Econometrica, Vol. 81, No. 3 (May, 2013), 1147–1184

LAND-PRICE DYNAMICS AND MACROECONOMIC FLUCTUATIONS

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We argue that positive co-movements between land prices and business investment are a driving force behind the broad impact of land-price dynamics on the macroeconomy. 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.

KEYWORDS: Land prices, co-movements, competing demand for land, collateral channel, reallocation channel.

1. 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 dynamic links between land-price dynamics and macroeconomic

[1]We are grateful to four referees and the editor for instrumental comments and suggestions, which have led to a significant improvement of this paper. An earlier version of this paper was entitled "Do Credit Constraints Amplify Macroeconomic Fluctuations?" (Liu, Wang, and Zha (2009a)). For helpful discussions, we thank Susanto Basu, Larry Christiano, Russell Cooper, Morris Davis, Steve Durlauf, Marty Eichenbaum, John Fernald, Kris Gerardi, Mark Gertler, Simon Gilchrist, Mike Golosov, Pat Higgins, Matteo Iacoviello, Nobu Kiyotaki, Dirk Krueger, Junior Maih, Jim Nason, Lee Ohanian, Alberto Oritz-Bolanos, Sergio Rebelo, Richard Rogerson, Julio Rotemberg, Tom Sargent, Frank Schorfheide, Chris Sims, Mark Spiegel, Harald Uhlig, Dan Waggoner, Carl Walsh, Yi Wen, John Williams, and seminar participants at Federal Reserve Banks of Atlanta and San Francisco, the 2009 NBER Summer Workshop on Impulse and Propagation Mechanisms, University of Pennsylvania, University of Wisconsin, Georgetown University, UCLA, UCSD, UC Riverside, UC Santa Cruz, UC Davis, USC, the European University Institute, Banque de France, Bank of New Zealand Conference on Twenty Years of Inflation Targeting. We thank David Lang, Jacob Smith, and Diego Vilan for research assistance, and Anita Todd and Sam Zuckerman for editorial assistance. Wang acknowledges the financial support from Hong Kong Research Grant Council (Project 643908). Zha thanks the National Science Foundation for research support (Grant 1127665). The views expressed herein are those of the authors and do not necessarily reflect the views of the Federal Reserve Banks of Atlanta and San Francisco or the Federal Reserve System or the National Bureau of Economic Research.

 DOI: 10.3982/ECTA8994

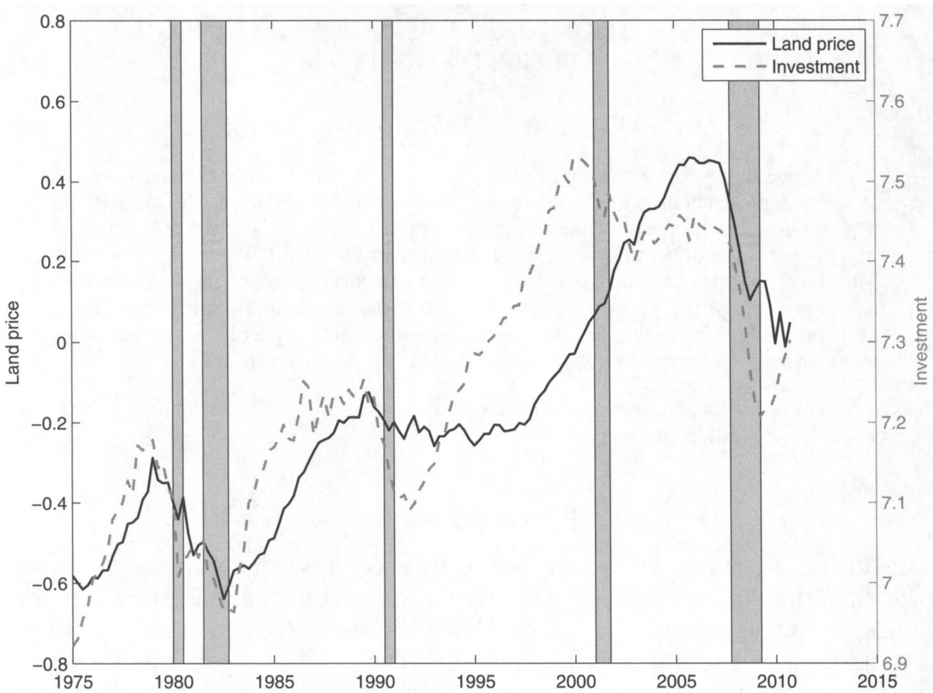

FIGURE 1.—Real land price and investment (both in log units). The shaded bars mark the NBER recession dates.

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 empirical 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.[2] Figure 2 displays the estimated impulse responses of real land prices, business investment, consumption of nondurables and services, and aggregate labor hours following a shock to the land-price series. These impulse responses are estimated from a four-variable Bayesian vector autoregression (BVAR) model with the Sims and Zha (1998) prior. A positive shock to land prices leads to persistent increases not just in land prices, but also in all the macroeconomic variables. The co-movement between land prices and business investment is particularly evident.

