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Three Essays on Monetary Policy and Business Cycles

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Abstract

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Doctor of Philosophy

Three Essays on Monetary Policy and Business Cycles

by Toyoichiro SHIROTA

My dissertation consists of three essays about business cycles and monetary policy.

The first essay (Chapter 1) studies the major determinant of business cycles in a medium scale dynamic stochastic general equilibrium model. Some recent studies argue that spillovers from land prices into the aggregate economy are the crucial drivers of business cycles. Other studies stress the importance of investment shocks at business cycle frequencies. This essay evaluates these two strands of the literature in a single unified framework by estimating a New Keynesian dynamic stochastic general equilibrium model with a collateral constraint on investment financing. The results are twofold: (i) when these features are combined, neither shocks that drive most of land-price fluctuations nor investment shocks are the primary source of U.S. business cycles; and (ii) technology shocks play an important role in business cycles.

The second essay (Chapter 2) develops a model which can explain the flattening of the Phillips curve under low trend inflation. After the Great Recession, associated with the decline in trend inflation, major economies face a weak linkage between aggregate prices and economic activities. This phenomenon is called as flattening of the Phillips curve. A challenge to standard sticky price models is that they cannot explain this empirical fact. This essay incorporates the variable elasticity demand into a standard sticky price model and tries to resolve the discrepancy between standard sticky price models and the empirical fact. In the analysis, we first set out a two-period, partial equilibrium model and study the firm's pricing behavior under trend inflation. Then, we develop a general equilibrium model. The analysis in this essay clarifies that the key is the curvature of the demand curve.

The third essay (Chapter 3) empirically examines whether shock size matters for the US monetary policy. We use a nonlinear local projection method and find that large monetary policy shocks are less powerful than the small shocks. The empirical results are robust even after considering the period of early Volker's chairmanship and outliers. Furthermore, this study suggests that the monetary policy design, rather than menu cost pricing and information effects, is a relevant cause of the shock size dependency of policy effects. Finally, this study re-examines some other asymmetries of monetary policy effects through the lens of shock-size distribution.

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[1]

1.1 Introduction

The discussion of what drives business cycles dates back at least to the classic studies of Kydland and Prescott (1982) and Sims (1980). After the Great Recession in the late 2000s, debate over the source of business cycles has gained renewed attention, with a focus on the prominence of financial factors.

The literature, including Iacoviello (2005), Iacoviello and Neri (2010), and Liu, Wang, and Zha (2013), emphasizes the role of housing in the economy. By using dynamic stochastic general equilibrium (DSGE) models, these studies argue that spillovers from fluctuations in land (or housing) prices to other major variables are important sources of business cycles. Among them, Liu,

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[1]This chapter is the reprint of the article in *Journal of Macroeconomics*, vol. 57 (c).

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Wang, and Zha (2013) report that land-price dynamics driven by the housing demand account for approximately 28 percent of the variation in output and 39 percent of the variation in investments in a neoclassical model with a collateral constraint. Although their simple and tractable model provides a good analytical starting point, it differs from typical business cycle models, such as Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007), which recent literature often uses to decompose for business cycles.

Other studies, represented by Justiniano, Primiceri, and Tambalotti (2010) and Justiniano, Primiceri, and Tambalotti (2011), use a standard business cycle model with a rich shock propagation mechanism. These studies demonstrate that shocks to the marginal efficiency of investment (MEI) -disturbances in transformation of investment goods into productive capital- are the primary source of fluctuations in output and investments in the U.S.[2] Moreover, they argue that MEI shocks are proxies for financial factors because the estimated MEI shocks correlate highly with credit spreads. These studies reinforce the momentum toward developing models that enrich financial frictions.[3] However, Justiniano, Primiceri, and Tambalotti (2010) and Justiniano, Primiceri, and Tambalotti (2011) do not consider spillovers from land-price fluctuations in the economy.

