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Land-Price Dynamics and Macroeconomic Fluctuations

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LAND-PRICE DYNAMICS AND MACROECONOMIC FLUCTUATIONS

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ABSTRACT. We argue that positive co-movements between land prices and business invest-ment are a driving force behind the broad impact of land-price dynamics on the macroecon-omy. We develop an economic mechanism that captures the co-movements by incorporating two key features into a DSGE model: We introduce land as a collateral asset in firms' credit constraints and we identify a shock that drives most of the observed fluctuations in land prices. Our estimates imply that these two features combine to generate an empirically important mechanism that amplifies and propagates macroeconomic fluctuations through the joint dynamics of land prices and business investment.

I. INTRODUCTION

The recent financial crisis caused by a collapse of the housing market propelled the U.S. economy into the Great Recession. A notable development during the crisis period was a slump in business investment in tandem with a sharp decline in land prices (Figure 1). The crisis has generated substantial interest in understanding the links between the housing market and the macroeconomy. Although it is widely accepted that house prices could have an important influence on macroeconomic fluctuations, quantitative studies in a general equilibrium framework have been scant.

This paper aims to fill part of this gap by modeling, through econometric estimation, the links between land-price dynamics and macroeconomic fluctuations in a quantitative general

equilibrium framework. We focus on land prices because most of the fluctuations in house prices are driven by land prices rather than by the cost of structures (Davis and Heathcote, 2007). We first establish evidence that land prices move together with macroeconomic variables not just in the Great Recession period, but also for the entire sample period from 1975 to 2010.[1] The first column of Figure 2 displays the estimated impulse responses of land prices and business investment following a shock to the land price series. These impulse responses are estimated from a bivariate Bayesian vector autoregression (BVAR) model with the Sims and Zha (1998) prior. A positive shock to land prices leads to persistent increases in both land prices and business investment. The last two columns of the figure show that the shock also leads to persistent increases in labor hours and consumption, although the magnitudes of the responses are not as large as that of investment.

To understand these salient features of the data, we build a dynamic stochastic general equilibrium (DSGE) model that is a generalization of Kiyotaki and Moore (1997). A strand of recent DSGE literature on house prices assumes that a subset of households are credit constrained and these households use land or houses as collateral to finance consumption expenditures (Iacoviello, 2005; Iacoviello and Neri, 2010; Favilukis, Ludvigson, and van Nieuwerburgh, 2011). These models with credit-constrained households are capable of explaining positive co-movements between house prices and consumption expenditures, but in general they have difficulty delivering positive co-movements between land prices and business investment (Iacoviello and Neri, 2010). To overcome this difficulty, we assume that firms, instead of households, are credit constrained. In particular we assume that firms finance investment spending by using land as a collateral asset. Thus, in our model, a shock that drives up land prices raises firms' borrowing capacity and facilitates an expansion in investment and production.

In the data, collateralized loans are an important form of business borrowing. Nearly 70% of all commercial and industrial loans in the United States are secured by collateral assets (Berger and Udell, 1990). An important collateral asset for both small firms and large corporations is real estate. In the U.S. data, real estate represents a large fraction of the tangible assets held by nonfinancial corporate firms on their balance sheets. According to the Flow-of-Funds tables provided by the Federal Reserve Board, for the period from 1952 to 2010, tangible assets (the sum of real estate, equipment, and software) average about two-thirds of total corporate assets, and real estate averages about 58% of total tangible assets. For nonfarm noncorporate U.S. firms, real estate averages about 90% of tangible assets (which is in turn about 87% of total assets).

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[1]Our benchmark land price series is constructed based on the Federal Housing Finance Agency (FHFA) house price index, which is available from 1975 to 2010.

Formal empirical studies show that shocks to real estate prices have important effects on business investment, even for large corporations. For example, Chaney, Sraer, and Thesmar (2009) find that, over the 1993-2007 period, a dollar increase in collateral value enables a representative U.S. corporate firm to raise new borrowing by four cents and investment by six cents. Their analysis shows that shocks to real estate prices have a large impact on aggregate investment. Since fluctuations in real estate values are primarily driven by changes in land prices (Davis and Heathcote, 2007), these formal empirical findings, along with the balance-sheet data, constitute compelling evidence that land provides important collateral value for business investment spending.[2]

A novel feature of our model, relative to the DSGE literature, is that firms are credit constrained by land value. As our BVAR evidence shows, business investment responds more than do hours and consumption following a shock to land prices. The estimation of our DSGE model identifies a driving force behind the joint dynamics between land prices and business investment in influencing macroeconomic fluctuations. Because firms are credit constrained, a shock to housing demand originating in the household sector triggers competing demand for land between the household sector and the business sector and sets off a financial spiral that drives large fluctuations in land prices and strong co-movements of land prices with investment, hours, and consumption.

Figure 3 illustrates our model's propagation mechanism. Suppose the economy starts from the steady state (point A). Consider then the effect of a positive shock to housing demand. In the standard real business cycle (RBC) model with housing, this shock shifts the household's land demand curve upward. Land prices rise and land reallocates from the entrepreneur to the household (from point A to point B) and there are no further actions. As land shifts away from the business sector, investment falls. Thus, the unconstrained model predicts negative co-movements between land prices and business investment.

Now consider an economy in which entrepreneurs are credit constrained by land value. In this case, the initial rise in land prices through the shift in the household land demand curve raises the entrepreneur's net worth and expands her borrowing capacity. The expansion of net worth and credit shifts the entrepreneur's land demand curve upward, which reinforces the household's response and result in a further rise in the land price and a further expansion of credit, generating a static financial multiplier (point C). More importantly, the rise in the entrepreneur's net worth and the expansion of credit produce a dynamic financial multiplier: More credit allows for more business investment in the current period, which means more

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[2]Complementary to the study by Chaney, Sraer, and Thesmar (2009) for U.S. firms, Gan (2007) shows that, following the real estate market collapse in Japan in the early 1990s, drops in collateral values lowered corporate firms' borrowing capacity and had a large adverse impact on corporate investment. For every 10% drop in collateral value, investment by a representative corporate firm in Japan declined by about 0.8%.

capital stock in the future; since capital and land are complementary factors of production, more future capital stock raises the future marginal product of land, which relaxes the firm's credit constraint further, creating a ripple effect (from point C to point E). Thus, a shift in housing demand in a credit-constrained economy can lead to large fluctuations in land prices and produce a broader economic impact on investment, hours, and consumption.

To assess the quantitative importance of our model's propagation mechanism, we estimate the model using Bayesian methods and fit the model to aggregate U.S. time-series data. Our estimation indicates that, propagated through credit constraints on firms, a housing demand shock alone accounts for about 90% of land price fluctuations, 30-50% of investment fluctuations, and 20-40% of output fluctuations.

To quantify how much our model's propagation mechanism contributes to explaining both the BVAR facts and the recent sharp declines in land prices and business investment, we compute counterfactual simulations of history from the model based on the estimated time series of housing demand shocks. We find that the simulated data yield a driving force behind the observed, strong co-movements of land prices with investment, hours, and consumption.

Our work belongs to a burgeoning strand of literature that incorporates financial frictions into DSGE models. This literature builds on the seminal works by Kiyotaki and Moore (1997) and Bernanke, Gertler, and Gilchrist (1999) (henceforth BGG). Although the details of the financial friction differ, the transmission mechanisms in Kiyotaki and Moore (1997) and BGG are similar since they both provide a direct link between firms' assets and investment spending.

In recent papers, Christiano, Trabandt, and Walentin (2007) and Christiano, Motto, and Rostagno (2010) build on BGG and examine the empirical importance of the financial accelerator using time series data from the United States and the euro area. Gilchrist, Ortiz, and Zakrajsek (2009) examine the importance of credit spread for macroeconomic fluctuations by fitting a version of the BGG model to a measure of credit spread constructed with micro-level data, following the approach in Gilchrist, Yankov, and Zakrajsek (2009). Jermann and Quadrini (2009) find that a financial shock that affects firms' borrowing ability has a large impact on employment and aggregate output. Del Negro, Eggertsson, Ferrero, and Kiyotaki (2010) introduce nominal rigidities into the model of Kiyotaki and Moore (2008) to examine the effectiveness of unconventional monetary policy.[3]

Our paper has a different emphasis than previous literature. We focus on exploring the dynamic links between land prices and the macroeconomy. We identify and quantify a financial mechanism that propagates the effects of a shock that primarily influences land prices, which in turn generate macroeconomic fluctuations.

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[3]For a comprehensive survey of this literature, see Gertler and Kiyotaki (2010).

II. The Benchmark Model

The economy consists of two types of agents—a representative household and a representative entrepreneur. There are four types of commodities: labor, goods, land, and loanable bonds. The representative household's utility depends on consumption goods, land services (housing), and leisure; the representative entrepreneur's utility depends on consumption goods only. Goods production requires labor, capital, and land as inputs. The entrepreneur needs external financing for investment spending. Imperfect contract enforcement implies that the entrepreneur's borrowing capacity is constrained by the value of collateral assets, consisting of land and capital stocks. Following the literature, we assume that the household is more patient than the entrepreneur so that the collateral constraint is binding in and near the steady-state equilibrium.[4]

II.1. **The representative household.** The household has the utility function

$$\mathrm{E} \sum_{t=0}^{\infty} \beta^t A_t \left\{ \log(C_{ht} - \gamma_h C_{h,t-1}) + \varphi_t \log L_{ht} - \psi_t N_{ht} \right\}, \tag{1}$$

where C_{ht} denotes consumption, L_{ht} denotes land holdings, and N_{ht} denotes labor hours. The parameter $\beta \in (0,1)$ is a subjective discount factor, the parameter γ_h measures the degree of habit persistence, and the term E is a mathematical expectation operator. The term A_t represents a shock to the household's patience factor, φ_t a shock to the household's taste for land services, and ψ_t a shock to labor supply. For convenience, we label the land taste shock φ_t the "housing demand shock."

The intertemporal preference shock A_t follows the stochastic process

$$A_t = A_{t-1}(1 + \lambda_{at}), \quad \ln \lambda_{at} = (1 - \rho_a) \ln \bar{\lambda}_a + \rho_a \ln \lambda_{a,t-1} + \sigma_a \varepsilon_{at}, \tag{2}$$

where $\bar{\lambda}_a > 0$ is a constant, $\rho_a \in (-1, 1)$ is the persistence parameter, σ_a is the standard deviation of the innovation, and ε_{at} is an identically and independently distributed (i.i.d.) standard normal process.

The housing demand shock φ_t follows the stationary process

$$\ln \varphi_t = (1 - \rho_\varphi) \ln \bar{\varphi} + \rho_\varphi \ln \varphi_{t-1} + \sigma_\varphi \varepsilon_{\varphi t}, \tag{3}$$

where $\bar{\varphi} > 0$ is a constant, $\rho_\varphi \in (-1, 1)$ measures the persistence of the shock, $\sigma_\varphi > 0$ is the standard deviation of the innovation, and $\varepsilon_{\varphi t}$ is an i.i.d. standard normal process.

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[4]In Liu, Wang, and Zha (2009b), we provide a micro-foundation for the representative household's patience factor. In particular, we consider an economy with heterogeneous households and entrepreneurs, where the households face uninsurable idiosyncratic income risks and thus have a precautionary motive for saving. We show that the desire for precautionary saving will make the households appear more patient than the entrepreneurs at the aggregate level, provided that the households face more persistent idiosyncratic shocks than do the entrepreneurs.

The labor supply shock ψ_t follows the stationary process

$$\ln \psi_t = (1 - \rho_\psi) \ln \bar{\psi} + \rho_\psi \ln \psi_{t-1} + \sigma_\psi \varepsilon_{\psi t}, \tag{4}$$

where $\bar{\varphi} > 0$ is a constant, $\rho_\psi \in (-1, 1)$ measures the persistence, σ_ψ is the standard deviation, and $\varepsilon_{\psi t})$ is an i.i.d. standard normal process.

Denote by q_{lt} the relative price of land (in consumption units), R_t the gross real loan rate, and w_t the real wage; denote by S_t the household's purchase in period t of the loanable bond that pays off one unit of consumption good in all states of nature in period $t + 1$. In period 0, the household begins with $L_{h,-1} > 0$ units of housing and $S_{-1} > 0$ units of the loanable bond. The flow of funds constraint for the household is given by

$$C_{ht} + q_{lt}(L_{ht} - L_{h,t-1}) + \frac{S_t}{R_t} \leq w_t N_{ht} + S_{t-1}. \tag{5}$$

The household chooses C_{ht}, $L_{h,t}$, N_{ht}, and S_t to maximize (1) subject to (2)-(5) and the borrowing constraint $S_t \geq -\bar{S}$ for some large number $\bar{S}$.

II.2. **The representative entrepreneur.** The entrepreneur has the utility function

$$\mathrm{E} \sum_{t=0}^{\infty} \beta^t \left[\log(C_{et} - \gamma_e C_{e,t-1}) \right], \tag{6}$$

where C_{et} denotes the entrepreneur's consumption and γ_e is the habit persistence parameter.