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 as-

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

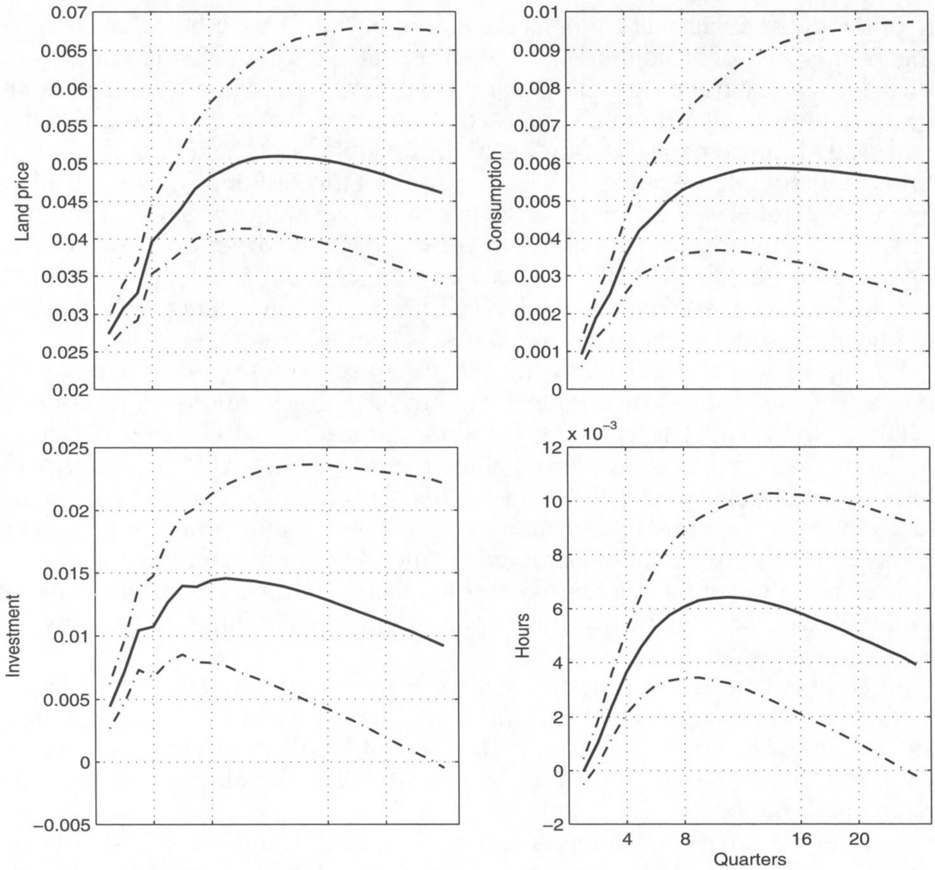

FIGURE 2.—Impulse responses to a shock to the land price from a recursive BVAR model with the land price ordered first. Solid lines represent the estimated responses and dotted-dashed lines represent the 68% probability bands.

sumes 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 firms on their balance sheets. According to the Flow of Funds tables provided by the Federal Reserve Board, tangible assets (the sum of real estate, equipment, and software) average about two-thirds of total corporate assets for the period from 1952 to 2010, 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).

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 (2012) found that, over the 1993–2007 period, a dollar increase in real estate value enables a representative U.S. corporate firm to raise investment by six cents. They further showed that the impact of real estate shocks on investment is stronger when estimated on a group of firms that is more likely to be credit constrained. While the authors cautioned against a direct translation of the micro estimates to macroeconomic effects, their micro evidence suggests that shocks to real estate prices have important effects on aggregate investment.[3]

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 in the Flow of Funds tables, constitute compelling evidence that land provides important collateral value for business investment spending.

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

[3]Complementary to the study by Chaney, Sraer, and Thesmar (2012) for U.S. firms, Gan (2007) showed 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%.

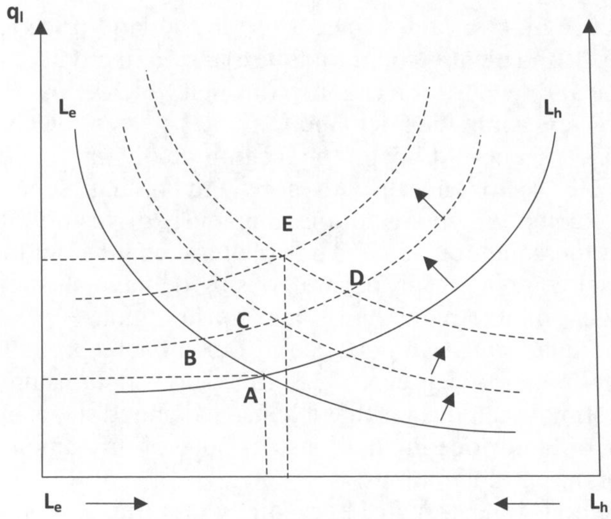

FIGURE 3.—Dynamic financial multiplier: An illustration. L_h denotes the household's holding of land, L_e denotes the entrepreneur's holding of land, and q_l denotes the price of land.

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 values. In this case, the initial rise in land prices through the shift in the household's land demand raises the entrepreneur's net worth and expands the entrepreneur's borrowing capacity. The expansions of net worth and credit shift the entrepreneur's land demand curve upward, triggering competing demand for land between the two sectors. This competing demand for land results 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 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 raises the current land price and thus relaxes the firm's credit constraint further, creating a ripple effect (from point C to point D). The expansion in production raises the household's wealth and shifts the household's land demand curve further up, reinforcing the rise in the land price (from point D to point E).

The mechanism described here contains two separate channels that reinforce each other. The first is a collateral channel, through which the land price affects macroeconomic variables since a rise in the land price raises the borrowers' net worth and creates room for an expansion in credit and production. The second is a land reallocation channel, through which a positive housing demand shock triggers competing demand for land between the constrained and the unconstrained agents. Although the magnitude of land reallocation is ambiguous, and which sector ends up with more land holdings depends on parameter values, the competing demand unambiguously drives up the equilibrium land price and the collateral value. The collateral channel and the land reallocation channel combine to propagate housing demand shocks into a broad economic impact on investment, hours, and consumption.

