Excessive Optimism, Leverage, and Boom and Bust Cycles

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February 2013

Abstract

This paper develops a model that allows asset price and debt booms to develop endogenously and affect the real economy. A key aspect of the model is the assumption that agents do not have perfect information about economic fundamentals, but instead learn through experience. According to this learning approach, agents make rational, optimal decisions based on available information, but the information they possess at any point in time may be sending misleading signals regarding fundamentals. We find that the presence of learning amplifies the effects of shocks on house prices, credit, and the overall economy. Of particular relevance to the recent episode, we find a chain of events such as a sustained relaxation of lending standards can, under certain conditions, create a sustained rise in house prices and credit that deviate substantially from true fundamentals and that spills over to the broader economy. Importantly, the model only generates such extreme outcomes under very particular and rare circumstances, a "perfect storm" of conditions and unusual shocks. Most of the time, the economy behaves like it would under rational expectations. Thus, one could observe decades of data without observing a massive housing boom and then suddenly one emerges.

*I thank George Evans and Bruce Preston and participants at workshops hosted by the Federal Reserve Bank of St. Louis and the Reserve Bank of New Zealand for helpful suggestions and comments. I also thank Kuni Natsuki for excellent research assistance. The opinions expressed are those of the author and do not necessarily reflect the views of anyone else in the Federal Reserve System. Correspondence: Federal Reserve Bank of San Francisco, 101 Market Street, San Francisco, CA 94105, Tel.: (415) 974-2121, e-mail: John.C.Williams@sf.frb.org.

1 Introduction

The events of the past decade have challenged economists to model the housing sector and housing finance and their role in shaping the behavior of the aggregate economy. Much of the literature exploring these issues relies on a complete-information, rational expectations framework. But such an approach fails to explain the massive runup in house prices and household debt and their subsequent collapse during the past 15 years in the United States. Figure 1 shows the ratio of house prices to rents in the United States, which soared to 80 percent above its long-run average in 2006 (see Shiller (2005) for a longer-run perspective). Indeed, between March 2002 and March 2006, the house price-to-rent ratio rose an average of more than 10 percent per year. The house prices boom and bust left its imprint on housing construction as well. Figure 2 shows housing starts, which boomed with house prices and plummeted when prices turned down.

This phenomenon of an extraordinary rise in house prices is not unique to the United States. Figure 3 shows house price-to-rent ratios for six countries. Based on this metric, the *ongoing* house price booms in Australia, Sweden, and the United Kingdom dwarf the most recent housing bubble. Gelain and Lansing (2013) show that Norway is undergoing an even large house price boom than these countries.

To confront the challenges posed by this evidence, this paper develops a model that allows asset price and debt booms to develop endogenously and that include key channels by which asset prices and credit flows affect the real economy. A goal is that these processes be driven by endogenous dynamics-not just exogenous shocks. A key aspect of the model–following on the work of Adam, Marcet, and Nicolini (2007), and Lansing (2010)–is the assumption that agents do not have perfect information about economic fundamentals, but instead learn through experience. According to this learning approach, agents make rational, optimal decisions based on available information, but the information they possess at any point in time may be sending misleading signals regarding fundamentals. This paper is closely related to Gelain et al (2012), who analyze a similar model but where agents form a type of adaptive expectations.

The learning approach provides a potentially powerful propagation mechanism from economic shocks to large, sustained house price movements. According to standard asset pricing theory, the value of a house depends on the service flow from owning the house (rent), the after-tax interest cost, and expected economic appreciation (after deducting physical depreciation). Under complete information and rational expectations, expected appreciation is tied down by economic fundamentalsin particular, expected future real rentsand a transversality condition. But, in models with learning, agents forecasts are not necessarily restricted in these ways. Instead, agents use forecasting rules based on finite past empirical observations. Households and financial intermediaries make rational spending, investment, and borrowing decisions subject to imperfect knowledge about the economy. As a result of these information imperfections, agents make ex post mistakes that can result in distortionary credit and asset price booms and busts.

We find that the presence of learning amplifies the effects of shocks on house prices, credit, and the overall economy. Of particular relevance to the recent episode, we find a chain of events such as a sustained relaxation of lending standards can, under certain conditions, create a sustained rise in house prices and credit that deviate substantially from true fundamentals and that spills over to the broader economy.[1] Importantly, the model only generates such extreme outcomes under very particular and rare circumstances, a "perfect storm" of conditions and unusual shocks. Most of the time, the economy behaves like it would under rational expectations. Thus, one could observe decades of data without observing a massive housing boom and then suddenly one emerges.

The paper is organized as follows. Section 2 described the model economy. Section 3 describes the formation of expectations and the model of learning. The simulation methodology is described in section 4. Section 5 reports model properties. Section 6 reports results from simulations based on alternative explanations for housing booms and crashes. Section 7 concludes.

[1] Like Justiniano et al (2012), we find no such effect in the model with rational expectations. In addition, we find that a sustained period of excessively easy monetary policy does not lead in this model to a housing boom, as hypothesized by Taylor (2007).

2 The Model

The model includes three critical features for the analysis of housing and housing finance in a general equilibrium context. First, households gain utility from the service flow from housing, creating fundamental demand for the housing. Second, following Iacoviello (2005), households differ in their rate of time preference. This creates a motive for lending across agents and an additional value of holding collateral for borrowing in the form of real estate. As a result, changes in the quantity and value of housing affect the ability of credit-constrained households to borrow and spend. Third, in the presence of learning, the model allows for imperfections in agents' knowledge to affect asset valuations and decisions.

