# Collateral Constraints and Macroeconomic Asymmetries*

Luca Guerrieri† Federal Reserve Board
Matteo Iacoviello‡ Federal Reserve Board

June 22, 2017

**Abstract**

Full information methods are used to estimate a nonlinear general equilibrium model where occasionally binding collateral constraints on housing wealth drive an asymmetry in the link between housing prices and economic activity. The estimated model shows that, as collateral constraints became slack during the housing boom of 2001-2006, expanding housing wealth made a small contribution to consumption growth. By contrast, the housing collapse that followed tightened the constraints and sharply exacerbated the recession of 2007-2009. The empirical relevance of this asymmetry is corroborated by evidence from state- and MSA-level data.

KEYWORDS: Housing; Collateral Constraints; Occasionally Binding Constraints; Nonlinear Estimation of DSGE Models; Great Recession.
JEL CLASSIFICATION: E32, E44, E47, R21, R31

## 1. Introduction

A growing number of theoretical and empirical papers has emphasized leverage, financial accelerator effects and housing prices as central elements to understand the boom and bust period that ended with the Great Recession.[1] In many of these papers, the key mechanism linking housing prices and economic activity is the role of housing wealth as collateral for borrowing. As housing prices rise, household borrowing rises, fueling a debt–driven consumption boom. As housing prices decline, households are forced to borrow less, and the deleveraging pushes the economic contraction into overdrive.

We evaluate the aggregate implications of this mechanism using a DSGE model and a novel approach. The starting point is the idea that financial frictions matter disproportionately more in a

*The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System. Stedman Hood, Aaron Markiewitz and Walker Ray performed superb research assistance. The authors thank Jesus Fernandez-Villaverde, Giorgio Primiceri, Amir Sufi and seminar participants for comments and suggestions. Supplementary material and replication codes are available on the authors' webpages.

†Luca Guerrieri, Division of Financial Stability, Federal Reserve Board, 20th and C St. NW, Washington, DC 20551. Email: luca.guerrieri@frb.gov.

‡Matteo Iacoviello, Division of International Finance, Federal Reserve Board, 20th and C St. NW, Washington, DC 20551. Email: matteo.iacoviello@frb.gov.

[1] See, for instance, Mian and Sufi (2011), Guerrieri and Lorenzoni (2011), Justiniano, Primiceri, and Tambalotti (2015), Ng and Wright (2013), Eggertsson and Krugman (2012), Midrigan and Philippon (2016), and Korinek and Simsek (2016).

recession than in a boom. Our novel approach is to use Bayesian methods to estimate a model which allows for, but does not impose, asymmetric effects of housing booms and busts, depending on whether housing collateral constraints are binding or not. Our estimates point to these asymmetric effects as a central mechanism to explain not just the depth of the Great Recession, but also the events that led to it. As the housing boom unfolded, collateral constraints turned slack, and expanding housing wealth made a small contribution to consumption growth. By contrast, the subsequent housing collapse tightened the constraints and, more than the zero lower bound (ZLB) on nominal interest rates, sharply exacerbated the Great Recession. Moreover, this asymmetry is not just a feature of the estimated model based on aggregate U.S. data. Evidence from both state- and MSA-level data shows that various measures of regional activity, including consumption, are more sensitive to housing prices when housing prices are low than when they are high.

To our knowledge, this paper is the first to combine key elements of the crisis, such as leverage, occasionally binding collateral constraints, house price fluctuations, and the ZLB, within a setting rich enough to tackle full information estimation. The amplification of the declines in house prices due to collateral constraints and deleveraging was very large in the 2007-2009 period, with collateral constraints accounting for about 70 percent of the observed decline in consumption. Without collateral constraints, for instance, the recession would have been curbed to such an extent that the Federal Funds rate would not have reached zero. Additionally, although the estimated model does not directly use data on household debt, the degree of cyclical variation in empirical and model-based measures of borrowing and leverage are remarkably similar, providing further support for the paper's findings.

At the core of our analysis is a standard monetary DSGE model augmented to include a housing collateral constraint along the lines of Kiyotaki and Moore (1997), Iacoviello (2005), and Liu, Wang, and Zha (2013). As in these papers, housing serves the dual role of durable good and collateral for borrowers. To this framework, we add two empirically realistic elements that generate important nonlinearities. First, the housing collateral constraint binds only occasionally, rather than at all times. Second, in line with recent U.S. experience, monetary policy is constrained by the ZLB. We use Bayesian estimation methods to validate the nonlinear dynamics of the model against quarterly U.S. data. The estimation involves inferring when the collateral constraint is binding, and when it is not, through observations that do not include the Lagrange multiplier for the constraint. Our model has the property that house price movements matter little for economic aggregates when borrowing constraints are slack. By contrast, when the constraints are binding, the interaction of house prices with borrowing and spending decisions has a first-order effect on the macroeconomy, especially when monetary policy is unable to adjust the interest rate.

Most importantly, the model fits the data better than two competing alternatives, one without collateral constraints, and one where collateral constraints always bind. Without the collateral constraint, the model collapses to a standard monetary business cycle model, like in Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007). Such a model omits the housing collateral channel and needs to layer, on top of the shocks driving housing prices, a collective attack of patience – in the form of implausibly large negative consumption preference shocks – to fit aggregate consumption during the Great Recession. Nonetheless, this attack of patience, as well as other potential alternatives such as technology shocks, has little bearing on housing prices, which still require their independent source of variation, reducing the likelihood of that model.

A model with permanently binding collateral constraints faces unpleasant trade-offs, too. It misses the asymmetry in the relationship between house prices and consumption, so that by matching the expansion in consumption during the housing boom preceding the Great Recession, it ends up overstating the consumption collapse. Moreover, this model misses an important channel of propagation. At the peak of the housing cycle, the expansion in housing wealth relaxes collateral constraints, so that households can initially rely on borrowing to buffet any drop in consumption associated with falling house prices. Only after house prices continue falling, do borrowing constraint start to bind, and consumption and house prices comove more notably.

Support in favor of the asymmetries uncovered by the model also comes from our analysis using regional data. State- and MSA-level data confirm the asymmetric estimates based on national data. The sensitivity to house prices of expenditures – and other measures of economic activity – is about twice as large when house prices are low than whey they are high, confirming the relevance of the key mechanism at the center of our aggregate model.

A spate of recent papers has quantified the importance of financial shocks and frictions using a general equilibrium framework. Recent notable examples include Del Negro, Eggertsson, Ferrero, and Kiyotaki (2017), Gertler and Karadi (2011), Jermann and Quadrini (2012), Christiano, Motto, and Rostagno (2014). The common thread among these papers is that financial shocks and frictions – including shocks and frictions in models with an explicit intermediation sector– are key elements of the Great Recession. The occasionally binding nature of the constraints and the estimation approach applied to a nonlinear DSGE model are the two elements that set our work apart. In our model, financial constraints endogenously become slack or binding, thus mimicking the role of time-varying financial shocks (or capital quality shocks) in models with an otherwise constant set of financial constraints. In this respect, our work extends the basic mechanisms in Mendoza (2010) who also considers occasionally binding financial constraints in a calibrated small open economy setting with an exogenous interest rate. Our extensions make it possible to construct quantitative counterfactual exercises and to consider policy alternatives in an empirically validated model for the United States.[2] One application of the paper uses the estimated model to gauge the effects of policies aimed at the housing market in the context of a deep recession.

A growing body of empirical evidence points to a prominent role for housing price declines in influencing borrowing, consumption, and other aggregate measures of economic activity. For instance, recent contributions include Case, Quigley, and Shiller (2005), Campbell and Cocco (2007), Mian and Sufi (2011), Abdallah and Lastrapes (2012) and Mian, Rao, and Sufi (2013). These contributions have not attempted to disentangle the root causes of the Great Recession with a general equilibrium approach that can account for the role of non-housing shocks, monetary policy, and the amplification channels connected to the zero lower bound on nominal interest rates. Moreover, the link between housing prices and economic activity in this body of work relies on the collateral role of housing wealth. Nonetheless, this work has not emphasized that such a channel implies asymmetric relationships for house price increases and declines with borrowing and other measures of aggregate activity, depending on whether collateral constraints bind or not. Our paper is also related to the work of Lustig and van Nieuwerburgh (2010), who find that in times when U.S. housing collateral is scarce nationally, regional consumption is about twice as sensitive to income shocks. However, the channel they emphasize – time variation

[2] Gust, Herbst, Lopez-Salido, and Smith (2017) estimate a nonlinear DSGE model that takes into account the ZLB on nominal interest rates, but do not consider financial frictions. Bocola (2016) estimates a small-open economy model for Italy, including financial frictions and occasionally binding funding constraints for banks.

in risk-sharing among regions – is different from ours. Finally, our paper is also related to Cao and Nie (2017), who attempt to disentangle the amplification mechanisms related to market incompleteness from those related to occasionally binding constraints.

## 2. The Basic Model: Collateral Constraints and Asymmetries

To fix ideas regarding the fundamental asymmetry introduced by collateral constraints, it is useful to consider a basic model and analyze its implications for how consumption responds to changes in house prices. In this section, general equilibrium links are sidestepped and the price of housing is assumed to be exogenous. These assumptions are relaxed in the DSGE model of the next section.

Consider the problem of a household that has to choose profiles for goods consumption $c_t$, housing $h_t$, and borrowing $b_t$. The household's problem is to maximize

$$E_0 \sum_{t=0}^{\infty} \beta^t \left( \log c_t + \mathsf{j} \log h_t \right), \tag{1}$$

where $E_0$ is the conditional expectation operator. The household is subject to the following constraints:

$$\begin{aligned} c_t + q_t h_t &= y + b_t - R b_{t-1} + q_t \left(1 - \delta_h\right) h_{t-1}, && (2) \\ b_t &\leq \mathsf{m} q_t h_t, && (3) \\ \log q_t &= \rho_q \log q_{t-1} + \varepsilon_{q,t}. && (4) \end{aligned}$$

Equation (2) is the budget constraint. Income $y$ is fixed and normalized to one. The term $b_t$ denotes one-period debt. The gross one-period interest rate is $R$. Housing, which depreciates at rate $\delta_h$, has a price $q_t$ in units of consumption. Equation (3) is a borrowing constraint that limits borrowing to a maximum fraction $\mathsf{m}$ of housing wealth. Equation (4) describes the price of housing, $q_t$, which follows an AR(1) stochastic process, where $\varepsilon_{q,t}$ is a zero-mean, i.i.d. process with variance $\sigma_q^2$.

Denoting with $\lambda_t \geq 0$ the Lagrange multiplier on the borrowing constraint, the Euler equation for consumption can be written as:

$$\frac{1}{c_t} = \beta R E_t \left( \frac{1}{c_{t+1}} \right) + \lambda_t. \tag{5}$$

Solving this equation for consumption and iterating forward yields:

$$c_t = \frac{1}{\lambda_t + \beta R E_t \left(\lambda_{t+1}\right) + \left(\beta R\right)^2 E_t \left(\lambda_{t+2}\right) + \ldots}. \tag{6}$$

Expressing the Euler equation as above shows that current consumption depends negatively on current and future expected borrowing constraints. Increases in $q_t$ loosen the borrowing constraint. So long as they $\lambda_t$ stays positive, increases and decreases in $q_t$ have roughly symmetric effects on $c_t$. However, large enough increases in $q_t$ lead to a fundamental asymmetry. The multiplier $\lambda_t$ cannot fall below zero. Consequently, large increases in $q_t$ can bring $\lambda_t$ to its lower bound and will have proportionally smaller effects on $c_t$ than decreases in $q_t$. Intuitively, an impatient borrower prefers a consumption profile that is declining over time. A temporary jump in house prices enables such a profile (high consumption today, low consumption tomorrow), without borrowing all the way up to the limit.

More formally, the household's state at time $t$ is its housing $h_{t-1}$, debt $b_{t-1}$ and the current realization of the house price $q_t$. The optimal decisions are given by the consumption choice $c_t = \mathcal{C}(q_t, h_{t-1}, b_{t-1})$, the housing choice $h_t = \mathcal{H}(q_t, h_{t-1}, b_{t-1})$ and the debt choice $b_t = \mathcal{B}(q_t, h_{t-1}, b_{t-1})$ that maximize expected utility subject to (2) and (3), given the house price process. Figure 1 shows the optimal leverage and the consumption function obtained from the model outlined above.[3] As the figure illustrates, high house prices are associated with slack borrowing constraints, and with a lower sensitivity of consumption to changes in house prices. Instead, when household borrowing is constrained – an outcome that is more likely when house prices are low and the initial stock of debt is high – the sensitivity of consumption to changes in house prices becomes large. This idea is developed further both in the DSGE model and in the empirical analysis to follow.

## 3. The DSGE Model: Demand Effects in General Equilibrium

To quantify the importance of the asymmetric relationship between house prices and consumption, the basic mechanisms described in Section 2 are embedded in an estimated general equilibrium model. The starting point is a standard monetary DSGE model along the lines of Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007). The model features nominal wage and price rigidities, a monetary authority using a Taylor rule, habit formation in consumption and investment adjustment costs.[4] To this framework we add three main elements. First, housing has a dual role: it is a durable good (which enters the utility function separately from consumption and labor), and it serves as collateral for "impatient" households. The supply of housing is fixed (its price varies endogenously), but housing reallocation takes place across "patient" and "impatient" households in response to an array of shocks. Second, the collateral constraint on borrowing is allowed to bind occasionally. The estimation exercise allows inferring when the constraint binds using observations that do not include the hidden Lagrange multiplier on the constraint. Third, in line with the U.S. experience since 2008, monetary policy is potentially constrained by the zero lower bound.

Our assumption that housing is in fixed supply and plays no role in production (unlike in Iacoviello and Neri 2010 and Liu, Wang, and Zha 2013) has the advantage that the model behaves essentially like the ones in Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007) when the borrowing constraint is slack. With a slack borrowing constraint, housing prices only passively respond to movements in the macroeconomy, but play no feedback effect on other macro variables.

The rest of this section describe the key model features. Appendix B provides additional details as well as a list of all the necessary conditions for an equilibrium.

### 3.1. Households

There is a continuum of measure 1 of agents in each of the two groups (patient and impatient). The economic size of each group is measured by its wage share, which is assumed to be constant. Within

[3] The policy functions in Figure 1 are obtained via value function iteration. The calibrated parameters are $\beta = 0.99$, j= 0.12, m= 0.9, $R = 1.005$, $\delta = 0.01$. The resulting steady-state ratio of housing wealth to annual income ratio is 1.5. For the house price process we set $\rho_q = 0.96$ and $\sigma_q = 0.0175$, in order to match a standard deviation of the quarterly growth rate of house prices equal to 1.77 percent, as in the data.

[4] The benchmark model abstracts from trends, excludes neutral technology shocks, and assumes fixed capacity utilization. All these assumptions –which have little bearing on the main results– are relaxed as part of sensitivity analysis presented in Appendix E.

each group, a representative household maximizes:

$$E_0 \sum_{t=0}^{\infty} \beta^t \mathsf{z}_t \left( \Gamma_c \log\left(c_t - \varepsilon_c c_{t-1}\right) + \mathsf{j}_t \Gamma_h \log\left(h_t - \varepsilon_h h_{t-1}\right) - \frac{1}{1+\eta} n_t^{1+\eta} \right); \tag{7}$$

$$E_0 \sum_{t=0}^{\infty} \left(\beta'\right)^t \mathsf{z}_t \left( \Gamma_c' \log\left(c_t' - \varepsilon_c c_{t-1}'\right) + \mathsf{j}_t \Gamma_h' \log\left(h_t' - \varepsilon_h h_{t-1}'\right) - \frac{1}{1+\eta} n_t'^{1+\eta} \right). \tag{8}$$

Variables accompanied by the prime symbol refer to impatient households. The terms $c_t$, $h_t$, $n_t$ are consumption, housing, and hours. The discount factors are $\beta$ and $\beta'$, with $\beta' < \beta$. The term $\mathsf{j}_t$ captures shocks to housing preferences. An increase in $\mathsf{j}_t$ shifts preferences away from consumption and leisure and towards housing, thus resulting in an increase in housing demand and, ultimately, housing prices. The term $\mathsf{z}_t$ captures a shock to intertemporal preferences. A rise in $\mathsf{z}_t$ increases households' willingness to spend today, acting as a consumption demand shock. The shock processes follow:

$$\log \mathsf{j}_t = (1-\rho_J)\log \bar{\mathsf{j}} + \rho_J \log \mathsf{j}_{t-1} + u_{j,t}, \tag{9}$$

$$\log \mathsf{z}_t = \rho_Z \log \mathsf{z}_{t-1} + u_{z,t}. \tag{10}$$

where $u_{j,t}$ and $u_{z,t}$ are n.i.i.d. processes with variance $\sigma_J^2$ and $\sigma_Z^2$. Above, $\varepsilon_c$ and $\varepsilon_h$ measure habits in consumption and housing services respectively. The terms $\Gamma_c$, $\Gamma_c'$, $\Gamma_h$, $\Gamma_h'$ are scaling factors that ensure that the marginal utilities of consumption and housing are independent of habits in the non-stochastic steady state.[5]

Patient households maximize utility subject to a budget constraint that in real terms reads:

$$c_t + q_t h_t + b_t + i_t = \frac{w_t n_t}{x_{w,t}} + q_t h_{t-1} + \frac{R_{t-1} b_{t-1}}{\pi_t} + r_{k,t} k_{t-1} + div_t. \tag{11}$$

Investment and capital are linked by:

$$k_t = \mathsf{a}_t \left( i_t - \phi \frac{\left(i_t - i_{t-1}\right)^2}{\bar{i}} \right) + \left(1 - \delta_k\right) k_{t-1}, \tag{12}$$

where $\bar{i}$ is steady–state investment, and the investment-specific technology $\mathsf{a}_t$ follows:

$$\log \mathsf{a}_t = \rho_K \log \mathsf{a}_{t-1} + u_{k,t},$$

where $u_{k,t}$ is a n.i.i.d. process with variance $\sigma_K^2$. Patient agents choose consumption $c_t$, investment $i_t$, capital $k_t$ (which depreciates at the rate $\delta_k$), housing $h_t$ (priced, in units of consumption, at $q_t$), hours $n_t$ and loans to impatient households $b_t$ to maximize utility subject to (11) and to (12). The term $\mathsf{a}_t$ is an investment shock affecting the technology transforming investment goods into capital goods. This type of shock has been identified as an important source of aggregate fluctuations (e.g., by Justiniano, Primiceri, and Tambalotti 2011). Loans are set in nominal terms and yield a riskless nominal return of $R_t$. The real wage is $w_t$ and the real rental rate of capital is $R_{k,t}$. The term $x_{w,t}$ denotes the markup (due to monopolistic competition in the labor market) between the wage paid by the wholesale firm and the wage paid to the households, which accrues to the labor unions. Finally, $\pi_t \equiv P_t/P_{t-1}$ is the gross

[5] Specifically, $\Gamma_c = (1-\varepsilon_c)/(1-\beta\varepsilon_c)$, $\Gamma_c' = (1-\varepsilon_c)/(1-\beta'\varepsilon_c)$, $\Gamma_h = (1-\varepsilon_h)/(1-\beta\varepsilon_h)$ and $\Gamma_h' = (1-\varepsilon_h)/(1-\beta'\varepsilon_h)$.

inflation rate, $div_t$ are lump-sum profits from final good firms and from labor unions.[6] The formulation in (12) allows for convex investment adjustment costs, parameterized by $\phi$.

Impatient households do not accumulate capital and do not own final good firms. Their budget constraint is given by:

$$c'_t + q_t h'_t + \frac{R_{t-1} b_{t-1}}{\pi_t} = \frac{w'_t n'_t}{x'_{w,t}} + q_t h'_{t-1} + b_t + div'_t. \tag{13}$$

Impatient households face a borrowing constraint that limits the amount they can borrow, $b_t$, to a fraction $\mathsf{m}$ of the house value. The constraint of the basic model of Section 2 is extended with an eye to empirical realism. Specifically, we allow for – but do not impose – the possibility that borrowing constraints adjust to reflect the market value of the housing stock only sluggishly. Accordingly, the constraint takes the form:

$$b_t \leq \gamma \frac{b_{t-1}}{\pi_t} + (1-\gamma)\, \mathsf{m} q_t h'_t, \tag{14}$$

where $\gamma > 0$ measures the degree of inertia in the borrowing limit, and $\mathsf{m}$ is the steady-state loan-to-value ratio.[7] This specification captures that borrowing constraints are fully reset only for those agents who refinance their mortgage and is consistent with the related empirical observation that measures of aggregate debt tend to lag house price movements.

### 3.2. Wholesale Firms

To allow for nominal price rigidities, we differentiate between competitive flexible price/wholesale firms that produce wholesale goods, and final good firms that operate in the final good sector under monopolistic competition subject to implicit costs to adjusting nominal prices. Wholesale firms hire capital and labor supplied by the two types of households to produce wholesale goods $y_t$. They solve:

$$\max \frac{y_t}{x_{p,t}} - w_t n_t - w'_t n'_t - r_{k,t} k_{t-1}. \tag{15}$$

Above, $x_{p,t} = P_t / P^w_t$ is the price markup of final over wholesale goods, where $P^w_t$ is the nominal price of wholesale goods. The production technology is:

$$y_t = n_t^{(1-\sigma)(1-\alpha)} n_t'^{\sigma(1-\alpha)} k_{t-1}^{\alpha}. \tag{16}$$

In Equation (16), the non-housing, wholesale sector produces output with labor and capital. The parameter $\sigma$ measures the labor income share that accrues in the economy to impatient households. When $\sigma$ approaches zero, so does the economic weight of impatient households, and the model collapses to a standard monetary model without collateral effects.

[6] The economy is cashless as in Woodford (2003).

[7] An interpretation of this borrowing constraint is that, with multi-period debt contracts, the borrowing constraint on housing is reset only for households that acquire new housing goods or choose to refinance. Of course, in the face of home equity line of credits, adjustments of the borrowing constraint may also reflect lenders' perceived changes in the collateral value. Justiniano, Primiceri, and Tambalotti (2015), who study the determinants of household leveraging and deleveraging in a calibrated dynamic general equilibrium model, adopt an analogous specification.

### 3.3. Final Goods Firms, Nominal Rigidities and Monetary Policy

There are Calvo-style price rigidities and wage rigidities in the final good sector. As in Bernanke, Gertler, and Gilchrist (1999), final good firms (owned by patient households) buy wholesale goods $y_t$ from wholesale firms in a competitive market, differentiate the goods at no cost, and sell them at a markup $x_{p,t}$ over the marginal cost. The CES aggregates of these goods are converted back into homogeneous consumption and investment goods by households. Each period, a fraction $1-\theta_\pi$ of final good firms set prices optimally, while a fraction $\theta_\pi$ cannot do so, and index prices to the steady state inflation $\overline{\pi}$. Combining the optimal pricing decision of the final good firms with the equation for the evolution of the aggregate price level results in a forward–looking Phillips curve that, after linearization, can be written as:

$$\log\left(\pi_t/\overline{\pi}\right) = \beta E_t \log\left(\pi_{t+1}/\overline{\pi}\right) - \varepsilon_\pi \log\left(x_{p,t}/\overline{x}_p\right) + \mathtt{u}_{p,t}, \tag{17}$$

where $\varepsilon_\pi = \left(1-\theta_\pi\right)\left(1-\beta\theta_\pi\right)/\theta_\pi$ measures the sensitivity of inflation to changes in the markup, $x_{p,t}$, relative to its steady-state value, $\overline{x}_p$, whereas the term $u_{p,t}$ denotes an i.i.d. price markup shock, $u_{p,t} \sim N\left(0, \sigma_P^2\right)$.