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

Our work belongs to a strand of burgeoning literature that incorporates financial frictions into DSGE models (examples include Carlstrom and Fuerst (1997), Cooley, Marimon, and Quadrini (2004), De Fiore and Uhlig (2005), Gertler, Gilchrist, and Natalucci (2007), and He, Wright, and Zhu (2011)). 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 in 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) built on BGG and examined the empirical importance of the financial accelerator using time series data from the United States and the euro area. Gilchrist, Ortiz, and Zakrajsek (2009) examined 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 (2012) found that a financial shock that affects firms' borrowing ability has a large impact on employment and aggregate output. Pintus and Wen (2010) argued that interactions between habit persistence and credit constraints help propagate business cycle shocks. Del Negro, Eggertsson, Ferrero, and Kiyotaki (2010) introduced nominal rigidities into the model of Kiyotaki and Moore (2008) to examine the effectiveness of unconventional monetary policy.[4]

Our paper has a different emphasis than the 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

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

of a shock that primarily influences land prices into macroeconomic fluctuations.

2. 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.[5]

2.1. *The Representative Household*

The household has the utility function

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

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 independent and identically distributed (i.i.d.) standard normal process.

[5]In Liu, Wang, and Zha (2009b), we provided a micro-foundation for the representative household's patience factor. In particular, we considered an economy with heterogeneous households and entrepreneurs, where the households face uninsurable idiosyncratic income risks and thus have a precautionary motive for saving. We showed 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 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.

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

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

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

2.2. *The Representative Entrepreneur*

The entrepreneur has the utility function

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

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

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

where Y_t denotes output, K_{t-1}, N_{et}, and $L_{e,t-1}$ denote the inputs of 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

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

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 ν_{qt} 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

$$B_t \le \theta_t \mathrm{E}_t[q_{l,t+1} L_{et} + q_{k,t+1} K_t], \tag{14}$$

where $q_{k,t+1}$ is the shadow price of capital in consumption units.[6] 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

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

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).

2.3. *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

[6]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.

the prices as given, the allocations solve the optimizing problems for the household and the entrepreneur, and (ii) all markets clear.

3. ESTIMATION

We log-linearized the model around the steady state in which the credit constraint is binding. We fit the log-linearized model to six 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. We estimate the model using the Bayesian method. The prior distributions are summarized in Table I. Appendices A and B provide more detailed descriptions of the data and the prior distributions.

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 (Sims and Uhlig (1991), Sims and Zha (1999)).

Table I reports the estimates of structural parameters at the posterior mode, along with 90% posterior probability intervals (the last three columns). Table II reports the estimates of shock parameters, along with 90% probability intervals.

According to Table I, the estimated habit parameters indicate 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 esti-

TABLE I

PRIOR AND POSTERIOR DISTRIBUTIONS OF STRUCTURAL PARAMETERS[a]

	Prior					Posterior		
Parameter	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

[a]"Low" and "High" denote the bounds of the 90% probability interval for the prior distribution.

TABLE II

PRIOR AND POSTERIOR DISTRIBUTIONS OF SHOCK PARAMETERS[a]

	Prior					Posterior		
Parameter	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

[a]"Low" and "High" denote the bounds of the 90% probability interval for the prior distribution.

mated investment adjustment cost parameter ($\Omega = 0.18$) is much smaller than the values reported in the DSGE literature without financial frictions.[7]

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.[8] The estimated values of β, $\bar{\varphi}$, ϕ, and δ are broadly in line with those reported in the literature (Iacoviello (2005)).

Table II shows that the two estimated financial shocks—a housing demand shock and a collateral shock—are both persistent and have large standard deviations relative to other shocks. The housing demand shock process is estimated to be very persistent mainly because the land price is a very persistent series. The 90% probability intervals indicate that all parameters in the model are tightly estimated.

[7]The DSGE literature without financial frictions reports a wide range of the estimated values of the investment adjustment cost parameter. For example, the estimated value of Ω is about 2.48 in Christiano, Eichenbaum, and Evans (2005), 5.48 in Smets and Wouters (2007), and about 2.00 in Liu, Waggoner, and Zha (2011). These estimates are all substantially larger than what we obtain in our model with credit constraints.

[8]Appendix D of the Supplemental Material (Liu, Wang, and Zha (2013)) describes our derivations of the first-order excess return.

4. 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.

4.1. *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 III reports variance decompositions

TABLE III

VARIANCE DECOMPOSITIONS OF AGGREGATE QUANTITIES[a]

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

[a]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).

for the land price and several key macroeconomic variables across the eight 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 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 (2011)). As we discuss in Section 5.5, 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 total factor productivity (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 reported weak amplification and propagation effects of credit constraints following a TFP shock.

Similarly 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 land 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%).

Similarly 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 nonnegligible 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 (2012), who showed that financial shocks that affect firms' ability to borrow play an important role for business cycles.

4.2. *What Shocks Drive the Land Price?*

Estimated variance decompositions show that a housing demand shock is the primary force driving fluctuations in 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 argued, 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.[9]

4.3. *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

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

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.

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 (Point B) and the entrepreneur's net worth, triggering competing demand for land between the two sectors that drives up the land price further (Point C). Consequently, business investment and production expand. The expansion adds to household wealth and raises the land price further (Point E). This ripple effect continues to propagate the macroeconomy through the dynamic interactions between the land price and investment, as shown by our empirical evidence presented in Section 4.4.

The mechanism described above is based on two channels that reinforce each other. The first is the collateral channel through which land prices influence the entrepreneur's net worth. The second is the land reallocation channel through which competing demand for a fixed amount of land between the two sectors unambiguously raises the land price.