The entrepreneur produces goods using capital, labor, and land as inputs. The production function is given by

$$Y_t = Z_t [L_{e,t-1}^\phi K_{t-1}^{1-\phi}]^\alpha N_{et}^{1-\alpha}, \tag{7}$$

where Y_t denotes output, K_{t-1}, N_{et}, and $L_{e,t-1}$ denote the inputs capital, labor, and land, respectively, and the parameters $\alpha \in (0, 1)$ and $\phi \in (0, 1)$ measure the output elasticities of these production factors. We assume that the total factor productivity Z_t is composed of a permanent component Z_t^p and a transitory component ν_t such that $Z_t = Z_t^p \nu_{zt}$, where the permanent component Z_t^p follows the stochastic process

$$Z_t^p = Z_{t-1}^p \lambda_{zt}, \quad \ln \lambda_{zt} = (1 - \rho_z) \ln \bar{\lambda}_z + \rho_z \ln \lambda_{z,t-1} + \sigma_z \varepsilon_{zt}, \tag{8}$$

and the transitory component follows the stochastic process

$$\ln \nu_{zt} = \rho_{\nu_z} \ln \nu_{z,t-1} + \sigma_{\nu_z} \varepsilon_{\nu_z t}. \tag{9}$$

The parameter $\bar{\lambda}_z$ is the steady-state growth rate of Z_t^p; the parameters ρ_z and ρ_{ν_z} measure the degrees of persistence; and the parameters σ_z and σ_{ν_z} measure the standard deviations. The innovations ε_{zt} and $\varepsilon_{\nu_z t}$ are i.i.d. standard normal processes.

The entrepreneur is endowed with K_{-1} units of initial capital stock and $L_{e,-1}$ units of initial land. Capital accumulation follows the law of motion

$$K_t = (1 - \delta)K_{t-1} + \left[1 - \frac{\Omega}{2}\left(\frac{I_t}{I_{t-1}} - \bar{\lambda}_I\right)^2\right] I_t, \tag{10}$$

where I_t denotes investment, $\bar{\lambda}_I$ denotes the steady-state growth rate of investment, and $\Omega > 0$ is the adjustment cost parameter.

The entrepreneur faces the flow of funds constraint

$$C_{et} + q_{lt}(L_{et} - L_{e,t-1}) + B_{t-1} = Z_t[L_{e,t-1}^\phi K_{t-1}^{1-\phi}]^\alpha N_{et}^{1-\alpha} - \frac{I_t}{Q_t} - w_t N_{et} + \frac{B_t}{R_t}, \tag{11}$$

where B_{t-1} is the amount of matured debt and B_t/R_t is the value of new debt.

Following Greenwood, Hercowitz, and Krusell (1997), we interpret Q_t as the investment-specific technological change. Specifically, we assume that $Q_t = Q_t^p \nu_{qt}$, where the permanent component Q_t^p follows the stochastic process

$$Q_t^p = Q_{t-1}^p \lambda_{qt}, \quad \ln \lambda_{qt} = (1 - \rho_q) \ln \bar{\lambda}_q + \rho_q \ln \lambda_{q,t-1} + \sigma_q \varepsilon_{qt}, \tag{12}$$

and the transitory component μ_t follows the stochastic process

$$\ln \nu_{qt} = \rho_{\nu_q} \ln \nu_{q,t-1} + \sigma_{\nu_q} \varepsilon_{\nu_q t}. \tag{13}$$

The parameter $\bar{\lambda}_q$ is the steady-state growth rate of Q_t^p; the parameters ρ_q and ρ_{ν_q} measure the degree of persistence; and the parameters σ_q and σ_{ν_q} measure the standard deviations. The innovations ε_{qt} and $\varepsilon_{\nu_q t}$ are i.i.d. standard normal processes.

The entrepreneur faces the credit constraint

$$B_t \leq \theta_t E_t[q_{l,t+1} L_{et} + q_{k,t+1} K_t], \tag{14}$$

where $q_{k,t+1}$ is the shadow price of capital in consumption units.[5] Under this credit constraint, the amount that the entrepreneur can borrow is limited by a fraction of the value of the collateral assets—land and capital. Following Kiyotaki and Moore (1997), we interpret this type of credit constraint as reflecting the problem of costly contract enforcement: if the entrepreneur fails to pay the debt, the creditor can seize the land and the accumulated capital; since it is costly to liquidate the seized land and capital stock, the creditor can recoup up to a fraction θ_t of the total value of collateral assets.

We interpret θ_t as a "collateral shock" that reflects the tightness of the credit market related to financial regulations or financial innovations. We assume that θ_t follows the stochastic process

$$\ln \theta_t = (1 - \rho_\theta) \ln \bar{\theta} + \rho_\theta \ln \theta_{t-1} + \sigma_\theta \varepsilon_{\theta t}, \tag{15}$$

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[5]Since the price of new capital is $1/Q_t$, Tobin's q in this model is given by $q_{kt}Q_t$, which is the ratio of the value of installed capital to the price of new capital.

where $\bar{\theta}$ is the steady-state value of θ_t, $\rho_\theta \in (0,1)$ is the persistence parameter, σ_θ is the standard deviation, and $\varepsilon_{\theta t}$ is an i.i.d. standard normal process.

The entrepreneur chooses C_{et}, N_{et}, I_t, $L_{e,t}$, K_t, and B_t to maximize (6) subject to (7) through (15).

II.3. **Market clearing conditions and equilibrium.** In a competitive equilibrium, the markets for goods, labor, land, and loanable bonds all clear. The goods market clearing condition implies that

$$C_t + \frac{I_t}{Q_t} = Y_t, \tag{16}$$

where $C_t = C_{ht} + C_{et}$ denotes aggregate consumption. The labor market clearing condition implies that labor demand equals labor supply:

$$N_{et} = N_{ht} \equiv N_t. \tag{17}$$

The land market clearing condition implies that

$$L_{ht} + L_{et} = \bar{L}. \tag{18}$$

Finally, the bond market clearing condition implies that

$$S_t = B_t. \tag{19}$$

A competitive equilibrium consists of sequences of prices $\{w_t, q_{lt}, R_t\}_{t=0}^{\infty}$ and allocations $\{C_{ht}, C_{et}, I_t, N_{ht}, N_{et}, L_{ht}, L_{et}, S_t, B_t, K_t, Y_t\}_{t=0}^{\infty}$ such that (i) taking the prices as given, the allocations solve the optimizing problems for the household and the entrepreneur and (ii) all markets clear.

III. Estimation

We log-linearized the model around the steady state in which the credit constraint is binding. We use Bayesian methods to fit the linearized model to 6 quarterly U.S. time series: the real price of land, the inverse of the quality-adjusted relative price of investment, real per capita consumption, real per capita investment (in consumption units), real per capita nonfarm nonfinancial business debt, and per capita hours worked (as a fraction of total time endowment). The sample covers the period from 1975:Q1 to 2010:Q4. The prior distributions are summarized in Table 1. We provide more detailed descriptions of the data and the prior distributions in Appendices A and B.[6]

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[6]Supplemental Appendix I derives the system of log-linearized equations and discusses the difficulty and challenge of estimating this credit-constraint model. The supplemental materials, along with dynare and C/C++ source code, are available at http://www.tzha.net/articles#CREDITCONSTRAINTS.

We follow Sims and Zha (1999) and report 90% probability intervals for model parameters and 68% probability intervals for impulse responses. The two levels of probability intervals are designed to better characterize the model's likelihood shape.

Table 1 reports the estimates of structural parameters at the posterior mode, along with 90% posterior probability intervals (the last 3 columns). Table 2 reports the estimates of shock parameters, along with 90% probability intervals.

The estimated habit parameters suggest that both types of agents have modest degrees of habit persistence, with the entrepreneur's habit formation slightly stronger than the household's (0.66 vs. 0.50). The estimated investment adjustment cost parameter ($\Omega = 0.18$) is much smaller than the values reported in the DSGE literature without financial frictions.

The estimated patience factor (0.0089) implies that the first-order excess return (i.e., the steady-state return from investment less the steady-state loan rate) is about 3.60% per annum. Thus, the entrepreneur assigns a substantial premium to existing loans.[7] The estimated values of β, $\bar{\varphi}$, ϕ, and δ are broadly in line with those reported in the literature (Iacoviello, 2005).

The estimation reveals that the two financial shocks—a housing demand shock and a collateral shock—are both persistent and have large standard deviations relative to other shocks. The 90% probability intervals indicate that all parameters in the model are tightly estimated.

IV. Economic Implications

In this section, we discuss the model's quantitative implications based on the estimated parameters. In particular, we identify a driving force behind the joint dynamics between land prices and key macroeconomic variables, and we evaluate the quantitative importance of the model's transmission mechanism for this driving force. In addition, we examine the extent to which the model can generate large declines in investment following a collapse in land prices, as we observe in the recent financial crisis.

IV.1. **Relative importance of the shocks.** Our estimated model helps us assess the relative importance of the shocks in driving fluctuations in the land price and macroeconomic variables. We do this through variance decompositions. Table 3 reports variance decompositions for the land price and several key macroeconomic variables across the 8 types of structural shocks at forecasting horizons between the impact period (1Q) and six years after the initial shock (24Q).

Variance decompositions show that a shock to the investment-specific technology (IST), either permanent or transitory, does not explain much of the fluctuations in the land price and

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[7]Supplemental Appendix I describes our derivations of the first-order excess return.

key macroeconomic variables. The DSGE literature shows that, in models without financial friction, IST shocks are not important for macroeconomic fluctuations if the model is fitted to time-series data of the relative price of investment; but if such shocks are treated as latent variables in estimation, they can be important (Justiniano, Primiceri, and Tambalotti, 2011; Liu, Waggoner, and Zha, Forthcoming). As we discuss below in Section V.4, even when we estimate our model without fitting to the investment price series, an IST shock still does not drive investment fluctuations because firms are credit constrained.

A neutral technology shock (i.e., a TFP shock), either permanent or transitory, contributes little to land price fluctuations. Although a TFP shock, especially the permanent component, accounts for a substantial fraction of fluctuations in output, its impact is not amplified through credit constraints since the shock does not move the land price. These findings are consistent with Kocherlakota (2000) and Cordoba and Ripoll (2004), who report weak amplification and propagation effects of credit constraints following a TFP shock.

Similar to a TFP shock, a labor supply shock or a patience shock explains a sizable fraction of fluctuations in output, investment, and labor hours, but these shocks do not contribute to land price fluctuations. These shocks do drive business cycle fluctuations, but they do not work through the financial channel created by credit constraints because they do not move asset prices.

In contrast, a housing demand shock drives most (about 90%) of land price fluctuations. Working through firms' credit constraints, moreover, a housing demand shock causes a substantial fraction of fluctuations in investment (about 30-40%), output (about 20-30%), and labor hours (about 35-45%).

Similar to a housing demand shock, a collateral shock is propagated through the credit constraint since it directly impacts upon the entrepreneur's borrowing capacity. In our estimation, the shock is persistent and accounts for a non-negligible fraction of fluctuations in investment, output, and hours (about 10-15%). The two financial shocks together (i.e., the housing demand shock and the collateral shock) account for about 30% of the fluctuations in output, 40-55% in business investment, and 50% in labor hours. This finding corroborates the results obtained by Jermann and Quadrini (2009), who show that financial shocks that affect firms' ability to borrow play an important role for business cycles.

IV.2. **What shocks drive the land price?** Estimated variance decompositions show that a housing demand shock is the primary force driving fluctuations in the the land price, while other shocks, including a TFP shock, have little impact on the land price. Since credit constraints can amplify and propagate a particular shock only when the shock can trigger fluctuations in the collateral value, it is important to understand why a housing demand shock can drive land price fluctuations but other shocks such as a TFP shock do not.

To illustrate an economic intuition, consider an example in which the representative household has linear utility in consumption and land services: $U(C, L_h) = C + \varphi L_h$. Suppose the taste shifter φ is constant. The land Euler equation implies that the land price is a discounted sum of future marginal rates of substitution (MRS) between land and consumption. In this case, the MRS is constant and equals φ. Since the interest rate is constant, the land price is simply $q_t = \varphi/(1 - \beta)$, which is constant unless φ varies. Thus, in this example, the land price does not respond to any shocks other than a housing demand shock.

This intuition carries over to a more general case with curvatures in the utility function. In our benchmark model with log-utility in consumption and land services, for instance, the land Euler equation (absent habit formation) is given by

$$q_{lt} = \beta \mathrm{E}_t \frac{C_{ht}}{C_{h,t+1}} q_{l,t+1} + \frac{\varphi_t C_{ht}}{L_{ht}}. \tag{20}$$

In the absence of housing demand shocks (i.e., with φ_t held constant), the MRS is as volatile as consumption and the land price is as volatile as the discounted sum of current and future consumption expenditures. Since the land price is much more volatile than consumption expenditures in the data, a TFP shock cannot generate the observed fluctuations in the land price and therefore it cannot be propagated through credit constraints, confirming the findings in Kocherlakota (2000) and Cordoba and Ripoll (2004).

In contrast, a housing demand shock directly influences the MRS and thus can drive large fluctuations in the land price without requiring consumption to be highly volatile at the same time. This finding is consistent with Davis and Heathcote (2007), who argue, based on a regression analysis, that land prices are "strongly influenced by the factors traditionally associated with housing demand." Our model provides a formal quantitative evaluation of a driving force behind land price fluctuations in the context of a DSGE model.[8]

IV.3. **The model's propagation mechanism.** To explain large fluctuations in land prices and strong co-movements between land prices and macroeconomic variables, we need both a shock to lift the land price on impact (which we identify as a housing demand shock) and a mechanism to propagate the shock's effect on the macroeconomy.

To understand the model's propagation mechanism, we analyze the optimal land holding decision (20) by the household, along with the land holding decision by the entrepreneur:

$$q_{lt} = \beta \mathrm{E}_t \frac{C_{et}}{C_{e,t+1}} \left[\alpha \phi \frac{Y_{t+1}}{L_{et}} + q_{l,t+1} \right] + \frac{\mu_{bt}}{\mu_{et}} \theta_t \mathrm{E}_t q_{l,t+1}. \tag{21}$$

To simplify exposition, we abstract from habit formation by setting $\gamma_h = \gamma_e = 0$. The term $\frac{\mu_{bt}}{\mu_{et}}$ in (21) is the shadow value of the entrepreneur's existing loans (in consumption units), which is strictly positive if and only if the credit constraint is binding.