Wage setting is modeled in an analogous way. Households supply homogeneous labor services to unions. The unions differentiate labor services as in Smets and Wouters (2007), set wages subject to a Calvo scheme and offer labor services to labor packers who reassemble these services into the homogeneous labor composites $n_c$ and $n_c'$. Wholesale firms hire labor from these packers. The pricing rules set by the union imply, after linearization, the following wage Phillips curves:[8]

$$\begin{aligned}
\log\left(\omega_t/\overline{\pi}\right) &= \beta E_t \log\left(\omega_{t+1}\overline{\pi}\right) - \varepsilon_w \log\left(x_{w,t}/\overline{x}_w\right) + \mathtt{u}_{w,t}, && (18)\\
\log\left(\omega_t'/\overline{\pi}\right) &= \beta' E_t \log\left(\omega_{t+1}'/\overline{\pi}\right) - \varepsilon_w' \log\left(x_{w,t}'/\overline{x}_w'\right) + \mathtt{u}_{w,t}, && (19)
\end{aligned}$$

where $\omega_t = \frac{w_t \pi_t}{w_{t-1}}$ and $\omega_t' = \frac{w_t' \pi_t}{w_{t-1}}$ denote wage inflation for each household type, and $\mathtt{u}_{w,t} \sim N\left(0, \sigma_W^2\right)$ denotes an i.i.d. wage markup shock.[9]

Monetary policy follows a modified Taylor rule that allows for interest rate smoothing and responds to year-on-year inflation and GDP[10] in deviation from their steady-state values, subject to the zero lower bound:

$$R_t = \max\left[1, R_{t-1}^{r_R}\left(\frac{\pi_t^A}{\overline{\pi^A}}\right)^{(1-r_R)r_\pi}\left(\frac{y_t}{\overline{y}}\right)^{(1-r_R)r_Y}\overline{R}^{1-r_R}\mathtt{e}_t\right]. \tag{20}$$

The term $\overline{R}$ is the steady-state nominal real interest rate in gross terms, and $\log \mathtt{e}_t = \rho_R \log \mathtt{e}_{t-1} + \mathtt{u}_{r,t}$ (with $\mathtt{u}_{r,t} \sim N\left(0, \sigma_R^2\right)$) denotes an autoregressive monetary policy shock.[11] As in Christiano, Eichenbaum, and Rebelo (2011) and Basu and Bundick (2017), the presence of the ZLB creates an additional, important nonlinearity. Shocks that move output and prices in the same direction can be amplified by the inability of central bank to adjust short-term interest rates.

[8] In a manner analogous to the price setting problem, markup shocks arise from random shocks to the elasticity of substitution among the varieties that enter the CES aggregate of the different labor types.

[9] There are two unions, one for each household type. While the unions choose slightly different wage rates, reflecting the different desired consumption profiles of the two household types, the Calvo probability of changing wages is assumed to be the same.

[10] Wholesale goods $y_t$ are different from the CES aggregates of these goods that comprise total GDP. The two are approximately equal within a local region of the steady state. See e.g. Iacoviello (2005).

[11] Year-on-year inflation (expressed in quarterly units, like the interest rate) is defined as $\pi_t^A \equiv \left(P_t/P_{t-4}\right)^{0.25}$.

## 4. Estimation of the DSGE Model

Figure 2 offers a first look at the data that motivates our analysis and elucidates the basic asymmetry captured by our model. The top panel superimposes the time series of U.S. house prices and aggregate consumption expenditures over the 1976–2011 period. The bottom panel is a scatterplot of changes in consumption and changes in house prices, together with the predicted values of a regression of consumption growth on a third-order polynomial in house price growth. The scatterplot highlights that most of the positive correlation is driven by periods with low house prices, during both the 1990-1991 and the 2007-2009 recessions. It is important to note that, while excluding periods with declines in house prices would result in almost no correlation between consumption and house prices, the nonlinearity is still evident with the exclusion of the post–2005 period, coinciding with the Great Recession and the housing bust. (In the appendix, Figure A.1 confirms this claim.)

We use Bayesian estimation methods to size the structural parameters of the model including the share of impatient households. A subset of the model parameters are calibrated based on information complementary to the estimation sample.

### 4.1. Calibration and Priors

The calibrated parameters are reported in Table 1. $\beta$ is set equal to 0.995, implying a steady-state 2% annual real interest rate. The capital share $\alpha = 0.3$ and the depreciation rate $\delta_k = 0.025$ imply a steady-state ratio of capital to annual output equal to 2.1, and an investment to output ratio of 0.21. The weight on housing in the utility function $\overline{j}$ is set at 0.04, implying a steady-state ratio of housing wealth to annual output of 1.5. The maximum loan-to-value ratio $\mathsf{m}$ is set at 0.9. The labor disutility parameter $\eta$ is set at 1, implying a unitary Frisch labor supply elasticity. The steady-state gross price and wage markups $\overline{x}_p$ and $\overline{x}_w$ are both set at 1.2. Finally, $\overline{\pi} = 1.005$, implying a 2% annual rate of inflation in steady state.

All other parameters are estimated using Bayesian methods. The prior distributions are reported in Table 1. Our choices hew closely to those of Smets and Wouters (2007), apart, of course, from parameters that were not present in their model. In particular, we assume a rather diffuse prior for the wage share of impatient households $\sigma$ (centered at 0.5) and for the inertial coefficient in the borrowing constraint $\gamma$ (also centered at 0.5). A key parameter in determining the asymmetries is the discount factor of the impatient agents, $\beta'$. Values of this parameter that fall below a certain threshold imply that impatient agents never escape the borrowing constraint. In that case, the model has no asymmetries (except for the presence of the ZLB), regardless of shocks size, and produces a large correlation between housing price growth and consumption growth, since the borrowing constraint always holds with equality. Conversely, when $\beta'$ takes on higher values, closer to the discount factor of patient agents, modest increases in house prices suffice to make the borrowing constraint slack (even though the constraint is expected to bind in the long run). The prior mean for $\beta'$ is set at 0.99 with a standard deviation of 0.0015.

### 4.2. Data

The estimation is based on observations for six series: total real household consumption, price (GDP deflator) inflation, wage inflation, real investment, real housing prices and the Federal Funds Rate.

The observations span the period from 1985Q1 to 2011Q4 (Appendix C describes the data in detail). The model features six shocks: investment-specific shocks, wage markup, price markup, monetary policy, intertemporal preferences and housing preferences. We do not include financial variables – such as household borrowing – among the observed variables for estimation, since the available measures of household debt are gross measures, also including debt held by agents who own a large amount of liquid assets, which are harder to map into our model with only debt contracted by (potentially) credit–constrained agents. However, we later show that the model's predictions for the behavior of household debt, conditional on the path of the chosen observed variables, closely match some of the available empirical proxies. Accordingly, the exclusion of debt measures from the set of observed variables has little bearing on the results.

Prior to estimation, a one-sided HP filter (with a smoothing parameter of 100,000) is used to remove the low-frequency components of consumption, investment and housing prices. The one-sided HP filter has two advantages. First, it yields plausible estimates of the trend and the cycle for these variables. For instance, according to the filter, consumption and house prices were respectively 8 and 30 percent below trend at the trough of the Great Recession. Second, as argued by Stock and Watson (1999), the one-sided filter is not affected by the correlation of current observations with subsequent observations. The analysis presented in Appendix E documents that the results are robust to the inclusion and joint estimation of linear deterministic trends.

### 4.3. Model Solution and Estimation

The model is solved nonlinearly to account for the occasionally binding constraint on borrowing and the non-negativity constraint on the interest rate. Depending on whether the zero lower bound binds or not, and depending on whether the collateral constraint on housing binds or not, the economy can be in one of four regimes. The solution method links the first-order approximation of the model around the same point under each regime. Importantly, the solution is not just linear, with different coefficients depending on each of the four regimes, but rather, it can be highly nonlinear. The dynamics in each regime may crucially depend on how long agents expect that regime to last. In turn, that duration expectation depends on the state vector. Appendix D describes the solution method and gauges its accuracy in detail.[12]

The solution of the model can be expressed as:

$$X_t = \mathbf{P}(X_{t-1}, \epsilon_t)X_{t-1} + \mathbf{D}(X_{t-1}, \epsilon_t) + \mathbf{Q}(X_{t-1}, \epsilon_t)\epsilon_t. \tag{21}$$

The vector $X_t$ collects all the variables in the model, except the innovations to the shock processes, which are separated in the vector $\epsilon_t$. The matrix of reduced-form coefficients $\mathbf{P}$ is state-dependent, as are the vector $\mathbf{D}$ and the matrix $\mathbf{Q}$. These matrices and vector are functions of the lagged state vector and of the current innovations. However, while the current innovations can trigger a change in the reduced-form coefficients, $X_t$ is still locally linear in $\epsilon_t$.

The solution in Equation (21) can be represented in terms of observed series by premultiplying the state vector $X_t$ by the matrix $\mathbf{H}_t$, which selects the observed variables. Accordingly, the vector

[12] Guerrieri and Iacoviello (2015) compare the performance of this solution method with other nonlinear methods for an array of models.

of observed series $Y_t$ is simply $Y_t = \mathbf{H}_t X_t$.[13] Because the reduced-form coefficients in Equation (21) endogenously depend on $\epsilon_t$, one cannot use the Kalman filter to retrieve the estimates of the innovations in $\epsilon_t$. Instead, following Fair and Taylor (1983), we recursively solve for $\epsilon_t$, given $X_{t-1}$ and the current realization of $Y_t$, the following system of non-linear equations:[14]

$$Y_t = \mathbf{H}_t\mathbf{P}(X_{t-1}, \epsilon_t)X_{t-1} + \mathbf{H}_t\mathbf{D}(X_{t-1}, \epsilon_t) + \mathbf{H}_t\mathbf{Q}(X_{t-1}, \epsilon_t)\epsilon_t. \tag{22}$$

The vector $X_t$ contains unobserved components, so the filtering scheme requires an initialization. We assume that the initial $X_0$ coincides with the model's steady state and train the filter using the first 20 observations. Given that $\epsilon_t$ is assumed to be drawn from a multivariate Normal distribution with covariance matrix $\mathbf{\Sigma}$, a change in variables argument implies that the logarithmic transformation of the likelihood $f$ for the observed data $Y^T$ can be written as:

$$log(f(Y^T)) = -\frac{T}{2}\log(\det(\mathbf{\Sigma})) - \frac{1}{2}\sum_{t=1}^{T}\epsilon_t'\left(\mathbf{\Sigma}^{-1}\right)\epsilon_t + \sum_{t=1}^{T}\log(|\det\frac{\partial \epsilon_t}{\partial Y_t}|). \tag{23}$$

The inverse transformation from the shocks to the observations needed to form the Jacobian matrix $\frac{\partial \epsilon_t}{\partial Y_t}$ is only given implicitly by $(\mathbf{H}_t\mathbf{Q}(X_{t-1}, \epsilon_t))\epsilon_t - (Y_t - \mathbf{H}_t\mathbf{P}(X_{t-1}, \epsilon_t)X_{t-1} - \mathbf{H}_t\mathbf{D}_t) = 0$. To proceed by implicit differentiation, we verify that the determinant of $\mathbf{H}_t\mathbf{Q}(X_{t-1}, \epsilon_t)$ is nonzero. Accordingly, the implicit transformation is locally invertible and the Jacobian of the inverse transformation is:

$$\frac{\partial \epsilon_t}{\partial Y_t} = (\mathbf{H}_t\mathbf{Q}(X_{t-1}, \epsilon_t))^{-1}. \tag{24}$$

Derivation of this Jacobian relies on local linearity in $\epsilon_t$ of the model's solution (i.e., $\frac{\partial \mathbf{P}(X_{t-1},\epsilon_t)}{\partial \epsilon_t} = \frac{\partial \mathbf{D}(X_{t-1},\epsilon_t)}{\partial \epsilon_t} = \frac{\partial \mathbf{Q}(X_{t-1},\epsilon_t)}{\partial \epsilon_t} = 0$, where these derivatives are defined), a property that is further discussed in Appendix D. Using this result and recognizing that $|\det((\mathbf{H}_t\mathbf{Q}(X_{t-1}, \epsilon_t))^{-1})| = 1/|\det(\mathbf{H}_t\mathbf{Q}(X_{t-1}, \epsilon_t))|$, the logarithmic transformation of the likelihood in Equation (23) can be expressed as:

$$log(f(Y^T)) = -\frac{T}{2}\log(\det(\mathbf{\Sigma})) - \frac{1}{2}\sum_{t=1}^{T}\epsilon_t'\left(\mathbf{\Sigma}^{-1}\right)\epsilon_t - \sum_{t=1}^{T}\log(|\det\mathbf{H}_t\mathbf{Q}(X_{t-1}, \epsilon_t)|). \tag{25}$$

In our case, the Jacobian of the inverse transformation for the change in variables is known from the model's solution and does not require any additional calculations. This property of the solution allows for an evaluation of the likelihood in a matter of seconds, affording us crucial time savings relative to the general approach in Fair and Taylor (1983), and making estimation possible.

[13] The matrix $\mathbf{H}_t$ that selects the observed variables is time-varying because we drop the interest rate from the observed vector at the zero lower bound. In that case, we also assume that monetary policy shock is zero, unless the notional rate implied by the model is positive when the observed rate is still zero. In that case, we select the notional rate as observed and reinstate the monetary policy shock.

[14] There is in principle the possibility of multiple solutions for $\epsilon_t$ to the extent that Equation (22) is highly nonlinear in $\epsilon_t$. Our specific application has not shown evidence of this multiplicity. In theory, however, our approach to constructing the likelihood does not depend crucially on a one to one mapping between $Y_t$ and $\epsilon_t$. Standard results could be invoked to allow for a general correspondence between $Y_t$ and $\epsilon_t$ when constructing the likelihood function.

## 5. Model Estimation Results

This section discusses key parameter estimates and then highlights the non-linear nature of the reaction to positive and negative shocks. Counterfactual experiments show that collateral constraints on housing wealth played a key role in exacerbating the economic collapse of the Great Recession. A smaller but important contribution to the economic collapse stemmed from the zero lower bound on nominal interest rates. Additionally, the estimated model that excludes collateral constraints on housing wealth is forced to rely on consumption preference shocks to explain the severe drop in consumption of the Great Recession. A posterior odds ratio greatly favors the model with collateral constraints.

### 5.1. Estimated Parameters

The evaluation of the likelihood is combined with prior information about the parameters in order to construct and maximize the posterior as a function of the model's parameters, given the data. The posterior density of the model's parameters is constructed using a standard random walk Metropolis-Hastings algorithm (with a chain of 50,000 draws).

The posterior modes of the estimated parameters and other statistics are reported in Table 1. Crucially, there is a sizeable fraction of impatient agents, governed by $\sigma$. The choice of prior, a diffuse beta distribution, simply guarantees that this fraction remains bounded between 0 and 1. The posterior mode is estimated to be 0.50 and the 90% confidence interval ranges from 0.29 to 0.58. Accordingly, $\sigma = 0$, which would imply the exclusion of collateral constraints from the model, is highly unlikely. Moving to the parameters that govern nominal rigidities and monetary policy, the posterior modes for the Calvo parameters governing the frequency of price and wage adjustment are both equal to 0.92. This high degree of price and wage rigidity likely compensates the absence of real rigidities, such as variable capacity utilization, partial indexation of prices and wages, or firm-specific capital. The estimated interest rate reaction function gives less weight to output and more weight to inflation than our prior, which was centered around Taylor's canonical values of 0.5 for the output parameter (with output measured at an annual rate) and 1.5 for the inflation parameter. Finally, there is evidence of inertia in the borrowing constraint, as shown by the estimated value of $\gamma$ which equals 0.70. A positive value of $\gamma$ slows down the extent to which deleveraging takes place in periods of falling housing prices, thus creating inertia in consumption.

Given the parameter estimates, key empirical properties of the model line up well with the data in several respects. First, in response to small shocks that do not make the borrowing constraint slack or the ZLB bind, the model's impulse responses, for instance those to monetary shocks, are in line with the findings of existing studies, such as Christiano, Trabandt, and Walentin (2010).[15] Second, key moments in the data line up well with those of the estimated model.[16] For instance, the standard deviation of consumption is 2.2 percent in the model, compared to 2.9 percent in the data. The model also captures the high volatility of house prices – their standard deviation is 11.3 percent in the model, 12.5 percent in the data.

Finally, the variance decomposition shows that about three quarters of the house price volatility is driven by the housing preference shock (as in recent work by Liu, Wang, and Zha 2013). This point

[15] Figure A.3 in the appendix reports the impulse response to all shocks.

[16] Our nonlinear model does not admit a closed form for the moments of the variables. The model statistics are thus computed on simulated series (using a long simulation with $T = 5,000$).

is elaborated on in two experiments described below. The first experiment focuses on a comparison of positive and negative housing shocks. The second experiment presents a decomposition that highlights the role of housing shocks in the collapse of the Great Recession.

### 5.2. Responses to Positive and Negative Shocks to Housing Prices

Figure 3 illustrates the fundamental asymmetry in the estimated model and confirms key insights from the basic model. The figure considers the effects of shocks to housing preferences, governed by the process $\mathrm{j}_t$ in Equation (9). Two series of innovations to $\mathrm{j}_t$ occur between periods 1 and 8. One of the two series of innovations lowers house prices by 20 percent. The other raises house prices by 20%. From period 9 onwards, there are no more innovations and the shock $\mathrm{j}_t$ follows the autoregressive component of the stochastic process. All parameters are set to their estimated posterior mode.

The dashed lines denote the effects of the decline in house prices. This decline reduces the collateral capacity of constrained households, who borrow less and are forced to curtail their non-housing consumption even further. At its trough, consumption is nearly 3 percent below its steady state. The nominal and real rigidities imply that the decline in aggregate consumption translates into lower demand for labor from firms. As a consequence, hours worked fall about 2 percent below the baseline.

The solid lines plot the responses to a shock of the same magnitude and profile but with opposite sign. In this case, house prices increase 20 percent. As in the partial equilibrium model described in Section 2, a protracted increase in house prices can make the borrowing constraint slack. The Lagrange multiplier for the borrowing constraint bottoms out at zero and remains at zero for some time, before rising as house prices revert to baseline. When the constraint is slack, the borrowing constraint channel remains operative only in expectation. Thus, impatient households discount that channel more heavily the longer the constraint is expected to remain slack. As a consequence, the response of consumption to the house price increases considered in the figure is not as dramatic as the reaction to the equally-sized house price declines. At its peak, consumption rises about 1 percent above its baseline, a magnitude one third as big as for the house price decline.In turn, the increase in hours is muted, peaking at about 0.5 percent above the baseline.

In experiments not reported here, we have found modest asymmetries for other shocks that affect house prices and consumption. These shocks are likely to generate significant asymmetries only insofar as they affect house prices or collateral capacity. However, the asymmetry uncovered here is independent of the particular stochastic structure of the model, and needs not rely on housing demand shocks only. Potentially, in any housing model with occasionally binding constraints, one can find substantial asymmetries as long as the model can match the observed swings in house prices.

### 5.3. Shock Decomposition

To highlight the role of house price declines in accounting for the consumption collapse of the Great Recession, Figure 4 decomposes house prices and consumption in terms of the underlying shocks. By construction, the marginal contributions of each shock sum to the observed series.[17] In the upper panel

[17] For nonlinear models the marginal and average contributions of each shock need not coincide. The marginal contributions vary with the order in which the shocks are turned on (marginalized). In Figure 4, the order is 1) housing preference shock, 2) investment technology shock, 3) price markup shock, 4) monetary policy shock, 5) wage markup shock, and 6) intertemporal preference shock. Alternative orderings did not change the results.

of Figure 4, the decomposition for house prices shows that housing demand shocks explain the lion's share of the movements in house prices. This finding is consistent with results in Liu, Wang, and Zha (2013), as well as with the approach taken by Berger, Guerrieri, Lorenzoni, and Vavra (2015) to explain the recent housing boom–bust in a calibrated OLG housing model. This finding is also is consistent with a view that the housing boom that preceded the Great Recession was rooted in forces largely uncorrelated with economic conditions. The figure also highlights that, although they play a smaller role, other shocks also influence house prices. For instance, investment technology shocks played a sizable role in the housing price boom.

A striking feature of the shock decomposition for consumption is that about 70 percent of the consumption decline through 2009 can be traced to housing demand shocks that impact consumption through the collateral channel. By contrast, these shocks would have no implications for consumption in the absence of collateral constraints. Furthermore, the same shocks only accounted for a modest part of the rise in consumption prior to the Great Recession, when collateral constraint became slack.

Figure 4 also highlights that our nonlinear model can rationalize how the house price collapse starting at the end of 2005 did not, at first, have an outsize effect on consumption. Since the preceding house price boom had relaxed borrowers' collateral constraints, the initial reductions in house prices could be counteracted by increasing borrowing rather than curbing consumption. Accordingly, in the model as in the data, debt lags house prices, and leverage keeps rising well after house prices start declining, as further discussed in Section 5.6. Only as house prices kept falling, did borrowers' collateral constraints tighten and consumption took a large hit.

### 5.4. The Asymmetric Contribution of Housing to Business Cycles

Two nonlinear features of the model help account for the large consumption collapse of the Great Recession: occasionally binding collateral constraints, and, to a smaller extent, the zero lower bound on nominal interest rates. The role of these features is showcased with three experiments. The first experiment feeds the estimated sequence of shocks for the benchmark model with collateral constraints into a model that does not encompass those constraints, but that is otherwise identical to the benchmark model and that is not re-estimated. The second experiment considers the opposite case, in which collateral constraints are always binding. The third experiments focuses on the zero lower bound on nominal interest rates.

By construction, the estimated sequence of shocks, when fed back into the benchmark model, allows to exactly match for the observed data. Moreover, one can recover the path of all unobserved variables, including the Lagrange multiplier on the borrowing constraint. Figure 5 compares the observed data against the outcomes of three counterfactual experiments.

The first experiment –"No Collateral Constraint"–, drops impatient households from the model, so that collateral constraints are ruled out. Housing prices are still matched. However, consumption diverges markedly from the observed data. When the Lagrange multiplier is estimated to be binding in the 2007-2009 recession, a large gap opens up between the observed and counterfactual consumption levels. Between 2008 and 2012, the model without collateral constraints misses the collateral channel linked to housing wealth, and predicts a very small decline in consumption. Remarkably, without collateral constraints the recession would have been curbed to such an extent that the Federal Funds rate would not have reached zero.