This study assesses these views within one unified framework and considers the shock that is a more relevant major driver of business cycles. To this end, we introduce land as a collateral asset in investment financing into a standard medium-scale DSGE model similar to Justiniano, Primiceri, and Tambalotti (2011). Because a medium-scale DSGE model suitably encompasses several views on the sources of business cycles, it provides a good

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[2]Among the most influential studies in this area is Smets and Wouters (2007). They argue that labor supply shocks primarily drive fluctuations in business cycles using an estimated medium-scale DSGE model. Justiniano, Primiceri, and Tambalotti (2010) fault Smets and Wouters (2007)'s conclusions for depending on their definition of investment. As explained in data section, our investment data for estimation is the same definition of Justiniano, Primiceri, and Tambalotti (2010).

[3]Wieland et al. (2016) summarize recent developments in this active area.

experimental field for our objective.

In our estimated U.S. model, housing demand shocks determine most of the land-price fluctuations. They account for 75 percent of land-price fluctuations. However, they are not the primary source of business cycles. Housing demand shocks account for 14.8 and 23.0 percent of the variation in output and investment at business cycle frequencies. These numbers are approximately half of the numbers in the study of Liu, Wang, and Zha (2013). Furthermore, MEI shocks account for only 2.6 and 6.7 percent of output and investment fluctuations, respectively. In contrast, technology shocks substantially affect macroeconomic variables at business cycle frequencies. 43.8 percent of the variation in output is attributable to technology shocks.[4] Neither housing demand shocks nor MEI shocks are primary drivers of business cycles.

It is worth noting the reason why our results differ from those of Liu, Wang, and Zha (2013) and Justiniano, Primiceri, and Tambalotti (2010). Discrepancies in the studies of Liu, Wang, and Zha (2013) and ours stem from an assumption of the labor elasticity. The indivisible labor setting adopted in Liu, Wang, and Zha (2013) implicitly presumes an infinite Frisch elasticity of labor supply (e.g. Hansen (1985)), whereas we allow this elasticity to be finite and estimate it using data as in standard medium-scale DSGE models. The amplification effects of a positive housing demand shock will be dampened in our specification because a lower Frisch elasticity results in lesser substitution effects and greater income effects.

Discrepancies in the studies of Justiniano, Primiceri, and Tambalotti (2010) and ours stem from the collateral constraint and data used in estimations. A favorable MEI shock creates procyclical movements in consumption and investments but also creates countercyclical movements in stock prices because

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[4]Kaihatsu and Kurozumi (2014) also point out that technology shocks are the major source of business cycles using an estimated DSGE model.

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a MEI shock is a supply shock of capital accumulation. In a model with collateral constraint, countercyclical movements in stock prices are transmitted into movements in credits because stocks are pledged assets for collateral. Hence, credits respond countercyclically to a MEI shock in the model. However, credits move procyclically in actual data. Therefore, MEI shocks fail to be a major source of business cycles when a model is estimated using credit data.

This study also relates to Brzoza-Brzezina and Kolasa (2013), who find the collateral constraint mechanism to be not crucial in fitting their model to the U.S. data. In our model, spillovers from housing demand through land prices are modeled explicitly and estimated using land price data; however, Brzoza-Brzezina and Kolasa (2013) consider only a collateral constraint on the value of capital. Hence, our results complement those of Brzoza-Brzezina and Kolasa (2013).

In the remainder of this paper, Section 1.2 provides an overview of our model. Section 1.3 presents our estimation method and data. Section 1.4 describes the estimation results and discusses their implications. Section 1.5 concludes the study.

1.2   The model

A standard medium-scale DSGE model is estimated that shares major features with Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007) and Justiniano, Primiceri, and Tambalotti (2011). It contains nominal and real frictions that affect the decisions of economic agents. One key difference from models commonly used in the literature is the collateral constraint, a lá Kiyotaki and Moore (1997), whereby a lender has to post collateral to obtain external funds because of limited enforcement of financial contracts. We extend the model to include a collateral constraint on investment financing

so that it can describe spillovers from the housing market into investments through land prices.[5]

The economy is populated by capital owners, households, final-goods producers, intermediate-goods producers and the government. Agents' problems and other constructions are as follows.

1.2.1 Capital owners

A representative capital owner receives utility from consuming $C_{c,t}$ in each period and invests in capital K_t and land $L_{c,t}$, which are rented to intermediate-goods firms in competitive markets. Its objective is to maximize the following lifetime utility,

$$E_t \sum_{s=0}^{\infty} \hat{\beta}^s \log \left(C_{c,t+s} - \gamma_c C_{c,t+s-1} \right),$$

where $\gamma_c \in [0,1]$ is a parameter in the capital owner's formation of consumption habits. $\hat{\beta} \in (0,1)$ is a capital owner's subjective discount factor.