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[8]We discuss some interpretations of housing demand shocks in Appendix C.

According to Equation (20), the cost of acquiring a marginal unit of land is q_{lt} units of consumption goods; the benefit of having the marginal unit of land, which is summarized on the right-hand side of (20), consists of the marginal utility of land services (in consumption units) and the discounted resale value of land. At the margin, the marginal cost equals the marginal benefit. Equation (21) indicates that, since the entrepreneur is credit constrained, acquiring a marginal unit of land yields benefits not only from the future marginal product of land and the resale value, but also from the shadow value of land as a collateral asset.

These Euler equations can be intuitively thought of as the land demand equations by the two types of agents, as illustrated in Figure 3 and discussed in the introduction. The figure plots the relation between the current land price q_{lt} and the quantity of land held by the household (L_{ht}) and the relation between q_{lt} and the quantity of land held by the entrepreneur (L_{et}). In plotting these land demand curves, we treat other variables such as the future land price, consumption growth, the marginal product of land, and exogenous shocks as shift factors. We assume that the initial equilibrium (Point A) is at the steady state.

Consider a housing demand shock that raises the household's marginal utility of land. The higher land demand from the household raises the land price and the entrepreneur's net worth, triggering competing demand for land between the two sectors that drives up the land price further, setting off a financial multiplier that leads to a large increase in the land price and a significant expansion of business investment and production.[9]

IV.4. **Effects of amplification and propagation.** We have argued that a housing demand shock is an important source of fluctuations in the land price and macroeconomic variables. We have also argued that our model's mechanism amplifies and propagates a housing demand shock but not a technology shock.

One way to examine the effectiveness of the model's propagation mechanism is to compare impulse responses of macroeconomic variables in the benchmark economy with endogenous credit limit to those in a counterfactual economy with exogenously fixed credit limit. Unlike the benchmark model in which a firm's debt interacts with asset prices, debt in the counterfactual economy does not vary endogenously (it varies only if there is a collateral shock). Comparing impulse responses across the two economies thus informs us of the quantitative importance of the endogenous interactions between debt and asset prices in propagating economic shocks.

Figure 4 displays the impulse responses of the land price and key macroeconomic variables following a permanent technology shock (the left column) and those following a housing

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[9]In Supplement Appendix II, we discuss our model's implications for the reallocation of land following a housing demand shock. We present some evidence that supports our model's implications for land reallocation.

demand shock (the right column). The impulse responses of macroeconomic variables to a TFP shock in the benchmark economy (solid lines) are not much different from those in the counterfactual economy (dashed lines). Indeed, the impulse responses in the counterfactual economy lie well within the standard error bands of the impulse responses estimated in our benchmark model (measured by dotted-dashed lines). This result is similar to the findings by Kocherlakota (2000) and Cordoba and Ripoll (2004). As we have discussed before, credit constraints do not propagate the effects of a TFP shock because the shock do not lift asset prices.

In contrast, the model does propagate the effects of a housing demand shock, as is evident in the right column of Figure 4. The housing demand shock drives much larger fluctuations in the land price than does the TFP shock. More important is the finding that the housing demand shock generates much larger responses of consumption, investment, and labor hours in the benchmark model (solid lines) than in the counterfactual economy (dashed lines). Firms' credit constraints are thus very effective in propagating a housing demand shock because the shock directly impacts upon the land price, triggering a dynamic financial multiplier through interactions between the land price and investment spending.

Consumption decisions, in particular the entrepreneur's, have implications for investment dynamics in response to a shock to the land price. The right column of Figure 4 shows that a housing demand shock leads to a slow, highly persistent, and hump-shaped response of aggregate consumption. Being impatient, the entrepreneur would have a desire to consume every penny borrowed if the utility function were linear. With concave utility, the entrepreneur would like to smooth consumption by investing part of the loans; and this intertemporal smoothing incentive is reinforced by habit persistence. Thus, the entrepreneur's habit persistence dampens consumption and amplifies an investment response to land price shocks.[10]

IV.5. **Historical counterfactuals.** Empirical studies have documented co-movements between housing prices and consumption expenditures (Campbell and Mankiw, 1989; Zeldes, 1989; Case, Quigley, and Shiller, 2005; Mian and Sufi, 2010). Some recent work examines the effects of changes in housing prices on consumption in a DSGE framework with households facing collateral constraints (Iacoviello, 2005; Iacoviello and Neri, 2010; Kiyotaki, Michaelides, and Nikolov, 2010; Favilukis, Ludvigson, and van Nieuwerburgh, 2011). In this section, we compare the relative importance of the effects of a housing demand shock

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[10]Since entrepreneurs own the firms, their consumption can be interpreted as dividend payout from firms. Thus, our model's mechanism for explaining the joint dynamics in the land price and investment requires some form of dividend smoothing. In a similar vein, Jermann and Quadrini (Forthcoming) show that, for financial shocks to have an impact on real variables (such as employment), it is important to incorporate costly adjustments in dividend payout.

on consumption with the effects on business investment and labor hours, both in the data and in the simulated model.

We begin with the data. Figure 2 reveals that, in the data, consumption, business investment, and labor hours move together with the land price. A positive shock to the land price raises investment and hours by more than it does consumption. In particular, following a shock to the land price, the peak response of business investment is about 25% of the peak response of the land price, while the peak response of consumption is much smaller at about 12% of the peak land-price response.[11]

We now show that the two types of financial shocks identified in our structural model—a housing demand shock and a collateral shock—are a driving force behind these facts. For this purpose, we calculate what would have happened if only the financial shocks had occurred throughout the history. Since our model is structural, it is internally coherent to perform this counterfactual exercise. We implement this exercise by first estimating the time-series paths of all shocks based on our estimated parameters. Conditioning on the estimated initial state variables and the estimated sequence of housing demand shocks or the estimated sequences of both housing demand and collateral shocks (with all other shocks turned off accordingly), we simulate the data from our DSGE model. We then compare the BVAR impulse responses estimated with the simulated data to those implied by the actual data.

Figure 5 displays the BVAR impulse responses following a shock to the land price based on simulated data from the benchmark DSGE model conditioned on housing demand shocks alone. The 3 columns in each figure reports the impulse responses of the land price and each of the 3 macroeconomic variables—business investment, labor hours, and consumption—following a positive shock to the land price. The way these impulse responses are calculated is exactly the same as the bivariate BVAR applied to the actual data. The figure shows that a housing demand shock is a primary cause of the positive co-movements of the land price with business investment, labor hours, and consumption.

When we turn on both housing demand shocks and collateral shocks, the model is able to generate the magnitude of impulse responses of macroeconomic variables and the persistence of co-movements between the land price and these macroeconomic variables comparable to those in the actual data, as a simple comparison between Figure 6 and Figure 2 reveals.[12]

The findings suggest that, working through the endogenous credit-constraint channel, financial shocks—in particular housing demand shocks—lead to macroeconomic responses

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[11]The size of the consumption response relative to the land-price response from our BVAR is consistent with the magnitude of wealth effects of housing prices on consumption (of about 12%) reported by Iacoviello and Neri (2010).

[12]By construction, had all the other shocks in our DSGE model been left in place, the simulations would have matched the observed data exactly and the impulse responses from the BVAR applied to these simulated data would have been exactly the same as those applied to the actual data.

that form a dominant force behind most of the co-movements between the land price and macroeconomic variables observed in the data.

IV.6. **Shedding light on the Great Recession.** As discussed in the introduction and documented in Figure 1, our model is motivated by the collapse in land prices and the subsequent deep recession. During the Great Recession period from 2007:Q3 to 2009:Q2, in particular, the real land price plummeted by 25% and business investment fell by 22%. To what extent can our model generate the observed declines in land prices and business investment observed in the Great Recession?

To quantify the model's role in explaining the history, we calculate the paths of land prices and business investment conditional on the estimated housing demand shocks alone (with all other shocks shut off), using the same method as in Section IV.5. As can be seen from Figure 7, housing demand shocks play a crucial role in driving the sharp declines of both land prices and business investment from 2006:Q1 through 2010:Q4. Fluctuations in land prices are almost entirely accounted for by housing demand shocks in our model; the effects of these shocks are propagated through credit constraints to generate the declines in business investment.

Comparing to the actual data (thin lines in Figure 7), these results suggest that shocks originating in the household sector are primarily responsible for the joint declines in land prices and business investment observed during the recent financial crisis period. They reinforce our finding that since land is an important collateral asset for firms' borrowing capacity and investment spending, financial shocks are transmitted through firms' credit constraints to fluctuations in the macroeconomy.

V. Sensitivity

In this section we evaluate the sensitivity of our results by studying several variations of the benchmark model, the data, and the estimation approach. We highlight our main findings below and provide the details in Supplemental Appendix III.

V.1. **Allowing land supply to grow.** In the benchmark model, we assume that aggregate land supply is fixed. With fixed land supply, a shock to housing demand raises the land price as households and firms compete for the limited amount of land. As the land price rises, firms are able to borrow more to expand investment and production, leading to a boom.

The assumption of fixed land supply is, of course, not our literal interpretation of what happens in the actual economy. Indeed, some microeconomic evidence suggests that land supply elasticity varies substantially across regions and cities (Glaeser, Gyourko, and Saks, 2005). Land growth in U.S. urban areas can be restricted by zoning and other land-use restrictions. More important is an urban land development that is limited by geographic

factors such as the presence of wetland and steep terrains (Saiz, Forthcoming). While het-
erogeneity abounds with man-made rules and geographic factors, Davis and Heathcote (2007)
show that *aggregate* land supply grows very slowly. Taking into account population growth,
per capital land growth is close to zero, consistent with our assumption in the model.

One may, however, be interested in knowing how the model's implications would change
if we allow aggregate land supply to have trend growth at an exogenous rate of $\bar{\lambda}_l$. The
land growth captures low-frequency expansions of residential and commercial land. The
market clearing condition for land becomes $L_{ht} + L_{et} = \bar{\lambda}_l^t \bar{L}$. To obtain balanced growth
and maintain a well-defined equilibrium, we assume that the stocks of land holdings in each
sector grow with the same trend. Within any finite horizon the growth rates of land in the
two sectors may differ following economic shocks that lead to land reallocation. We find that
incorporating land supply growth does not affect the steady-state ratios, nor does it affect
dynamic deviations of endogenous variables from the balanced growth path.[13]

V.2. **Incorporating working capital.**

Our benchmark model has intertemporal loans only
and abstracts from working capital. We now consider a broader set of debt instruments
by incorporating working capital in the model. In particular, we follow the approach in
Christiano, Motto, and Rostagno (2010) and Mendoza (2010) by assuming that a fraction
ϕ_w of wage payment needs to be financed by working capital. The total amount of debt,
including intertemporal debt and working capital, cannot exceed a fraction of firms' collateral
assets—land and capital. Thus, the borrowing constraint is given by

$$B_t \leq \theta_t E_t[q_{l,t+1} L_{et} + q_{k,t+1} K_t] - \phi_w w_t N_{et} R_t. \tag{22}$$

All other aspects of the model are the same as in the benchmark.

We re-estimate this model with working capital. The estimation results are very similar to
those in our benchmark model. Our results, therefore, are robust when we allow for working
capital.

V.3. **No patience shocks.**

The DSGE literature often finds that an intertemporal prefer-
ence shock (i.e., patience shock) is important in driving business cycles. A patience shock
is sometimes interpreted as a shock to risk premia (Smets and Wouters, 2007). In our es-
timated model, a patience shock accounts for a sizable fraction of investment fluctuations

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[13]In Supplemental Appendix III, we derive the balanced growth path in the model with land supply growth
and show that equilibrium dynamics remain unchanged relative to our benchmark model. We hope that our
mechanism for explaining how the effects of a shock on land prices can spill over into the macroeconomy
will lay the groundwork for building an ambitious and empirically plausible general equilibrium model that
takes into account some arguably more realistic setups in which land supply responds to man-made rules
that are endogenous to changes in the land price and in which land price dispersion responds to wage and
productivity dispersions.

(about 15-20%), making it the second most important shock that drives investment fluctuations after the housing demand shock (Table 3). Therefore it is important to examine whether abstracting from this shock would change the model's quantitative implications in a significant way. When we re-estimate the model without patience shocks, we find that a housing demand shock remains to be the most important driving force for investment dynamics, accounting for about 30-40% of investment fluctuations (see the column under "No Patience" in Table 4).

V.4. **Latent IST shocks.** Justiniano, Primiceri, and Tambalotti (2011) argue that if the price of investment goods is not used in fitting the model, investment-specific shocks can be interpreted as "financial" shocks and may have a large impact on macroeconomic fluctuations. When we re-estimate the model by treating IST shocks as a latent variable (i.e., without fitting to the time-series data of the relative price of investment), we find that a housing demand shock still accounts for 23-46% of investment fluctuations (see the column under "Latent IST" in Table 4).

V.5. **CoreLogic data.** The land price series we use for the benchmark model is constructed based on the FHFA home price index. In Supplemental Appendix III, we discuss some advantages and disadvantages of using this home price index relative to using some other measures such as the CoreLogic home price index. To examine whether our main findings are robust to different land price series, we fit our model to the data in which the FHFA land price series is replaced by the CoreLogic land price series. With the CoreLogic land price data, a housing demand shock accounts for over 50% of investment fluctuations (see the column under "CoreLogic" in Table 4) and remains to be the most important shock in shaping investment variations.