2.1 Technology

The business sector production technology converts labor into one of three final goods: private nondurable consumption goods, private housing investment goods, and government nondurable consumption goods. The aggregate output of the business sector, Y_t, is given by the following production function:

$$Y_t = A_t L_t^{1-\alpha}, \tag{1}$$

where A_t denotes exogenous total factor productivity and L_t is aggregate labor input. Total factor productivity is assumed to follow an exogenous AR(1) process:

$$\log A_t = (1-\rho_a)\log \bar{A} + \rho_a \log A_{t-1} + \epsilon_{a,t}, \qquad \epsilon_a \sim N(0, \sigma_a^2).$$

One unit of business output can be used to create either one unit of non-durable private consumption, one unit of government nondurable consumption, or one unit of housing investment goods:

$$Y_t \leq C_t + G_t + I_t,$$

where I_t denotes housing investment goods.

The aggregate housing stock, denoted by H_t, depreciates each period at rate δ. The production of new housing is subject to quadratic adjustment costs::

$$H_{t+1} = (1-\delta)H_t + I_t\Big(1 - 0.5\psi(I_t/H_t - \delta)^2)\Big). \tag{2}$$

As is standard in models with nominal rigidities, there exists an intermediate goods sector that repackages final goods as imperfect substitutes. Partial indexation of non-optimized prices to lagged prices is assumed, with indexation parameter τ. The share of firms that may not reoptimize prices each period is given by ζ. Profit maximization yields the standard Calvo inflation equation:

$$\pi_t = \frac{1}{1+\beta_1\tau}\Big(\tau\pi_{t-1} + \beta_1\hat{\pi}_{t+1} + ((1-\zeta)(1-\beta_1\zeta)/\zeta)\log M_t\Big),$$

where $\log M_t = (1-\alpha)\log W_t - \log A_t + \mu_t$ is the log of marginal cost, and μ_t is a markup shock. The markup shock is assumed to follow and exogenous AR(1) process:

$$\mu_t = \rho_\mu \mu_{t-1} + \epsilon_{\mu,t}, \qquad \epsilon_\mu \sim N(0,\sigma_\mu^2).$$

2.2 Preferences

There are two types of households who differ in their preferences. There is a continuum of households of each type. Households live forever. The total population of households is fixed and normalized to unity. A fixed share θ of households are referred to as "type 1" or "patient" households. Preferences of these agents are given by:

$$V_0^1 = E_0\sum_{j=0}^{\infty}\beta_1^j\left(\ln(C_{1,t+j}-\eta C_{1,t+j-1}) + \nu_h\ln(H_{1,t+j}-\eta_h H_{1,t+j-1}) - \frac{\nu_{1,l}}{1+\chi}L_{1,t+j}^{1+\chi}\right), \quad (3)$$

where $C_{1,t}$ is per capital non-durable consumption of "type 1" households in period t, $H_{1,t}$ is per capita housing stock owned by these households, and $L_{1,t}$ is per capita labor input. Each household is endowed with one unit of labor input.

Preferences of "type II" or "impatient" households are given by:

$$V_0^2 = E_0\sum_{j=0}^{\infty}\beta_2^j\left(\ln(c_{2,t+j}-\eta c_{2,t+j-1}) + \nu_h\ln(h_{2,t+j}-\eta_h h_{2,t+j-1}) - \frac{\nu_{2,l}}{1+\chi}l_{2,t+j}^{1+\chi}\right), \quad (4)$$

where the notation is the same as before.

The two types of households differ in two different ways. First, and most importantly, type 1 households have a lower rate of discount than type 2 households; that is, $\beta_2 < \beta_1$. This difference is critical for the model as it creates a reason for nontrivial lending and borrowing conditions. Second, the households differ in the weight on disutility of work.

The second is less important, but is necessary for the calibration of the model. Otherwise, they are identical. In particular, the productivity of the labor input of the two types is assumed to be identical.

Given the difference in rates of time preference, impatient households desire to front load consumption relative to patient households. This creates a powerful inventive for intertemporal trade via borrowing by impatient households. It is assumed that there are frictions that interfere with the creation of a full set of contingent contracts. In particular, lenders have no power to force full repayment by borrowers. Instead, it is assumed that the only available debt contract is a renewable one-period collateralized loan. In case of default on a loan, lenders take ownership of collateral put up by the borrower, subject to transaction costs. The type of collateral is restricted to the housing stock owned by the borrower. The resulting borrowing constraint is given by:

$$B_t \leq \gamma_t \; \hat{Q}_{t+1} \; H_{2,t}/R_t, \tag{5}$$

where B_t is the amount borrowed, $\hat{Q}_{t+1}$ is the forecasted price of a unit of the housing stock in the following period, I_t is the nominal gross interest rate, and γ_t is the loan-to-value upper limit.

In principle, the equilibrium loan-to-value upper limit depends on a variety of factors reflecting institutional arrangements in lending and securitization markets. For the present purposes, these are not modeled explicitly. Instead, the loan-to-value constraint is allowed to fluctuate randomly according to:

$$\log \gamma_t = (1 - \rho_\gamma) \log \bar{\gamma} + \rho_\gamma \gamma_{t-1} + \epsilon_{\gamma,t}.$$

2.3 Monetary Authority and Government

The central bank is assumed to set the nominal interest rate, R_t, according to a simple Taylor Rule of the form:

$$\log R_t = \bar{r} + \pi_t + \phi_p(\pi_t - \pi_t^*),$$

where $\bar{r}$ is the steady-state real interest rate, π_t^* is the monetary policy shock, and $\phi_p > 0$. The monetary policy shock is assumed to follow an exogenous AR(1) process:

$$\pi_t^* = \rho_r \pi_{t-1}^* + \epsilon_{r,t}, \qquad \epsilon_r \sim N(0, \sigma_r^2).$$

Government purchases of nondurable goods is assumed to follow an exogenous AR(1) process:

$$\log G_t = (1 - \rho_g) \log \bar{G} + \rho_g \log G_{t-1} + \epsilon_{g,t}, \qquad \epsilon_g \sim N(0, \sigma_g^2).$$

Government expenditures are funded through lump sum taxes on type 1 households.

