "A Macroeconomic Model of Price Swings in the Housing Market." Working paper, Fed. Reserve Bank Saint Louis.
- Gerardi, Kristopher, Andreas Lehnert, Shane M. Sherlund, and Paul Willen. 2008. "Making Sense of the Subprime Crisis." *Brookings Papers Econ. Activity* 2008 (2): 69–159.

- Gerardi, Kristopher, Eric Rosenblatt, Paul Willen, and Vincent Yao. 2015. "Foreclosure Externalities: New Evidence." *J. Urban Econ.* 87:42–56.
- Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Andreas Weber. 2015. "Climate Change and Long-Run Discount Rates: Evidence from Real Estate." Working Paper no. 21767 (November), NBER, Cambridge, MA.
- Greenwald, Daniel L. 2016. "The Mortgage Credit Channel of Macroeconomic Transmission." Research Paper no. 5184-16, Sloan School Management, Massachusetts Inst. Technology.
- Guerrieri, Veronica, and Guido Lorenzoni. 2015. "Credit Crises, Precautionary Savings, and the Liquidity Trap." Manuscript, Univ. Chicago.
- Guerrieri, Veronica, and Harald Uhlig. 2016. "Housing and Credit Markets: Booms and Busts." In *Handbook of Macroeconomics*, vol. 2, edited by John B. Taylor and Harald Uhlig, 1427–96. Amsterdam: North-Holland.
- Guren, Adam M. 2018. "House Price Momentum and Strategic Complementarity." *J.P.E.* 126:1172–218.
- Guren, Adam M., Arvind Krishnamurthy, and Timothy J. McQuade. 2018. "Mortgage Design in an Equilibrium Model of the Housing Market." Working Paper no. 24446 (March), NBER, Cambridge, MA.
- He, Chao, Randall Wright, and Yu Zhu. 2015. "Housing and Liquidity." *Rev. Econ. Dynamics* 18:435–55.
- Heathcote, Jonathan, Fabrizio Perri, and Giovanni L. Violante. 2010. "Unequal We Stand: An Empirical Analysis of Economic Inequality in the United States, 1967–2006." *Rev. Econ. Dynamics* 13:15–51.
- Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L. Violante. 2017. "Optimal Tax Progressivity: An Analytical Framework." *Q.J.E.* 132:1693–754.
- Hedlund, Aaron. 2016. "The Cyclical Dynamics of Illiquid Housing, Debt, and Foreclosures." *Quantitative Econ.* 7:289–328.
- Huo, Zhen, and José-Victor Ríos-Rull. 2016. "Financial Frictions, Asset Prices, and the Great Recession." Staff Report 526, Fed. Reserve Bank Minneapolis.
- Hurst, Erik. 2017. "Comment on 'Dynamics of Housing Debt in the Recent Boom and Great Recession.'" *NBER Macroeconomics Ann.* 32:312–17.
- Iacoviello, Matteo, and Marina Pavan. 2013. "Housing and Debt over the Life Cycle and over the Business Cycle." *J. Monetary Econ.* 60:221–38.
- Joint Center for Housing Studies. 2013. *America's Rental Housing: Evolving Markets and Needs*. Cambridge, MA: Joint Center for Housing Studies, Harvard Univ.
- . 2017. *America's Rental Housing*. Cambridge, MA: Joint Center for Housing Studies, Harvard Univ.
- Justiniano, Alejandro, Giorgio E. Primiceri, and Andrea Tambalotti. 2019. "Credit Supply and the Housing Boom." *J.P.E.* 127:1317–50.
- Kaplan, Greg, and Giovanni L. Violante. 2014. "A Model of the Consumption Response to Fiscal Stimulus Payments." *Econometrica* 82:1199–239.
- Keys, Benjamin J., Tomasz Piskorski, Amit Seru, and Vikrant Vig. 2013. "Mortgage Financing in the Housing Boom and Bust." In *Housing and the Financial Crisis*, edited by Edward L. Glaeser and Todd Sinai, 143–204. Chicago: Univ. Chicago Press (for NBER).
- Keys, Benjamin J., Amit Seru, and Vikrant Vig. 2012. "Lender Screening and the Role of Securitization: Evidence from Prime and Subprime Mortgage Markets." *Rev. Financial Studies* 25:2071–108.