VI. Two Key Issues

We address two important issues in this section. First, we quantify the importance of land collateral for the model's transmission mechanism. We do this by estimating an alternative model in which firms do not use land as a collateral asset and we compare the transmission mechanism of this alternative model to that of the benchmark. Second, we explore the implications of potential volatility changes in the land price data for our quantitative results.

VI.1. **Do we need land as a collateral asset?** In the data, real estate represents a large fraction of firms' tangible assets and, as discussed in the introduction, changes in real estate values have a significant impact on firms' investment spending. In our benchmark model, we assume that land is a collateral asset for firms. A positive housing demand shock raises the land price and thereby expands firms' borrowing capacity, enabling firms to finance expansions of investment and production.

In a similar fashion, a positive collateral shock directly lifts firms' borrowing capacity and thus helps firms to expand investment and production, as shown in Jermann and Quadrini (2009). Given the collateral shock, is it important to include land as a collateral asset for our mechanism to operate?

To answer this question, we study an alternative model specification in which land is not used as a collateral asset for firms and thus land prices do not influence investment decisions. Specifically, we consider the collateral constraint

$$B_t \le \theta_t \mathrm{E}_t q_{k,t+1} K_t, \tag{23}$$

and we impose $\phi = 0$ in the production function so that land is no longer used as collateral or a production input. The alternative model is otherwise identical to the benchmark model.

With these changes in the model, the land price and investment are driven by separate forces. While the land price is driven mostly by the household's housing demand, business investment is driven primarily by firms' optimizing decisions. Consequently, we should expect a collateral shock (θ_t) to play a more important role in explaining investment dynamics.

We estimate the alternative model using the same set of time series data. Since capital is the only collateral asset, the alternative model requires large fluctuations in the capital price (q_{kt}) to match the business debt data. Thus, the estimated value for the investment-adjustment cost parameter is much larger than in the benchmark model ($\Omega = 6.35$ vs. 0.18). Accordingly, as investment adjustment becomes more sluggish, the model implies larger values for habit persistence parameters in order to match the observed relative volatility between consumption and investment. This is what we find in the estimation.

Estimated variance decompositions confirm that, in this alternative model, fluctuations in the land price are driven mostly by a housing demand shock, as we find in the benchmark model but through a different mechanism. In the benchmark model, a housing demand shock triggers competing demand for land between the two sectors and, through firms' credit constraints, the land price and investment interact to amplify and propagate the initial shock. In the alternative model, a housing demand shock continues to drive land-price fluctuations but, by construction, there is no spillover of land-price dynamics to macroeconomic fluctuations.

Since changes in the land price do not have any impact on investment, a collateral shock becomes more important in driving investment fluctuations. Indeed, estimated variance decompositions show that a collateral shock accounts for 30-45% of investment fluctuations in the alternative model, a much larger fraction than in the benchmark model (15%).

The two financial shocks (housing demand and collateral shocks), either acting alone or together, have difficulty in explaining the observed co-movements between the land price and investment. Figure 8 compares the impulse responses of the land price and business investment to a land-price shock estimated in a BVAR using actual data (the left column)

with those estimated using simulated data from the alternative model conditioned on the time series of the two estimated financial shocks combined (the right column). As shown in the figure, the alternative model driven by the two financial shocks fails to generate significant responses of business investment to a land price shock.

This result, along with our findings in the benchmark model, suggests that including land as a collateral asset for the firm's investment decisions is both empirically relevant and theoretically necessary for explaining the observed co-movements between land prices and macroeconomic variables.

VI.2. **Volatility changes in land prices.** Our land price series spans the sample from 1975 to 2010, covering several recession periods with changes in macroeconomic volatility (Stock and Watson, 2003; Sims and Zha, 2006; Taylor, 2007). It is therefore important to investigate how our results are affected when volatility changes are explicitly taken into account. To accomplish this task, we generalize the benchmark model to allow for regime shifts in the volatility of a housing demand shock with the following heteroskedastic process

$$\ln \varphi_t = (1 - \rho_\varphi) \ln \bar{\varphi} + \rho_\varphi \ln \varphi_{t-1} + \sigma_\varphi(s_t) \varepsilon_{\varphi t}, \tag{24}$$

where the shock volatility $\sigma_\varphi(s_t)$ varies with the regime s_t. We assume that the shock volatility switches between two regimes ($s_t = 1$ or $s_t = 2$), with the Markov transition probabilities summarized by the matrix $P = [p_{ij}]$, where $p_{ij} = Prob(s_{t+1} = i | s_t = j)$ for $i, j \in \{1, 2\}$, $p_{12} = 1 - p_{22}$, and $p_{21} = 1 - p_{11}$.

We estimate this regime-switching DSGE model using the approach described in Liu, Waggoner, and Zha (Forthcoming). In the estimation, we adopt the same prior distributions for the parameters and use the same data set as in our benchmark model. The posterior mode estimates of the structural parameters and the shock parameters are very similar to those in the benchmark model. But the estimated volatility of a housing demand shock has two distinct regimes: a low-volatility regime (regime 1 with $\sigma_\varphi = 0.03$) and a high-volatility regime (regime 2 with $\sigma_\varphi = 0.08$). The posterior mode estimates of the Markov switching probabilities ($p_{11} = 0.9794$ and $p_{22} = 0.9662$) indicate that both regimes are highly persistent, although the low-volatility regime is more persistent than the high-volatility regime.[14]

Figure 9 shows the probability of the high volatility regime throughout the sample periods. It indicates that the high volatility regime is associated with periods of large declines in land prices (covering the two recessions between 1978 and 1983 and the recent deep recession).

According to the estimated variance decompositions, a housing demand shock accounts for about 20% of investment fluctuations in the low-volatility regime and 55-65% in the high-volatility regime (see the last two columns in Table 4). Since the high-volatility regime

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[14]All the estimation results for the regime-switching DSGE model are described in detail in Supplemental Appendix III.

captures periods with both large recessions and large declines in the land price, a housing demand shock plays a more important role for explaining the dynamics in land prices and business investment during recessions. This finding is consistent with Claessens, Kose, and Terrones (2011), who find that a recession is typically deeper than other recessions if there is a sharp fall in housing prices.

VII. Conclusion

We have presented evidence that land prices move together with macroeconomic variables over the business cycles. The recent financial crisis highlights this connection. We have studied a DSGE model incorporating an empirically important feature that land is a valuable collateral asset that firms use to finance investment spending. We have shown that, when firms are credit constrained, a housing demand shock originating in the household sector provides an impetus for the observed large fluctuations in land prices and for the persistent co-movements between land prices and business investment. Thus, our model provides a financial mechanism that propagates shocks to land prices to generate the observed macroeconomic fluctuations.

To bring out the transparency of the mechanism that drives our estimation results, our analysis abstracts from a host of features to which our model can be extended in future research. We abstract from investment in structures, for example, mainly because most of the fluctuations in housing prices are driven by fluctuations in land prices, not changes in the cost of structures (Davis and Heathcote, 2007). The cyclical behavior of residential investment, however, is an important subject studied in the literature. In particular, Fisher (2007) discusses the challenges in using a standard RBC model to explain why residential investment leads business investment and offers some solutions. Studying the lead-lag relations between structures investment and business investment in a model with financial frictions is an important subject for future research.

In our model, there are two types of collateral assets: land and capital. We find that shocks to land prices can explain a substantial fraction of investment fluctuations. We choose not to fit the model to stock prices because our model, like most DSGE models in the literature, is not equipped with the necessary frictions and shocks to explain joint dynamics between stock prices and macroeconomic variables. When we estimate a BVAR model with land prices, investment, and stock prices, we find that a positive shock to stock prices also leads to a large and persistent increase in investment, although it does not seem to move land prices. On the other hand, a positive shock to land prices leads to a positive but small increase in stock prices.[15] Thus, although stock prices do appear to co-move with investment, they are

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[15]For details of the BVAR results, see the section entitled "Stock prices, land prices, and investment" in Supplemental Appendix III.

likely to be driven by shocks other than those related to housing demand. In a related but very different setup, Christiano, Motto, and Rostagno (2010) fit a DSGE model to stock prices along with other macroeconomic variables. An ambitious project for future research is to fit a DSGE model to both land prices and stock prices.

The financial crisis has made it painfully clear that a better understanding of the interactions between the housing market and the macroeconomy could improve policy making. The financial mechanism identified in this paper provides a natural environment for evaluating the role of policy interventions in the throes of financial crisis.

References

BERGER, A. N., AND G. F. UDELL (1990): "Collateral, Loan Quality, and Bank Risk," *Journal of Monetary Economics*, 25, 21–42.

BERNANKE, B. S., M. GERTLER, AND S. GILCHRIST (1999): "The Financial Accelerator in a Quantitative Business Cycle Framework," in *The Handbook of Macroeconomics*, ed. by J. B. Taylor, and M. Woodford, vol. 1, chap. 21, pp. 1341–1393. Elsevier, first edn.

BOLDRIN, M., L. J. CHRISTIANO, AND J. D. FISHER (2001): "Habit Persistence, Asset Returns, and the Business Cycle," *American Economic Review*, 91(1), 149–166.

CAMPBELL, J. Y., AND N. G. MANKIW (1989): "Consumption, Income, and Interest Rates: Reinterpreting the Time Series Evidence," in *NBER Macroeconomics Annual*, ed. by O. J. Blanchard, and S. Fischer, vol. 4, pp. 185–216. MIT Press, Cambridge, MA.

CASE, K., J. QUIGLEY, AND R. SHILLER (2005): "Comparing Wealth Effects: The Stock Market versus the Housing Market," *Advances in Macroeconomics, Berkeley Electronic Press*, 5(1), 1–32.

CHANEY, T., D. SRAER, AND D. THESMAR (2009): "The Collateral Channel: How Real Estate Shocks affect Corporate Investment," Manuscript, University of Chicago.

CHRISTIANO, L., M. EICHENBAUM, AND C. EVANS (2005): "Nominal Rigidities and the Dynamics Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 113, 1–45.

CHRISTIANO, L., R. MOTTO, AND M. ROSTAGNO (2010): "Financial Factors in Economic Fluctuations," Manuscript, Northwestern University.

CHRISTIANO, L. J., M. TRABANDT, AND K. WALENTIN (2007): "Introducing Financial Frictions and Unemployment into a Small Open Economy Model," Manuscript, Sveriges Riksbank Working Paper Series No. 214.

CLAESSENS, S., M. A. KOSE, AND M. E. TERRONES (2011): "How Do Business and Financial Cycles Interact?," IMF Working Paper WP/11/88.

CORDOBA, J.-C., AND M. RIPOLL (2004): "Credit Cycles Redux," *International Economic Review*, 45(4), 1011–1046.

CUMMINS, J. G., AND G. L. VIOLANTE (2002): "Investment-Specific Technical Change in the United States (1947-2000): Measurement and Macroeconomic Consequences," *Review of Economic Dynamics*, 5, 243–284.

DAVIS, M. A., AND J. HEATHCOTE (2007): "The Price and Quantity of Residential Land in the United States," *Journal of Monetary Economics*, 54, 2595–2620.

DEL NEGRO, M., G. EGGERTSSON, A. FERRERO, AND N. KIYOTAKI (2010): "The Great Escape? A Quantitative Evaluation of the Feds Non-Standard Policies," Manuscript, Princeton University.

DEL NEGRO, M., AND F. SCHORFHEIDE (2008): "Forming Priors for DSGE Models (and How It Affects the Assessment of Nominal Rigidities)," Manuscript, Federal Reserve Bank of New York and University of Pennsylvania.

DENTON, F. T. (1971): "Adjustment of Monthly or Quarterly Series to Annual Totals: An Approach Based on Quadratic Minimization," *Journal of the American Statistical Association*, 66, 99–102.

FAVILUKIS, J., S. C. LUDVIGSON, AND S. VAN NIEUWERBURGH (2011): "The Macroeconomic Eects of Housing Wealth, Housing Finance, and Limited Risk-Sharing in General Equilibrium," Unpublished manuscript, New York University.

FISHER, J. D. M. (2007): "Why Does Household Investment Lead Business Investment over the Business Cycle?," *Journal of Political Economy*, 115(1), 141–168.

GAN, J. (2007): "Collateral, Debt Capacity, and Corporate Investment: Evidence from a Natural Experiment," *Journal of Financial Economics*, 85, 709–734.

GERTLER, M., AND N. KIYOTAKI (2010): "Financial Intermediation and Credit Policy in Business Cycle Analysis," Manuscript, New York University and Princeton University.

GILCHRIST, S., A. ORTIZ, AND E. ZAKRAJSEK (2009): "Credit Risk and the Macroeconomy: Evidence from an Estimated DSGE Model," Manuscript, Boston University.

GILCHRIST, S., V. YANKOV, AND E. ZAKRAJSEK (2009): "Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets," *Journal of Monetary Economics*, 56, 471–493.

GLAESER, E. L., J. GYOURKO, AND R. E. SAKS (2005): "Why Have Housing Prices Gone Up?," *American Economic Review*, 95(2), 329–333.

GORDON, R. J. (1990): *The Measurement of Durable Goods Prices*. University of Chicago Press, Chicago,Illinois.

GREENWOOD, J., Z. HERCOWITZ, AND P. KRUSELL (1997): "Long-Run Implications of Investment-Specific Technological Change," *American Economic Review*, 87, 342–362.

HUGGETT, M., G. VENTURA, AND A. YARON (2009): "Sources of Lifetime Inequality," Manscript.

IACOVIELLO, M. (2005): "House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle," *American Economic Review*, 95(3), 739–764.