2.4 Equilibrium conditions

Households choose labor supply and purchases of nondurable consumption and housing units to maximize utility subject to their budget constraints, taking prices as given. Businesses maximize profits, taking other firms' prices and wages as given. In equilibrium, impatient households will borrow up to the limit allowed by the value of their collateral. Subject to this this constraint, impatient households will spend all of their available income net of spending on housing:

$$C_{2,t} = W_t L_{2,t} + B_t - B_{t-1} R_{t-1} - Q_t [H_{2,t} - (1 - \delta_h) H_{2,t-1}],$$

where W_t is the wage rate and Q_t is the price of a unit of housing. Aggregate labor input equals the sum of the labor input of the two types of households:

$$L_t = \theta L_{1,t} + (1 - \theta) L_{2,t}.$$

Similarly, aggregate consumption and the aggregate housing stock equal the sums of the respective values for the two types of households:

$$C_t = \theta C_{1,t} + (1 - \theta) C_{2,t},$$

$$H_t = \theta H_{1,t} + (1 - \theta) H_{2,t}.$$

Consistent with the methodology underlying the U.S. national income accounts, real gross domestic product (GDP) is measured as the chain-weighted sum of the output of the business sector and the service flow from owner-occupied housing. In the model, the service flow of owner-occupied housing is assumed to equal the rental value of housing times the stock of housing.

3 Expectations

Agents are assumed to form expectations based on information observed in the previous period. Two models of expectations formation are analyzed. The first is rational expectations, where agents' forecasts of future variables are equal to those generated by the structural model. The second is perpetual least square learning. In the case of perpetual learning, agents are assumed to form expectations using an estimated reduced-form forecasting model. Specifically, agents reestimate their forecasting model using a constant-gain least squares algorithm that weights recent data more heavily than past data (see, for example, Sargent 1999, Cogley and Sargent 2001, and Evans and Honkapohja 2001, for related treatments of learning.) In this formulation of learning, agents' forecasts are always subject to sampling variation, that is, the coefficients of the forecasting models do not eventually converge to fixed values but rather perpetually fluctuate in the vicinity of the values implied by the rational expectations equilibrium..

Under perpetual learning, at the end of each simulation period, agents update their estimates of the forecasting model using data through the current simulation period. It is assumed that the agents know the minimum state space representation of the structural model and specify their forecasting model accordingly. That is, the forecasting model is neither under- nor over-parameterized to the forecasting model that would obtain under rational expectations and no learning. In the model,the following 13 variables constitute the minimum state variable set of states (in logs): $\{H_1, H_2, C_1, C_2, B, I, R, \pi, A, G, \gamma, \mu, \pi^*\}$. In the forecasting model, this set of state variables is augmented to include a constant.

Let Z_t denote the vector consisting of the variables to be forecast, and let X_t be the vector of variables in the forecasting model. Let c_t denote be the vector of coefficients of the forecasting model and let r_t denote the weighted average of past values of $X_t X_t'$. Using data through period t, the estimated coefficients of the forecasting model can be written in recursive form:

$$c_t = \quad c_{t-1} + \kappa R_t^{-1} X_t (Z_t - X_t' c_{t-1}), \tag{6}$$

$$r_t = \quad r_{t-1} + \kappa (X_t X_t' - r_{t-1}), \tag{7}$$

where κ is the parameter governing the rate of learning.

In practice, the matrix r_t may not always be full rank. To circumvent this problem, in each model simulation period, the rank of r_t is evaluated. Following the approach of Orphanides and Williams (2007), if this matrix is less than full rank, agents are assumed to apply a standard Ridge regression (Hoerl and Kennard, 1970), with r_t replaced by $r_t + 0.00001 * I(m)$, where $I(m)$ is the $m \times m$ identity matrix and m is the number of rows of r.

3.1 Model parameters

The main purpose of the simulations is qualitative rather than quantitative analysis of the mechanisms at play. Therefore, the choice of parameter values is best viewed as illustrative rather than a serious effort at model calibration or estimation. Table 1 reports the parameter values used in the simulations.

A key additional parameter in the learning model is the updating parameter, κ, that describes the rate at which past data are discarded in estimating the forecasting model. Estimates of this parameter tend to be imprecise and sensitive to model specification, but tend to lie between 0 and 0.05 (see, for example, Sheridan (2003), Orphanides and Williams (2005a), Branch and Evans (2006), Milani (2007), Eusepi and Preston (2008), and Sinha (2010.) In the following, a range of learning rates is considered in order to explore the sensitivity of the model's behavior to the rate of learning.

4 Simulation Methodology

Model simulations are used to compute statistics that characterize the model's properties. In all cases, a log-linearized version of the model's structural equations are used. In the case of rational expectations, model simulations are straightforward. In the case of learning, however, the model is inherently nonlinear, which introduces a number of special issues.

In all cases, the innovations are generated from Gaussian distributions with variances reported above (using the MATLAB random number generator). The innovations are assumed to be serially and contemporaneously uncorrelated. To compute unconditional model moments, the model is simulated for 41,000 periods; the first 1000 periods are discarded to mitigate the effects of initial conditions. The unconditional moments are computed from the remaining 40,000 periods of simulated data.