This second channel works in the following way. When the entrepreneur's net worth increases following an increase in the land price, the entrepreneur is able to borrow more to finance investment and production. As production expands, the entrepreneur needs to acquire more land and labor (as well as capital), triggering competing demand for land between the two sectors (between Points B and C or between Points D and E in Figure 3) and further pushing up the land price. Although the extent to which land is reallocated depends on parameter values, the competition for land between the two sectors raises the land price unambiguously. In fact, as illustrated in Figure 3, our model has the property that the smaller the amount of land reallocation in equilibrium, the greater the impact of housing demand shocks on the land price. In our estimated model, the entrepreneur ends up with owning moderately more land in equilibrium (with an increase in the entrepreneur's land holdings of a bit less than 3% of total land). The two channels—the land reallocation and the collateral constraint—reinforce each other and lead to dynamic expansions of investment, hours, and output as the land price increases.[10]

4.4. *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 where the credit limit is endogenously determined with those in a counterfactual economy where the credit limit is exogenously fixed. 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 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 re-

[10]In Appendix E of the Supplemental Material, we present some quantitative results on land reallocation in our estimated model. We also discuss limitations of the available land quantity data, which prevent us from directly confronting the model's implications for land reallocation against the data.

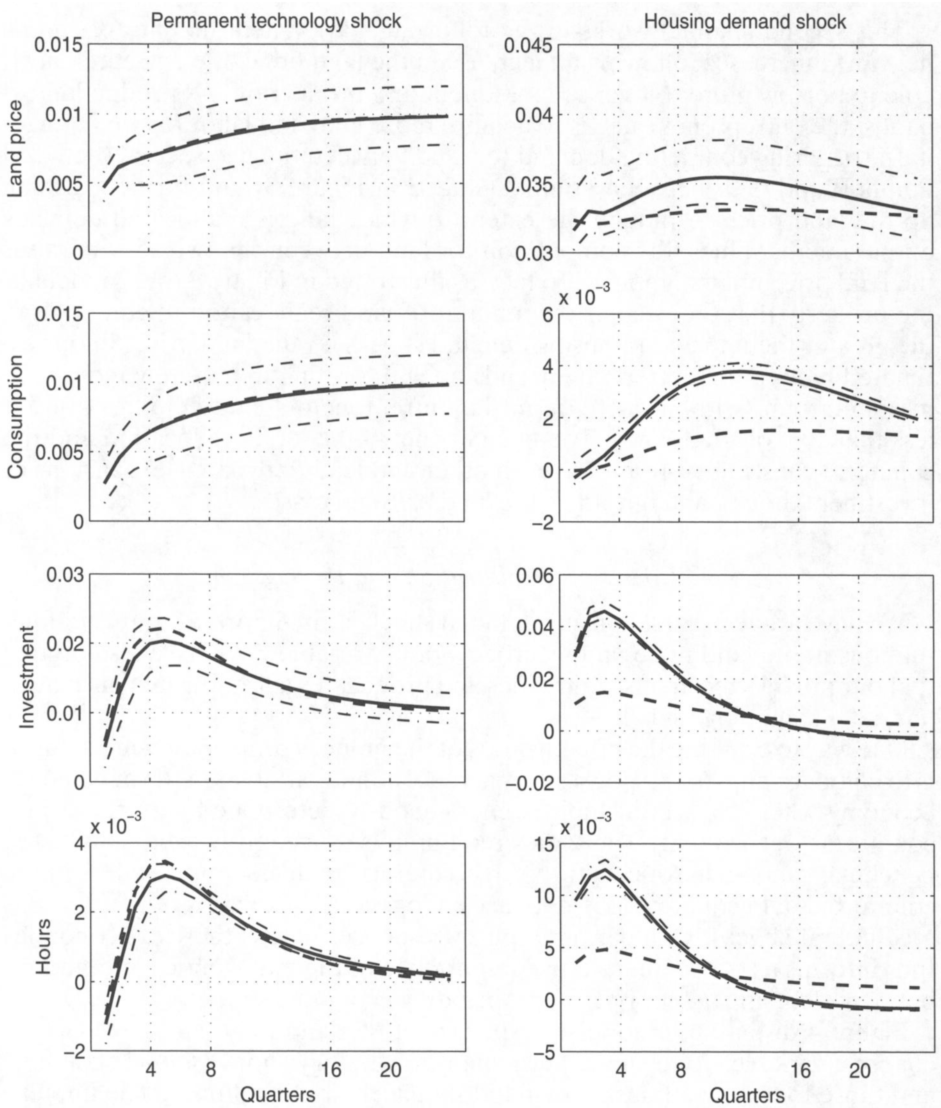

FIGURE 4.—Impulse responses to a positive (one standard deviation) shock to neutral technology growth (left column) and to a positive (one standard deviation) shock to housing demand (right column). Thick solid lines represent the estimated responses and thin dotted-dashed lines demarcate the 68% probability bands. Thick dashed lines represent the responses in the counterfactual economy with fixed credit limit.

sult 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 does not lift land prices.

In contrast, credit constraints do propagate the effects of a housing demand shock, as is evident in the right column of Figure 4. Consistent with the intuition described in Section 4.2, the housing demand shock generates much larger fluctuations in the land price than does the TFP shock. More importantly, the housing demand shock drives much larger responses of consumption, investment, and labor hours in the benchmark model (solid lines) than in the counterfactual economy (dashed lines).[11] Credit constraints are thus very effective in propagating a housing demand shock because the shock directly affects 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, however, 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 increases investment responses to a shock that raises the land price.[12]

4.5. *Shedding Light on the Great Recession*

As discussed in the Introduction, our study is motivated by the collapse in land prices and the subsequent sharp contraction in macroeconomic activity during the Great Recession. 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 declines in land prices and business investment observed in the Great Recession?