IACOVIELLO, M., AND S. NERI (2010): "Housing Market Spillovers: Evidence from an Estimated DSGE Model," *American Economic Journal: Macroeconomics*, 2, 125–164.

JERMANN, U., AND V. QUADRINI (2009): "Macroeconomic Effects of Financial Shocks," *American Economic Review* (forthcoming).

———— (Forthcoming): "Macroeconomic Effects of Financial Shocks," American Economic Review.

JUSTINIANO, A., G. PRIMICERI, AND A. TAMBALOTTI (2011): "Investment Shocks and the Relative Price of Investment," *Review of Economic Dynamics*, 14, 101–121.

KIYOTAKI, N., A. MICHAELIDES, AND K. NIKOLOV (2010): "Winners and Losers in Housing Markets," Central Bank of Cyprus Working Paper 2010-5.

KIYOTAKI, N., AND J. MOORE (1997): "Credit Cycles," *Journal of Political Economy*, 105(2), 211–248.

——— (2008): "Liquidity, Business Cycles, and Monetary Policy," Manuscript, Princeton University and London School of Economics.

KOCHERLAKOTA, N. (2000): "Creating Business Cycles Through Credit Constraints," *Federal Reserve Bank of Minneapolis Quarterly Review*, 24(3), 2–10.

LIU, Z., D. F. WAGGONER, AND T. ZHA (Forthcoming): "Sources of Macroeconomic Fluctuations: A Regime-Switching DSGE Approach," *Quantitative Economics*.

LIU, Z., P. WANG, AND T. ZHA (2009a): "Do Credit Constraints Amplify Macroeconomic Fluctuations?," Federal Reserve Bank of San Francisco Working Paper 2009-28.

——— (2009b): "Asset Pricing and Income Inequality in a Heterogeneous Agent Production Economy," Manuscript.

——— (2009c): "A Theory of Housing Demand Shocks," Manuscript.

MENDOZA, E. G. (2010): "Sudden Stops, Financial Crises, and Leverage," *American Economic Review*, 100, 1941–1966.

MIAN, A., AND A. SUFI (2010): "Household Leverage and the Recession of 2007 to 2009," NBER Working Papers 15896.

QUART, D. C., AND J. M. QUIGLEY (1989): "Inferring an Investment Return Series for Real Estate from Observations on Sales," *Real Estate Economics*, 17(2), 218–230.

——— (1991): "Price Formation and the Appraisal Function in Real Estate Markets," *Journal of Real Estate Finance & Economics*, 4(2), 127–146.

SAIZ, A. (Forthcoming): "The Geographic Determinants of Housing Supply," *Quarterly Journal of Economics*.

SIMS, C. A., AND T. ZHA (1998): "Bayesian Methods for Dynamic Multivariate Models," *International Economic Review*, 39(4), 949–968.

——— (1999): "Error Bands for Impulse Responses," *Econometrica*, 67(5), 1113–1155.

——— (2006): "Were There Regime Switches in US Monetary Policy?," *American Economic Review*, 96, 54–81.

SMETS, F., AND R. WOUTERS (2007): "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach," *American Economic Review*, 97, 586–606.

STOCK, J. H., AND M. W. WATSON (2003): "Has the Business Cycles Changed? Evidence and Explanations," in *Monetary Policy and Uncertainty: Adapting to a Changing Economy*, pp. 9–56. Federal Reserve Bank of Kansas City, Jackson Hole, Wyoming.

TAYLOR, J. B. (2007): "Housing and Monetary Policy," NBER Working Paper 13682.

ZELDES, S. P. (1989): "Consumption and Liquidity Constraints: An Empirical Investigation," *Journal of Political Economy*, 97, 305–346.

TABLE 1. Prior and posterior distributions of structural parameters

| Parameter | Prior | | | | | Posterior | | |
	Distribution	a	b	Low	High	Mode	Low	High
γ_h	Beta(a,b)	1.00	2.00	0.025	0.776	0.4976	0.4496	0.5621
γ_e	Beta(a,b)	1.00	2.00	0.025	0.776	0.6584	0.3392	0.8009
Ω	Gamma(a,b)	1.00	0.50	0.102	5.994	0.1753	0.1502	0.2406
$100(g_\gamma - 1)$	Gamma(a,b)	1.86	3.01	0.100	1.500	0.4221	0.2282	0.5029
$100(\bar{\lambda}_q - 1)$	Gamma(a,b)	1.86	3.01	0.100	1.500	1.2126	1.0577	1.3297
β	Simulated			0.9563	0.9946	0.9855	0.9833	0.9909
$\bar{\lambda}_a$	Simulated			0.0000	0.0509	0.0089	0.0015	0.0119
$\bar{\varphi}$	Simulated			0.0000	0.0697	0.0457	0.0395	0.0603
ϕ	Simulated			0.0655	0.0701	0.0695	0.0693	0.0700
δ	Simulated			0.0291	0.0485	0.0368	0.0354	0.0396

Note: "Low" and "High" denote the bounds of the 90% probability interval for the prior distribution.

TABLE 2. Prior and posterior distributions of shock parameters

Parameter	Prior						Posterior		
	Distribution	a	b	Low	High		Mode	Low	High
ρ_a	Beta(a,b)	1.0000	2.0000	0.0256	0.7761		0.9055	0.8567	0.9291
ρ_z	Beta(a,b)	1.0000	2.0000	0.0256	0.7761		0.4263	0.2728	0.5488
ρ_{ν_z}	Beta(a,b)	1.0000	2.0000	0.0256	0.7761		0.0095	0.0095	0.4346
ρ_q	Beta(a,b)	1.0000	2.0000	0.0256	0.7761		0.5620	0.4584	0.6631
ρ_{ν_q}	Beta(a,b)	1.0000	2.0000	0.0256	0.7761		0.2949	0.0814	0.6062
ρ_φ	Beta(a,b)	1.0000	2.0000	0.0256	0.7761		0.9997	0.9987	0.9999
ρ_ψ	Beta(a,b)	1.0000	2.0000	0.0256	0.7761		0.9829	0.9752	0.9948
ρ_θ	Beta(a,b)	1.0000	2.0000	0.0256	0.7761		0.9804	0.9773	0.9917
σ_a	Inv-Gam(a,b)	0.3261	1.45e-04	0.0001	2.0000		0.1013	0.0782	0.7223
σ_z	Inv-Gam(a,b)	0.3261	1.45e-04	0.0001	2.0000		0.0042	0.0033	0.0051
σ_{ν_z}	Inv-Gam(a,b)	0.3261	1.45e-04	0.0001	2.0000		0.0037	0.0033	0.0048
σ_q	Inv-Gam(a,b)	0.3261	1.45e-04	0.0001	2.0000		0.0042	0.0034	0.0050
σ_{ν_q}	Inv-Gam(a,b)	0.3261	1.45e-04	0.0001	2.0000		0.0029	0.0023	0.0037
σ_φ	Inv-Gam(a,b)	0.3261	1.45e-04	0.0001	2.0000		0.0462	0.0431	0.0570
σ_ψ	Inv-Gam(a,b)	0.3261	1.45e-04	0.0001	2.0000		0.0073	0.0067	0.0087
σ_θ	Inv-Gam(a,b)	0.3261	1.45e-04	0.0001	2.0000		0.0112	0.0102	0.0126

Note: "Low" and "High" denote the bounds of the 90% probability interval for the prior distribution.

TABLE 3. Variance decompositions of aggregate quantities

Horizon	Patience	Ngrowth	Nlevel	Bgrowth	Blevel	Housing	Labor	Collateral
Land price								
1Q	4.09	1.97	1.35	0.01	0.03	89.99	2.55	0.00
4Q	3.30	3.19	0.34	0.06	0.01	90.74	2.25	0.11
8Q	2.91	3.84	0.22	0.08	0.01	90.28	2.41	0.25
16Q	2.29	4.88	0.17	0.05	0.00	89.58	2.68	0.35
24Q	1.77	5.68	0.13	0.13	0.00	89.27	2.72	0.29
Investment								
1Q	19.37	1.13	14.30	3.01	2.34	35.46	12.06	12.33
4Q	18.80	5.64	4.95	0.88	0.44	41.19	12.02	16.08
8Q	17.23	9.19	3.70	3.63	0.32	38.71	12.56	14.65
16Q	14.91	12.71	3.11	9.86	0.29	33.70	13.00	12.42
24Q	13.56	14.41	2.83	14.13	0.26	30.67	12.63	11.51
Output								
1Q	12.28	6.92	16.07	5.34	0.57	27.82	21.85	9.17
4Q	11.22	17.14	4.73	1.75	0.11	31.80	21.13	12.12
8Q	9.68	25.20	3.19	0.99	0.07	28.32	22.22	10.32
16Q	7.43	35.70	2.29	1.47	0.06	21.82	23.85	7.38
24Q	5.97	42.82	1.84	2.35	0.05	17.37	23.87	5.74
Hours								
1Q	12.46	0.43	1.48	6.40	0.35	44.87	20.20	13.82
4Q	11.88	0.61	2.69	2.61	0.11	44.94	24.08	13.09
8Q	10.72	1.27	2.25	1.84	0.12	42.50	29.75	11.56
16Q	9.29	1.49	1.95	1.95	0.11	37.54	37.68	9.99
24Q	8.68	1.42	1.81	1.96	0.11	34.75	41.45	9.83

Note: Columns 2 to 9 report the contributions of a patience shock (Patience), permanent and transitory shocks to neutral technology (Ngrowth and Nlevel), permanent and transitory shocks to biased technology (Bgrowth and Blevel), a housing demand shock (Housing), a labor supply shock (Labor), and a collateral shock (Collateral).

TABLE 4. Contributions (in percent) to investment fluctuations from a housing demand shock

Horizon	No patience	Latent IST	CoreLogic	High vol	Low vol
1Q	34.10	41.10	55.74	60.49	19.19
4Q	39.31	46.35	58.68	66.31	23.39
8Q	37.27	39.02	57.90	63.96	21.59
16Q	31.74	28.48	54.60	58.85	18.16
24Q	28.66	23.48	52.18	55.46	16.19