In the case of learning, the model's behavior depends on the values of the state variables describing the learning process, specifically, the matrices r and c. In the stochastic simulations used to compute unconditional moments, the initial conditions for r and c are set to the values corresponding to the reduced form of the rational expectations equilibrium of the model. All other model variables are set to their steady-state values, assumed to equal zero. For the impulse response functions, a set of 400 impulse responses are computed to approximation the distribution of model impulse responses. Each impulse response is computed at initial conditions for all state variables drawn from an approximation to the ergodic distribution generated by a stochastic simulation of the model under learning.

The nonlinear nature of the model can generate explosive behavior in simulations even though the rational expectations equilibrium of the model is stable and unique. These problems become more prevalent with learning rates above 0.02. To mitigate the effects of such explosive dynamics, a "projection facility" is introduced that forces the model to be stable in every simulation period. Specifically, each simulation period the full model's solution (incorporating the forecasting model) is checked for unstable dynamics. If the maximum root of the full model solution exceeds unity, agents are assumed to use the coefficients c of the most recent forecasting model that generated a stable solution. The updating of the coefficients of the forecasting model is assumed to continue as normal, and agents switch to the "current" model as soon as possible.

In very rare circumstances when the forecasting model is generating an unstable full-model solution, the model can get "stuck" in this situation. That is, as the new data flow in, the forecasting model keeps generating an unstable solution and never gets updated. To overcome this problem, in cases where the forecasting model is not updated for 40 consecutive periods, the normal updating procedure is abandoned and the coefficients c of the forecasting model are reset to their respective initial values, and the simulation is continued.

5 Simulated Model Properties

Table 2 reports unconditional moments for various parameterizations of the model. The upper panel of the table reports results for the baseline parameterization of the model. The other panels report results for alternative parameter values. These alternative parameterizations are used to highlight the effect of key features of the model. The first line in the upper panel reports the results under rational expectations for the baseline case. The next three lines report results under learning for alternative values of the learning rate κ. Note that the model under RE is identical to the model with learning and $\kappa = 0$ under the assumptions of the simulations and learning process. Therefore, as the learning rate increases, the model is deviating further from the assumption of rational expectations.

The presence of perpetual learning increases the variability of the economy, including house prices and housing investment. The time variation in the coefficients of forecasting model adds noise to the economy. The higher the learning rate, the greater the variability induced by learning. For a learning rate of 0.02 or above the economy fluctuates wildly, at least under the specified monetary policy rule.

The presence of learning amplifies the variability of house prices and housing investment, but this leaves very little imprint on employment and output if prices are close to flexible. The second panel shows the results for the case of near-flexible prices where $\zeta = 0.1$. Absent nominal rigidities, increased fluctuations in the housing sector due to learning are mostly offset in the consumption sector, leaving the aggregate economy nearly unaffected.

Under rational expectations, the shocks to the loan-to-value limit have very little effect on the economy, but under learning these shocks contribute to greater aggregate variability. The third panel reports the results when the standard deviation of the shocks to γ is one tenth as large as in the baseline parameterization.

The final two columns of Table 2 report summary statistics on asset price expectations in the model. Under rational expectations, expected asset price appreciation is negatively correlated with the level of asset prices, as one would expect. Learning tends to shrink this correlation somewhat, as discussed in Gelain et al (2012). In addition, learning tends to increase the variability of expected house prices relative to the variability of realized house prices. This finding confirms that learning can help explain excess volatility in expectations, as discussed in Orphanides and Williams (2005b) and Sinha (2010).

6 Bubbles and Crashes

In this section, specific explanations for housing bubble are examined in the context of the model. The model simulations are of particular sequences of shocks, which from the point of view of agents would be exceedingly rare. In the case of learning, values of κ of 0.02 and 0.03 are considered. (Simulations with $\kappa = 0.01$ are not reported, but the results are between those of rational expectations and the case of $\kappa = 0.03$.)

The first explanation to consider is that of Taylor (2007), who argues that easy monetary policy contributed to the housing boom. Dokko et al (2011) use model simulations to show that sustained deviations of monetary policy from a rule are unlikely to cause a housing bubble of the type witnessed in the first half of the 2000s. One limitation of their approach is that they assume that the formation of expectations is constant. This assumption makes their model economy "well behaved" in response to the sequence of monetary policy shocks.

In the case of rational expectations, sustained easy monetary policy fails to generate a housing or credit boom. The black lines in Figure 4 shows the results of model simulations of an unanticipated sequence of monetary policy shocks under the assumption of rational expectations. In this and following figures, all variables, except the inflation rate, are shown in real terms. For this experiment, the model economy experiences 16 consecutive monetary policy shocks, each of magnitude 0.0025. Both GDP and inflation experience sustained increases, consistent with the presence of sustained monetary stimulus. Interestingly, sustained monetary stimulus in this model causes a modest decline in household debt and house prices, not a boom.

In the presence of learning, a sustained period of monetary stimulus *may* generate a a modest boom in house prices and household debt. The word "may" is critical. As discussed earlier, in the model with learning there is no unique impulse response; instead, the responses to shocks depends on the state of the economy. Figure 4 reports two sets of responses to the sequence of monetary policy shocks under learning. These represent different slices of the distributions of possible outcomes from the set of shocks. In this and following figure, the simulations are sorted based on the magnitude of the real house price response. Specifically, the 400 simulations are sorted based on the response of house prices in the 20th period of the simulation. The blue lines in the figure show the simulated outcomes for the simulation conditional on it producing the median response of house prices in the 20th period.[2] As seen in the figure, the median responses defined in this way are not that different from the corresponding responses under rational expectations. That is,under learning, the "typical" response of house prices, household debt, and other macroeconomic variables to sustained expansionary monetary policy is roughly the same as under rational expectations in this model. However, in some circumstances that depend on the initial conditions of the simulation, household debt and house prices respond positively to the sequence of monetary policy shocks. This outcome is illustrated by the red lines in the figure that show the responses conditional on the response of house prices being at the 95th percentile of the distribution. Although the presence of learning does amplify the response of house prices, it also amplifies the response of other macroeconomic variables. In other words, the shocks primarily set off an inflationary boom in the overall economy rather than a housing boom per se.