[11]Since capital and land inputs are predetermined, labor demand is unchanged in the impact period of a housing demand shock. Thus, the initial rise in labor hours is a consequence of a shift in labor supply: as the land price rises, the household is willing to work harder for intertemporal smoothing of housing consumption. This effect on labor supply is reinforced by a large initial response of the entrepreneur's net worth to the rise of the land price. Unlike the representative agent model, an increase in the entrepreneur's wealth (net worth) drives up the demand for loans and results in an increase of the loan rate. The rise of loan demand strengthens the household's willingness to work harder to supply more loans. The persistent increase of the land price sustains the rise of the entrepreneur's wealth. As the entrepreneur's production and investment expands as a consequence of increased collateral value, labor demand rises persistently as well.

[12]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 (2012) showed that, for financial shocks to have an impact on real variables (such as employment), it is important to incorporate costly adjustments in dividend payout.

To quantify the model's ability in explaining the history, we calculate what would have happened if only the housing demand 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 sequence of housing demand shocks and the estimates of model parameters, we simulate the data from our DSGE model.

Figure 5 shows the counterfactual paths of land prices and business investment (thick lines) along with the actual paths in the data (thin lines). The counterfactual paths generated from the DSGE model driven by housing demand shocks track the actual paths in the data fairly well. The sharp declines in land prices in the Great Recession period are mostly accounted for by housing demand shocks (see the left panel of the figure). The effects of these shocks are propagated to generate large declines in business investment, with the magnitude of declines similar to what we observe in the Great Recession (see the right panel of the figure).

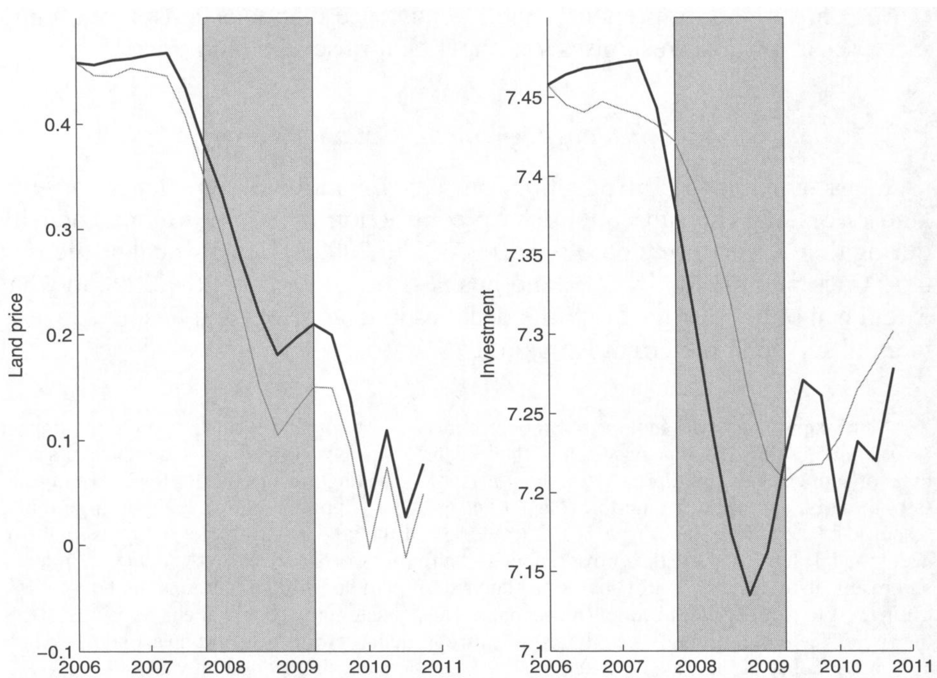

FIGURE 5.—The financial crisis episode: Counterfactual paths of the land price and investment, conditional on estimated housing demand shocks only. Each graph shows the actual path in log value (thin line), counterfactual path from the benchmark model (thick line), and the Great Recession period (shaded area).

Although our estimation indicates that the collateral channel provides an empirically important link between land prices and macroeconomic activity, it is clearly not the only mechanism that connects the collapse in the housing market to the sharp contraction in macroeconomic activity in the Great Recession. For example, Gorton and Metrick (2012) argued that the loss of investor confidence following the housing market collapse led to a drying up of liquidity and a run on the repo market. Financial instruments previously perceived as liquid, such as mortgage-backed securities and collateralized debt obligations, became illiquid. Adrian and Shin (2010) argued that the decline in the value of these securities may have caused a deterioration in the balance sheet of financial intermediaries and set off a chain of tightening in lending. Thus, the link between land prices and macroeconomic fluctuations is broader than the propagation mechanism emphasized in this paper.

5. SENSITIVITY

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

5.1. *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 (2013)). While heterogeneity abounds with man-made rules and geographic factors, Davis and Heathcote (2007) showed that *aggregate* land supply grows very slowly. Taking into account population growth, per capita 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]

5.2. *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

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

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

We reestimate 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 (see Section F.1 of the Supplemental Material).

5.3. *External Capital Producers*

Our collateral constraint is based on the market price of land and the shadow value of capital. Since the entrepreneur faces internal adjustment costs for capital, capital as a collateral asset is not as pledgeable as is land. To what extent do our results depend on this particular specification of the collateral constraint?

To answer this question, we study an alternative model in which capital is produced by a competitive sector and the capital producer is owned by the

[13]In Appendix F of the Supplemental Material, 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.