The second experiment –labelled “Always Binding Constraint”–, assumes that borrowers’ collateral constraints are always binding. A large gap between the observed and counterfactual consumption levels peaks in the year 2000, coinciding with an inflection in the rate of growth in house prices. According to the baseline model, rapidly growing house prices relaxed the collateral constraints of borrowers, weakening the link between house price growth, credit, and consumption. By contrast, always binding constraints, in the counterfactual experiment, imply a more pronounced expansion of credit and consumption relative to the observed movements. Remarkably, collateral constraints that always bind also imply an overshooting of the consumption decline in reaction to the house price collapse of the Great Recession. As house prices started falling in 2005, slack borrowing constraints buffeted the consumption declines, as borrowers could use additional credit as a margin of adjustment. By contrast, in the counterfactual model with permanently binding constraints borrowers were forced to curtail consumption even before the house price declines gained momentum, eventually leading to a counterfactually large decline in consumption, about 2 percentage points larger than observed.

The third experiment (labelled “No ZLB”) gauges how much of the decline in consumption was due to the zero lower bound constraint. As shown in the Figure, absent the zero lower bound, nominal interest rates would have fallen to minus 2 percent, and the trough of consumption would have been about two percentage points higher (i.e., less severe) than the trough observed.

### 5.5. Statistical Comparisons with Other Models

The experiments discussed in the previous section do not allow for the re-estimation of the shock processes and of the parameters for each of the model variants considered. To complete the analysis, we also estimated the model without borrowers and the model with permanently binding constraints keeping the observation set unchanged relative to the one used for the benchmark model. The posterior modes for all the parameters for these two variants are reported in the appendix. The log marginal data density for the benchmark model with occasionally binding constraints is 2270.8. The variant without borrowing and lending has the lowest log marginal data density, 2266.8, and the variant with permanently binding an intermediate value of 2268.7. These results imply posterior odds ratios of 55 to 1 and 8 to 1 in favor of the benchmark model over these two variants, respectively.

Figure 5 offers some clues to account for the superior performance of the benchmark model. A model without borrowing and lending needs to amplify the decline in consumption during the Great Recession with additional shocks relative to the benchmark model. In our estimation exercise, the variant without borrowing and lending needs to resort to much larger intertemporal preference shocks to fit the observed data.[18]

The estimation of the model with a permanently binding collateral constraint points to a lower fraction of impatient households relative to the benchmark model, with $\sigma$ moving down from 0.50 to 0.44, and also a lower discount factor for impatient households, declining from 0.992 to 0.986. Both changes tend to buffet the correlation of house prices and consumption but this change is not sufficient to overcome the symmetry between house price expansions and contractions, which results in a lower marginal data density for this model relative to the benchmark model.

[18] Referring to Column 2 of Table A.1 in the appendix, the standard deviation of the innovations to the intertemporal preference shock process, $\sigma_Z$ jumps from 0.016 for the benchmark model to 0.030 for the model without borrowers. Nonetheless, the standardized shocks during the Great Recession are still noticeably smaller for the benchmark model, boosting the likelihood and the marginal data density of the benchmark model.

In sum, the results show that lower house prices and weaker households balance sheets were the main culprits for the consumption collapse during the Great Recession.

### 5.6. Implications of the Model for the Behavior of Household Debt

Financial variables – such as household borrowing – are not included in the observation set since available measures of household indebtedness are imperfect proxies for the debt stock in the model. An additional way to validate the model is to compare the evolution of financial time series that were not used as inputs in the estimation exercise against their closest model counterparts. Consider, in particular, measures of leverage and net borrowing. Using the model, these two series are constructed as follows:

$$lev_t = 100 \times \frac{b_t}{q_t h_t'} \tag{26}$$

$$bor_t = 100 \times \frac{\Delta\left(P_t b_t\right)}{4\overline{P}\overline{y}}. \tag{27}$$

Above, leverage is defined as the ratio of debt to housing wealth,[19] and borrowing is defined as the change ($\Delta$) in nominal debt (scaled by steady-state annual GDP), expressed in percentage terms. Leverage falls slowly when house prices rise, because the borrowing constraint is inertial and slack, but rises sharply when house prices fall, because the constraint tightens. Due to the occasionally binding constraint, the model also predicts that borrowing rises less than the sum of housing prices and housing investment when housing prices rise, and falls more than the sum of housing prices and housing investment when housing prices fall.

The top panel of Figure 6 compares leverage in the model with its data counterpart, constructed as the ratio of household debt to housing wealth from the Financial Accounts of the United States.[20] In the model as in the data, household leverage falls throughout the early 1990s and moves little until the end of the housing boom. In the model as in the data, leverage spikes up at the beginning of the housing crash, and drops thereafter as debt declines more than housing prices.

Data measures for household debt move both because of net originations and because of charge-offs on the existing stock. Movements in charge-offs, which were important during the latest recession, complicate the comparison between model and observed measures of the stock of debt. Accordingly, the bottom panel looks at a flow measure of debt, comparing new borrowing in the model with its data counterpart. New borrowing in the data is proxied using mortgage equity withdrawal, constructed as the difference between households' new mortgage borrowing and the estimated borrowing to finance new residential construction (divided by trend GDP).[21] Again, bearing in mind that no debt variable

[19] We correct for the fact that the model only tracks net debt (that is, savers' gross debt is zero) by excluding the savers' housing stock from the model's definition of leverage. Including the savers' housing stock in the denominator makes little difference for the results.

[20] See the note to Figure 6 for the data references. The observed measure of leverage shows an upward trend in the sample period and this trend comes to a halt during the Great Recession. In the figure, this trend was removed using a one sided HP-filter with $\lambda = 100,000$, as for our benchmark model. Ideally, one would compare the model against micro data, such as those underlying the Survey of Consumer Finances. However, the SCF is triennal, and measures of leverage constructed from the SCF, while informative for trends, are of limited use for business cycle analysis.

[21] New borrowing is thus the change in the stock of debt excluding charge-offs and netting out new construction, two features excluded from our model. Our model does not feature a construction sector, implying that new residential investment is zero at all times. By subtracting borrowing used to finance new construction from total mortgage borrowing,

was used in the estimation, the model's object tracks its data proxy remarkably well.

### 5.7. Sensitivity Analysis

We perform a battery of checks in order to gauge the robustness of the results. These checks are fully described in the appendix and merely listed here. First, our findings are insensitive to the assumption that the initial vector of endogenous variables, $X_0$, is equal to its steady-state value. Second, our filtering algorithm, when applied to data generated from the posterior mode of the model, can accurately recover the true structural shocks when the structural parameters are known. Third, when our entire estimation strategy is applied to data generated from the posterior mode of the model, the estimated parameters are close to their true values. The sensitivity analysis also considers an alternative detrending strategy, different shock structures and the addition of variable capacity utilization.

## 6. Regional Evidence on Asymmetries

The model estimated on national-level data motivates additional empirical analysis that uses a panel of data from U.S. states and Metropolitan Statistical Areas (MSA). The advantage of these data is that variation in house prices and economic activity is greater at the regional than at the aggregate level, as documented for instance by Del Negro and Otrok (2007), who find large heterogeneity across states in regard to the relative importance of the national factors. Note that, in any event, the state-level series aggregated back to the national level track their National Income and Product Accounts (NIPA) counterparts.[22]

To set the stage, Figure 7 shows house prices at the regional level and several measures of activity, namely employment in the service sector, auto sales, electricity consumption and mortgage originations. The figure focuses on two points in time, 2005 and 2008 for all the 50 U.S. states and the District of Columbia. For each state, each panel presents two dots: the green dot (concentrated in the north–east region of the graph) shows the lagged percent change in house prices and the percent change in the indicator of economic activity in 2005, at the height of the housing boom. The red dot represents analogous observations for the 2008 period, in the midst of the housing crash. Fitting a piecewise linear regression to these data yields a correlation between house prices and activity that is smaller when house prices are high. This evidence on asymmetry is bolstered by the large cross-sectional variation in house prices across states over the period in question.

### 6.1. State-Level Evidence

We use annual data from the early 1990s to 2011 on house prices and measures of economic activity for the 50 U.S. states and the District of Columbia. We choose measures of economic activity that best match the model counterparts for consumption, employment and credit.[23]

model and data are put on equal footing.

[22] For instance, over the sample period, the correlation between NIPA motor vehicle consumption growth (about 1/3 of durable expenditure) and retail auto sales growth is 0.89; and the correlation between services consumption growth and electricity usage growth is 0.54.

[23] None of the currently available measures of regional consumption aligns with national consumption data in a fully satisfactory way. See for instance the discussion in Awuku-Budu, Guci, Lucas, and Robbins (2013). Total consumption is proxied with electricity consumption and with automobile sales.

The main specification takes the following form:

$$\Delta \log y_{i,t} = \alpha_i + \gamma_t + \beta_{POS}\mathcal{I}_{i,t}\Delta \log hp_{i,t-1} + \beta_{NEG}\left(1-\mathcal{I}_{i,t}\right)\Delta \log hp_{i,t-1} + \delta X_{i,t-1} + \varepsilon_{i,t} \tag{28}$$

where $y_{i,t}$ is an index of economic activity and $hp_{i,t}$ is the inflation-adjusted house price index in state $i$ in period $t$; $\alpha_i$ and $\gamma_t$ represent state and year fixed effects; and $X_{i,t}$ is a vector of additional controls. Changes in house prices are interacted with a state-specific indicator variable $\mathcal{I}_{i,t}$ that, in line with the model predictions, takes a value equal to one when house prices are high, and equal to 0 when house prices are low. House prices are classified as high when they are above a state-specific linear trend separately estimated for the 1976-2011 period, a classification that lines up with the findings of the estimated model in Figure 4. Using this approach, the fraction of states with high house prices is about 20 percent in the 1990s, rising gradually to peak at 100 percent in 2005 and 2006, and dropping to 27 percent at the end of the sample. The results were similar using two alternative definitions of $\mathcal{I}_{i,t}$. Under the first alternative definition, $\mathcal{I}_{i,t}$ equals to one when real house price inflation is positive. Under the second definition, $\mathcal{I}_{i,t}$ equals to one when the ratio of house prices to income is high relative to its trend (in log). The benchmark specification uses one-year lags of house prices and other controls. The results were also little changed when instrumenting current or lagged house prices with one or more lags.

Tables 2 to 4 present estimates when the indicators of economic activity $y_{i,t}$ are employment in the service sector, auto sales and electricity usage respectively.

Table 2 presents the results when the measure of regional activity is employment in the non-tradeable service sector. U.S. states trade heavily with each other, so that employment in sectors that mainly cater to the local economy better isolates the local effects of movements in local house prices.[24] The first two specifications do not control for time effects. They show that the asymmetry is strong and economically relevant, and that house prices matter, at statistically conventional levels, both when high and when low. After controlling for time effects in the third specification, the coefficient on high house prices is little changed, but the coefficient on low house prices is lower. A large portion of the declines in house prices in our sample took place against the background of the zero lower bound on policy interest rates. As discussed in the model results, the zero lower bound is a distinct source of asymmetry for the effect of change in house prices. Time fixed effects allow us to parse out the effects of the national monetary policy reaching the zero lower bound and, in line with our theory, compress the elasticity of employment to low house prices. In the last two specifications, after controlling for income and lagged employment, the only significant coefficient is the one on low house prices. In column five, the coefficient on high house prices is positive, although it is low and not significantly different from zero. The coefficient on low house prices, instead, is positive and significantly different from zero, thus implying that house prices matter more for economic activity when they are low. In addition, the test for the difference between the coefficient on low house prices and the coefficient on high house prices

[24] The BLS collects state-level employment data by sectors broken down according to NAICS (National Industry Classification System) starting from 1990. According to this classification (available at http://www.bls.gov/ces/cessuper.htm), the goods-producing sector includes Natural Resources and mining, construction and manufacturing. The service-producing sector includes wholesale trade, retail trade, transportation, information, finance and insurance, professional and business services, education and health services, leisure and hospitality and other services. A residual category includes unclassified sectors and public administration. We exclude from the service sector wholesale trade (which on average accounts for about 6 percent of total service sector employment) since wholesale trade does not necessarily cater to the local economy.

confirms that the difference is significantly larger than zero.

Table 3 reports results when the measure of activity is retail automobile sales. Auto sales are an excellent indicator of local demand since autos are almost always sold to state residents and since durable goods are notoriously sensitive to business cycles. After adding lagged car sales and personal income as controls, the coefficients on low and high house prices are both positive, but the coefficient on low house prices (estimated at 0.2) is nearly three times as large.

Table 4 reports the results using residential electricity usage as a proxy for consumption. Even though electricity usage only accounts for 3 percent of total consumption, electricity usage is a useful proxy for nondurable consumption. Most activities involve the use of electricity, and electricity cannot be easily stored. Accordingly, the flow usage of electricity may even provide a better measure of the utility flow derived from a good than the actual purchase of the good. Even in cases when annual changes in weather conditions may affect year-on-year consumption growth, their effect can be filtered out using state-level observations on heating and cooling degree days, which are conventional measures of weather-driven electricity demand. These weather measures are used as controls in all specifications reported. As the table shows, in all regressions low house prices affect consumption growth more than high house prices. After time effects, lagged income growth and lagged consumption growth are controlled for (last column), the coefficient on high house prices is 0.12, the coefficient on low house prices is nearly twice as large at 0.19, and their difference is statistically larger than 0 at the 10 percent significance level.

Because the effects of low and high house prices on consumption work in our model through tightening or relaxing borrowing constraints, it is important to check whether measures of leverage also depend asymmetrically on house prices. Appendix F confirms that mortgage originations depend asymmetrically on house prices too.

### 6.2. MSA-Level Evidence

Tables 5 and 6 present the results of evidence based on MSAs data, focusing on employment and auto sales. MSAs account for about 80 percent of the population and employment in the entire United States. In Table 5, the results from the MSA-level regressions reinforce those obtained at the state level. After controlling for income, lagged employment and time effects, the elasticities of employment to house prices are 0.05 and 0.09 when house prices are high and low, respectively. These elasticities are larger than those found at the state level.

A legitimate concern with the panel and time-series regressions discussed so far is that the correlation between house prices and activity could be due to some omitted factor that simultaneously drives both house prices and activity. Even if this were the case, our regressions would still be of independent interest, since – even in absence of a causal relationship – they would indicate that comovement between house prices and activity is larger when house prices are low, as predicted by the model.

To support claims of causality, one needs to isolate exogenous from endogenous movements in house prices. Table 6 follows Mian and Sufi (2011) and Saiz (2010) in an attempt to distinguish an independent driver of housing demand that better aligns with its model counterpart. The insight is to use the differential elasticity of housing supply at the MSA level as an instrument for house prices, so as to disentangle movements in housing prices due to general changes in economic conditions from movements in the housing market that are directly driven by shifts in housing demand in a particular area. Because such elasticity is constant over time, we cannot exploit the panel dimension of our dataset, and instead use the elasticity in two separate periods by running two distinct regressions of car sales on house prices. The first regression is for the 2002-2006 housing boom period, the second for the 2006-2010 housing bust period. In practice, we rely on the following differenced instrumental variable specifications:

$$\log hp_t - \log hp_s = b_0 + b_1 \text{ Elasticity} + \varepsilon_b \tag{29}$$

$$\log car_t - \log car_s = c_0 + c_1 (\widehat{\log hp_t - \log} hp_s) + \varepsilon_c \tag{30}$$

where $s = 2002$ and $t = 2006$ in the first set of regressions, and $s = 2006$ and $t = 2010$ in the second.

The first stage, OLS regressions show that the elasticity measure is a powerful instrument in driving house prices, with an $R^2$ from the first stage regression around 0.20 in both subperiods. The second stage regressions show how car sales respond to house prices dramatically more in the second period, in line with the predictions of the model and with the results of the panel regressions. In the $2002 - 2006$ period, the elasticity of car sales to house prices is 0.24. In the $2006 - 2010$ period, in contrast, this elasticity doubles to 0.49. [25]

## 7. Debt Relief and Borrowing Constraints

The theoretical and empirical results show that movements in house prices can produce asymmetries that are economically and statistically significant. We now consider whether these asymmetries are also important for gauging the effects of policies aimed at the housing market in the context of a deep recession. To illustrate our ideas, consider one simple example of such policies, a lump-sum transfer from patient to impatient households. This policy could mimic voluntary debt relief from the creditors, or a scheme where interest income is taxed and interest payments are subsidized in lump-sum fashion, so that the end result is a transfer of resources from the savers to the borrowers.

We consider this experiment against two different sets of initial conditions. In one case, house prices are below steady state, and the collateral constraint binds; in the other case, house prices are above steady state, and the constraint is slack. The initial house price levels are brought about by a sequences of unexpected shocks to housing preferences.

Figure 8 shows the combined response of house prices to the initial housing preference shocks and to the two transfer shocks. Both transfer shocks are unforeseen and are sized at one percent of steady-state aggregate consumption. Each transfer is governed by an AR(1) process with coefficient equal to 0.5. The first transfer starts in period 6. A series of unforeseen innovations to the shock process phases in the transfer, until it reaches a peak of one percent of steady-state consumption. Then, the auto-regressive component of the shock reduces the transfer back to 0. The first transfer happens against a background of housing price declines and tight borrowing constraints. The second transfer, starting in period 51, mimics the first but happens against a backdrop of housing price increases and slack borrowing constraints.

The top left panel of Figure 8 shows house prices in deviation from their steady state. The transfer

[25] Using ZIP-code level data and a sample that runs from 2007 to 2009, Mian, Rao, and Sufi (2013) find a large elasticity (equal to 0.74) of auto sales to housing wealth during the housing bust, in line with our findings. Importantly, they also find that this elasticity is smaller in zip codes with a high fraction of non-housing wealth to total wealth.

shocks have a negligible effect on house prices, but their timing coincides with the series of housing preference shocks that change house prices. Accordingly, the marginal effect of the transfer shocks differs strikingly depending on the initial house prices, as shown in the remaining panels in Figure 8. The consumption response of borrower households is dramatically different depending on the backdrop variation in house prices. When house prices are low, the borrowing constraint is tight and the marginal propensity to consume of borrower households is elevated. When house prices are high, the borrowing constraint becomes slack and the marginal propensity to consume of borrower households drops down closer to that for saver households. In reaction to the transfer, consumption of the savers declines less, and less persistently, against a backdrop of housing price declines. In that case, there are expansionary spillovers from the increased consumption of borrowers to aggregate hours worked and output. Taking together the responses of savers and borrowers, the effects of the transfer on aggregate consumption are sizable when house prices are low, and small when house prices are elevated. As a consequence, actions such as mortgage relief can almost pay for themselves through their expansionary effects on economic activity in a scenario of binding borrowing constraints.

## 8. Conclusions

Housing prices matter more during severe recessions than during booms through their asymmetric effects on collateral constraints. These constraints were a key catalyst for the economic collapse of the Great Recession.

The estimated model allows the assessment of costs and benefits of alternative policies aimed at restoring the efficient functioning of the housing market. For instance, policies such as debt relief can produce outsize spillovers to aggregate consumption in periods when collateral constraints are tight. The estimates of these spillover effects are larger than estimates based on samples dominated by house price increases, as inference based on these periods can severely underpredict the sensitivity of consumption to movements in housing wealth.

The paper has emphasized the role of housing as collateral for households and the effects of changes in housing wealth on consumption. However, the mechanism at the heart of our argument has even broader applicability. For instance, to the extent that fixed assets are used for collateral by entrepreneurs, local governments or exporters, the asymmetries highlighted here for consumption could also be relevant for fixed investment, government spending, or the trade balance.[26]

[26] See for instance Adelino, Schoar, and Severino (2015), Chaney, Sraer, and Thesmar (2012) for investment; Barboza (2011) for government spending; Klapper, Laeven, and Rajan (2012) for trade credit.

## References


Abdallah, C. S. and W. D. Lastrapes (2012). Home equity lending and retail spending: Evidence from a natural experiment in texas. *American Economic Journal: Macroeconomics* (4), 94–125. [3]

Adelino, M., A. Schoar, and F. Severino (2015). House prices, collateral, and self-employment. *Journal of Financial Economics 117*(2), 288 – 306. [21]

Awuku-Budu, C., L. Guci, C. Lucas, and C. Robbins (2013). Experimental pce-by-state statistics. Bea working papers, Bureau of Economic Analysis. [17]

Barboza, D. (2011, October 20). China to allow some local governments to issue bonds. *The New York Times*. [21]

Basu, S. and B. Bundick (2017). Uncertainty shocks in a model of effective demand. *Econometrica 85*(3), 937–958. [8]

Berger, D., V. Guerrieri, G. Lorenzoni, and J. Vavra (2015). House prices and consumer spending. Technical report, National Bureau of Economic Research. [14]

Bernanke, B., M. Gertler, and S. Gilchrist (1999). The financial accelerator in a quantitative business cycle framework. Handbook of Macroeconomics, pp. 1341–1393. Elsevier. [8]

Bocola, L. (2016). The pass-through of sovereign risk. *Journal of Political Economy 124*(4), 879–926. [3]

Campbell, J. and J. Cocco (2007). How do house prices affect consumption? evidence from micro data. *Journal of Monetary Economics 54*, 591–621. [3]

Cao, D. and G. Nie (2017). Amplification and asymmetric effects without collateral constraints. *American Economic Journal: Macroeconomics, forthcoming*. [4]

Case, K., J. Quigley, and R. Shiller (2005). Comparing wealth effects: The stock market versus the housing market. *Advances in Macroeconomics 5*(1), 1235–1235. [3]

Chaney, T., D. Sraer, and D. Thesmar (2012). The collateral channel: How real estate shocks affect corporate investment. *The American Economic Review 102*(6), 2381–2409. [21]

Christiano, L., M. Eichenbaum, and S. Rebelo (2011). When is the government spending multiplier large? *Journal of Political Economy 119*(1), 78 – 121. [8]

Christiano, L. J., M. Eichenbaum, and C. L. Evans (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy 113*(1), 1–45. [2, 5]

Christiano, L. J., R. Motto, and M. Rostagno (2014). Risk shocks. *American Economic Review 104*(1), 27–65. [3]

Christiano, L. J., M. Trabandt, and K. Walentin (2010). Dsge models for monetary policy analysis. Handbook of Monetary Economics, pp. 285 – 367. Elsevier. [12]

Del Negro, M., G. Eggertsson, A. Ferrero, and N. Kiyotaki (2017). The great escape? a quantitative evaluation of the fed's liquidity facilities. *The American Economic Review 107*(3), 824–857. [3]

Del Negro, M. and C. Otrok (2007). 99 luftballons: Monetary policy and the house price boom across us states. *Journal of Monetary Economics 54*(7), 1962–1985. [17]

Eggertsson, G. B. and P. Krugman (2012). Debt, deleveraging, and the liquidity trap: A fisher-minsky-koo approach*. *The Quarterly Journal of Economics 127*(3), 1469–1513. [1]

Fair, R. C. and J. B. Taylor (1983). Solution and Maximum Likelihood Estimation of Dynamic Nonlinear Rational Expectations Models. *Econometrica 51*(4), 1169–85. [11]

Gertler, M. and P. Karadi (2011). A model of unconventional monetary policy. *Journal of Monetary Economics 58*(1), 17–34. [3]