[2] To reduce the noise in the graphs, the figures show the median value of the simulations in the vicinity of the indicated points. In particular, the lines labeled "median" show the median response of the sorted simulations between the 47.5 and 52.5 percentiles. Similarly, the lines labeled "95 %" show the median response of the sorted simulations between the 92.5 and 97.5 percentiles.

The second explanation considered is a sustained and accumulating easing of credit standards, followed by a sharp return to more "normal" credit standards. This experiment is represented in the model simulations by a series of 16 unanticipated positive shocks, each of magnitude 0.01, to the loan-to-value cutoff value γ_t, followed by four periods of negative shocks that bring the value of γ back to baseline. Figure 5 shows the results of these experiments.

Under rational expectations, the gradual easing of credit standards generates a buildup of household debt and little rise in house prices. The subsequent tightening of credit standards sends household debt back to normal levels and a moderate rise in house prices as type II households build up collateral.

In some circumstances, the learning process can greatly amplify the effects on household debt, house prices, and the overall economy reminiscent of the events of the actual housing boom and bust. Figure 5 shows the results for the baseline model with $\kappa = 0.02$; Figure 6 shows the results assuming $\kappa = 0.03$. As before, the "typical" responses, represented by the blue lines, do not differ much from those under rational expectations. However, in the representation simulation with a larger rise in house prices and the higher learning rate, the easing of credit standards is accompanied by a rise in *both* household debt and house prices. During this period, expected appreciation of future house prices is consistently above that implied by rational expectations. The rise in GDP is also steady and outsized. The curtailment of easy lending standards engenders an abrupt drop in house prices and household debt, a reversal of expected house price appreciation, a collapse in GDP, and a period of price deflation.

7 Conclusions and Further Research

This paper examines channels by which asset price and credit bubbles and crashes can endogenously occur in a model with financial frictions and imperfect knowledge. Consistent with previous research, we find that the presence of financial frictions alone cannot explain sizable the asset price and credit runups and collapses experienced in the United States and elsewhere. Nor can they explain the very large effects of these on the macroeconomy. However, it is possible to explain these types of events in a model that combines financial frictions and a reasonable degree of imperfect knowledge on the part of economic agents. Importantly, these are very rare events in the model–it takes a "perfect storm" of conditions and shocks to generate sizable bubbles and crashes that wreak havoc on the overall economy.

One source of shock that is found to contribute to asset and credit variability is changes in the credit constraint facing households. In the current paper, this is treated as an exogenous shock; future work should aim to endogenous this behavior. An natural question to analyze in the context of this model is the appropriate role of monetary and regulatory policies in stabilizing the economy and maximizing welfare.

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Figure 1: Ratio of House Prices to Rents in the United States