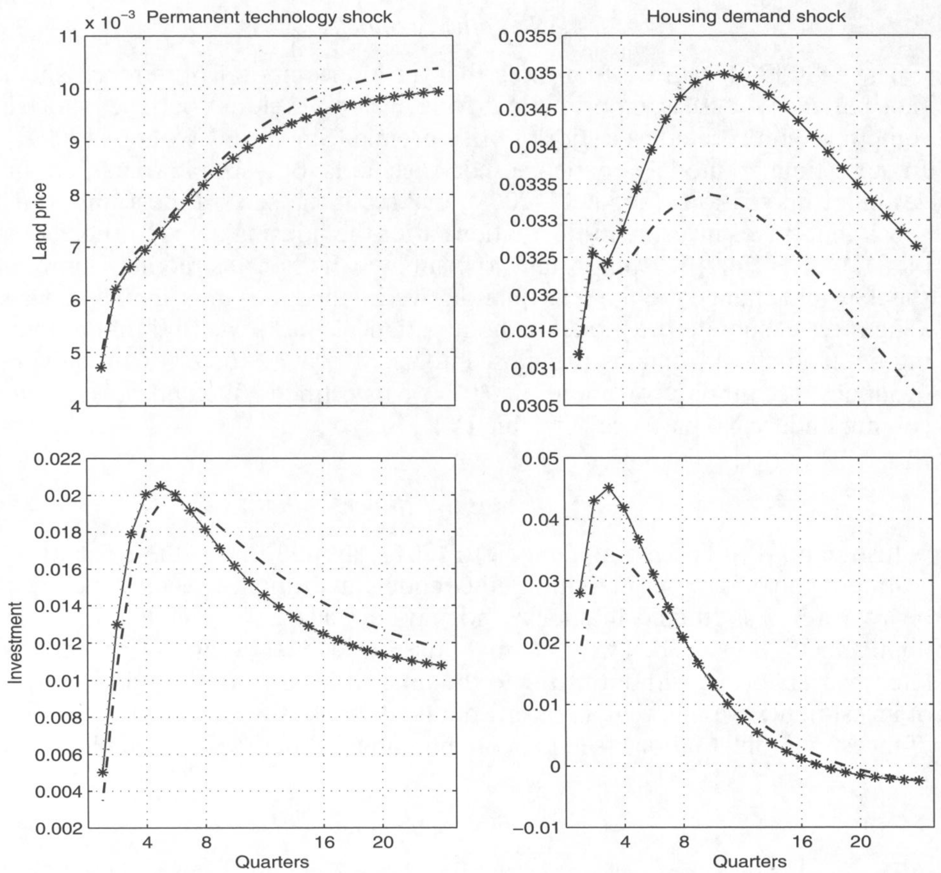

FIGURE 6.—Impulse responses to a positive shock to neutral technology growth (left column) and to a positive shock to housing demand (right column). The lines marked with asterisks represent the responses in the benchmark model; the dotted-dashed lines represent those in the model with flexible weights on land and capital in the collateral constraint; the dotted lines represent those in the model with capital adjustments external to the entrepreneur. Note that the dotted lines overlap the lines with asterisks in some of the figures.

household. In that model, the capital price reflects the market value of capital rather than the shadow value. Thus, capital and land are equally pledgeable. We estimate the alternative model to fit the same set of time series data. The estimation results are almost identical to those in our benchmark model. As shown in Figure 6 and further discussed in Section F.2.7 of the Supplemental Material, the impulse responses following shocks to both TFP growth and housing demand under the alternative model are very close to those under the benchmark model. Thus, our results do not hinge on the specific form of the collateral constraint in the benchmark model.

5.4. *No Patience Shocks*

The DSGE literature often finds that an intertemporal preference 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 estimated model, a patience shock accounts for a sizable fraction of investment fluctuations (about 15–20%), making it the second most important shock that drives investment fluctuations after the housing demand shock (Table III). Therefore, it is important to examine whether abstracting from this shock would change the model's quantitative implications in a significant way. When we reestimate the model without patience shocks, we find that a housing demand shock remains the most important driving force for investment dynamics, accounting for about 30–40% of investment fluctuations (see the column under "No patience" in Table IV).

5.5. *Latent IST Shocks*

Justiniano, Primiceri, and Tambalotti (2011) argued 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 reestimate 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 IV).

5.6. *CoreLogic Data*

The land-price series we use for the benchmark model is constructed based on the FHFA home price index. In Appendix F of the Supplemental Material,

TABLE IV

CONTRIBUTIONS (IN PERCENT) TO INVESTMENT FLUCTUATIONS FROM A HOUSING DEMAND SHOCK[a]

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

[a]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 "CoreLogic" displays the results from the benchmark model with the Core Logic data on the land price; and the columns "High vol" and "Low vol" report the contributions under the high and low volatility regimes from the regime-switching benchmark model.

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 remains the most important driving force for investment dynamics and accounts for over 50% of investment fluctuations (see the column under "CoreLogic" in Table IV).

5.7. *Nonlinearity*

Our model is solved and estimated based on a log-linearized equilibrium system. It is well known that a log-linearized system may be a poor approximation to the underlying nonlinear model. One important source of nonlinearity comes from the credit constraint that may occasionally bind. This and other sources of nonlinearity can make the parameter estimates obtained for the log-linearized model potentially different from those for the underlying nonlinear model.

Estimating a fully nonlinear DSGE model with occasionally binding credit constraints, however, is beyond the scope of this paper since our model has a large number of endogenous state variables. We thus follow most of the DSGE literature and estimate the log-linearized version. In addition, we follow Iacoviello (2005), Iacoviello and Neri (2010), and Jermann and Quadrini (2012) and assume that the credit constraints are always binding. Even with these simplifications, the estimation task is computationally challenging, as described in Section D.6 of the Supplemental Material.[14]

We report, in Section D.5 of the Supplemental Material, the sample path of the Lagrangian multiplier associated with the credit constraint conditional on the sequence of shocks that replicate the six time series fitted to our model. Since the Lagrangian multiplier is considerably greater than zero, the credit constraint for our log-linearized model seems binding.[15]

6. THREE KEY ISSUES

We address three important issues in this section. First, we quantify the importance of land as a collateral asset in the model's transmission mechanism.