Guerrieri, L. and M. Iacoviello (2015). OccBin: A toolkit for solving dynamic models with occasionally binding constraints easily. *Journal of Monetary Economics 70*(C), 22–38. [10]

Guerrieri, V. and G. Lorenzoni (2011). Credit crises, precautionary savings, and the liquidity trap. NBER Working Papers 17583, National Bureau of Economic Research, Inc. [1]

Gust, C., E. Herbst, D. Lopez-Salido, and M. E. Smith (2017). The empirical implications of the interest-rate lower bound. Technical report. [3]

Iacoviello, M. (2005). House prices, borrowing constraints, and monetary policy in the business cycle. *American Economic Review 95*(3), 739–764. [2, 8]

Iacoviello, M. and S. Neri (2010). Housing market spillovers: Evidence from an estimated dsge model. *American Economic Journal: Macroeconomics 2*(2), 125–64. [5]

Jermann, U. and V. Quadrini (2012). Macroeconomic effects of financial shocks. *American Economic Review 102*(1), 238–71. [3]

Justiniano, A., G. Primiceri, and A. Tambalotti (2011). Investment Shocks and the Relative Price of Investment. *Review of Economic Dynamics 14*(1), 101–121. [6]

Justiniano, A., G. E. Primiceri, and A. Tambalotti (2015). Household leveraging and deleveraging. *Review of Economic Dynamics 18*(1), 3–20. [1, 7]

Kiyotaki, N. and J. Moore (1997). Credit Cycles. *Journal of Political Economy 105*(2), 211–48. [2]

Klapper, L., L. Laeven, and R. Rajan (2012). Trade credit contracts. *Review of Financial Studies 25*(3), 838–867. [21]

Korinek, A. and A. Simsek (2016). Liquidity trap and excessive leverage. *American Economic Review 106*(3), 699–738. [1]

Liu, Z., P. Wang, and T. Zha (2013). Land-price dynamics and macroeconomic fluctuations. *Econometrica 81*(3), 1147–1184. [2, 5, 12, 14]

Lustig, H. and S. van Nieuwerburgh (2010). How much does household collateral constrain regional risk sharing? *Review of Economic Dynamics 13*(2), 265 – 294. [3]

Mendoza, E. G. (2010). Sudden Stops, Financial Crises, and Leverage. *American Economic Review 100*(5), 1941–66. [3]

Mian, A., K. Rao, and A. Sufi (2013). Household Balance Sheets, Consumption, and the Economic Slump. *The Quarterly Journal of Economics 128*(4), 1687–1726. [3, 20]

Mian, A. and A. Sufi (2011). House prices, home equity-based borrowing, and the us household leverage crisis. *American Economic Review 101*(5), 2132–56. [1, 3, 19]

Midrigan, V. and T. Philippon (2016). Household leverage and the recession. Mimeo, New York University. [1]

Ng, S. and J. H. Wright (2013). Facts and challenges from the great recession for forecasting and macroeconomic modeling. *Journal of Economic Literature 51*(4), 1120 – 1154. [1]

Saiz, A. (2010). The geographic determinants of housing supply. *The Quarterly Journal of Economics 125*(3), 1253–1296. [19, 30]

Smets, F. and R. Wouters (2007). Shocks and frictions in us business cycles: A bayesian dsge approach. *American Economic Review 97*(3), 586–606. [2, 5, 8, 9]

Stock, J. H. and M. W. Watson (1999). Forecasting inflation. *Journal of Monetary Economics 44*(2), 293–335. [10]

Woodford, M. (2003). *Interest and prices: Foundations of a theory of monetary policy*. Princeton University Press Princeton, N.J. [7]

Table 1: Calibrated and Estimated Parameter Values

| | Calibrated Parameters | Value |
|---|---|---|
| m | Maximum LTV | 0.9 |
| $\eta$ | labor disutility | 1 |
| $\beta$ | discount factor, patient agents | 0.995 |
| $\overline{\pi}$ | steady-state gross inflation rate | 1.005 |
| $\alpha$ | capital share in production | 0.3 |
| $\delta_k$ | capital depreciation rate | 0.025 |
| $\overline{j}$ | housing weight in utility | 0.04 |
| $\overline{x}_p$ | steady-state price markup | 1.2 |
| $\overline{x}_w$ | steady-state wage markup | 1.2 |

| | Estimated Parameters | Prior [mean, std] | Posterior | | | |
|---|---|---|---|---|---|---|
| | | | Mode | 5% | Median | 95% |
| $\beta'$ | discount factor, impatient | beta [0.984, 0.006]* | **0.9922** | 0.9780 | 0.9884 | 0.9929 |
| $\varepsilon_c$ | habit in consumption | beta [0.7, 0.1] | **0.6842** | 0.6351 | 0.7214 | 0.8074 |
| $\varepsilon_h$ | habit in housing | beta [0.7, 0.1] | **0.8799** | 0.6633 | 0.8087 | 0.9498 |
| $\phi$ | investment adjustment cost | gamma [5, 2] | **4.1209** | 3.0756 | 5.0509 | 9.6887 |
| $\sigma$ | wage share, impatient | beta [0.333, 0.20] | **0.5013** | 0.2915 | 0.4421 | 0.5838 |
| $r_\pi$ | inflation resp. Taylor rule | normal, 1.5, 0.25] | **1.7196** | 1.5379 | 1.8129 | 2.1102 |
| $r_R$ | inertia Taylor rule | beta [0.75, 0.1] | **0.5509** | 0.4779 | 0.5681 | 0.6606 |
| $r_Y$ | output response Taylor rule | beta [0.125, 0.025] | **0.0944** | 0.0577 | 0.0915 | 0.1231 |
| $\theta_\pi$ | Calvo parameter, prices | beta [0.5, 0.075] | **0.9182** | 0.8913 | 0.9149 | 0.9343 |
| $\theta_w$ | Calvo parameter, wages | beta [0.5, 0.075] | **0.9163** | 0.8941 | 0.9159 | 0.9364 |
| $\gamma$ | inertia borrowing constraint | beta [0.75, 0.1] | **0.6945** | 0.4466 | 0.6443 | 0.8196 |
| $\rho_J$ | AR(1) housing shock | beta [0.75, 0.1] | **0.9835** | 0.9595 | 0.9797 | 0.9906 |
| $\rho_K$ | AR(1) investment shock | beta [0.75, 0.1] | **0.7859** | 0.7249 | 0.7831 | 0.8369 |
| $\rho_R$ | AR(1) monetary shock | beta [0.5, 0.1] | **0.6232** | 0.4931 | 0.6142 | 0.7123 |
| $\rho_Z$ | AR(1) intertemporal shock | beta [0.75, 0.1] | **0.7556** | 0.6136 | 0.7250 | 0.8146 |
| $\sigma_J$ | std. housing demand shock | invgamma [0.01, 1] | **0.0737** | 0.0513 | 0.0863 | 0.1490 |
| $\sigma_K$ | std. investment shock | invgamma [0.01, 1] | **0.0360** | 0.0286 | 0.0423 | 0.0718 |
| $\sigma_P$ | std. price markup shock | invgamma [0.01, 1] | **0.0030** | 0.0027 | 0.0031 | 0.0036 |
| $\sigma_R$ | std. interest rate shock | invgamma [0.01, 1] | **0.0013** | 0.0012 | 0.0013 | 0.0015 |
| $\sigma_W$ | std. wage markup shock | invgamma [0.01, 1] | **0.0100** | 0.0089 | 0.0101 | 0.0116 |
| $\sigma_Z$ | std. intertemporal shock | invgamma [0.01, 1] | **0.0163** | 0.0144 | 0.0186 | 0.0263 |

*Note*: The table reports calibrated parameters, priors and posterior estimates of the parameters for the full model. The posterior statistics are based on 50,000 draws from the posterior distribution.

*The prior distribution for $\beta'$ is truncated so that its lower and upper bound are 0.9 and 0.994 respectively.

Table 2: State-Level Regressions: Employment in Services and House Prices

| | % Change in Employment ($\Delta emp_t$) | | | | |
|---|---|---|---|---|---|
| $\Delta hp_{t-1}$ | **0.14***** | | | | |
| | (0.01) | | | | |
| $\Delta hp\_high_{t-1}$ | | **0.07***** | **0.08***** | **0.03*** | **0.02** |
| | | (0.01) | (0.01) | (0.02) | (0.01) |
| $\Delta hp\_low_{t-1}$ | | **0.24***** | **0.12***** | **0.08***** | **0.07***** |
| | | (0.02) | (0.02) | (0.02) | (0.02) |
| $\Delta emp_{t-1}$ | | | | **0.26***** | **0.23***** |
| | | | | (0.08) | (0.09) |
| $\Delta income_{t-1}$ | | | | | **0.07**** |
| | | | | | (0.03) |
| pval difference | | **0.000** | **0.100** | **0.013** | **0.017** |
| Time effects | **no** | **no** | **yes** | **yes** | **yes** |
| Observations | 1071 | 1071 | 1071 | 1020 | 1020 |
| States | 51 | 51 | 51 | 51 | 51 |
| R-squared | 0.12 | 0.16 | 0.66 | 0.72 | 0.73 |

*Note*: The table reports results for regressions that use annual observations from 1991 to 2011 for 50 States and the District of Columbia. Robust standard errors are shown in parentheses. The symbols ***,**,* denote estimates that are statistically different from 0 at the 1, 5 and 10% confidence level. In the table, pval is the p-value of the test for differences in the coefficients for high and low house prices.

Data Sources and Definitions: $\Delta hp$ is the inflation–adjusted (using the GDP deflator) percent change in the FHFA All Transactions House Price Index (available both at State- and MSA-level). $\Delta emp$ is the percent change in employment in the Non-Tradable Service Sector which includes: Retail Trade, Transportation and Utilities, Information, Financial Activities, Professional and Business Services, Education and Health Services, Leisure and Hospitality, and Other Services (source: BLS Current Employment Statistics: Employment, Hours, and Earnings - State and Metro Area). $\Delta income$ is the percent change in the inflation–adjusted state-level disposable personal income (source: Bureau of Economic Analysis).

Table 3: State-Level Regressions: Auto Sales and House Prices

| | % Change in Auto Sales ($\Delta auto_t$) | | | | |
|---|---|---|---|---|---|
| $\Delta hp_{t-1}$ | **0.24*** ** | | | | |
| | (0.03) | | | | |
| $\Delta hp\_high_{t-1}$ | | **-0.05** | **0.16*** ** | **0.11*** ** | **0.07** ** |
| | | (0.04) | (0.04) | (0.03) | (0.03) |
| $\Delta hp\_low_{t-1}$ | | **0.62*** ** | **0.33*** ** | **0.27** ** | **0.20** ** |
| | | (0.05) | (0.06) | (0.11) | (0.09) |
| $\Delta auto_{t-1}$ | | | | **0.23** | **0.21** |
| | | | | (0.17) | (0.17) |
| $\Delta income_{t-1}$ | | | | | **0.34*** ** |
| | | | | | (0.11) |
| pval difference | | **0.000** | **0.040** | **0.137** | **0.155** |
| Time effects | **no** | **no** | **yes** | **yes** | **yes** |
| Observations | 969 | 969 | 969 | 918 | 918 |
| States | 51 | 51 | 51 | 51 | 51 |
| R-squared | 0.02 | 0.06 | 0.86 | 0.87 | 0.88 |

*Note*: The table reports the results of state-level regressions using annual observations from 1992 to 2011 for 50 States and the District of Columbia. Robust standard errors are shown in parentheses. The symbols ***,**,* denote estimates that are statistically different from zero at the 1, 5 and 10% confidence levels. In the table, pval is the p-value of the test for differences in the coefficients for high and low house prices.

Data Sources and Definitions: $\Delta auto$ is the percent change in inflation–adjusted auto sales, "Retail Sales: Motor vehicle and parts dealers" from Moody's Analytics Database. Auto sales data are constructed with underlying data from the US Census Bureau and employment statistics from the BLS. The two Census Bureau surveys are the quinquennial Census of Retail Trade, a subset of the Economic Census, and the monthly Advance Retail Trade and Food Services Survey. See Table 2 for other variable definitions.

Table 4: State-Level Regressions: Electricity Consumption and House Prices

| | % Change in Electricity Consumption ($\Delta elec_t$) | | | | |
|---|---|---|---|---|---|
| $\Delta hp_{t-1}$ | **0.11*** ** | | | | |
| | (0.02) | | | | |
| $\Delta hp\_high_{t-1}$ | | **0.03** | **0.09*** ** | **0.14*** ** | **0.12*** ** |
| | | (0.02) | (0.02) | (0.03) | (0.03) |
| $\Delta hp\_low_{t-1}$ | | **0.24*** ** | **0.16*** ** | **0.22*** ** | **0.19*** ** |
| | | (0.03) | (0.03) | (0.04) | (0.04) |
| $\Delta elec_{t-1}$ | | | | **-0.41*** ** | **-0.41*** ** |
| | | | | (0.02) | (0.02) |
| $\Delta income_{t-1}$ | | | | | **0.15*** ** |
| | | | | | (0.05) |
| pval difference | | **0.000** | **0.105** | **0.058** | **0.090** |
| Time effects | **no** | **no** | **yes** | **yes** | **yes** |
| Weather Controls* | **yes** | **yes** | **yes** | **yes** | **yes** |
| Observations | 1071 | 1071 | 1071 | 1020 | 1020 |
| States | 51 | 51 | 51 | 51 | 51 |
| R-squared | 0.04 | 0.04 | 0.08 | 0.12 | 0.12 |

*Note*: The table reports state-level regressions using annual observations from 1990 to 2011 for 50 States and the District of Columbia. Robust standard errors are shown in parentheses. The symbols ***,**,* denote estimates statistically different from zero at the 1, 5 and 10% confidence level. In the table, pval is the p-value of the test for difference in the coefficients for low-house prices and high-house prices.

Data Sources and Definitions: $\Delta elec$ is the percent change in Residential Electricity Consumption (source: the U.S. Energy Information Administration's Electric Power Monthly publication. Electricity Power Annual: Retail Sales - Total Electric Industry - Residential Sales, NSA, Megawatt-hours). See Table 2 for other variable definitions. All regressions in the Table control separately for number of heating degree days and number of cooling degree days in each state (source: U.S. National Oceanic and Atmospheric Administration's National Climatic Data Center).

Table 5: MSA Level: Employment in Services and House Prices

| | % Change in Employment ($\Delta emp_t$) | | | | |
|---|---|---|---|---|---|
| $\Delta hp_{t-1}$ | **0.134*** ** | | | | |
| | (0.006) | | | | |
| $\Delta hp\_high_{t-1}$ | | **0.104*** ** | **0.058*** ** | **0.049*** ** | **0.048*** ** |
| | | (0.008) | (0.007) | (0.008) | (0.008) |
| $\Delta hp\_low_{t-1}$ | | **0.183*** ** | **0.099*** ** | **0.095*** ** | **0.094*** ** |
| | | (0.009) | (0.008) | (0.010) | (0.010) |
| $\Delta emp_{t-1}$ | | | | **0.033** | **0.031** |
| | | | | (0.041) | (0.041) |
| $\Delta income_{t-1}$ | | | | | **0.021* ** |
| | | | | | (0.011) |
| pval difference | | **0.0000** | **0.0003** | **0.0001** | **0.0000** |
| Time effects | no | no | yes | yes | yes |
| Observations | 5390 | 5390 | 5390 | 5147 | 5147 |
| MSA | 262 | 262 | 262 | 262 | 262 |
| R-squared | 0.09 | 0.10 | 0.37 | 0.39 | 0.39 |

*Note*: The table reports MSA-level regressions using annual observations from 1992 to 2011 for 262 MSAs (102 MSAs were dropped since they had incomplete or missing data on employment by sector). Robust standard errors are shown in parentheses. The symbols ***,**,* denote estimates statistically different from zero at the 1, 5 and 10% confidence level. In the table, pval is the p-value of the test for difference in the coefficients for low-house prices and high-house prices.

Data Sources and Definitions: $\Delta income$ is the percent change in MSA-level inflation-adjusted personal income (source: BEA, Local and Metro Area Personal Income Release). For employment ($\Delta emp$) and house prices ($\Delta hp$), see Table 2.

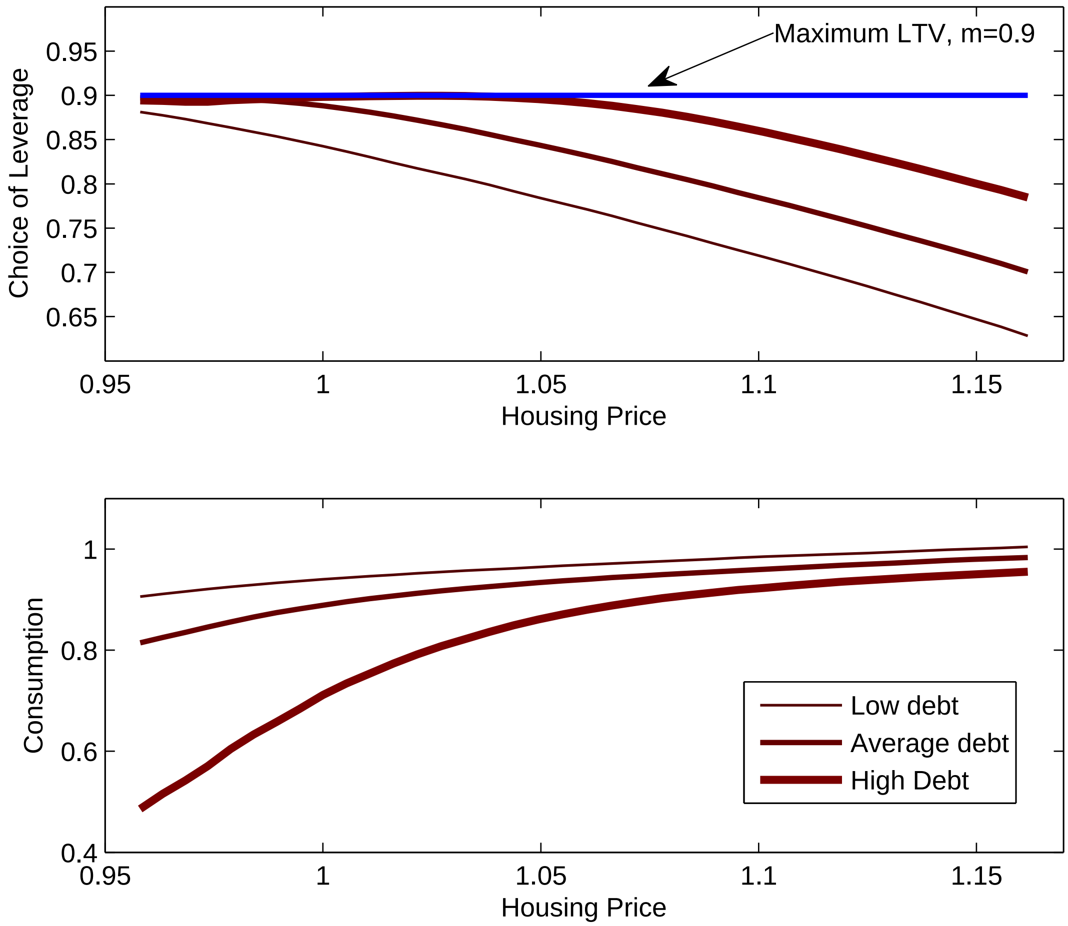
Table 6: MSA Level: Auto Registrations and House Prices

| | Cross-sectional Regressions | | | |
|---|---|---|---|---|
| | Sample 2002-2006 (Housing Boom) | | Sample 2006-2010 (Housing Bust) | |
| | $\Delta hp$ | $\Delta car$ | $\Delta hp$ | $\Delta car$ |
| *Elasticity* | **-7.26*****<br>(0.87) | | **4.69*****<br>(0.57) | |
| $\Delta hp$ | | **0.24*****<br>(0.06) | | **0.49*****<br>(0.08) |
| Method | OLS | IV | OLS | IV |
| Observations | 254 | 254 | 254 | 254 |
| R-squared | 0.22 | 0.35 | 0.21 | 0.48 |

*Note*: The table reports regressions using housing supply elasticity at the MSA level as an instrument for house prices in a regression of MSA car registrations on MSA house prices. The symbols ***,**,* denote estimates statistically different from zero at the 1, 5 and 10% confidence level. The housing supply elasticity is taken from Saiz (2010) and measures limits on real-estate development due to geographic factors that affect the amount of developable land, as well as factors like zoning restrictions. The elasticity data are available for 269 cities: 15 areas were dropped because they were covering primary metropolitan statistical areas (PMSA), which are portions of metropolitan areas, rather than complete MSAs.

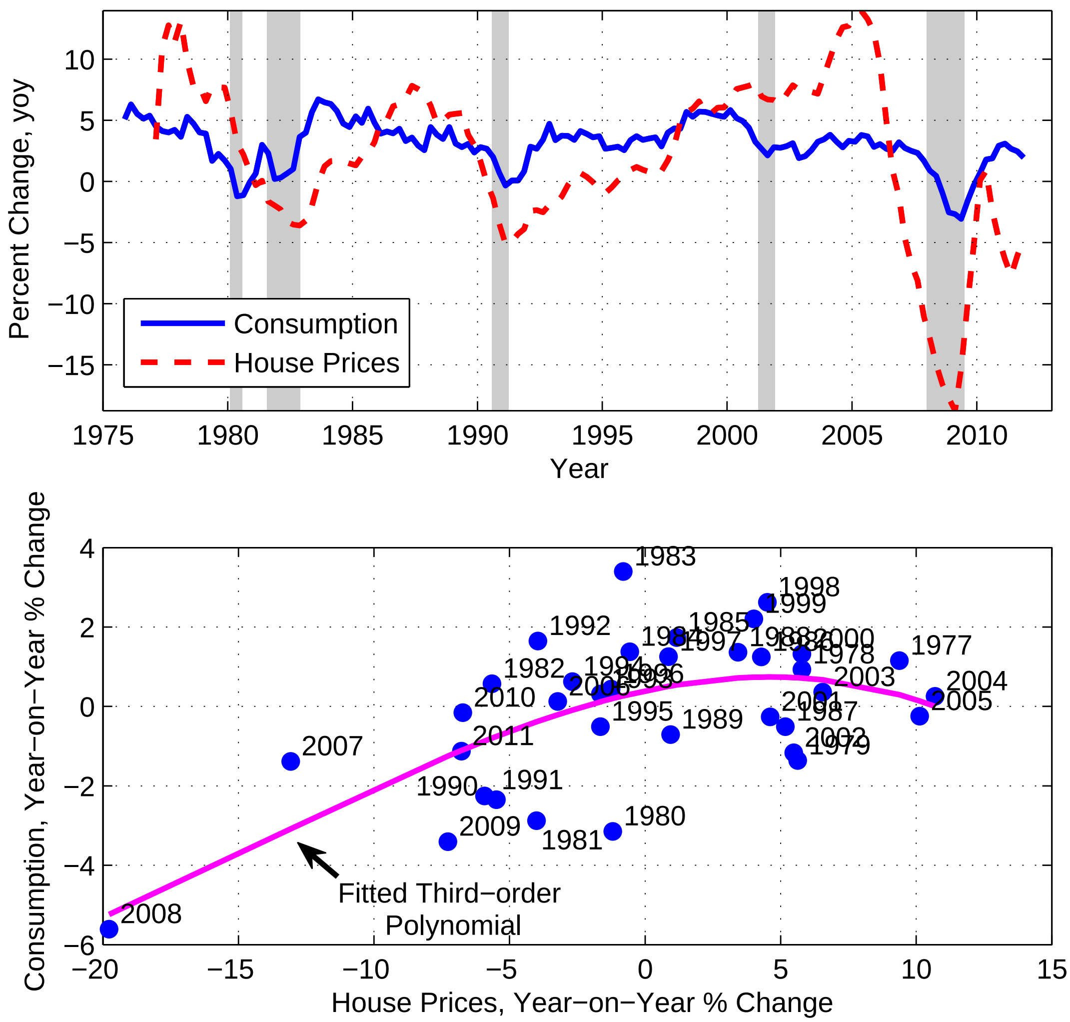
Data Sources: Car Registrations are retail (total less rental, commercial and government) auto registrations from Polk Automotive Data. $\Delta car$ is the percent change in car registrations. See Table 2 for other data sources.