- Kiyotaki, Nobuhiro, Alexander Michaelides, and Kalin Nikolov. 2011. "Winners and Losers in Housing Markets." *J. Money, Credit and Banking* 43:255–96.
- Krusell, Per, and Anthony A. Smith Jr. 1998. "Income and Wealth Heterogeneity in the Macroeconomy." *J.P.E.* 106:867–96.

- . 2006. “Quantitative Macroeconomic Models with Heterogeneous Agents.” In *Advances in Economics and Econometrics: Theory and Applications, Ninth World Congress*, vol. 1, edited by Richard Blundell, Whitney K. Newey, and Torsten Persson, 298–340. Econometric Soc. Monographs, no. 41. Cambridge: Cambridge Univ. Press.
- Landvoigt, Tim. 2017. “Housing Demand during the Boom: The Role of Expectations and Credit Constraints.” *Rev. Financial Studies* 30:1865–902.
- Landvoigt, Tim, Monika Piazzesi, and Martin Schneider. 2015. “The Housing Market(s) of San Diego.” *A.E.R.* 105:1371–407.
- Levitin, Adam J., and Susan M. Wachter. 2011. “Explaining the Housing Bubble.” *Georgetown Law J.* 100:1177–258.
- Loutschina, Elena. 2011. “The Role of Securitization in Bank Liquidity and Funding Management.” *J. Financial Econ.* 100:663–84.
- McClements, L. D. 1977. “Equivalence Scales for Children.” *J. Public Econ.* 8:191–210.
- Mian, Atif, Kamalesh Rao, and Amir Sufi. 2013. “Household Balance Sheets, Consumption, and the Economic Slump.” *Q.J.E.* 128:1687–726.
- Mian, Atif, and Amir Sufi. 2009. “The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis.” *Q.J.E.* 124:1449–96.
- . 2014. “What Explains the 2007–2009 Drop in Employment?” *Econometrica* 82:2197–223.
- . 2016a. “Household Debt and Defaults from 2000 to 2010: The Credit Supply View.” Manuscript, Princeton Univ.
- . 2016b. “Who Bears the Cost of Recessions? The Role of House Prices and Household Debt.” In *Handbook of Macroeconomics*, vol. 2, edited by John B. Taylor and Harald Uhlig, 255–96. Amsterdam: North-Holland.
- Midrigan, Virgiliu, and Thomas Philippon. 2016. “Household Leverage and the Recession.” CEPR Discussion Paper no. 11407, Centre for Economic Policy Research, London.
- Mitman, Kurt. 2016. “Macroeconomic Effects of Bankruptcy and Foreclosure Policies.” *A.E.R.* 106:2219–55.
- Nathanson, Charles G., and Eric Zwick. 2017. “Arrested Development: Theory and Evidence of Supply-Side Speculation in the Housing Market.” Working Paper no. 23030 (January), NBER, Cambridge, MA.
- Ngai, L. Rachel, and Kevin D. Sheedy. 2017. “The Decision to Move House and Aggregate Housing-Market Dynamics.” Manuscript, London School Econ.
- Pennington-Cross, Anthony. 2006. “The Value of Foreclosed Property.” *J. Real Estate Res.* 28:193–214.
- Piazzesi, Monika, and Martin Schneider. 2016. “Housing and Macroeconomics.” *Handbook of Macroeconomics*, vol. 2, edited by John B. Taylor and Harald Uhlig, 1547–640. Amsterdam: North-Holland.
- Piazzesi, Monika, Martin Schneider, and Selale Tuzel. 2007. “Housing, Consumption and Asset Pricing.” *J. Financial Econ.* 83:531–69.
- Posner, Eric A., and Luigi Zingales. 2009. “A Loan Modification Approach to the Housing Crisis.” *American Law and Econ. Rev.* 11:575–607.
- Saiz, Albert. 2010. “The Geographic Determinants of Housing Supply.” *Q.J.E.* 125:1253–96.
- Soo, Cindy K. 2015. “Quantifying Animal Spirits: News Media and Sentiment in the Housing Market.” Working paper, Univ. Michigan.