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

[15]This finding by no means implies that the credit constraint is always binding in the underlying nonlinear model. Appendix D of the Supplemental Material provides additional supporting evidence by computing impulse responses based on two nonlinear models, one where we impose that the credit constraint is always binding and the other where we allow the credit constraint to be occasionally binding.

Second, we discuss the role of adjustment costs in propagating investment fluctuations through changes in the land price. Third, we explore the implications of potential volatility changes in land prices.

6.1. *How Important is 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 the real estate value 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 the firm's borrowing capacity, enabling the firm to finance expansions of investment and production.

How important is land as a collateral asset in our macroeconomic model? To answer this question, we study an alternative model specification with the general setup of a collateral constraint as

$$B_t \leq \theta_t \mathrm{E}_t[\omega_l q_{l,t+1} L_{et} + \omega_k q_{k,t+1} K_t], \tag{23}$$

where ω_l is the weight put on land value and ω_k is that put on capital value. The weight parameters ω_l and ω_k cannot be identified separately, but one can identify the relative weight ω_k/ω_l. This model nests our benchmark model as a special case when $\omega_k/\omega_l = 1$.

We estimate this alternative model to fit the same set of time series data, and we allow the data to determine the relative importance of land and capital in the collateral constraint. The estimation implies a relative weight for capital collateral of about 1.2 (i.e., $\omega_k/\omega_l = 1.2$).[16] This result indicates that land is an important asset as collateral. As shown in Figure 6, the impulse responses to a housing demand shock are very close to those from the benchmark model (see Section F.2.5 of the Supplemental Material).

6.2. *Adjustment Costs and Propagation Through Land Prices*

Our estimated model implies that land-price fluctuations have a large impact on investment spending. This result relies on the estimate of low adjustment costs for investment. To illustrate this point, consider a partial equilibrium model in which the representative firm earns profits from existing capital

[16]The marginal data density for this model is 2389.2 in log value, as compared to 2343.9 for the benchmark model, indicating that the data favor the alternative model relative to the benchmark. Most of the improvement in marginal data density and likelihood comes from the change in the relative weight of capital value, not from other estimated parameter values. It is worth noting that large differences in marginal data densities between two models do not necessarily translate into large differences in dynamics of variables (Sims and Zha (2006)). For other potential problems of using marginal data densities or posterior odds ratios blindly to select a model, see Geweke and Amisano (2011) and Waggoner and Zha (2012). For the accuracy and convergence of our computations, see Section D.4 of the Supplemental Material.

and issues new debt to pay off matured debt, finance new investment, and pay dividends. The flow of funds constraint is given by

$$(24) \qquad q_k K' + RB + D = r_k K + (1-\delta) q_k K + B',$$

where K' and B' denote next-period capital and debt, D denotes dividends, R denotes the rate of interest, and r_k denotes earnings per unit of capital. The firm relies on external financing for investment spending and faces the borrowing constraint

$$B' \le \theta\big(q_k K' + q_l L\big),$$

where L is the quantity of land that the firm owns. The borrowing constraint is assumed to bind so that the firm does not pay dividends. We can solve for the new capital from these two equations to obtain

$$(25) \qquad K' = \frac{r_k + (1-\delta) q_k}{(1-\theta) q_k} K + \frac{\theta}{1-\theta} \frac{q_l}{q_k} L - \frac{RB}{(1-\theta) q_k}.$$

This expression makes it clear that the strength of the partial equilibrium effects of land prices on investment spending depends on the relative value of land in production (i.e., $q_l L / q_k$). It is also clear that, to obtain amplification effects on investment through land prices, the land price must rise more rapidly than the capital price.

This result holds for our general equilibrium model because the estimated adjustment costs for investment are low. Thus, the transmission mechanism in our model differs from other work in the DSGE literature where economic shocks are transmitted to investment fluctuations through capital prices.[17] For the transmission through capital prices to work, it is necessary to have large adjustment costs. For example, Christiano, Motto, and Rostagno (2010) estimated a fully specified DSGE model to fit stock price data and several macroeconomic time series. Their estimation implies a very large investment adjustment cost parameter (their posterior mode estimate of Ω is about 26, compared to 0.18 in our model). As we increase the relative weight of capital value ω_k / ω_l in our model, the estimated adjustment costs for investment increase and the spillover of land-price dynamics to macroeconomic fluctuations is reduced. As a result, the effect of a housing demand shock on investment decreases.

The partial equilibrium example discussed here and the estimation results in our benchmark DSGE model consistently suggest that including land as a collateral asset for the firm's investment decisions should be both empirically relevant and theoretically necessary for explaining the observed co-movements

[17]Notable examples in this literature are Bernanke, Gertler, and Gilchrist (1999), Gilchrist, Ortiz, and Zakrajsek (2009), and Christiano, Motto, and Rostagno (2010).

between land prices and macroeconomic variables. A more ambitious project for future research is to develop a richer DSGE model designed to fit both land prices and capital prices.