Figure 1: House Prices and Consumption in the Basic Model



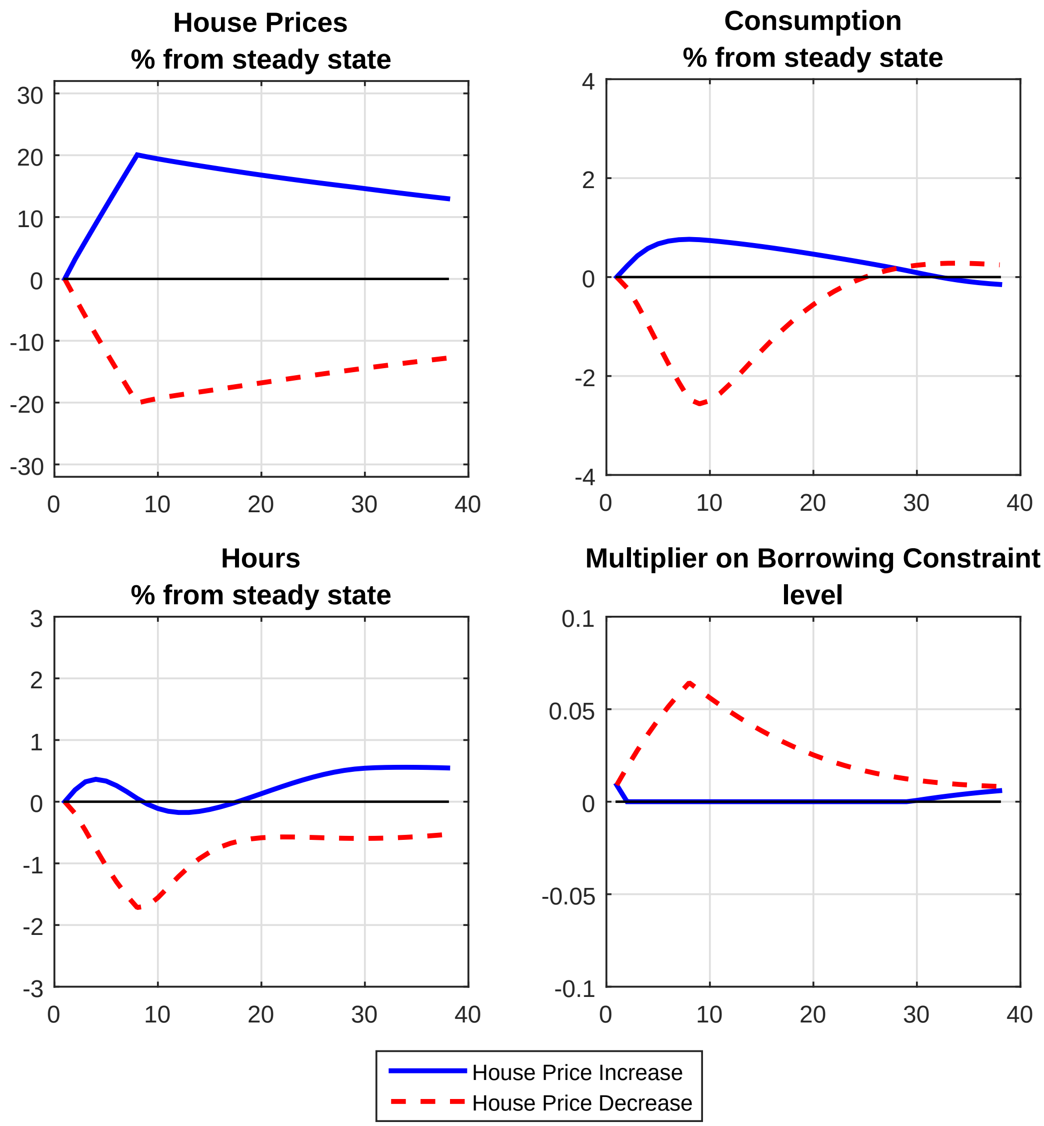

*Note*: The figure shows the optimal choices of leverage and consumption as a function of the housing price for three different levels of debt, low, normal and high, when housing is at its nonstochastic steady-state value. In the top panel, low house prices move the household closer to the maximum borrowing limit given by $\mathsf{m}= 0.9$. This is more likely to happen at high levels of debt (thick line). In the bottom panel, the higher house prices are, the more likely is the household not to be credit constrained, and the consumption function becomes flatter. At high levels of debt, the household is constrained for a larger range of realizations of house prices, and the consumption function is steeper when house prices are low.

Figure 2: House Prices and Consumption in U.S. National Data



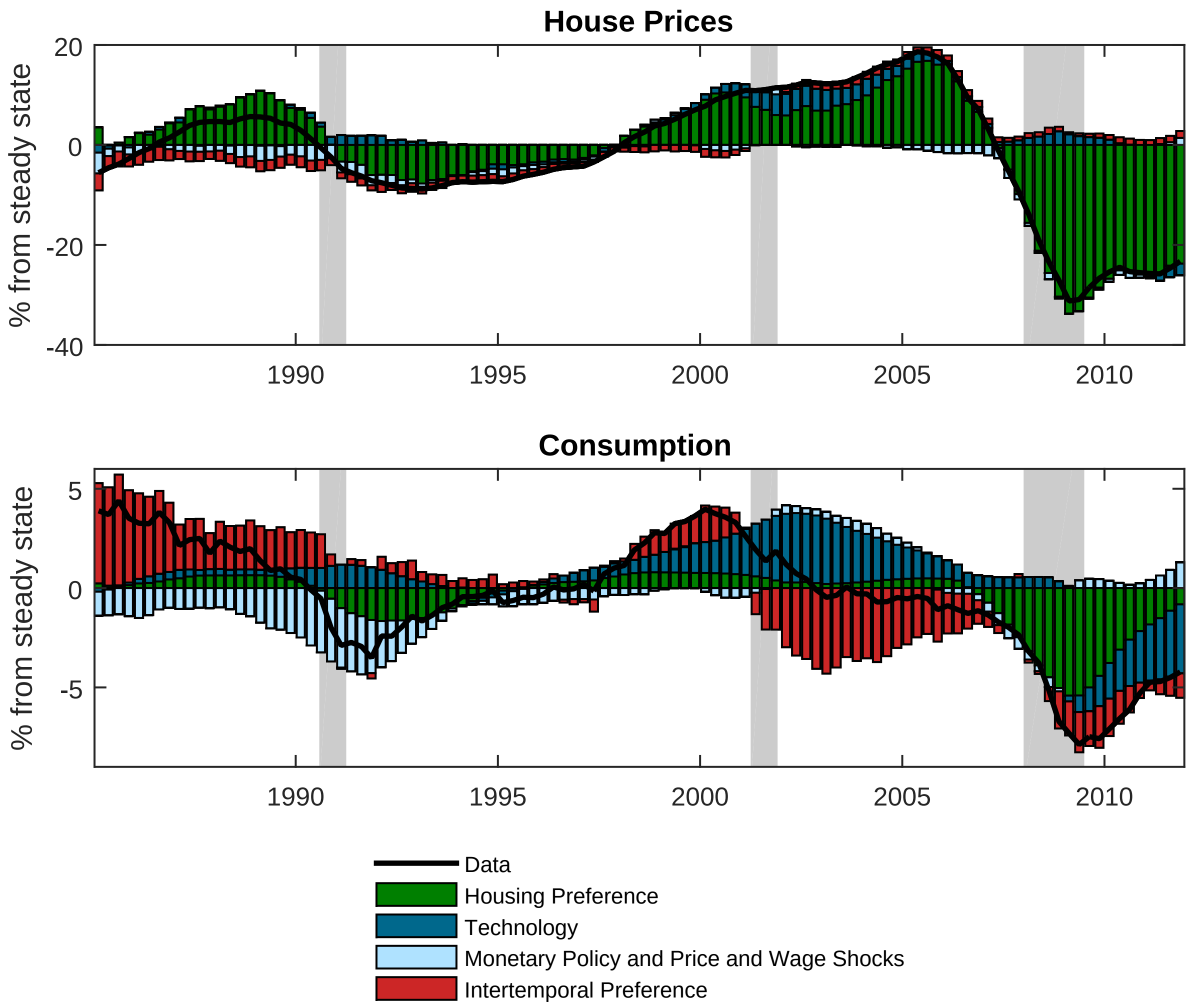

*Note*: Data sources are as follows: House Prices: CoreLogic National House Price Index, seasonally adjusted (Haver mnemonics: USLPHPIS@USECON), divided by the GDP deflator (DGDP@USECON). Consumption: Real Personal Consumption Expenditures, Department of Commerce–Bureau of Economic Analysis (CH@USECON). In the top panel, the shaded areas indicate NBER recessions. In the bottom panel, consumption growth and house price growth are expressed in deviation from their sample mean. The data sample runs from 1976Q1 through 2011Q4.

Figure 3: Impulse Responses to Positive and Negative Housing Demand Shocks in the DSGE Model



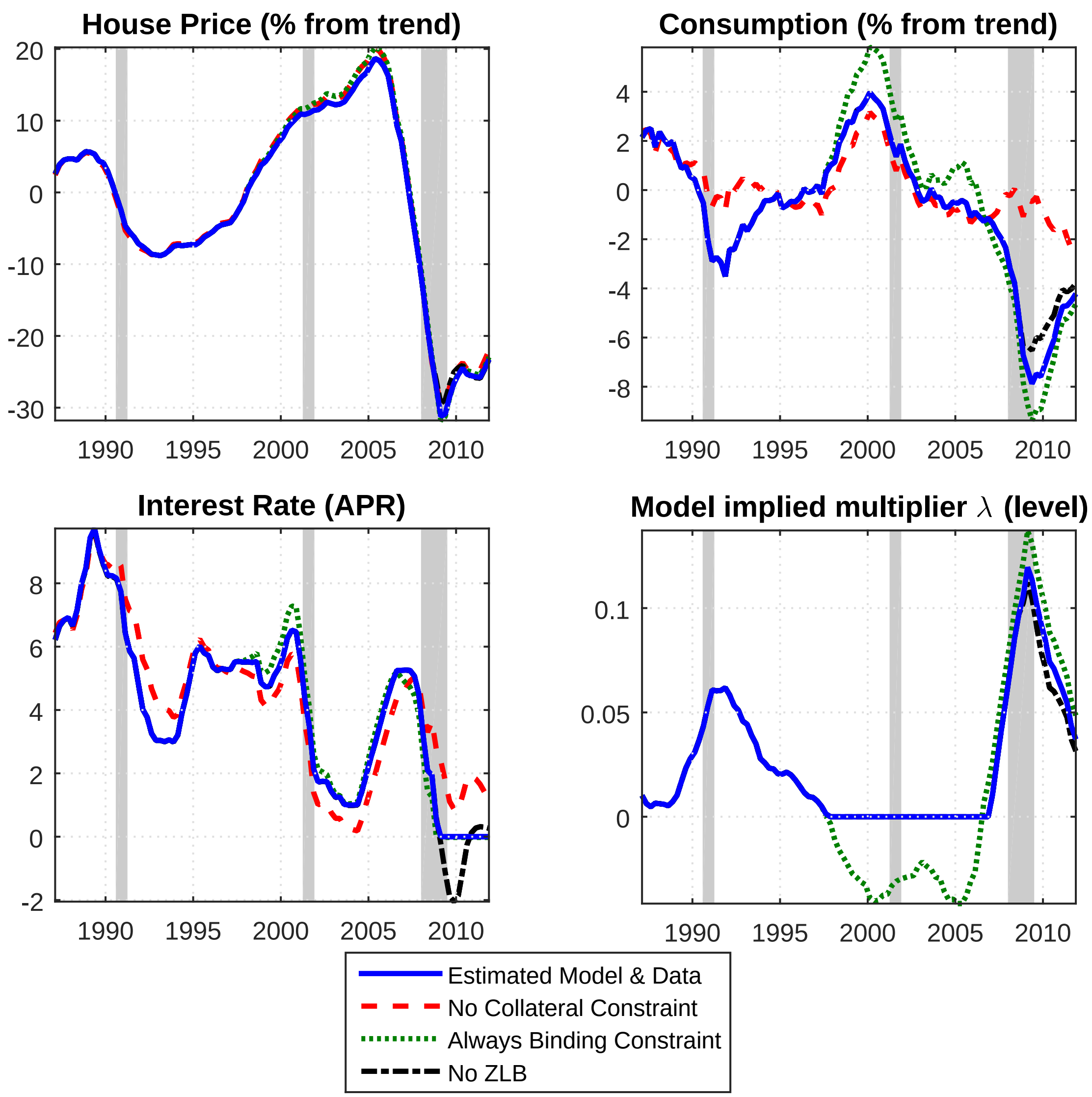

*Note*: The units for the horizontal axes are quarters. The simulation shows the dynamic responses to sequence of housing demand shocks of equal size but opposite sign that move house prices up (solid lines) and down (dashed lines) by 20 percent relative to the steady state.

Figure 4: Historical Decomposition of House Prices and Consumption in the Estimated Model



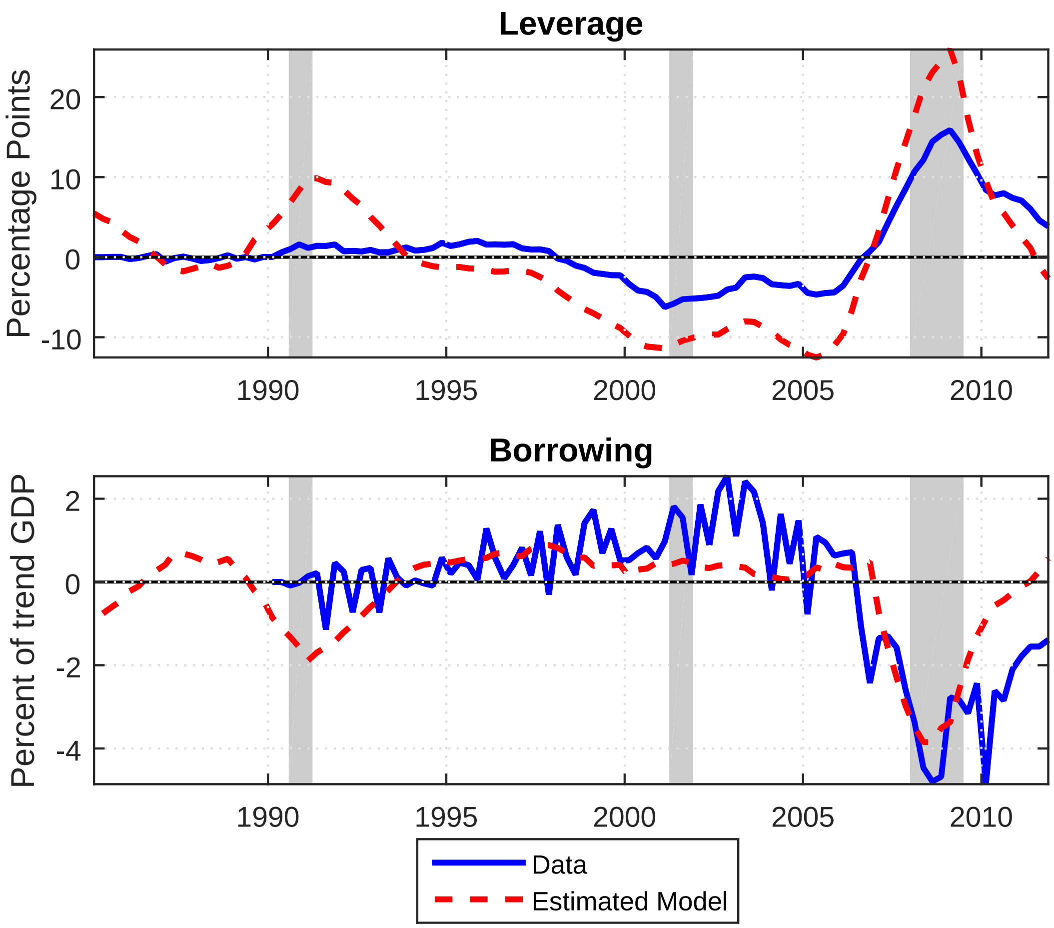

*Note*: The shocks were marginalized in the following order: 1) housing preference shock, 2) investment technology shock, 3) price markup shock, 4) monetary policy shock, 5) wage markup shock, and 6) intertemporal shock.

Figure 5: Counterfactuals of the Estimated Model




*Note*: The simulation shows the filtered series for house prices, consumption, interest rates and the Lagrange multiplier in the estimated model. The dashed lines show their paths feeding in the same shocks but in absence of constrained households (setting $\sigma$=0). The dash-dotted lines show the paths feeding in the same shocks but in absence of the zero lower bound on interest rates.

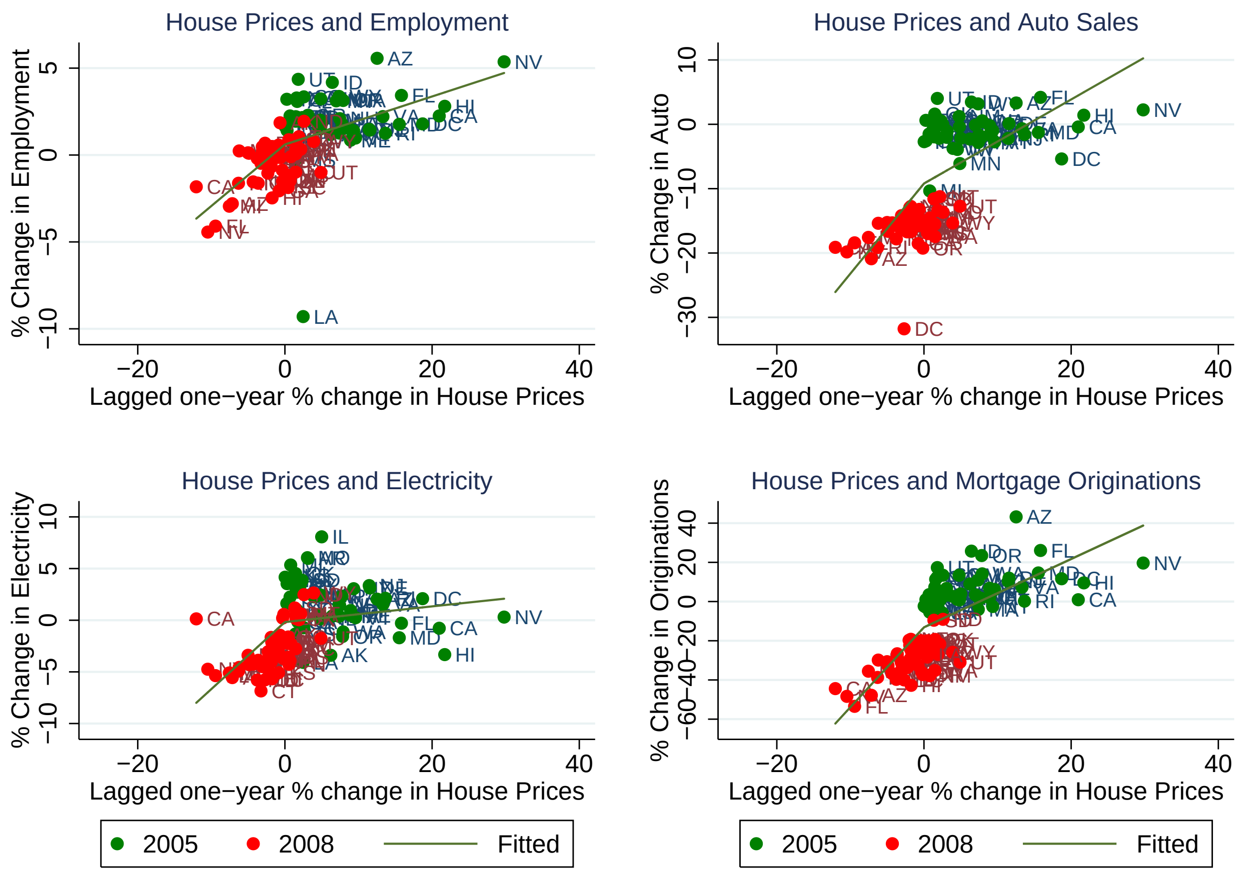
Figure 6: Leverage and Borrowing in the Model and in the Data




*Note*: The top panel compares smoothed leverage in the estimated model (dashed line) with its data analogue. Leverage in the data is the Households' Total Liabilities (Haver Analytics code: PL15ABN5@FFUNDS) divided by Households' Real Estate (PA15TOO5@FFUNDS), from the Flows of Funds Tables.