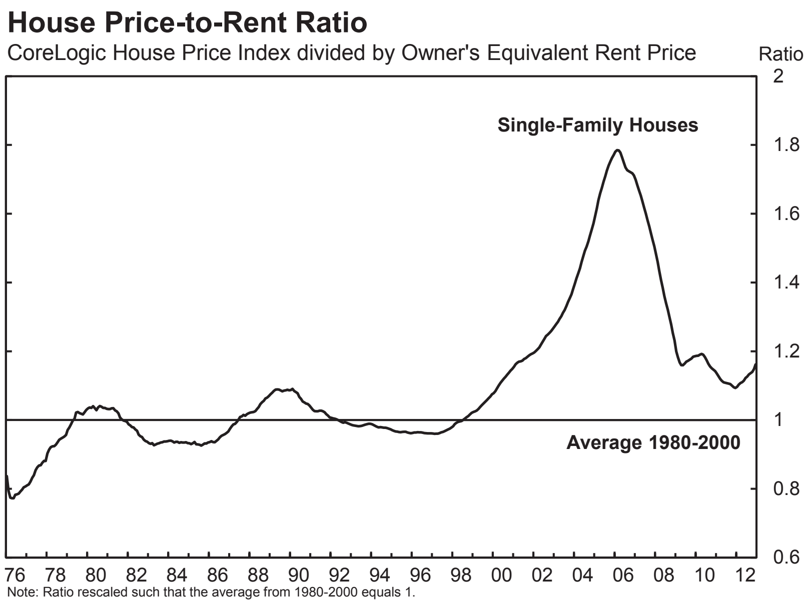

Figure 2: U.S. Construction Booms and Busts

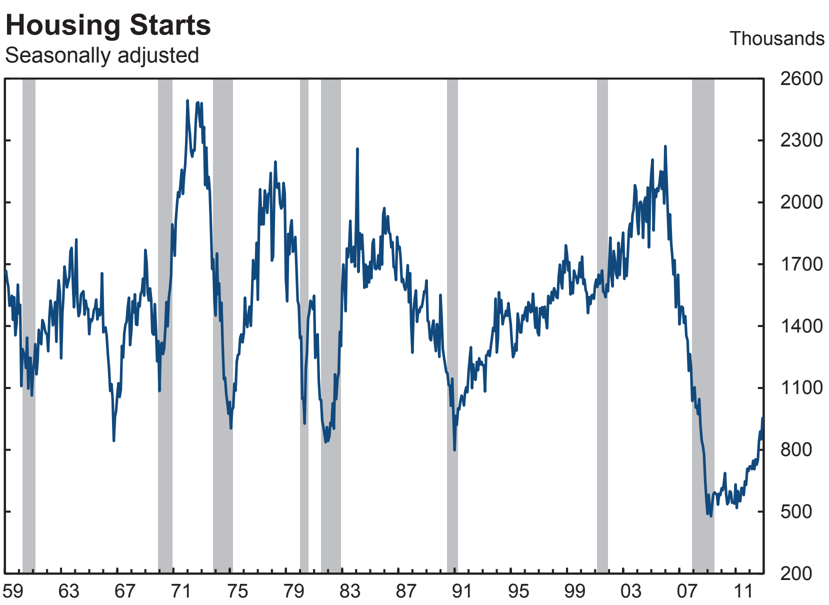

Figure 3: International Evidence on House Prices

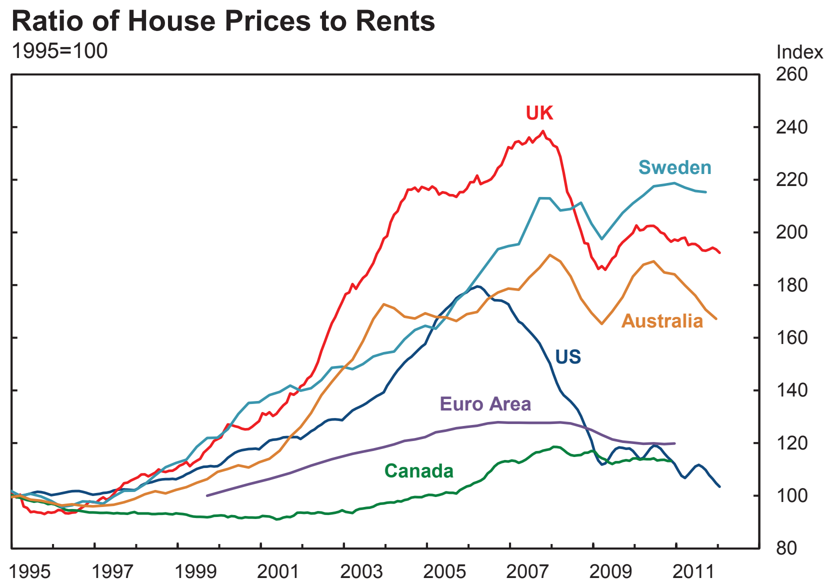

Figure 4: Sustained Easy Monetary Policy

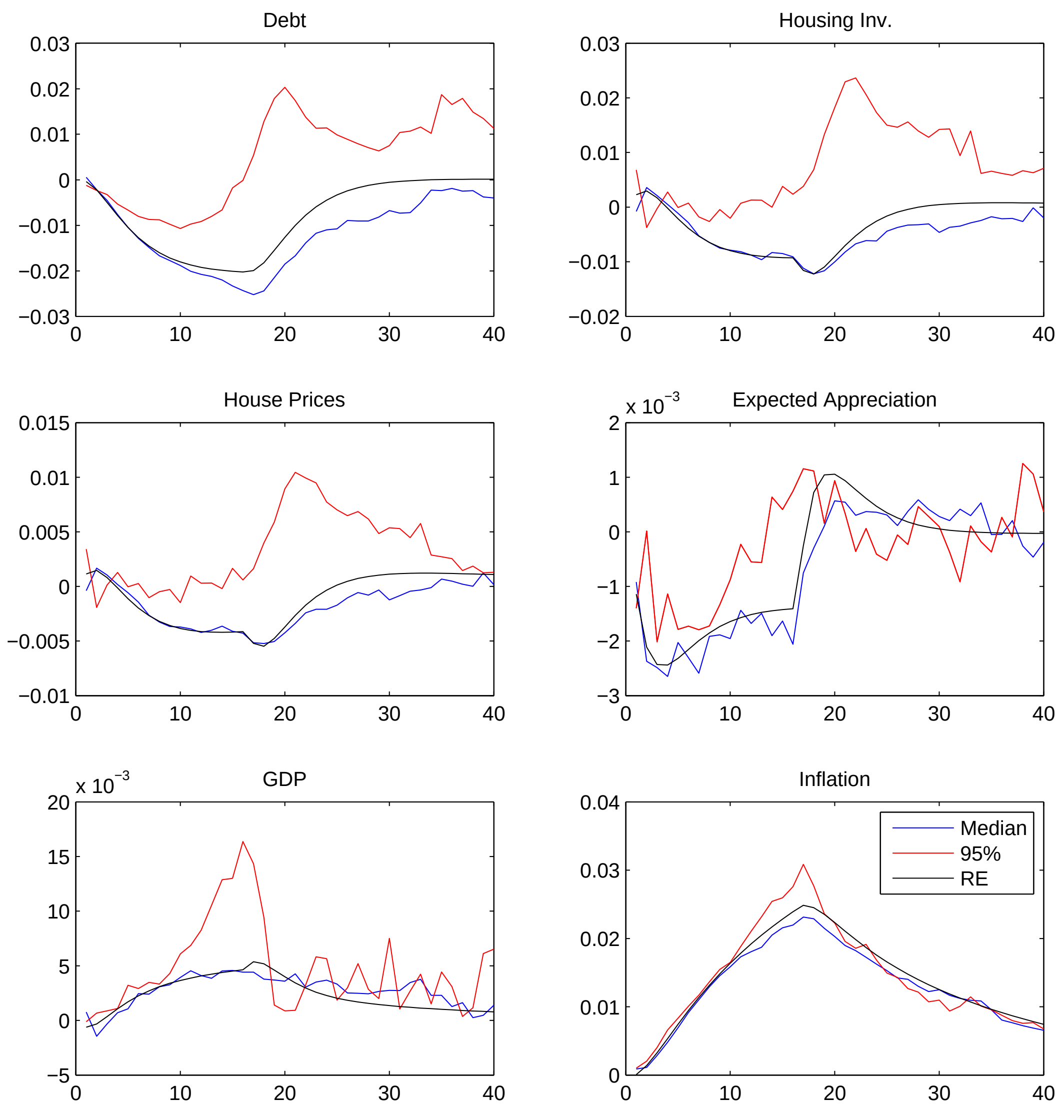

Figure 5: Sustained Increase and Sharp Decline in LTV: $\kappa = 0.02$

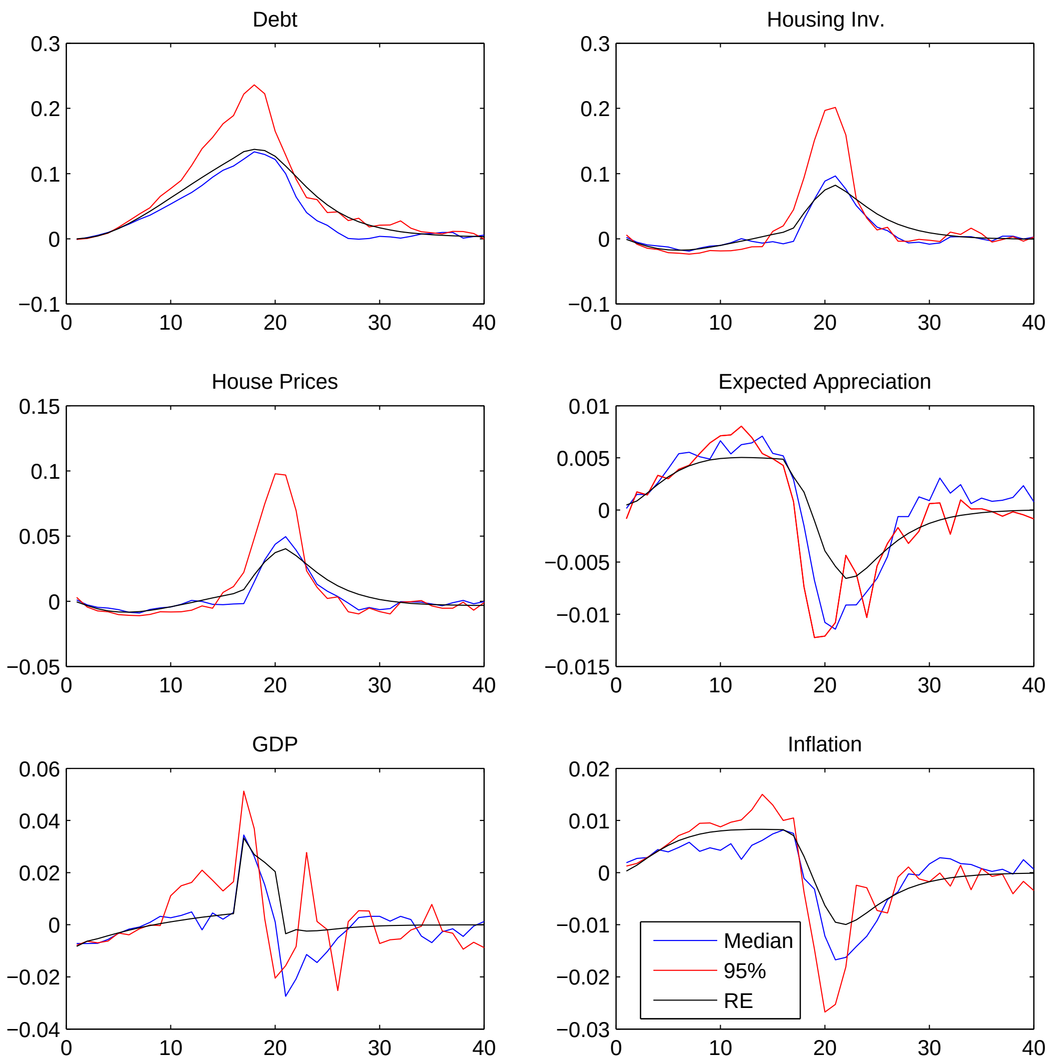

Figure 6: Sustained Increase and Sharp Decline in LTV: $\kappa = 0.03$

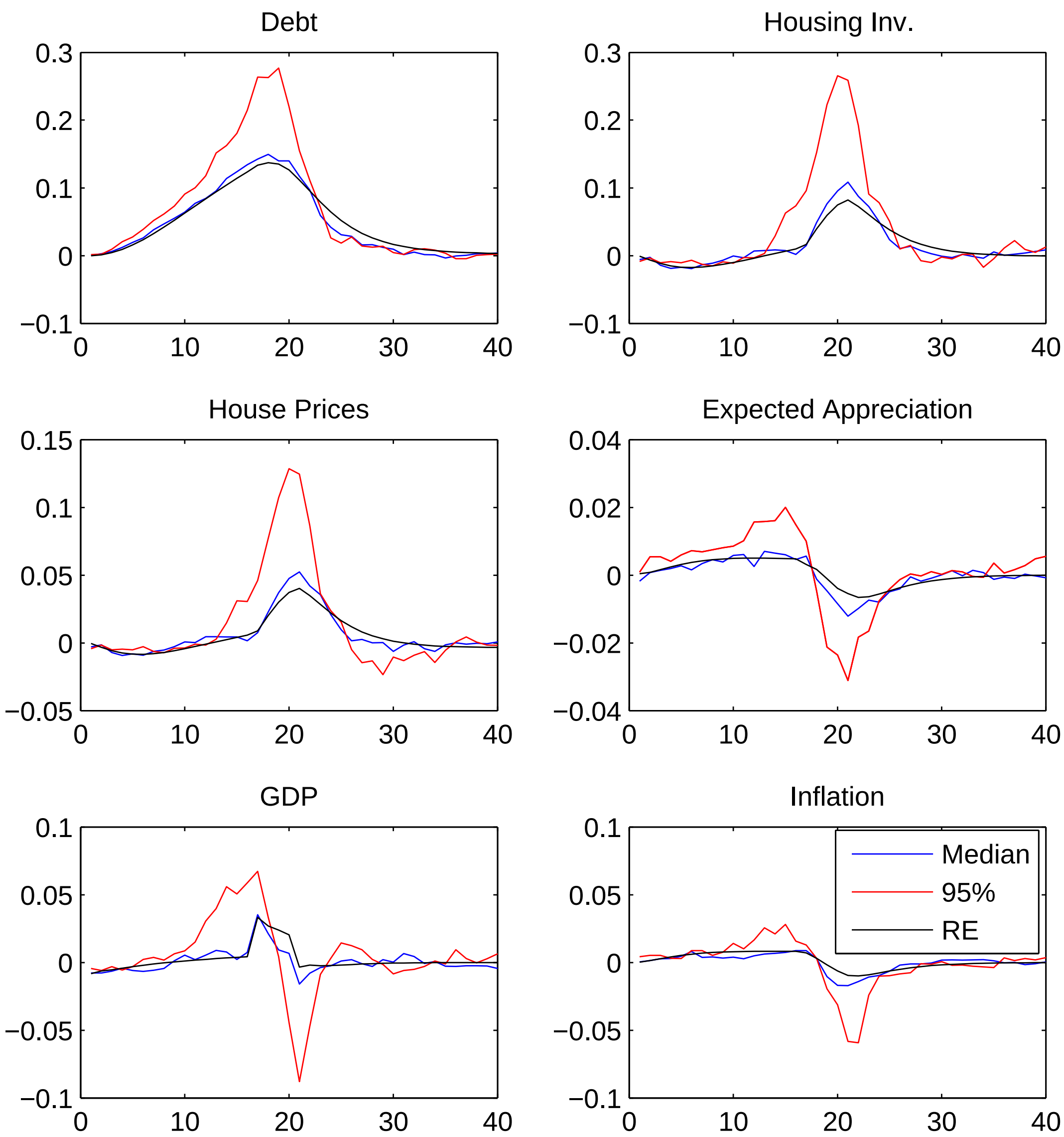

Table 1: Baseline Model Parameters

	Technology	
α	Capital share	0.360
ψ	Construction adjustment costs	0.500
δ_h	Housing depreciation rate	0.015