The capital owner confronts a flow of funds constraint and a capital accumulation process with quadratic investment adjustment costs that penalize deviations from steady-state investment growth, $\Delta \bar{I}$,

$$r_t^k K_{t-1} + r_t^l L_{c,t-1} + E_t \frac{B_t}{R_t / \pi_{t+1}} \quad = \quad C_{c,t} + \frac{I_t}{A_t^i} + B_{t-1} + q_{l,t} \left(L_{c,t} - L_{c,t-1} \right),$$

$$K_t \quad = \quad (1 - \delta) K_{t-1} + \zeta_t \left[1 - \frac{\Omega}{2} \left(\frac{I_t}{I_{t-1}} - \Delta \bar{I} \right)^2 \right] I_t,$$

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[5]Iacoviello (2005), Iacoviello and Neri (2010) and Liu, Wang, and Zha (2013) estimate DSGE models with a collateral constraint using US data. In the former two studies, a part of households face a collateral constraint on consumption. These models focus on the housing investment and have difficulties in reproducing positive co-movements between land prices and business investments. In the latter study, a capital owner faces a collateral constraint on business fixed investment. Since we examine the propagation of housing demand shocks through business investment, we adopt a modeling strategy similar to that of Liu, Wang, and Zha (2013).

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where r_t^k and r_t^l are rental rates of capital and land, respectively, B_t is quantity of bonds, R_t is the nominal gross return on bonds, $q_{l,t}$ is land prices in terms of final goods, $\Omega > 0$ is a parameter of investment adjustment cost, $\delta \in (0,1)$ is a depreciation rate, and ζ_t represents an exogenous shock in the efficiency with which a final good is transformed into physical capital. Justiniano, Primiceri, and Tambalotti ([2011](#)) call it an MEI shock. A_t^i is an exogenous shock in investment-specific technology. The stochastic processes of all shocks are summarized in the latter part of this section.

Because of limited enforcement of financial contracts, the capital owner can raise funds up to a fraction θ_t of the total value of collateral assets,

$$B_t \leq \theta_t E_t \left(q_{l,t+1} L_{c,t} + q_{k,t+1} K_t \right), \tag{1.1}$$

where θ_t is the loan-to-value (LTV) ratio of pledged assets to collateral and $q_{k,t}$ is the real shadow price of capital. We call θ_t a collateral constraint shock and assume it is exogenous.

1.2.2 Households

Each household is continuously indexed as j within a unit interval. It receives utility from consumption $C_{h,t}(j)$ and landholdings $L_{h,t}(j)$, and incurs disutility from labor supply $N_t(j)$.[6] Each household is a monopolistic supplier of specialized labor. We presume that the household can access a portfolio of state-contingent securities, which ensures that, in equilibrium, consumption and asset holdings are identical for all households. The household's objective

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[6]As presented in a later section, the model is non-stationary because the growth rate of technological progress follows stationary AR(1) process. To ensure existence of a balanced growth path, we presume the utility function is log in consumption and separable with labor. Conditions for the existence of balanced growth path is discussed in King, Plosser, and Rebelo ([1988](#)).

is to maximize the following lifetime utility,

$$E_t \sum_{s=0}^{\infty} \beta^s \nu_{t+s} \left[\log\left(C_{h,t+s} - \gamma_h C_{h,t+s-1}\right) + \varphi_{t+s} \log\left(L_{h,t+s}\right) - \frac{N_{t+s}(j)^{1+\chi}}{1+\chi} \right],$$

given a flow of funds constraint,

$$C_{h,t} + q_{l,t}\left(L_{h,t} - L_{h,t-1}\right) + E_t \frac{B_t^d}{R_t / \pi_{t+1}} + T_t \leq W_t(j) N_t(j) + B_{t-1}^d + \Pi_t + Q_t(j),$$