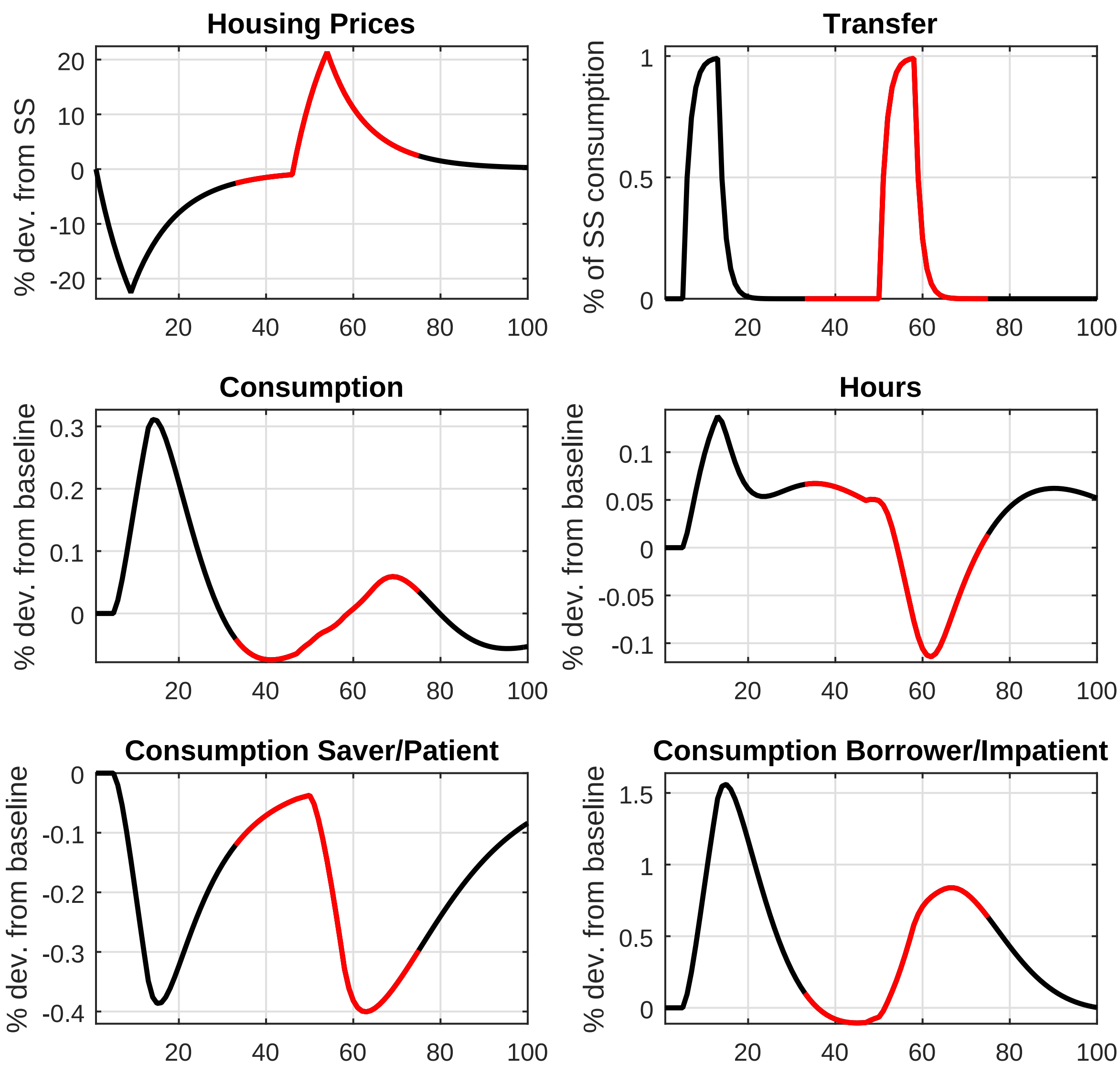
The bottom panel compares smoothed borrowing in the estimated model (dashed line, divided by steady-state annual GDP) with its data analogue. Borrowing in the data is Net Mortgage Originations less estimated debt on residential investment (MEW1@USECON), divided by trend GDP from the Congressional Budget Office (GDPPOTQ@USECON). In each panel, the data series are detrended using a one-sided HP filter (smoothing parameter of 100,000).

Figure 7: House Prices and Economic Activity by State




*Note*: Each panel shows house price growth and activity growth across U.S. states in 2005 and 2008. The solid lines show the fitted values of a regression of activity growth on house prices growth broken down into positive and negative changes.

Figure 8: Transfer from Lenders to Borrowers with Low and High House Prices




*Note*: The figure shows responses to two unexpected lump-sum transfers from savers to borrowers sized at one percent of steady-state consumption. The first transfer (periods 6-13) happens against a backdrop of low house prices and tight collateral constraints. The second transfer (periods 51-58) happens against a backdrop of high house prices and slack collateral constraints. The initial house price levels obtain in response to a housing preference shock. The responses of consumption, hours, savers' and borrowers' consumption are shown in deviation from baseline to isolate the partial effect of the transfer shocks. Variables are plotted in red when the constraint is slack.

# Appendix to “Collateral Constraints and Macroeconomic Asymmetries”

Luca Guerrieri* Federal Reserve Board

Matteo Iacoviello† Federal Reserve Board

June 22, 2017

## Appendix A. House Prices and Consumption in U.S. Data Excluding the Great Recession

Figure A.1 shows that the nonlinearity in the scatter plot between house prices and consumption in U.S. data is in post–1975 data also excluding the collapse in house prices which started around 2005.

## Appendix B. Equilibrium Conditions of the DSGE Model

We list here the equations describing the equilibrium of the DSGE model.

Let $u_{c,t}$ (and $u_{c',t}$), $u_{h,t}$ (and $u_{h',t}$), $u_{n,t}$ (and $u_{n',t}$) denote the time-$t$ marginal utility of consumption, marginal utility of housing and marginal disutility of labor (inclusive of the shock terms: that is, $u_t = \mathsf{z}_t \left( \Gamma_c \log\left(c_t - \varepsilon_c c_{t-1}\right) + \mathsf{j}_t \Gamma_h \log\left(h_t - \varepsilon_h h_{t-1}\right) - \frac{1}{1+\eta} n_t^{1+\eta} \right)$, and $u_{c,t}$ is the derivative of $u_t$ with respect to $c_t$). Let $\Delta$ be the first difference operator, and let overbars denote steady states. The set of necessary conditions for an equilibrium is given by:

- Budget constraint for patient households:

$$c_t + q_t \Delta h_t + i_t - \frac{R_{t-1} b_{t-1}}{\pi_t} = \frac{w_t n_t}{x_{w,t}} + r_{k,t} k_{t-1} - b_t + div_t, \tag{B.1}$$

  where lump-sum dividends from ownership of final goods firms and from labor unions are given by $div_t = \frac{x_{p,t}-1}{x_{p,t}} y_t + \frac{x_{w,t}-1}{x_{w,t}} w_t n_t$.

- Capital accumulation equations for patient households:

$$u_{c,t} q_{k,t} \left( 1 - \phi \frac{\Delta i_t}{\bar{i}} \right) = u_{ct} - \beta E_t \left( u_{c,t+1} q_{k,t+1} \phi \frac{\Delta i_{t+1}}{\bar{i}} \right), \tag{B.2}$$

$$u_{c,t} \frac{q_{k,t}}{\mathsf{a}_t} = \beta E_t \left( u_{c,t+1} \left( r_{k,t+1} + q_{k,t+1} \frac{1-\delta_k}{\mathsf{a}_{t+1}} \right) \right) \tag{B.3}$$

*Luca Guerrieri, Division of Financial Stability, Federal Reserve Board, 20th and C St. NW, Washington, DC 20551. Email: luca.guerrieri@frb.gov.

†Matteo Iacoviello, Division of International Finance, Federal Reserve Board, 20th and C St. NW, Washington, DC 20551. Email: matteo.iacoviello@frb.gov.

$$k_t = \mathsf{a}_t \left( i_t - \frac{\phi}{2} \frac{\Delta i_t^2}{\bar{i}} \right) + (1 - \delta_k)\, k_{t-1} \tag{B.4}$$

where $q_{k,t}$ is the Lagrange multiplier on the capital accumulation constraint.

- Other optimality conditions for patient households:

$$u_{c,t} = \beta E_t \left( u_{c,t+1} R_t / \pi_{t+1} \right), \tag{B.5}$$

$$\frac{w_t}{x_{w,t}} u_{c,t} = u_{n,t}, \tag{B.6}$$

$$q_t u_{c,t} = u_{h,t} + \beta E_t q_{t+1} u_{c,t+1}. \tag{B.7}$$

- Budget and borrowing constraint and optimization conditions for impatient households:

$$c_t' + q_t \Delta h_t' + \frac{R_{t-1}}{\pi_t} b_{t-1} = \frac{w_t'}{x_{w,t}'} n_t' + b_t + div_t', \tag{B.8}$$

$$b_t \leq \gamma \frac{b_{t-1}}{\pi_t} + (1 - \gamma)\, \mathsf{m} q_t h_t', \tag{B.9}$$

$$(1 - \lambda_t)\, u_{c',t} = \beta' E_t \left( \frac{R_t - \gamma \lambda_{t+1}}{\pi_{t+1}} u_{c',t+1} \right), \tag{B.10}$$

$$\frac{w_t'}{x_{w,t}'} u_{c',t} = u_{n',t}\ , \tag{B.11}$$

$$q_t u_{c',t} = u_{h',t} + \beta' q_{t+1} u_{c',t+1} + u_{c',t} \lambda_t (1 - \gamma)\, \mathsf{m} q_t, \tag{B.12}$$

where lump-sum dividends from labor unions are given by $div_t' = \frac{x_{w',t} - 1}{x_{w',t}} w_t' n_t'$, and $\lambda_t$ is the Lagrange multiplier on the borrowing constraint (normalized by the marginal utility of consumption $u_{c',t}$).

- Firm problem, aggregate production, and Phillips curves:

$$\begin{aligned}
y_t &= n_t^{(1-\sigma)(1-\alpha)} n_t'^{\sigma(1-\alpha)} k_{t-1}^{\alpha}, && \text{(B.13)}\\
(1-\alpha)(1-\sigma)\, y_t &= x_{p,t} w_t n_t, && \text{(B.14)}\\
(1-\alpha)\, \sigma y_t &= x_{p,t} w_t' n_t', && \text{(B.15)}\\
\alpha y_t &= x_{p,t} r_{k,t} k_{t-1}, && \text{(B.16)}\\
\log(\pi_t/\overline{\pi}) &= \beta E_t \log(\pi_{t+1}/\overline{\pi}) - \varepsilon_\pi \log(x_{p,t}/\overline{x}_p) + \mathsf{u}_{p,t}, && \text{(B.17)}\\
\log(\omega_t/\overline{\pi}) &= \beta E_t \log(\omega_{t+1}\overline{\pi}) - \varepsilon_w \log(x_{w,t}/\overline{x}_w) + \mathsf{u}_{w,t}, && \text{(B.18)}\\
\log(\omega_t'/\overline{\pi}) &= \beta' E_t \log(\omega_{t+1}'/\overline{\pi}) - \varepsilon_w' \log(x_{w,t}'/\overline{x}_w') + \mathsf{u}_{w,t}. && \text{(B.19)}
\end{aligned}$$

Above, $\omega_t = \frac{w_t \pi_t}{w_{t-1}}$ and $\omega_t' = \frac{w_t' \pi_t}{w_{t-1}'}$ denote wage inflation for each household type, and $\varepsilon_\pi = \frac{(1-\theta_\pi)(1-\beta\theta_\pi)}{\theta_\pi}$, $\varepsilon_w = \frac{(1-\theta_w)(1-\beta\theta_w)}{\theta_w}$, $\varepsilon_w' = \frac{(1-\theta_w)(1-\beta'\theta_w)}{\theta_w}$.

- Monetary policy:

$$R_t = \max\left( 1, R_{t-1}^{r_R} \left( \frac{\pi_t^A}{\overline{\pi}^A} \right)^{(1-r_R) r_\pi} \left( \frac{y_t}{\overline{y}} \right)^{(1-r_R) r_Y} \overline{R}^{1-r_R} \mathsf{e}_{r,t} \right), \tag{B.20}$$

where $\pi_t^A$ is year-on-year inflation (expressed in quarterly units) and is defined as $\pi_t^A \equiv (P_t/P_{t-4})^{0.25}$.

- Market clearing:

$$h_t + h'_t = 1. \tag{B.21}$$

By Walras' law, the good's market clears, so that $y_t = c_t + c'_t + k_t - (1-\delta_k)\, k_{t-1}$.

Equations B.1 to B.21, together with the laws of motion for the exogenous shocks described in Section 3 of the paper, define a system of 21 equations in the following variables: $c$, $c'$, $h$, $h'$, $i$, $k$, $y$, $b$, $n$, $n'$, $w$, $w'$, $\pi$, $q$, $R$, $\lambda$, $x_p$, $x_w$, $x'_w$, $r_k$, $q_k$.

We use the methods described in Appendix D and more fully described in Guerrieri and Iacoviello (2015) to solve the model subject to the two occasionally binding constraints given by equations B.9 and B.20.

## Appendix C. Estimation Details

**Data.** Data sources for the estimation are as follows:

1. Consumption

   Model Variable: $\widetilde{C}_t = \log \frac{c_t + c'_t}{\bar{c} + \bar{c}'}$.

   Data: Real Personal Consumption Expenditures, from Bureau of Economic Analysis – BEA – (Haver Analytics code: CH@USECON), log transformed and detrended with one-sided HP filter (smoothing parameter equal to $100,000$).

2. Price Inflation

   Model Variable: $\widetilde{\pi}_t = \log \frac{\pi_t}{\bar{\pi}}$.

   Data: quarterly change in GDP Implicit Price Deflator, from BEA (DGDP@USECON), minus 0.5 percent.

3. Wage Inflation

   Model Variable: $\widetilde{\omega}_t = \log \frac{\sigma \omega_t + (1-\sigma)\omega'_t}{\bar{\pi}}$.

   Data: Real Compensation per Hour in Nonfarm Business Sector (LXNFR@USECON), log transformed, detrended with one-sided HP filter (smoothing parameter equal to $100,000$), first differenced, and expressed in nominal terms adding back price inflation.

4. Investment

   Model Variable: $\widetilde{i}_t = \log \frac{i_t}{\bar{i}}$.

   Data: Real Private Nonresidential Fixed Investment, from BEA (FNH@USECON), log transformed and detrended with one-sided HP filter (smoothing parameter equal to $100,000$).

5. House Prices

   Model Variable: $\widetilde{q}_t = \log \frac{q_t}{\bar{q}}$.

   Data: Corelogic House Price Index (USLPHPIS@USECON) divided by GDP Implicit Price Deflator, log transformed and detrended with one-sided HP filter (smoothing parameter equal to $100,000$).

6. Interest Rate

   Model Variable: $\widetilde{r}_t = R_t - 1$.

   Data: Effective Federal Funds Rate, annualized percent (FEDFUNDS@USECON), divided by 400 to express in quarterly units.

## Appendix D. DSGE Model: Solution Method and Accuracy Checks

**Solution Method.** We use a nonlinear solution method to find the equilibrium allocations of the model in Section 3. The method resolves the problem of computing decision rules that approximate the equilibrium well both when the borrowing constraint binds, and when it does not (similar reasoning applies to the nonnegativity constraint on the interest rate, as described at the end of this section).

The economy features two regimes: a regime when collateral constraints bind; and a regime in which they do not, but are expected to bind in the future.[i] With binding collateral constraints, the linearized system of necessary conditions for an equilibrium can be expressed as

$$\mathcal{A}_1 E_t X_{t+1} + \mathcal{A}_0 X_t + \mathcal{A}_{-1} X_{t-1} + \mathcal{B}\epsilon_t = 0, \tag{D.1}$$

where $\mathcal{A}_1$, $\mathcal{A}_0$, and $\mathcal{A}_{-1}$ are matrices of coefficients conformable with the vector $X$ collecting the model variables in deviation from the steady state for the regime with binding constraints; and $\epsilon$ is the vector collecting all shock innovations (and $\mathcal{B}$ is the corresponding conformable matrix). Similarly, when the constraint is not binding, the linearized system can be written as

$$\mathcal{A}_1^* E_t X_{t+1} + \mathcal{A}_0^* X_t + \mathcal{A}_{-1}^* X_{t-1} + \mathcal{B}^*\epsilon_t + \mathcal{C}^* = 0, \tag{D.2}$$

where $\mathcal{C}^*$ is a vector of constants. When the constraint binds, we use standard linear solution methods to express the decision rule for the model as

$$X_t = \mathcal{P} X_{t-1} + \mathcal{Q}\epsilon_t. \tag{D.3}$$

When the collateral constraints do not bind, we use a guess-and-verify approach. We shoot back towards the initial conditions, from the first period when the constraints are guessed to bind again. For example, if the constraints do not bind in $t$ but are expected to bind the next period, the decision rule for period $t$ can be expressed, starting from D.2 and using the result that $E_t X_{t+1} = \mathcal{P} X_t$ , as:

$$X_t = -\left(\mathcal{A}_1^* \mathcal{P} + \mathcal{A}_0^*\right)^{-1} \left(\mathcal{A}_{-1}^* X_{t-1} + \mathcal{B}^*\epsilon_t + \mathcal{C}^*\right). \tag{D.4}$$

We proceed in a similar fashion to compute the allocations for the case when collateral constraints are guessed not to bind for multiple periods, or when they are foreseen to be slack starting in periods beyond $t$. As shown by equation D.4, the model dynamics when constraints are not binding depend both on the current regime (through the matrices $\mathcal{A}_1^*, \mathcal{A}_0^*$ and $\mathcal{A}_{-1}^*$) and on the expectations of future regimes when constraints will bind again (through the matrix $\mathcal{P}$, which is a nonlinear function of the matrices $\mathcal{A}_1$, $\mathcal{A}_0$ and $\mathcal{A}_{-1}$).

[i] If one assumes that the constraints are not expected to bind in the future, the regime with slack borrowing constraints becomes unstable, since borrowers' consumption falls over time and their debt rises over time until it reaches the debt limit, which contradicts the initial assumption.

It is straightforward to generalize the solution method described above for multiple occasionally binding constraints.[ii] The extension is needed to account for the zero lower bound (ZLB) on policy interest rates as well as the possibility of slack collateral constraints. In that case, there are four possible regimes: 1) collateral constraints bind and policy interest rates are above zero, 2) collateral constraints bind and policy interest rates are at zero, 3) collateral constraints do no bind and policy interest rates are above zero, 4) collateral constraints do not bind and policy interest rates are at zero. Apart from the proliferation of cases, the main ideas outlined above still apply.

**Local linearity of the Policy Functions.** The solution of the model can be described by a policy function of the form:

$$X_t = \mathbf{P}(X_{t-1}, \epsilon_t)X_{t-1} + \mathbf{D}(X_{t-1}, \epsilon_t) + \mathbf{Q}(X_{t-1}, \epsilon_t)\epsilon_t. \tag{D.5}$$

The vector $X_t$ collects all the variables in the model, except the innovations to the shock processes, which are separated in the vector $\epsilon_t$. The matrix of reduced-form coefficients $\mathbf{P}$ is state-dependent, as are the vector $\mathbf{D}$ and the matrix $\mathbf{Q}$. These matrices and vector are functions of the lagged state vector and of the current innovations. However, while the current innovations can trigger a change in the reduced-form coefficients, $X_t$ is still locally linear in $\epsilon_t$. To illustrate this point, Figure A.2 shows how the policy function for impatient agents' consumption $c'_t$ – one of the elements of $X_t$ – depends on the realization of the housing preference shock $u_{j,t}$ – one of the elements of $\epsilon_t$ – when all the other elements of $X_{t-1}$ are held at their steady–state value. The top panel shows the consumption function. This function is piecewise linear, with each of the rays corresponding to a given number of periods in which the borrowing constraint is expected to be slack. The bottom panel shows the derivative of the consumption function with respect to $u_{j,t}$. As the consumption function is piecewise linear, the derivative is not defined at the threshold values of the shock $u_{j,t}$ that change the expected duration of the regime. However, each of these threshold points for different shocks is a set of measure zero.[iii]

Realizations of the shock $u_{j,t}$ above a threshold will imply that the borrowing constraint is temporarily slack. When the constraint is slack, the constraint will be expected to be slack for a number of periods which increases with the size of the shock. Accordingly, consumption will respond proportionally less, and the $\mathbf{Q}_{c',u_j}$ element of the matrix $\mathbf{Q}$ that defines the impact sensitivity of $c'$ to $u_j$ will be smaller.

**Accuracy of Numerical Solution.** We assess the accuracy of the solution method for the DSGE model by computing the errors of the model's intertemporal equations. The errors arise both because of the linearization of the original nonlinear model, and because the method abstracts from precautionary motives due to possibility of future regime switches. We focus here on the intertemporal errors for the consumption and housing demand equations of patient and impatient agents, equations B.5, B.7, B.10 and B.12, and we compute the errors using standard monomial integration for the expectation terms and simulating the model under the estimated filtered shocks (see Judd, Maliar, and Maliar 2011 for a description of the monomial method). Across these equations, the mean absolute errors – expressed in consumption units – are about $4 \times 10^{-4}$, that is, \$4 for every \$10,000 spent, a level that can be deemed negligible.

[ii] For an array of models, Guerrieri and Iacoviello (2015) compare the performance of the piecewise perturbation solution described above against a dynamic programming solution obtained by discretizing the state space over a fine grid. Their results show that this solution method efficiently and quickly computes accurate policy functions.

[iii] It is straightforward to prove that the points where the derivative of the decision rule is not defined are of measure zero given a choice of process for the stochastic innovations. By construction, there are only countably many of these points. If there were uncountably many, a shock could lead to a permanent switch in regimes, which is ruled out by the solution method.

As standard practice (for instance, see Bocola 2016), Figure A.4 plots the histogram of the logarithm with base 10 of the absolute value of these errors. On average, residual log errors are $-2.9$ and $-2.92$ for the consumption and the housing Euler equations of the borrower, and $-4.1$ and $-3.6$ for the consumption and housing Euler equations of the saver, indicating a miss of about \$1 per \$1000 of consumption for the borrower's Euler equations, and of about \$1 per \$10,000 of consumption for the saver's Euler equations.

The small intertemporal errors indicate that precautionary motives, while potentially important, are, on average, quantitatively small. Nonetheless, one may suspect that, in the housing boom that preceded the crisis, agents would have wanted to engage in precautionary saving to insure against bad shocks, and that, during the crisis, uncertainty about the path and duration of the zero lower bound on interest rates would have affected macroeconomic outcomes through precautionary behavior. To assess this possibility, we modify our solution algorithm to account for the possibility of future shocks. At each point for which the solution is sought, this alternative algorithm augments the state space with sequences of anticipated shocks and corrects current decisions by gauging the difference between the augmented expectations and the original expectations.

To understand the modifications of our solution algorithm that allow for precautionary behavior, consider, as an example, a forward-looking equation of the form:

$$q_t = \max\left(0, \beta E_t q_{t+1} + \varepsilon_t\right), \quad \varepsilon_t \sim \text{NIID}\left(0, \sigma^2\right). \tag{D.6}$$

The perfect foresight solution assumes that the variance of $\varepsilon_{t+j}$ is zero for $j > 0$. Under this assumption, $E_t^{PF} q_{t+1} = 0$, where $E^{PF}$ denotes the expectation operator under perfect foresight. Accordingly, the solution under perfect foresight is $q_t = \varepsilon_t$ if $\varepsilon_t \geq 0$, and $q_t = 0$ if $\varepsilon_t < 0$ or, more succinctly:

$$q_t^{PF} = \max\left(0, \varepsilon_t\right). \tag{D.7}$$

We modify the solution by extending the expectation operator $E_t$ as follows. We augment the time-$t$ state space with two anticipated shocks to $\varepsilon_{t+1}$ of equal size, opposite sign and equal probability. When integrating the expectations of $\varepsilon_{t+1}$, this approach is equivalent to considering two integration nodes and weights, following the lead of Judd, Maliar, and Maliar (2011). Under this scheme, the two integration nodes are $\sigma$ are $-\sigma$, each with weight $1/2$. Accordingly, the expectation of $q_{t+1}$ can be defined as follows:

$$E_t^{RE1} q_{t+1} = (1/2) \max\left(0, \sigma\right) + (1/2) \max\left(0, -\sigma\right) = (1/2)\,\sigma, \tag{D.8}$$

where $E_t^{RE1}$ denotes the expectation taken assuming knowledge that additional shocks will occur in period $t+1$. The solution for $q_t$ becomes:

$$q_t^{RE1} = \max\left(0, \beta\sigma/2 + \varepsilon_t\right). \tag{D.9}$$

We can proceed in similar fashion to add $n-$period ahead anticipated shocks (to $\varepsilon_{t+1}$, $\varepsilon_{t+2}, \ldots\ \varepsilon_{t+n}$), and choose optimally the number of anticipated shocks that yield the largest reduction in intertemporal errors. We have found that $4-$period ahead anticipated shocks yield the largest decline in the errors to the intertemporal equations in the proximity of regime switches.[iv]

As this modification of the solution algorithm comes at a very large cost in terms of speed, we make comparisons holding the filtered shocks and the estimated model parameters unchanged.[v] The modified algorithm reduces the errors of the intertemporal equations, particularly in periods when the constraints are close to switching. For instance, when the collateral constraint is slack but expected to bind in the future, or vice versa – an occurrence which happens, according to our estimates, with some frequency

[iv] The optimal number of anticipated shocks is, in general, depends on the stochastic structure of model and its calibration. For the simple example in the text, the optimal number of anticipated shocks is 3 when $\beta = 0.99$ and $\sigma = 0.05$.