ζ	Calvo prices	0.750
τ	Price indexation	0.750
	Preferences	
β_1	Discount rate (patient)	0.990
β_2	Discount rate (impatient)	0.950
χ	Labor preferences	0.500
η	Habit (consumption, housing)	0.750
ν_h	Housing utility	0.200
$\nu_{l,1}$	Labor disutility (patient)	1.000
$\nu_{l,2}$	Labor disutility (impatient)	2.000
θ	Share patient households	0.200
$\bar{\gamma}$	Steady-state LTV	0.720
	Government and Monetary	
$\bar{G}$	Government share of output	0.180
ϕ_p	Taylor rule coefficient	0.500
	Shocks	
ρ	Shock autocorrelation	0.950
σ	Innovation standard deviation	1.000

Table 2: Model Properties

	Standard Deviations							
	L	GDP	I	H	Q	π	Corr($\Delta\hat{Q}, Q$)	SD($\hat{Q}$)/SD(Q)
Baseline								
RE	4.0	3.6	7.4	3.1	3.4	2.9	-0.39	0.94
$\kappa = 0.010$	4.4	3.8	7.8	3.3	3.5	3.0	-0.32	0.95
$\kappa = 0.015$	5.8	4.8	8.7	3.8	3.9	3.2	-0.31	0.96
$\kappa = 0.020$	6.7	5.1	10.0	3.7	4.7	3.5	-0.22	1.01
Near-flexible prices: $\zeta = 0.1$								
RE	3.3	3.5	6.8	2.9	3.1	3.0	-0.52	0.86
$\kappa = 0.010$	3.3	3.6	7.3	3.0	3.4	3.1	-0.42	0.91
$\kappa = 0.015$	3.3	3.6	7.6	3.1	3.5	3.2	-0.40	0.93
$\kappa = 0.020$	3.4	3.8	9.6	3.3	4.5	3.4	-0.05	1.15
Smaller LTV shocks: $\sigma_\gamma = 0.001$								
RE	4.0	3.5	7.2	3.1	3.3	2.9	-0.39	0.94
$\kappa = 0.010$	4.3	3.7	7.5	3.3	3.4	2.9	-0.32	0.95
$\kappa = 0.015$	4.6	3.7	7.7	3.3	3.5	3.0	-0.30	0.96
$\kappa = 0.020$	8.5	6.7	9.3	3.4	4.3	3.6	-0.40	0.94