where $\beta \in (0,1)$ is a household's subjective discount factor, $\gamma_h \in [0,1]$ is a degree of habit persistence, $\chi \geq 0$ is an inverse of the Frisch's labor supply elasticity, T_t are lump-sum taxes, $W_t(j)$ are real wages, B_t^d are bond holdings, and Π_t are per-capita profits accruing to households from the ownership of firms. $Q_t(j)$ are net cash flows from household j's portfolio of state-contingent securities. Following Kiyotaki and Moore (1997), households are more patient than capital owners. Therefore, $1 > \beta > \hat{\beta}$. ν_t and φ_t are exogenous shocks in intertemporal preference (patience) and household's taste for landholdings, respectively. Following Liu, Wang, and Zha (2013), we label the land taste shock φ_t the "housing demand" shock.

Regarding the specification of labor disutility, Liu, Wang, and Zha (2013) adopt the indivisible labor setting of Hansen (1985) assuming that the Frisch's elasticity of labor supply is infinite, whereas standard medium scale DSGE models including Justiniano, Primiceri, and Tambalotti (2010) and Justiniano, Primiceri, and Tambalotti (2011) estimate the (inverse) Frisch's elasticity. We will estimate this parameter and analyze the effects caused by the difference in specifications in the later section.

A large number of "employment agencies" transform a bundle of specialized labor $N_t(j)$ into homogeneous labor inputs sold to intermediate-goods producers in a competitive market. Their transformation function is a constant elasticity of substitution (CES) form, $N_t = [\int_0^1 N_t(j)^{1/(\epsilon_{w,t}+1)} dj]^{\epsilon_{w,t}+1}$.

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Elasticity of substitution, $\epsilon_{w,t}$, follows the exogenous stochastic process.[7]

Profit maximization in a competitive market implies that the demand function for a specialized labor input j is given by

$$N_t(j) = \left[\frac{W_t(j)}{W_t} \right]^{-(1+\epsilon_{w,t})/\epsilon_{w,t}} N_t, \tag{1.2}$$

where W_t are real wages paid by intermediate-goods producers for homogeneous labor input and an aggregate index of wages for specialized labor.

As in Erceg, Henderson, and Levin (2000), a certain fraction, $\xi_w \in [0,1)$, of households cannot set their wages optimally at time t and follow the wage indexation rule, $W_t(j) = W_{t-1}(j) (\pi_{t-1})^{\iota_w} (\bar{\pi})^{1-\iota_w} \bar{Z}$ where $\iota_w \in [0,1]$ is the degree of indexation to the past inflation, $\pi_{t-1} \equiv P_{t-1}/P_{t-2}$. $\bar{\pi}$ and $\bar{Z}$ are steady-state inflation and economy-wide technological progress, respectively and subsequently explained.

The remaining households have an opportunity to reset their wages optimally to maximize (1.3) subject to the labor demand function (1.2),

$$E_t \sum_{s=0}^{\infty} \xi_w^s \beta^s \left\{ -v_{t+s} + \lambda_{t+s} W_t(j) \Pi_{k=1}^s (\pi_{t+k-1})^{\iota_w} (\bar{\pi})^{1-\iota_w} \bar{Z} \right\} N_{t+s}(j), \tag{1.3}$$

where λ_t is the Lagrange multiplier on the households' flow of funds constraint.

1.2.3 Final-goods producers

Final-goods producers produce a final good Y_t that combines a continuum of intermediate goods $\{Y_t(i)\}_{i \in [0,1]}$ and sell it in a competitive market. Their production function is a CES form, $Y_t = \left[\int_0^1 Y_t(i)^{1/(\epsilon_{p,t}+1)} di \right]^{\epsilon_{p,t}+1}$. An elasticity of substitution, $\epsilon_{p,t}$, follows an exogenous stochastic process. Profit

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[7]As suggested in Chang and Schorfheide (2003), this shock is observationally equivalent to a labor supply shock. Hence, labor supply shocks in the household utility function are omitted to avoid the collision in identification.

maximization in a competitive market implies that the demand function for an intermediate good *i* is

$$Y_t(i) = \left[\frac{P_t(i)}{P_t}\right]^{-(1+\epsilon_{p,t})/\epsilon_{p,t}} Y_t \tag{1.4}$$

where P_t is an aggregate price index.