[v] Solving the model for a particular sequence of shocks takes a fraction of a second using the algorithm that we employ for Bayesian estimation. The modified algorithm that corrects for uncertainty about future shocks takes several minutes to solve. While useful for assessing the accuracy of the solution, it is unusable for filtering and estimation.

between 1998 and 2006, the consumption Euler errors (expressed in base 10 logs) for the borrower and saver fall from $-3.0$ and $-4.0$ to $-3.1$ and $-4.3$, respectively. Despite the smaller intertemporal errors, the modified solution method implies only negligible differences in the model's business cycle properties: as shown by Figure A.5, the discrepancies between the model's simulated series are barely visible, except perhaps in periods close to regime switches, when precautionary considerations ought to be heightened.

The modified solution method predicts a slightly smaller increase in total consumption (0.05 percentage point lower) at the peak of the housing boom, and a slightly larger decline in consumption at the trough of the housing price collapse (half a percentage point larger). The smaller increase in consumption during the boom owes to the presence of precautionary saving, as borrowers take on less debt in anticipation of future negative shocks. The larger decrease in consumption during the bust owes to the uncertainty about the zero lower bound. As elucidated, for instance, by Basu and Bundick (2017), at the ZLB, uncertainty about future shocks causes an additional decline in output over and above the decline caused by the shocks that led to the ZLB in the first place. Aside from these two episodes, the differences between the solution methods are barely visible. Accordingly, we conclude that the shocks and frictions in our model do not imply large precautionary motives.

As a further check, we confirmed that our solution method works well in comparison to standard – yet slower – global solution methods when global methods can be easily deployed, as is the case for the partial equilibrium model of Section 2. Starting from the non-stochastic steady state of the model, Figure A.6 plots the responses of consumption, leverage and debt to positive and negative house price shocks using both a standard global method (value function iteration) and the algorithm used to solve the DSGE model for estimation purposes. As the figure shows, the two algorithms deliver very similar dynamics for the variables of interest.

## Appendix E. Specification Checks and Sensitivity Analysis

First, we check that our findings are insensitive to the assumption that the initial vector of endogenous variables, $X_0$, is equal to its steady-state value. Second, we show that our algorithm can accurately recover the "true" structural shocks when the structural parameters are known. Third, we show that when our estimation strategy is applied to data generated from the posterior mode of the model, the estimated parameters are close to their true values. As for sensitivity analysis, we consider an alternative detrending strategy, different shock structure and variable capacity utilization.

**Initialization Scheme.** Our estimation procedure makes use of the assumption that all variables are known and equal to their nonstochastic steady state in the first period. The first 20 observations are used to train the filter. As a robustness exercise, we have estimated our model under different assumptions about the values of the initial state vector $X_0$.[vi] We confirmed the initial conditions were essentially irrelevant by period 20 and that our estimated parameters were minimally affected by the initial condition. Table A.1 compares the benchmark results with the estimation results assuming a different known initial condition (see Column 4), randomly sampled from the distribution of the model state variables based on the model's estimated mode.

**Filtering.** Our estimation procedure relies on using a nonlinear equation solver in order to filter, in each period $t$, the sequence of shocks $\epsilon_t$ that reproduces the observations in the vector $Y_t$. It is possible

[vi] By treating the initial distribution of $X_0$ as known, we eliminate the conditionality of the likelihood function for the observed data $Y^T$ on both $X_0$ and $Y_0$. Without this assumption, one needs to integrate the likelihood for $Y^T$ over the distribution for $X_0$ implied by the specification of the model and the observed data, and simulation-based methods (such as the particle filter or the unscented Kalman filter) become necessary.

that small numerical errors in retrieving $\epsilon_t$ at each point in time may propagate over time and lead to inaccuracies in computing the filtered shocks. To explore the practical relevance of this possibility, we generate an artificially long sample of observables from our model. Drawing from the posterior mode, we generate a time series of artificial observations of length $T = 500$. We then use our procedure to filter these shocks back and compare the filtered shocks to the "true" ones used to generate our artificial data set. The correlation between the "true" shocks and the filtered ones is, for all shocks, extremely high, ranging from 0.998 for the monetary shock to 0.999992 for the wage shock.

**Identifiability.** Following Schmitt-Grohé and Uribe (2012), with estimated parameters set to their posterior mode, we generate a sample of 120 observations (comparable in size to our actual dataset) and then estimate the model parameters using the same methods and procedures applied to the observed data, both with our Bayesian approach and with uninformative priors – maximum likelihood estimation (MLE). At no point does our estimation procedure make use of knowledge of the true parameter values. In this case, too, our estimation strategy comes close to uncovering the true shocks and the true values of the parameters in question. For instance, the estimated wage share of impatient households at the mode is 0.52 in the Bayesian approach, 0.38 in the MLE case. All the other estimated coefficients are reported in columns 5 and 6 of Table A.1.

**Detrending Method.** We use a one-sided HP filter to construct the data analogues to our model variables prior to estimation. As an alternative, we have incorporated linear deterministic trends in the model and estimated the parameters governing the trends jointly with the other parameters. Specifically, we have assumed three separate deterministic trends for neutral technology, investment goods technology, and housing supply technology. Given our assumptions about preferences and technology, these three separate trends yield a balanced growth path in which real consumption (together with real wages), real investment, and real house prices grow at different rates (even if the nominal shares of consumption, investment and housing expenditures remain constant). The model with deterministic trends implies slightly more persistent and more volatile shocks, presumably in order to account for the larger and more persistent deviations of the observations around their constant trends. The additional estimation results are reported in Column 7 of Table A.1.

**Allowing for Neutral Technology Shocks and Variable Capacity Utilization.** Our benchmark specification includes six shocks (investment-specific shocks, wage markup, price markup, monetary policy, intertemporal preferences, and preferences for housing). As a robustness exercise, we also considered an additional shock, a shock to the level of neutral technology (denoted by $\mathsf{a}^N$) paired with variable capacity utilization (denoted by $z_t$). To introduce shocks to neutral technology, Equation (B.13) is modified as follows:

$$y_t = \mathsf{a}_t^N n_t^{(1-\sigma)(1-\alpha)} n_t'^{\sigma(1-\alpha)} (z_t k_{t-1})^{\alpha}. \tag{E.1}$$

where the process for $\mathsf{a}^N$ is

$$\log(\mathsf{a}_t^N) = \rho_A \log(\mathsf{a}_{t-1}^N) + u_{a,t}. \tag{E.2}$$

The parameter $\rho_A$ is the AR(1) coefficient and $u_{a,t}$ is an innovation which is normally, independently and identically distributed. With variable utilization, the capital accumulation equation becomes

$$k_t = \mathsf{a}_t \left( i_t - \phi \frac{(i_t - i_{t-1})^2}{\bar{i}} \right) + (1 - \delta_{k,t})\, k_{t-1}, \tag{E.3}$$

and, in turn, the depreciation rate $\delta_{k,t}$ becomes time-varying and evolves according to

$$\delta_{k,t} = \delta_k + b_K \zeta_K z_t^2/2 + b_K (1 - \zeta_K) z_t + b_K (\zeta_K/2 - 1), \tag{E.4}$$

where the parameter $\zeta_K > 0$, between 0 and 1, measures the curvature of the capital-utilization function, and where $b_K = 1/\beta - (1 - \delta_K)$ is a normalization that guarantees that steady-state utilization is unity. We assume a decentralization (as in Iacoviello and Neri 2010) where patient households rent capital services (given by $z_t k_{t-1}$) to wholesale firms and choose the capital utilization rate subject to the additional constraint given by equation (E.4).

We also introduce an additional observation equation:

$$TFP_t = (\hat{\mathtt{a}}_t^N) + Sh_i(\hat{\mathtt{a}}_t); \tag{E.5}$$

where the observed measure of total factor productivity, $TFP_t$, is the (detrended) utilization-adjusted total-factor productivity of Fernald 2012, where $Sh_i$ is the investment share in total absorption, and where the hat symbol denotes a variable expressed in deviation from its steady state. The observation equation takes into account that there are two sources of changes for total factor productivity in our model, the neutral technology $\mathtt{a}^N$ and the investment-specific technology $\mathtt{a}$.

The model with the neutral technology shocks and variable capacity implies a higher fraction of impatient households and minor changes in the rest of the estimated parameters. As a result, the housing collapse plays a larger role than in our benchmark model in accounting for the consumption decline in the Great Recession. The additional estimation results are reported in Column 8 of Table A.1.

As an alternative to the level shocks for neutral technology, we also consider growth rate shocks, allowing for a small error correction component. In this case,

$$\log(\mathtt{a}_t^N) - \log(\mathtt{a}_{t-1}^N) = \rho_A \left(\log(\mathtt{a}_{t-1}^N) - \log(\mathtt{a}_{t-2}^N)\right) - \rho_{ECM} \log(\mathtt{a}_{t-1}^N) + u_{a,t}; \tag{E.6}$$

where $\rho_{ECM} = 0.0025$, a small number that ensures long-run convergence of neutral technology towards its non stochastic steady state at the rate of one percent a year. The mode of the estimated parameters under this configuration is reported in Column 9 of Table A.1

Figure A.7 provides a comparison of the contribution of technology shocks for the evolution of key variables across specifications. In each case, the solid lines show the observed variables (detrended). The shaded areas show the evolution of those same variables when only the estimated technology shocks are turned on – both investment-specific and neutral, if present. (Recall that, by construction, the model matches the observations when all shocks are turned on.) The top row of the figure shows the results for our baseline setup, that considers only investment-specific technology shocks. The middle and bottom rows show sensitivity analysis for the inclusion of neutral technology shocks, in levels for the middle row, and in growth rates for the bottom row.

The figure shows some common patterns: 1) In all cases, the technology shocks account for the bulk of the observed investment movements; 2) The addition of the neutral shocks has an impact on consumption, but the timing is generally off, so that the contributions of the technology shocks need to be offset by other shocks; 3) in all cases, the technology shocks only make a modest contribution to the evolution of house prices, though this contribution is marginally beefier when including shocks to the growth rate of technology.

## Appendix F. State-Level Evidence on Mortgage Originations

Because the effects of low and high house prices on consumption work in our model through tightening or relaxing borrowing constraints, it is important to check whether measures of credit also depend asymmetrically on house prices. Table A.2 shows how mortgage originations at the state level respond to changes in house prices. We choose mortgage originations because they are available for a long time period, and because they are a better measure of the flow of new credit to households than the stock of existing debt. In all of the specifications in Table A.2, mortgage originations depend asymmetrically on house prices, too.

## References


Basu, S. and B. Bundick (2017). Uncertainty shocks in a model of effective demand. *Econometrica 85*(3), 937–958. [A.7]

Bocola, L. (2016). The pass-through of sovereign risk. *Journal of Political Economy 124*(4), 879–926. [A.6]

Fernald, J. (2012). A quarterly, utilization-adjusted series on total factor productivity. Technical report, Federal Reserve Bank of San Francisco. [A.9]

Guerrieri, L. and M. Iacoviello (2015). OccBin: A toolkit for solving dynamic models with occasionally binding constraints easily. *Journal of Monetary Economics 70*(C), 22–38. [A.3, A.5]

Iacoviello, M. and S. Neri (2010). Housing market spillovers: Evidence from an estimated dsge model. *American Economic Journal: Macroeconomics 2*(2), 125–64. [A.9]

Judd, K. L., L. Maliar, and S. Maliar (2011, 07). Numerically stable and accurate stochastic simulation approaches for solving dynamic economic models. *Quantitative Economics 2*(2), 173–210. [A.5, A.6]

Schmitt-Grohé, S. and M. Uribe (2012). What's news in business cycles. *Econometrica 80*(6), 2733–2764. [A.8]

Table A.1: Estimation Results: Robustness Analysis

| | | | | Specification Checks | | | Sensitivity | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1. Bench. | 2. No Constr. | 3. Always Binding | 4. Different Init.Cond. | 5. Bayes Artif.Data | 6. MLE Artif.Data | 7. Lin. Trend | 8. N. Tech. Level | 9. N. Tech. Growth |
| $\beta'$ | 0.9922 | | 0.9860 | 0.9915 | 0.9868 | 0.9898 | 0.9844 | 0.9910 | 0.9874 |
| $\varepsilon_c$ | 0.6842 | 0.8211 | 0.7005 | 0.7002 | 0.6568 | 0.6755 | 0.7178 | 0.7534 | 0.7540 |
| $\varepsilon_h$ | 0.8799 | 0.7717 | 0.8622 | 0.8973 | 0.9057 | 0.8873 | 0.9047 | 0.9095 | 0.9045 |
| $\phi$ | 4.1209 | 5.1604 | 4.5890 | 6.3518 | 3.8579 | 5.4071 | 4.9318 | 1.4724 | 2.1126 |
| $\sigma$ | 0.5013 | | 0.4421 | 0.5383 | 0.3760 | 0.5210 | 0.4343 | 0.5729 | 0.3395 |
| $r_\pi$ | 1.7196 | 1.8042 | 1.8773 | 1.9417 | 1.8660 | 1.9267 | 1.8554 | 1.6403 | 1.0058 |
| $r_R$ | 0.5509 | 0.5412 | 0.5616 | 0.6133 | 0.5771 | 0.5017 | 0.6059 | 0.5429 | 0.5767 |
| $r_Y$ | 0.0944 | 0.0905 | 0.0955 | 0.0946 | 0.1195 | 0.1114 | 0.0630 | 0.1112 | 0.1043 |
| $\theta_\pi$ | 0.9182 | 0.9035 | 0.9075 | 0.9184 | 0.8430 | 0.8975 | 0.9467 | 0.9271 | 0.9491 |
| $\theta_w$ | 0.9163 | 0.8857 | 0.9125 | 0.9120 | 0.8717 | 0.9209 | 0.9274 | 0.9290 | 0.9655 |
| $\gamma$ | 0.6945 | | 0.6181 | 0.7189 | 0.6610 | 0.7188 | 0.6425 | 0.7858 | 0.6901 |
| $\rho_J$ | 0.9835 | 0.9863 | 0.9806 | 0.9829 | 0.9332 | 0.9798 | 0.9867 | 0.9857 | 0.9865 |
| $\rho_K$ | 0.7859 | 0.7888 | 0.7834 | 0.7499 | 0.7969 | 0.8403 | 0.8142 | 0.8232 | 0.8136 |
| $\rho_R$ | 0.6232 | 0.6537 | 0.6296 | 0.6210 | 0.5430 | 0.6559 | 0.7442 | 0.6013 | 0.5929 |
| $\rho_Z$ | 0.7556 | 0.6639 | 0.7419 | 0.7695 | 0.7084 | 0.7404 | 0.8251 | 0.6996 | 0.7633 |
| $\sigma_J$ | 0.0737 | 0.0745 | 0.0820 | 0.0745 | 0.1612 | 0.0822 | 0.0710 | 0.0647 | 0.0663 |
| $\sigma_K$ | 0.0360 | 0.0409 | 0.0395 | 0.0535 | 0.0366 | 0.0434 | 0.0377 | 0.0192 | 0.0206 |
| $\sigma_P$ | 0.0030 | 0.0030 | 0.0031 | 0.0029 | 0.0034 | 0.0031 | 0.0031 | 0.0030 | 0.0030 |
| $\sigma_R$ | 0.0013 | 0.0013 | 0.0013 | 0.0013 | 0.0016 | 0.0013 | 0.0014 | 0.0013 | 0.0013 |
| $\sigma_W$ | 0.0100 | 0.0103 | 0.0100 | 0.0103 | 0.0104 | 0.0098 | 0.0097 | 0.0099 | 0.0096 |
| $\sigma_Z$ | 0.0163 | 0.0297 | 0.0172 | 0.0177 | 0.0154 | 0.0166 | 0.0197 | 0.0208 | 0.0214 |
| $\tau_C$ | | | | | | | 0.0073 | | |
| $\tau_K$ | | | | | | | 0.0107 | | |
| $\tau_q$ | | | | | | | 0.0043 | | |
| $\zeta_K$ | | | | | | | | 0.5234 | 0.5474 |
| $\rho_A$ | | | | | | | | 0.8427 | 0.7452 |
| $\sigma_A$ | | | | | | | | 0.0078 | 0.0067 |

*Note*: Each column reports the mode of the estimated parameters for various specifications. Column (1) reports estimates for the benchmark model. Column (2) refers to model without collateral-constrained households. Column (3) refers to the model where the collateral constraint if always binding. Column (4) is the estimated mode using a different initial condition. Columns (5) and (6) report Bayesian and maximum likelihood estimates (MLE) using artificial data generated by the model with parameters set at the values in (1). Column (7) report the model with linear deterministic trends, where $\tau_C$, $\tau_K$, $\tau_q$ are the implied growth rates for real consumption, real investment, real house prices. Column (8) refers to the model with shocks to the level of neutral technology and variable utilization, where $\rho_A$ and $\sigma_A$ are the AR(1) coefficient and standard deviation of those shocks. The parameter $\zeta_K$ is the curvature (between 0 and 1) of the utilization cost function, where 0 (1) indicates that utilization can be changed at a small (large) cost. Column (9) reports estimates for the model with shocks to the growth rate of neutral technology, where $\rho_A$ and $\sigma_A$ are the AR(1) coefficient and standard deviation of those shocks.

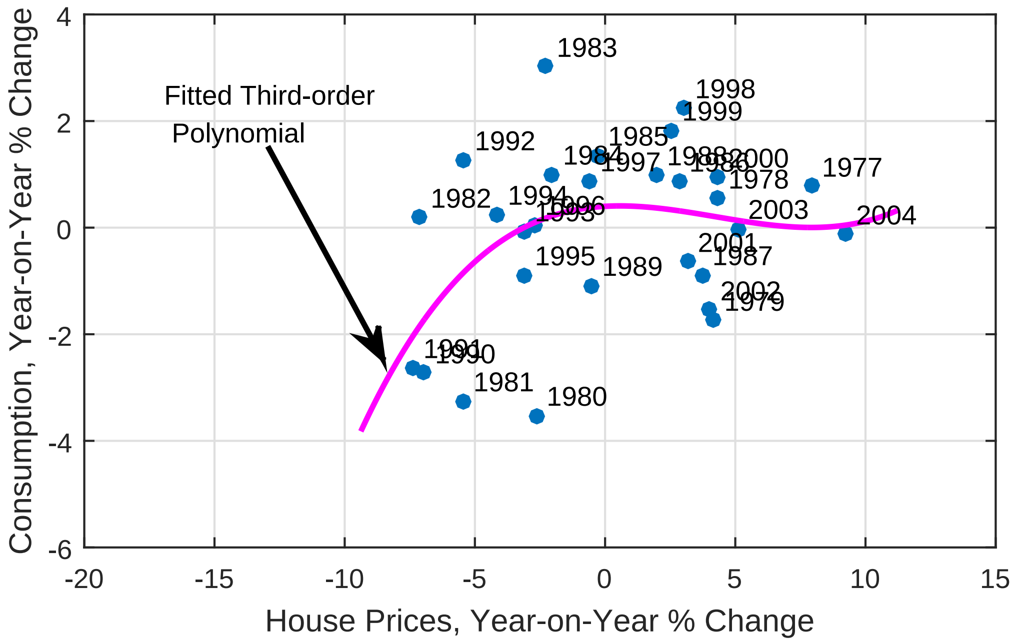
Table A.2: State-Level Regressions: Mortgage Originations and House Prices

| | % Change in Mortgage Originations ($\Delta mori_t$) | | | | |
|---|---|---|---|---|---|
| $\Delta hp_{t-1}$ | **1.10*** ** | | | | |
| | (0.18) | | | | |
| $\Delta hp\_high_{t-1}$ | | **-0.41*** | **1.08*** ** | **1.46*** ** | **1.54*** ** |
| | | (0.24) | (0.16) | (0.21) | (0.33) |
| $\Delta hp\_low_{t-1}$ | | **3.13*** ** | **1.85*** ** | **2.53*** ** | **2.67** ** |
| | | (0.59) | (0.68) | (0.90) | (1.11) |
| $\Delta mori_{t-1}$ | | | | **-0.20*** ** | **-0.20*** ** |
| | | | | (0.02) | (0.02) |
| $\Delta income_{t-1}$ | | | | | **-0.63** |
| | | | | | (1.04) |
| pval difference | | **0.000** | **0.211** | **0.160** | **0.181** |
| Time effects | **no** | **no** | **yes** | **yes** | **yes** |
| Observations | 1020 | 1020 | 1020 | 969 | 969 |
| States | 51 | 51 | 51 | 51 | 51 |
| R-squared | 0.01 | 0.03 | 0.58 | 0.53 | 0.53 |

*Note*: The table report state-level regressions using annual observations from 1992 to 2011 for 50 States and the District of Columbia. Robust standard errors are shown in parentheses. The symbols ***,**,* denote estimates statistically different from zero at the 1, 5 and 10% confidence level. In the table, pval is the p-value of the test for differences in the coefficients for high and low house prices.