Note: The column "No patience" displays the results from the benchmark model with the patience shock removed; the column "Latent IST" reports the results from the benchmark model without fitting to the data on the relative price of investment goods; the column labeled by "CoreLogic" displays the results from the benchmark model with the Core Logic data on the land price; and the columns labeled by "High vol" and "Low vol" report the contributions under the high and low volatility regimes from the regime-switching benchmark model.
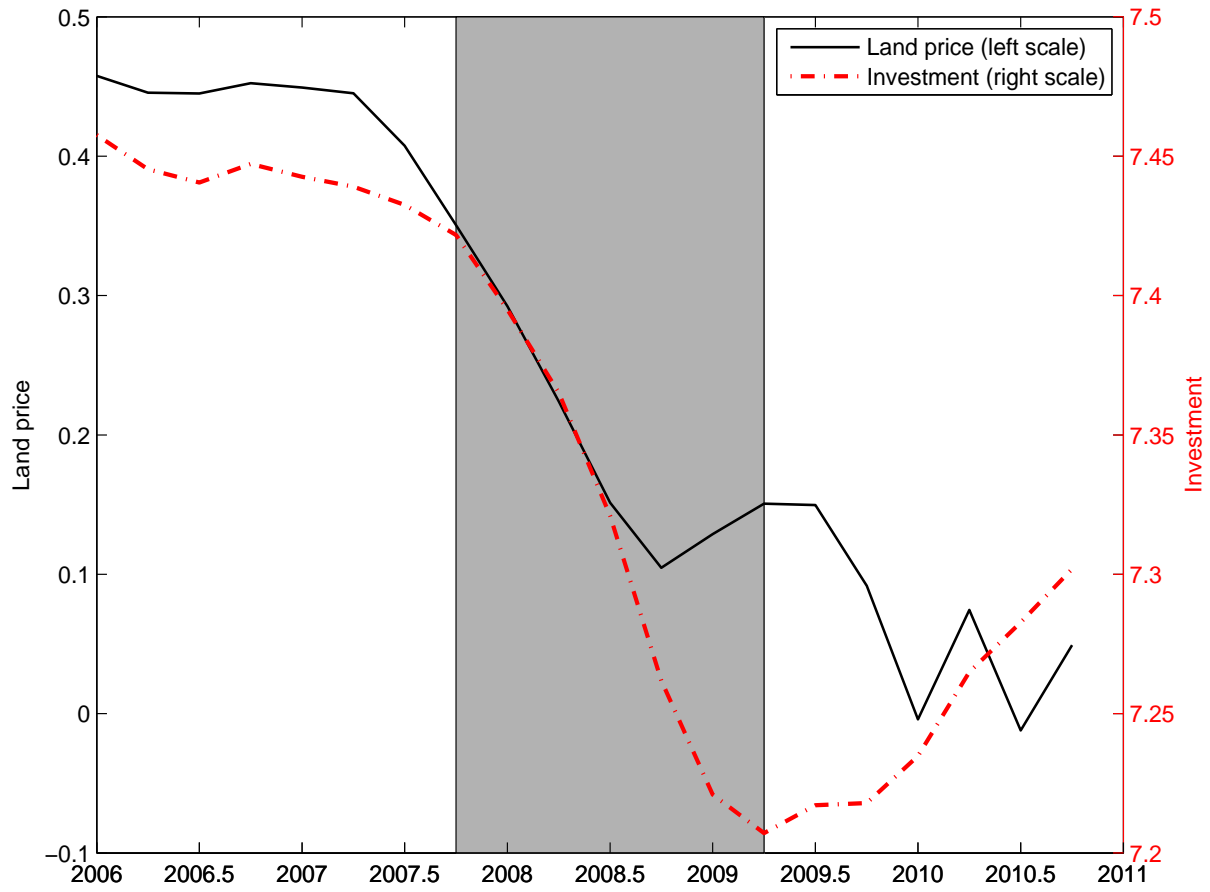
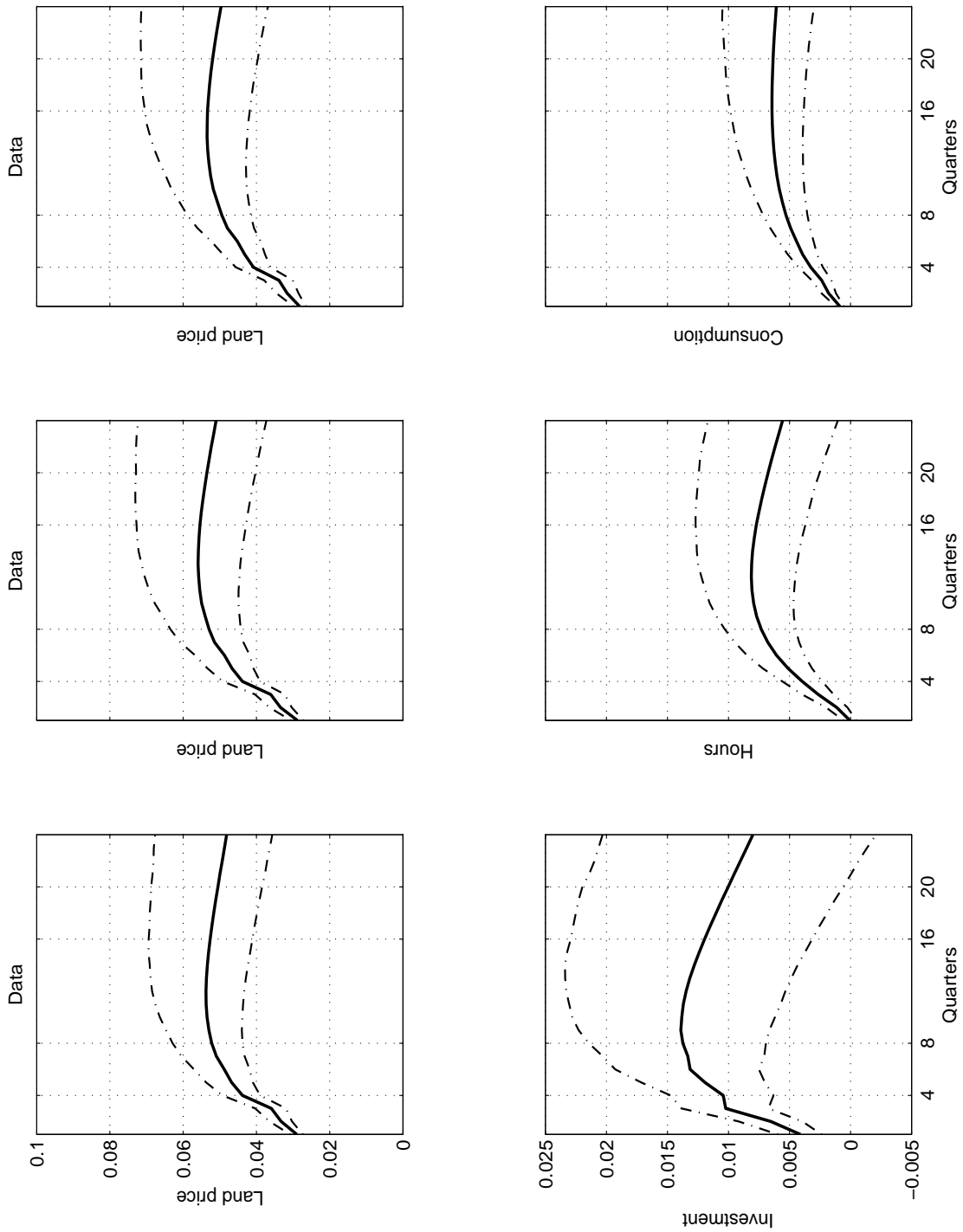FIGURE 1. The financial crisis episode: Log real land price and log investment.