6.3. *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 (Uhlig (1997), Stock and Watson (2003), Sims and Zha (2006)). Recent empirical studies show that the U.S. housing market has also experienced volatility changes in this sample period (Taylor (2007), Stock and Watson (2010)). 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:

$$\ln \varphi_t = (1 - \rho_\varphi) \ln \bar{\varphi} + \rho_\varphi \ln \varphi_{t-1} + \sigma_\varphi(s_t)\varepsilon_{\varphi t}, \tag{26}$$

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 $p_{ij} = \text{Prob}(s_{t+1} = i | s_t = j)$ 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 (2011). 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.[18]

Figure 7 shows the probability of the high-volatility regime throughout the sample history. 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

[18]All the estimation results for the regime-switching DSGE model are described in detail in Appendix F of the Supplemental Material. In that same Appendix, we present estimation results for a variety of regime-switching models, including a regime-switching model with three volatility regimes. We find that the data favor the two-regime specification.

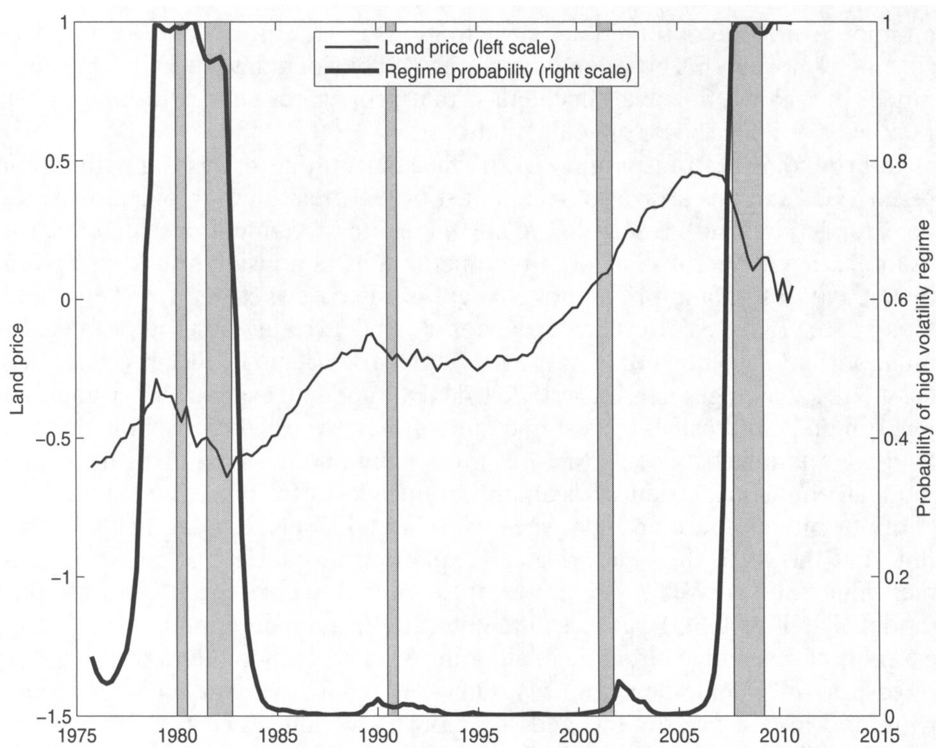

FIGURE 7.—Log real land prices (left scale) and the posterior probability of the high-volatility regime estimated from the regime-switching model (right scale). The shaded bars mark the NBER recession dates.

regime and 55–65% in the high-volatility regime (see the last two columns in Table IV). Since the high-volatility regime 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 found that a recession is typically deeper than other recessions if there is a sharp fall in housing prices.

7. 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 into 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) discussed the challenges in using a standard RBC model to explain why residential investment leads business investment and offered 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 the land price 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 among land prices, stock prices, as well as 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.[19] Thus, although stock prices do appear to co-move with investment, they are 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) fitted 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 collateral channel and the land reallocation channel that we identify to be empirically important are just one of many plausible mechanisms through which housing price fluctuations can have broader macroeconomic impacts. Other important mechanisms are discussed in a large body of literature, for example, Gorton and Metrick (2012), Adrian and Shin (2010), and Brunnermeier (2009). A rigorous econometric test of which mechanism fits the data better is a challenging but important task in future research.

[19]For details of the BVAR results, see Appendix F of the Supplemental Material.

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:

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

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/methodology/intercensal_nat_meth.pdf. Source: Bureau of Labor Statistics (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: Bureau of Economic Analysis (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 1975:Q1–1991:Q1, spliced to be consistent with the Purchase Only FHFA Home Price Index (USPHPI@USECON) for 1991:Q1 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's (1990) 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's (1971) method to interpolate these annual series at quarterly frequency. We then use the Tornqvist procedure to construct the quality-adjusted price index from the interpolated individual quarterly price series. Source: BEA.

NomConsNHSplusND: Nominal personal consumption expenditures: nonhousing services and nondurable goods. Source: BEA.

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

FNE@USECON: Nominal private nonresidential investment: equipment and 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 (2011)). 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 I.

For the second subset of parameters (i.e., those in Ψ_2), we fix the values of three 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.[20] 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 five 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

[20]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 Appendix E of the Supplemental Material, 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.

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.[21]

Since the prior distributions for the parameters in Ψ_2 are of unknown form, the 90% probability bounds, reported in Table I (the lower panel), are generated through simulations, with the simulated prior distributions reported in Table I (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 combined the Bayesian 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 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 shock 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) presented 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

[21]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 nonhousing services. Investment is the private expenditures on consumer durable goods and fixed investment in equipment and software. These time series are provided by the 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 the 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 BLS.

outside of the model. In Liu, Wang, and Zha (2009c), we presented a theory of housing demand shocks. In particular, we considered an economy with heterogeneous households that experience idiosyncratic and uninsurable liquidity shocks and 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 showed 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 deregulations 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 of Favilukis, Ludvigson, and van Nieuwerburgh (2011), who reported that shocks to the loan-to-value ratios (which they interpreted as changes in financial regulations) are important for generating fluctuations in the house price-rent ratio.

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Manuscript received December, 2009; final revision received April, 2012.