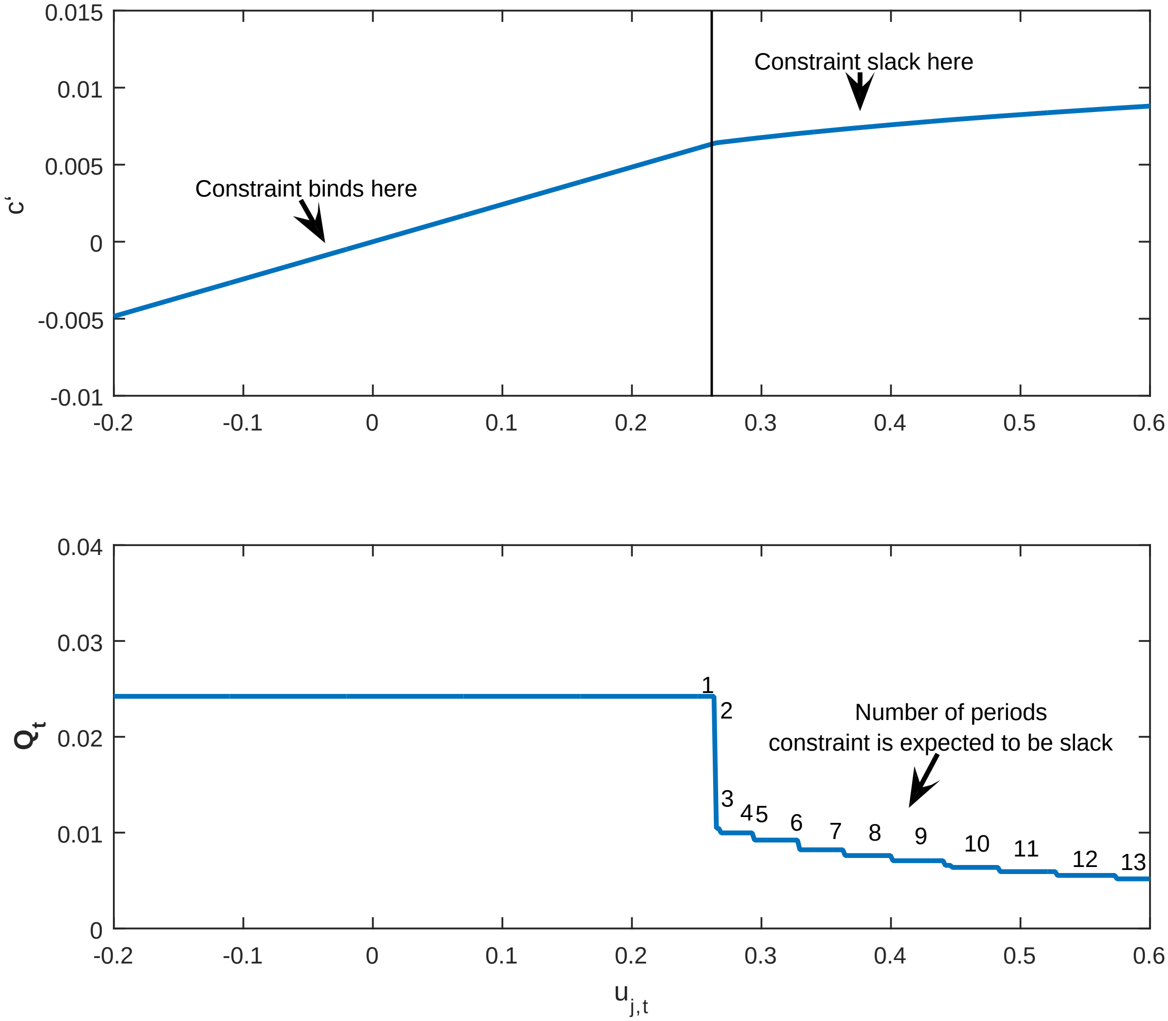
Data Sources and Definitions: $\Delta mori$ is the percent change in "Mortgage originations and purchases: Value" from the U.S. Federal Financial Institutions Examination Council: Home Mortgage Disclosure Act. See Table 2 for other variable definitions.

Figure A.1: House Prices and Consumption in U.S. National Data, excluding the post-2005 period



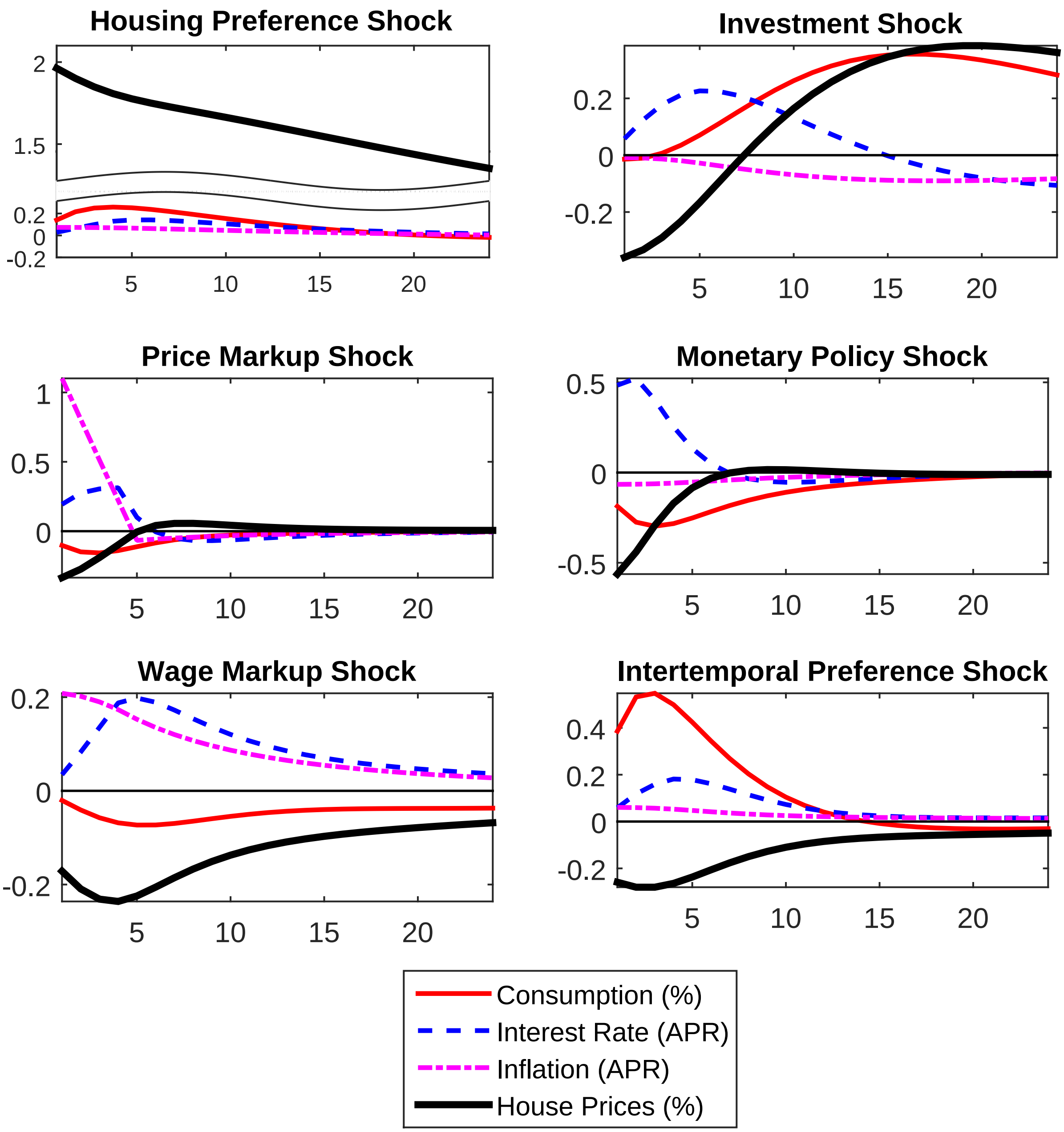

Consumption growth and house price growth are expressed in deviation from their sample mean. The data sample is from 1976Q1 to 2004Q4.

Figure A.2: Local Linearity of the Policy Functions



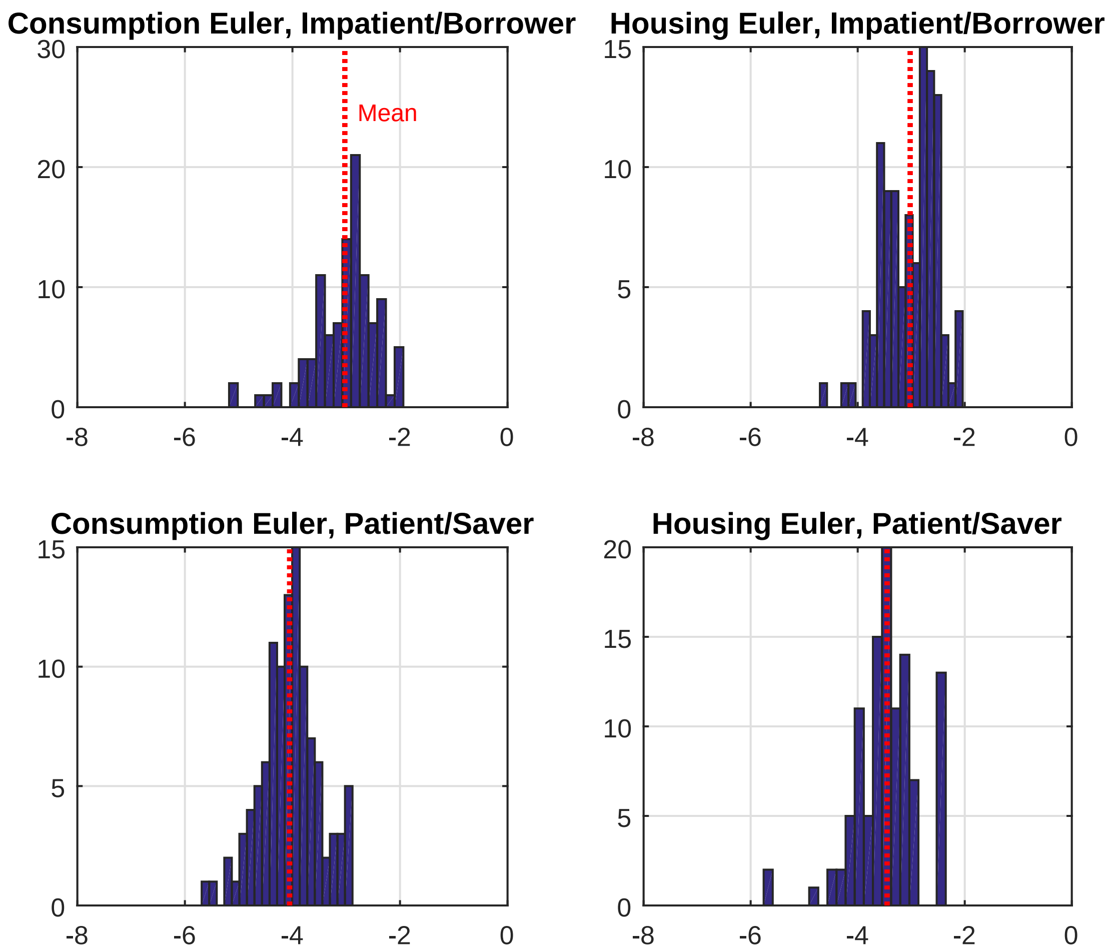

*Note*: The top panel plots consumption of the impatient agent (in deviation from the steady state) as a function of various realizations of the housing preference shock. The bottom panel plots the slope of the consumption function. The consumption function has a kink when the borrowing constraint becomes binding, and becomes flatter the larger the realization of the housing preference shock.

Figure A.3: Impulse Responses to All Shocks for the Estimated Model



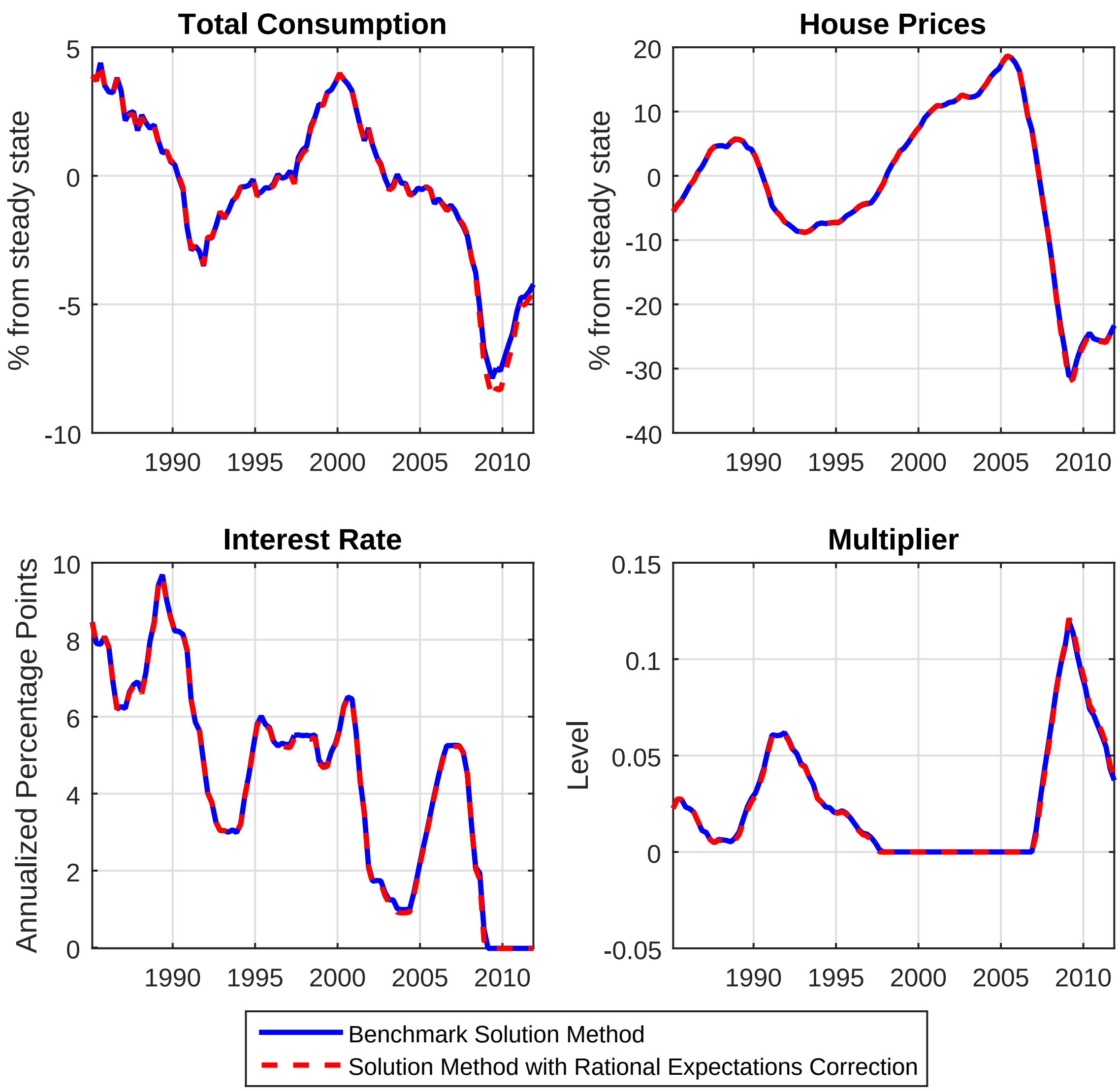

*Note*: Horizontal axes: horizon in quarters. The panels show the impulse responses of house prices, consumption, interest rate and inflation to an estimated one standard deviation shock in the estimated model.

Figure A.4: Accuracy of Solution Method: Intertemporal Errors for the DSGE Model



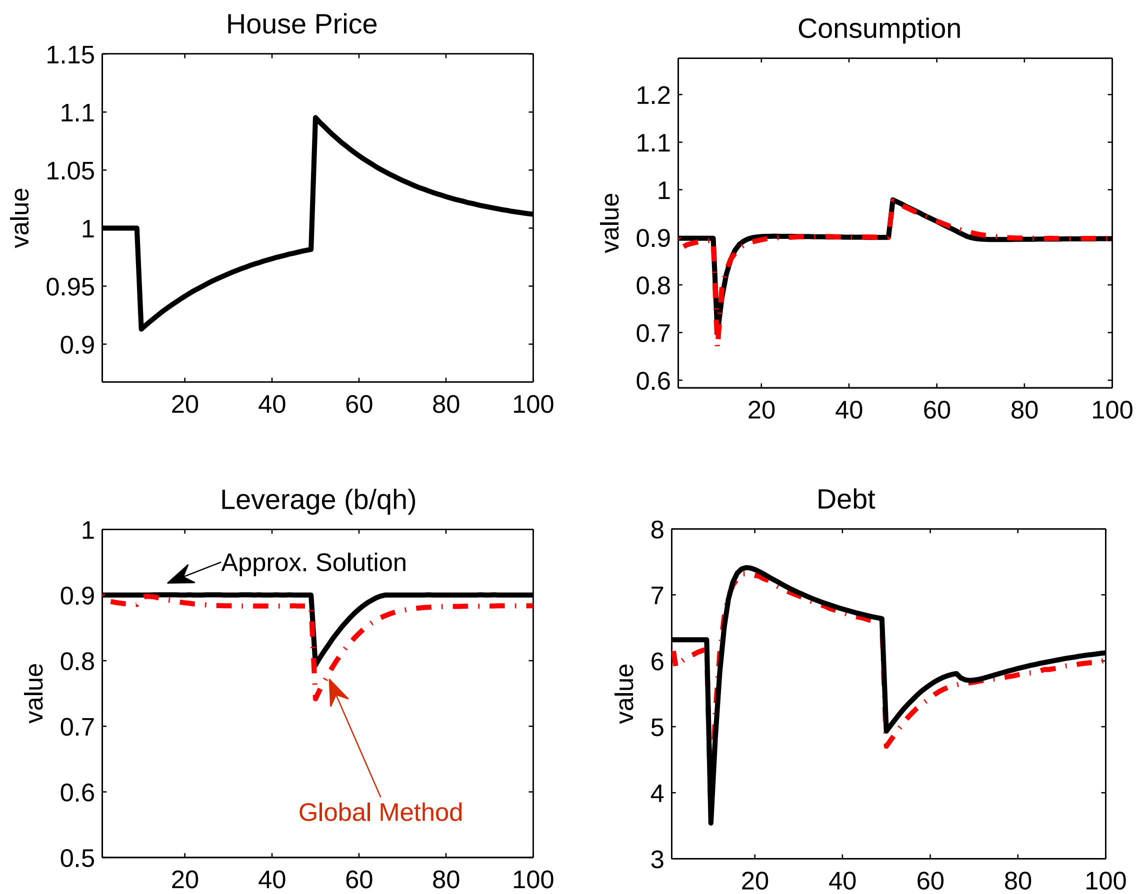

*Note*: For each Euler equation, the histograms report residual equation errors in decimal log basis. The dotted lines mark the mean residual equation error.

Figure A.5: Accuracy of Solution Method: Simulated Time Series



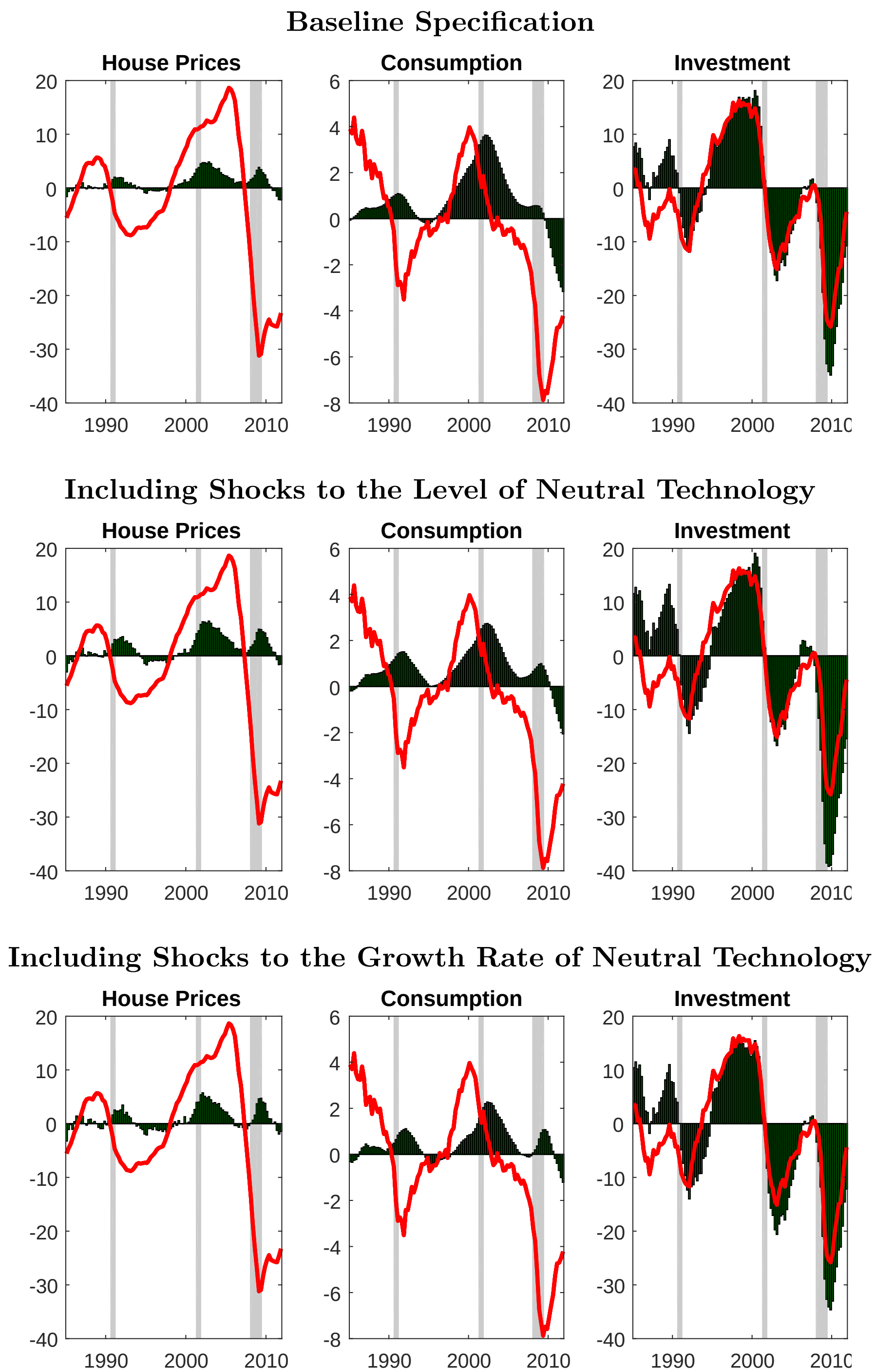

*Note*: Comparing simulated time series with and without rational expectations correction.

Figure A.6: Accuracy of Solution Method: Comparison of Impulse Responses for the Basic Model




*Note*: The units show in the horizontal axes are quarters. Impulse responses of the basic model to a negative house price shock in period 10 and a positive house price shock in period 50. The economy is at the nonstochastic steady state in period 1. The solid lines plot the responses using the approximate solution method used for the estimation of the DSGE model. The dashed lines plot the impulse responses using the global solution method (value function iteration).

Figure A.7: The Contribution of Technology Shocks To the Evolution of Key Observed Variables Under Alternative Model Specifications




The only technology shocks in the baseline specification are shocks to the level of investment-specific technology. The alternative specifications layer on neutral technology shocks. In each panel, the red solid lines denote observed variables (detrended), while the black bars show the evolution of those same variables when only the estimated technology shocks are turned on – both investment-specific and neutral technology shocks. (Recall that, by construction, the model matches the observations when all shocks are turned on.) Finally, the shaded areas denote recession periods, following the chronology determined by the NBER Business Cycle Dating Committee.