FIGURE 2. Impulse responses from a recursive bivariate BVAR model with the land price ordered first. Each column displays impulse responses to a shock to the land price. Solid lines represent the estimated responses and dotted-dashed lines represent the 68% posterior probability bands.
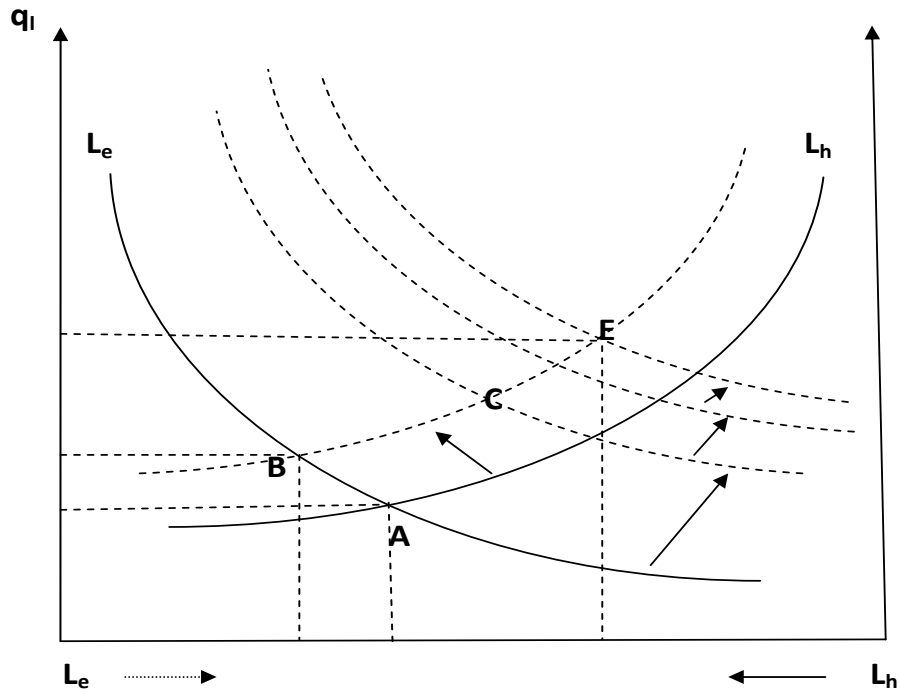
FIGURE 3. Dynamic financial multiplier: an illustration. L_h denotes the household's holding of land, L_e denotes the entrepreneur's holding of land, and q_l denotes the price of land.
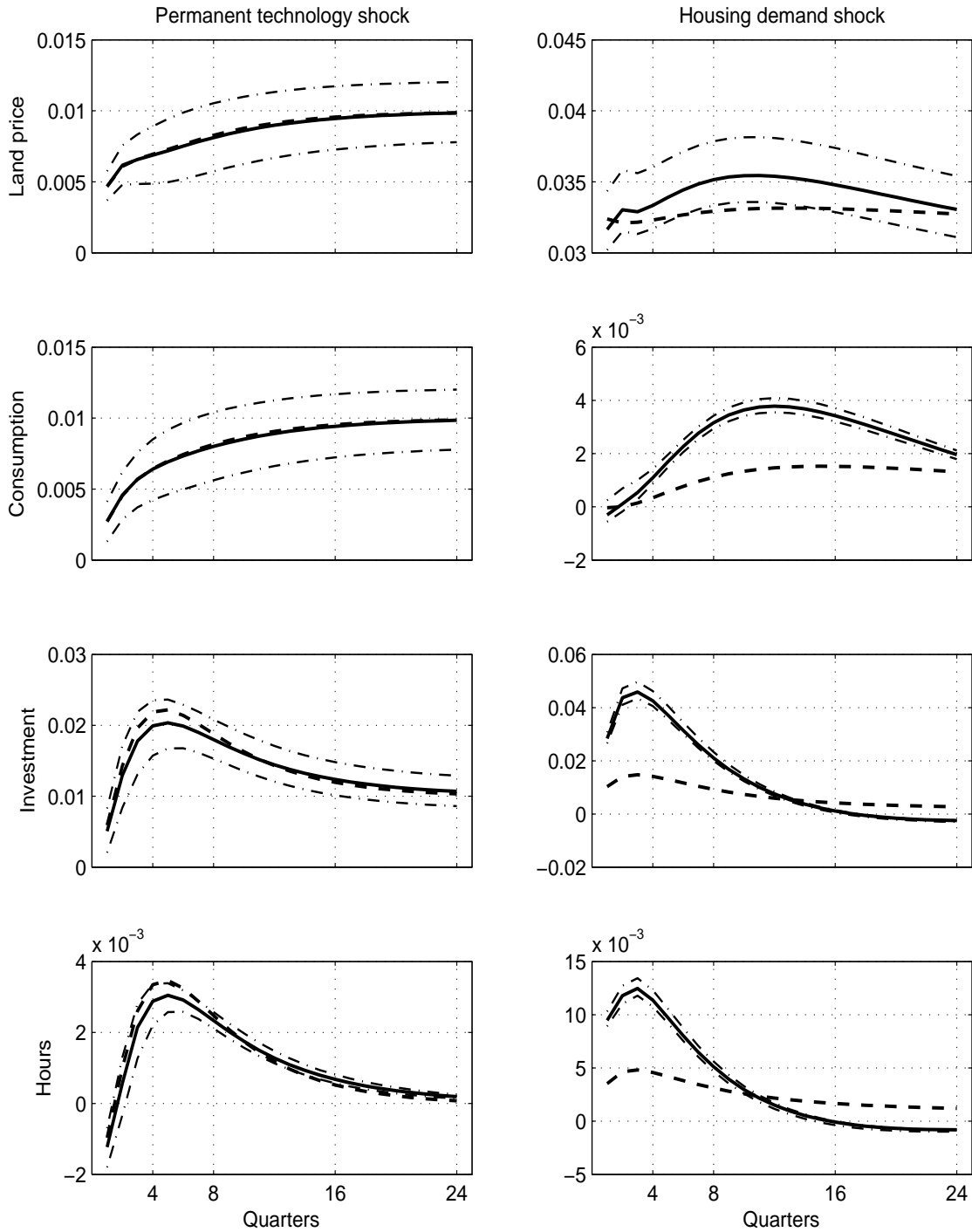
FIGURE 4. Impulse responses to a positive (one-standard-deviation) shock to neutral technology growth (left column) and to a positive (one-standard-deviation) shock to housing demand (right column). Thick solid lines represent the estimated responses and thin dotted-dashed lines demarcate the 68% probability bands. Thick dashed lines represent the responses in the counterfactual economy with fixed credit limit.
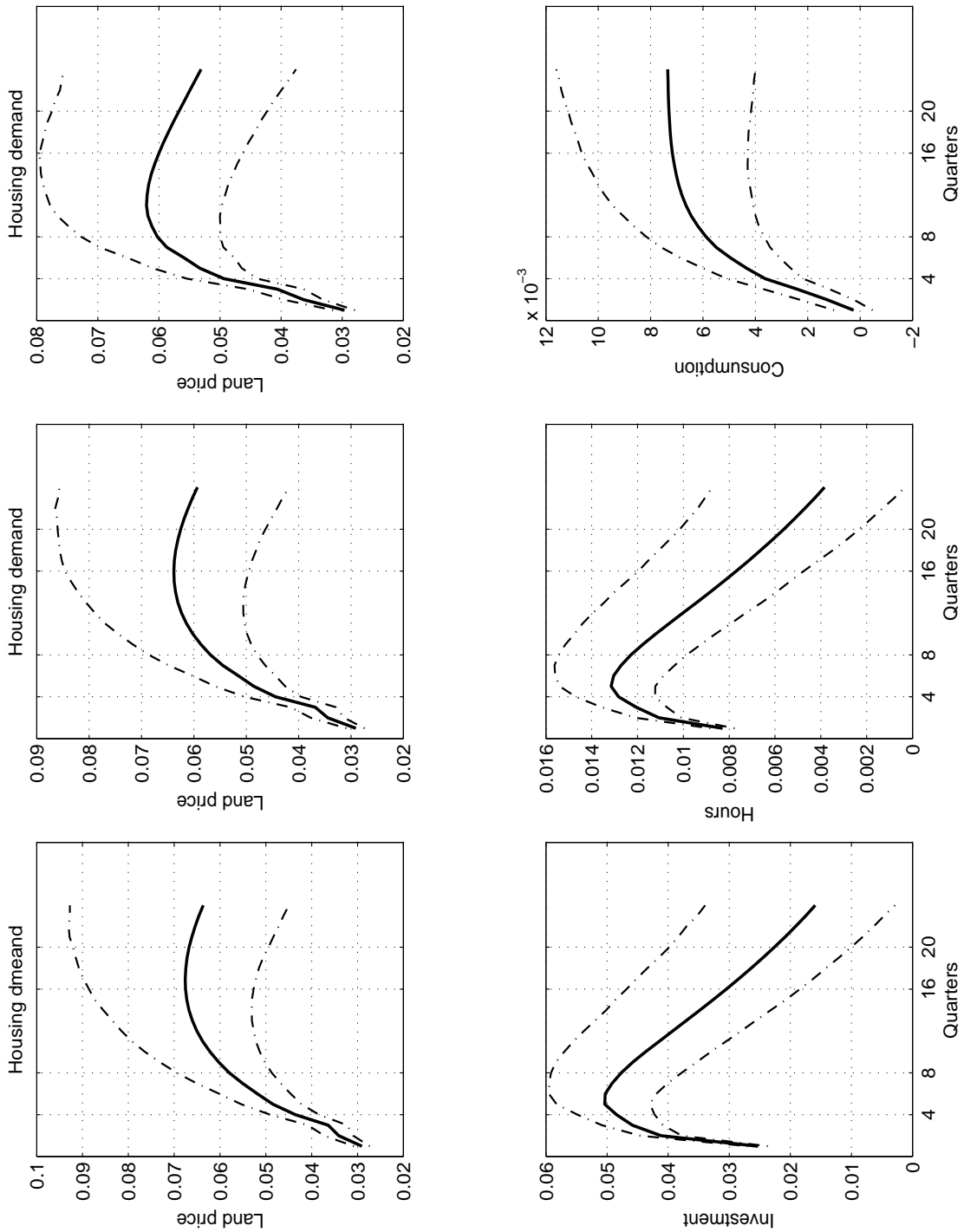
FIGURE 5. Impulse responses to a shock to the land price from a recursive bivariate BVAR model based on the simulated data from the benchmark DSGE model with estimated housing demand shocks only. Solid lines represent the estimated responses and dotted-dashed lines represent the 68% probability bands.
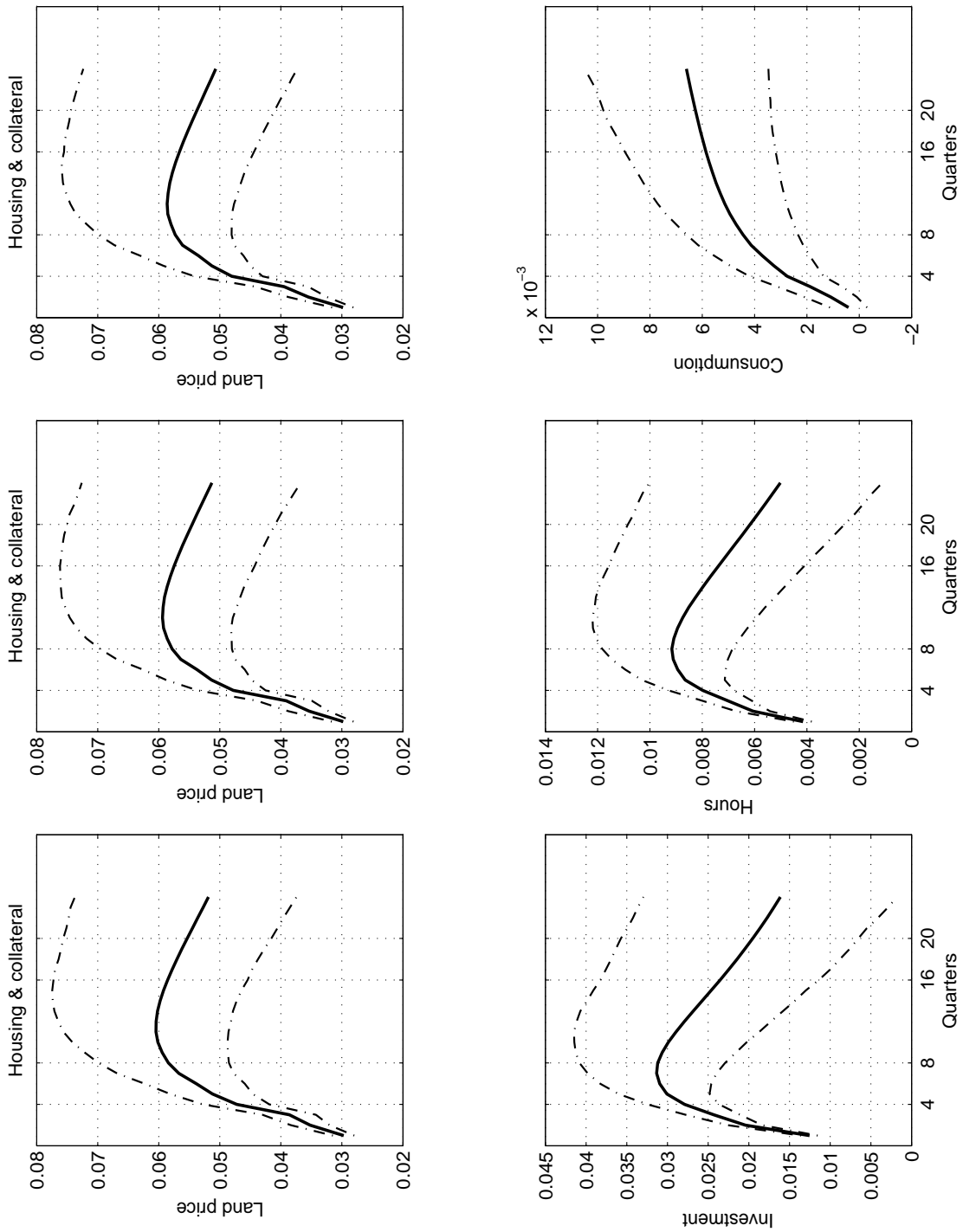
FIGURE 6. Impulse responses to a shock to the land price from a recursive bivariate BVAR model based on the simulated data from the benchmark DSGE model with estimated housing demand shocks and collateral shocks combined. Solid lines represent the estimated responses and dotted-dashed lines represent the 68% probability bands.
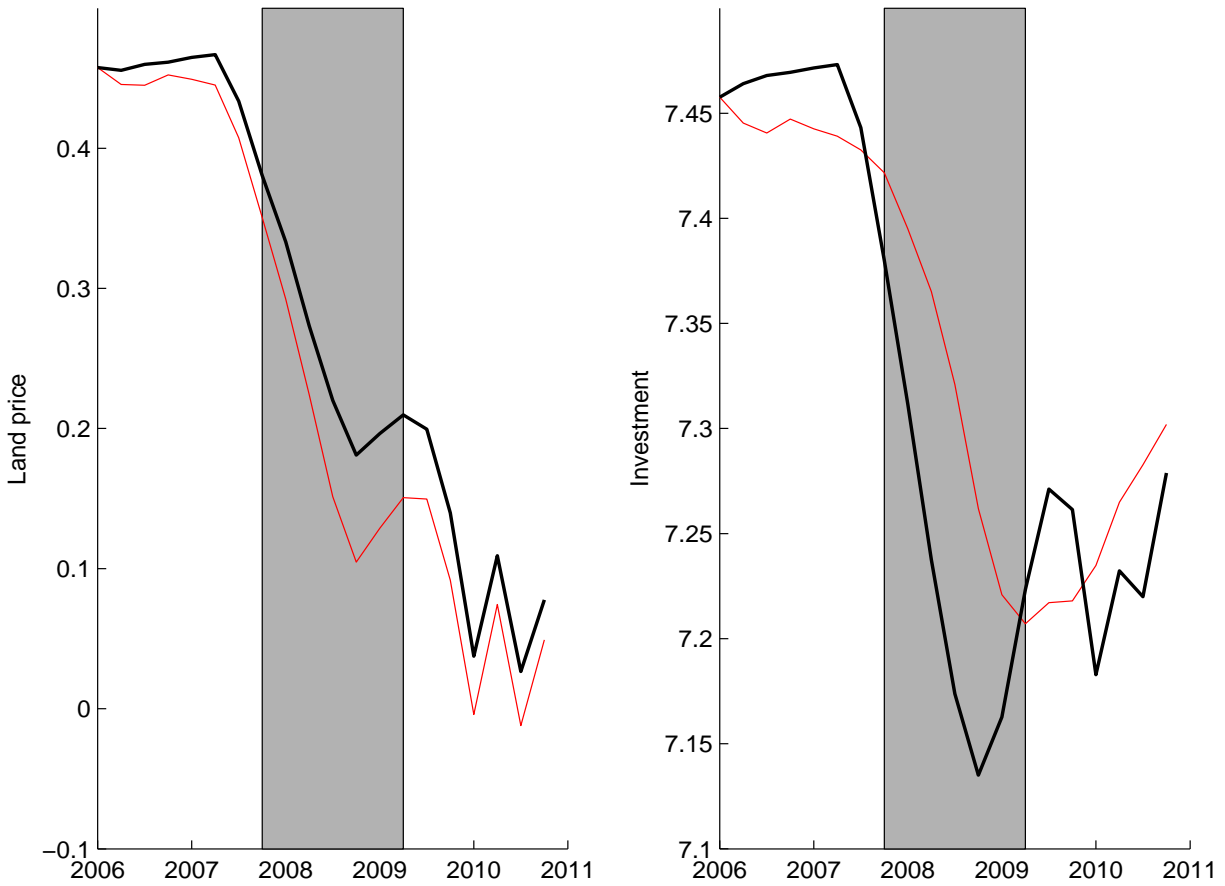
FIGURE 7. The financial crisis episode: Counterfactual paths of the land price and investment, conditional on estimated housing demand shocks only. Each graph shows the actual path in log value (thin line), counterfactual path from the benchmark model (thick line), and the Great Recession period (shaded area).
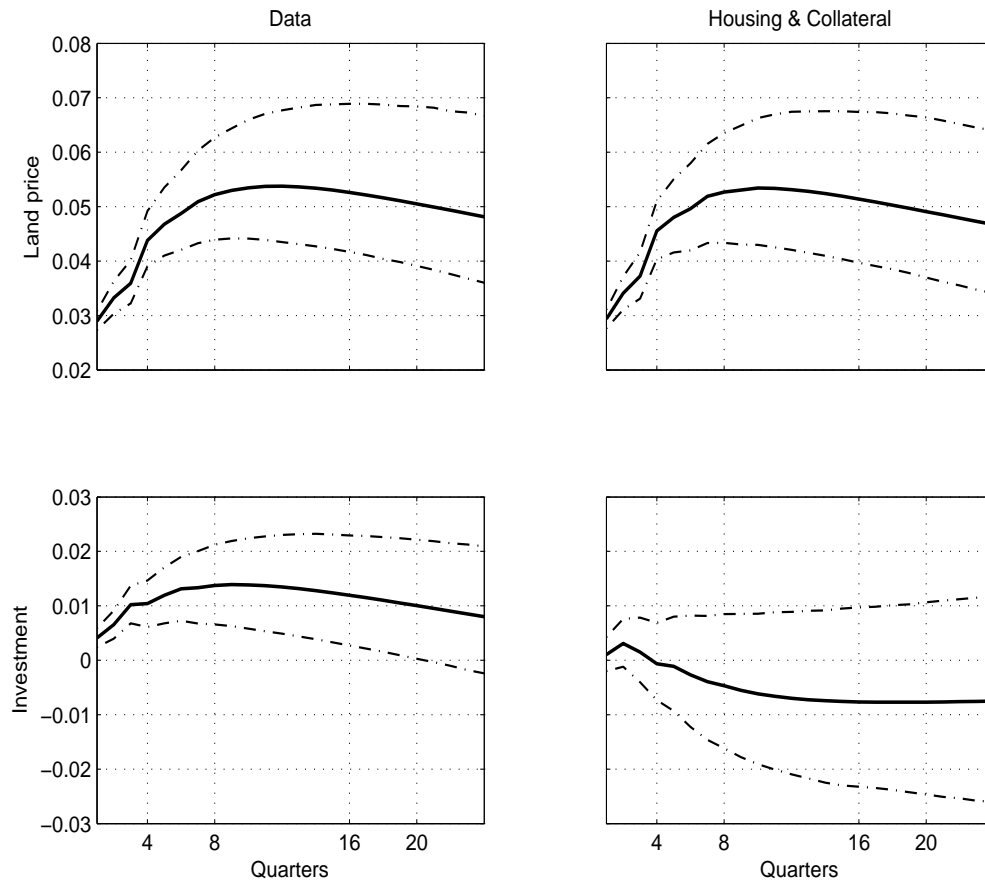
FIGURE 8. Impulse responses to a shock to the land price from a recursive bivariate BVAR model. Solid lines represent the estimated responses and dotted-dashed lines represent the 68% probability bands. The first column is based on the actual data. The second column on the counterfactual data generated with both housing demand and collateral shocks from the alternative model.
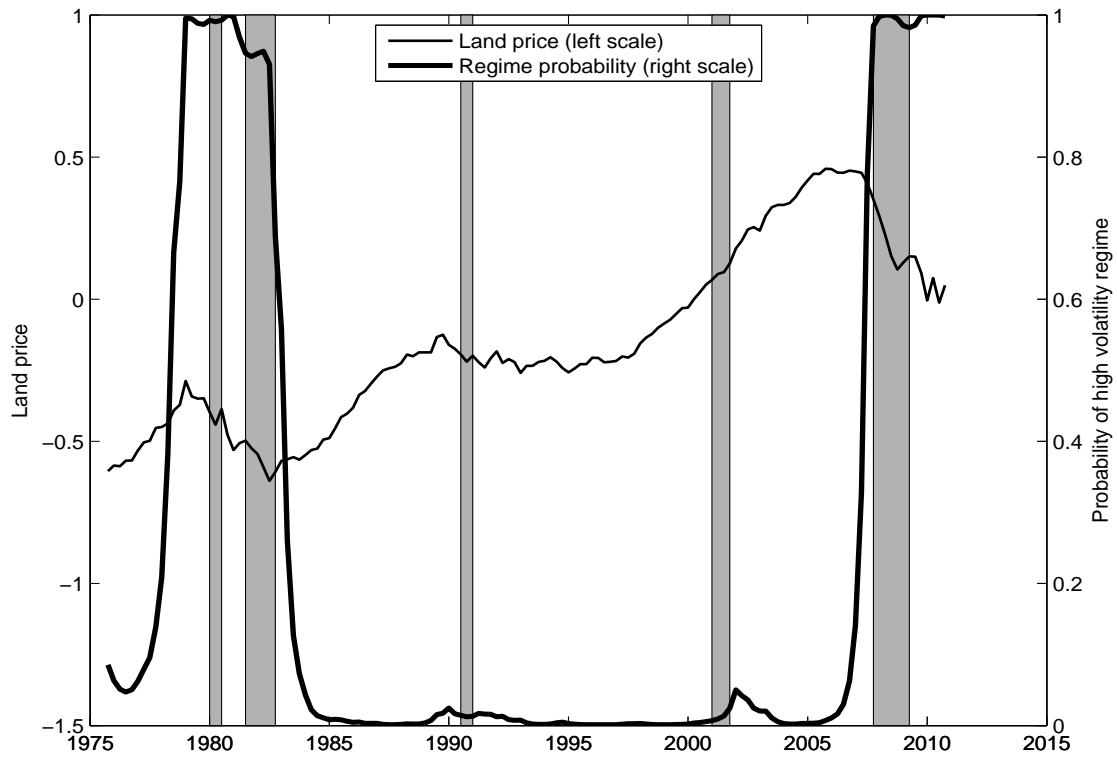
FIGURE 9. Log real land prices (left scale) and the posterior probability of the high-volatility regime estimated from the regime-switching model (right scale). The shaded area marks NBER recession dates.

APPENDIX A. DATA DESCRIPTION

All data are either taken directly from the Haver Analytics Database or constructed by Patrick Higgins at the Federal Reserve Bank of Atlanta. The construction methods are described below.

The model estimation is based on six U.S. aggregate variables: the relative price of land (q_{lt}^{Data}), the inverse of the relative price of investment (Q_t^{Data}), real per capita consumption (C_t^{Data}), real per capita investment in consumption units (I_t^{Data}), real per capita nonfinancial business debt (B_t^{Data}), and per capita hours (L_t^{Data}). All these series are constructed to be consistent with the corresponding series in Greenwood, Hercowitz, and Krusell (1997), Cummins and Violante (2002), and Davis and Heathcote (2007). The sample period covers the first quarter of 1975 through the fourth quarter of 2010.

These series are defined as follows:

- $q_{lt}^{\text{Data}} = \frac{\text{LiqLandPricesSAFHFASplice}}{\text{PriceNonDurPlusServExHous}}$;
- $Q_t^{\text{Data}} = \frac{\text{PriceNonDurPlusServExHous}}{\text{GordonPriceCDplusES}}$;
- $C_t^{\text{Data}} = \frac{(\text{NomConsNHSplusND})/\text{PriceNonDurPlusServExHous}}{\text{LNNReviseQtr}}$;
- $I_t^{\text{Data}} = \frac{(\text{CD@USECON} + \text{FNE@USECON})/\text{PriceNonDurPlusServExHous}}{\text{LNNReviseQtr}}$;
- $B_t^{\text{Data}} = \frac{(\text{PL10TCR5@FFUNDS} + \text{PL11TCR5@FFUNDS})/\text{PriceNonDurPlusServExHous}}{\text{LNNReviseQtr}}$;
- $L_t^{\text{Data}} = \frac{\text{LXNFH@USECON}}{\text{LNNReviseQtr}}$.

The original data, the constructed data, and their sources are described below.

LNNReviseQtr: Civilian noninstitutional population with ages 16 years and over by eliminating breaks in population from 10-year censuses and post 2000 American Community Surveys using the "error of closure" method. This fairly simple method is used by the Census Bureau to get a smooth monthly population series to reduce the unusual influence of drastic demographic changes. The detailed explanation can be found in `http://www.census.gov/popest/archives/methodology/intercensal\_nat\_meth.html`. Source: BLS.

PriceNonDurPlusServExHous: Consumption deflator. The Tornqvist procedure is used to construct this deflator as a weighted aggregate index from nondurables consumption and services (housing services excluded). Source: BEA.

LiqLandPricesSAFHFASplice: Liquidity-adjusted price index for residential land. The series is constructed in the following steps. We first adjust seasonally the FHFA Home Price Index (USHPI@USECON) for 1975Q1-1991Q1, spliced to be consistent with the Purchase Only FHFA Home Price Index (USPHPI@USECON) for 1991Q1 to present. We then use this home price index to construct the land price series with the Davis and Heathcote (2007) method (`http://www.marginalq.com/morris/landdata_files/2006-11-Davis-Heathcote-Land.appendix.pdf`). The

adjustment methods of Quart and Quigley (1989, 1991) are used to take account of time-on-market uncertainty. Finally, the CoreLogic land price index is constructed in the same way except that the FHFA Home Price Index is replaced by the CoreLogic Home Price Index. The CoreLogic home price index series provided by Core Logic Databases is similar to the Case-Shiller (CS) Home Price Index but covers far more counties than the CS series.

GordonPriceCDplusES: Quality-adjusted price index for consumer durable goods, equipment investment, and software investment. This is a weighted index from a number of individual price series within this category. For each individual price series from 1947 to 1983, we use Gordon (1990)'s quality-adjusted price index. Following Cummins and Violante (2002), we estimate an econometric model of Gordon's price series as a function of time trend and several macroeconomic indicators in the National Income and Product Account (NIPA), including the current and lagged values of the corresponding NIPA price series; the estimated coefficients are then used to extrapolate the quality-adjusted price index for each individual price series for the sample from 1984 to 2008. These constructed price series are annual. We use Denton (1971)'s method to interpolate these annual series at quarterly frequency. We then use the Tornquist procedure to construct the quality-adjusted price index from the interpolated individual quarterly price series. Source: BEA.

NomConsNHSplusND: Nominal personal consumption expenditures: non-housing services and nondurable goods. Source: BEA.

CD@USECON: Nominal personal consumption expenditures: durable goods. Source: BEA.

FNE@USECON: Nominal private nonresidential investment: equipment & software. Source: BEA.

PL10TCR5@FFUNDS: Nonfarm nonfinancial corporation business liabilities: credit market debt. Source: BEA.

PL11TCR5@FFUNDS: Nonfarm noncorporate business liabilities: credit market instruments. Source: BEA.

LXNFH@USECON: Nonfarm business sector: hours of all persons (1992=100). Source: BLS.

Appendix B. Prior Description

We partition the model parameters into three subsets. The first subset of parameters includes the structural parameters on which we have agnostic priors. This set of parameters, collected in the vector $\Psi_1 = \{\gamma_h, \gamma_e, \Omega, , g_\gamma, \bar{\lambda}_q\}$, consists of the habit persistence parameters

γ_h and γ_e, investment-adjustment cost parameter Ω, the growth rate of per capita output g_γ, and the growth rate of per capita investment $\bar{\lambda}_q$.

The second subset of parameters includes the structural parameters for which we use the steady-state relations to construct informative priors. This set of parameters, collected in the vector $\Psi_2 = \{\beta, \bar{\lambda}_a, \bar{\varphi}, \bar{\psi}, \phi, \alpha, \theta, \delta\}$, consists of the subjective discount factor β, the patience factor $\bar{\lambda}_a$, the housing preference parameter $\bar{\varphi}$, the leisure preference parameter $\bar{\psi}$, the elasticity parameters in the production function ϕ and α, the average loan-to-asset ratio θ, and the capital depreciation rate δ.

The third subset of parameters consists of those describing the shock processes.

For the first subset of parameters (i.e., those in Ψ_1), we assume that the priors for γ_h and γ_e follow the beta distribution with the shape parameters given by $a = 1$ and $b = 2$. Thus, we assign positive density to $\gamma_h = \gamma_e = 0$ and let the probability density decline linearly as the value of γ_h (or γ_e) increases from 0 to 1. These hyper-parameter values imply that a lower probability (5%) bound for γ_h and γ_e is 0.0256 and an upper probability (95%) bound is 0.7761. This 90% probability interval covers most calibrated values for the habit persistence parameter used in the literature (e.g., Boldrin, Christiano, and Fisher (2001) and Christiano, Eichenbaum, and Evans (2005)). The prior for the investment adjustment cost parameter Ω follows the gamma distribution with the shape parameter $a = 1$ and the rate parameter $b = 0.5$. These hyper-parameters imply that the probability density at $\Omega = 0$ is positive and that the 90% prior probability interval for Ω ranges from 0.1 to 6, which covers most values used in the DSGE literature (e.g., Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), and Liu, Waggoner, and Zha (Forthcoming)). The priors for the steady-state growth rates of output and of capital follow the gamma distribution with the 90% probability interval covering the range between 0.1 and 1.5, corresponding to annual growth rates between 0.4% and 6%. The prior distributions for the parameters in Ψ_1 are reported in the top panel of Table 1.

For the second subset of parameters (i.e., those in Ψ_2), we fix the values of 3 parameters and estimate the rest. In particular, we fix the value of α at 0.3, corresponding to an average

labor income share of 70%. We fix the value of $\bar{\theta}$ at 0.75, corresponding to an average loan-to-value ratio of 0.75, as in the data for the nonfarm nonfinancial business sector.[16] The value of $\bar{\psi}$ is adjusted so that the steady-state market hours are about 25% of time endowment.

To construct the prior distributions for the remaining 5 parameters in Ψ_2, we first simulate the parameters in Ψ_1 from their prior distributions and then, for each simulation, we impose the steady-state restrictions on both Ψ_1 and Ψ_2 such that the model matches the following moment conditions: (1) the average real prime loan rate is 4% per annum (Huggett, Ventura, and Yaron, 2009); (2) the capital-output ratio is on average 1.15 at annual frequency; (3) the investment-capital ratio is on average 0.209 at annual frequency; (4) the average ratio of commercial land to private output is about 0.65 at annual frequency; and (5) the average ratio of residential land to private output is about 1.45 at annual frequency.[17]

Since the prior distributions for the parameters in Ψ_2 are of unknown form, the 90% probability bounds, reported in Table 1 (the lower panel), are generated through simulations, with the simulated prior distributions reported in Table 1 (the lower panel). As shown in the table, the steady-state restrictions lead to informative probability intervals for the marginal prior distributions of the parameters and thus help identify the structural parameters in Ψ_2. Our method for constructing the prior distributions for Ψ_2 is similar to the approach studied by Del Negro and Schorfheide (2008), who combine the Baynesian approach and the standard calibration approach for eliciting priors.

The third subset of parameters are summarized by $\Psi_3 = \{\rho_i, \sigma_i\}$ for $i \in \{a, z, \nu_z, q, \nu_q, \varphi, \psi, \theta\}$, where ρ_i and σ_i denote the persistence parameters and the standard deviations of the eight

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[16]We measure business debt by the sum of credit market instruments for nonfarm nonfinancial corporate businesses and those for nonfarm noncorporate businesses. We measure the assets for these firms by the value of commercial land and equipment and software. Given the reported value of commercial real estate in the Flow of Funds tables, we impute the value of land by multiplying the value of real estate by 0.5. This calculation implies a ratio of business debt to tangible assets (i.e., land plus equipment and software) of about 0.75. Since measures of land value are extremely fragmentary and noisy as we discuss in Supplemental Appendix II, it is possible that our imputation overstates the land share in real estate and thus the actual loan-to-value ratio might be higher than 0.75.

[17]Since we have a closed-economy model with no government spending, we measure private domestic output by a sum of personal consumption expenditures and private domestic investment. Consumption is the private expenditures on nondurable goods and non-housing services. Investment is the private expenditures on consumer durable goods and fixed investment in equipment and software. These time series are provided by the Bureau of Economic Analysis (BEA) through Haver Analytics. Accordingly, we measure capital stock using the annual stocks of equipment, software, and consumer durable goods. We measure the value of land in the household sector based on annual stocks of residential assets. The commercial land-output ratio corresponds to ratio of the nominal value of land input and the nominal value of output in the private nonfarm and nonfinancial business sector for the period 1987-2007 taken from the Bureau of Labor Statistics (BLS).

structural shocks. We adopt agnostic priors for these parameters. Specifically, the priors for the persistent parameters follow the beta distribution with the 90% probability interval given by $[0.0256, 0.7761]$; the priors for the standard deviations follow the inverse gamma distribution with the 90% probability interval given by $[0.0001, 2.0]$. We have examined the sensitivity of our estimates by extending both the lower and the upper bounds of this interval and found that the results are not sensitive.

Appendix C. What is a housing demand shock?

Given the central role that housing demand shocks play in our model, it is useful to discuss what this type of financial shocks might represent. One interpretation is that a housing demand shock simply represents an exogenous shift in the household's taste for housing services. Iacoviello and Neri (2010) present evidence that supports this view.

Another interpretation is that a housing demand shock in our stylized aggregate model, like any shocks in the model including different technology shocks, is a reduced form representation of frictions or some "deeper" shocks that are outside of the model. In Liu, Wang, and Zha (2009c), we present a theory of housing demand shocks. In particular, we consider an economy with heterogeneous households who experience idiosyncratic and uninsurable liquidity shocks and who face collateral constraints in borrowing. In the aggregated version of that model, there is a term in the housing Euler equation that corresponds to housing demand shocks in our current model. We show that this term is a decreasing function of the tightness of the collateral constraints (i.e., the loan-to-value ratios) at the micro-level. Thus, financial innovations or de-regulations that relax the households' collateral constraints and expand the households' borrowing capacity in the disaggregated model would translate into a positive housing demand shock at the aggregate level. This interpretation is consistent with the findings in Favilukis, Ludvigson, and van Nieuwerburgh (2011), who report that shocks to the loan-to-value ratios (which they interpret as changes in financial regulations) are important for generating fluctuations in the house price-rent ratio.

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