1.2.4 Intermediate-goods producers

Each intermediate-goods producer *i* is a monopolistically competitive firm and indexed continuously within a unit interval. The producer is owned by households and produces an intermediate good *i*, according to the Cobb-Douglas production function of (1.5),

$$Y_t(i) = \max\left\{ A_t^n \left[L_{t-1}(i)^\phi K_{t-1}(i)^{1-\phi} \right]^\alpha N_t^d(i)^{1-\alpha} - Z_t F, 0 \right\}, \tag{1.5}$$

where $L_t(i), K_t(i)$ and $N_t^d(i)$ represent quantities of land, capital, and labor employed by firm *i*, *F* denotes a fixed cost of production, A_t^n is an exogenous neutral technological progress, and Z_t is an economy-wide technological progress that is a composite of neutral and investment-specific technologies.[8]

As in Calvo (1983), for every period, a certain fraction $\xi_p \in [0,1)$ of intermediate-goods producers chosen randomly cannot set the price optimally. Instead, they set their prices according to the price indexation rule, $P_t(i) = P_{t-1}(i)\left(\pi_{t-1}\right)^{\iota_p}\left(\bar{\pi}\right)^{1-\iota_p}$ where $\iota_p \in [0,1]$ is the degree of indexation to past inflation.

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[8]Given the production function in (1.5), Z_t is defined as $Z_t \equiv (A_t^n)^{1/[1-(1-\phi)\alpha]}(A_t^i)^{(1-\phi)\alpha/[1-(1-\phi)\alpha]}$.

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The remaining producers can reset prices to maximize the following discounted future profits subject to the demand function of (1.4),

$$E_t \sum_{s=0}^{\infty} \xi_p^s \frac{\beta^s \Lambda_{t+s}}{\Lambda_t} \left\{ \frac{P_t(i)}{P_{t+s}} \left[\Pi_{k=1}^s (\pi_{t+k-1})^{\iota_p} (\bar{\pi})^{1-\iota_p} \right] - V_{t+s} \right\} Y_{t+s}(i),$$

where Λ_t is the marginal utility of households' consumption and V_t is the real marginal cost.[9]

1.2.5 Government

To focus on the role of collateral constraint in the economy and make our results comparable to previous literature, we try to keep the other model's specifications such as the government's policy rules as they are accepted in standard DSGE models (i.e. Smets and Wouters (2007) and Justiniano, Primiceri, and Tambalotti (2010)).

Specifically, a monetary authority follows a generalized Taylor rule that gradually adjusts the nominal interest rate in response to inflation and output deviations from its hypothetical counterpart under the flexible price economy,

$$\frac{R_t}{\bar{R}} = \left(\frac{R_{t-1}}{\bar{R}} \right)^{\rho_r} \left[\left(\frac{\pi_t}{\bar{\pi}} \right)^{\phi_{\bar{\pi}}} \left(\frac{Y_t}{Y_t^*} \right)^{\phi_y} \right]^{1-\rho_r} \left[\frac{Y_t/Y_{t-1}}{Y_t^*/Y_{t-1}^*} \right]^{\phi_{dy}} mp_t,$$

where mp_t is an exogenous monetary policy shock. Further, government spending is a fraction of output, however its share is exogenously varying.

$$G_t = \left(1 - \frac{1}{g_t} \right) Y_t,$$

where g_t is an exogenous government spending shock.

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[9]An intermediate-goods producer solves a cost-minimization problem, taking input prices as given, regardless of whether the producer can adjust its price optimally. The solution yields the marginal cost function, $V_t = (\alpha\phi)^{-\alpha\phi}(\alpha(1-\phi))^{-\alpha(1-\phi)}(1-\alpha)^{1-\alpha}[(W_t)^{1-\alpha}(r_t^k)^{\alpha(1-\phi)}(r_t^l)^{\alpha\phi}]/Z_t$.

1.2.6 Process of exogenous shocks

We assume three types of exogenous-shock processes in this economy. The first type is specified in (1.6): a logarithm of shock x follows an autoregressive of order one (AR(1)) process around its steady-state value $\bar{x}$. MEI, collateral constraint, housing demand, patience, monetary policy, and government expenditure shocks belong to this family. The second type is specified in (1.7): the growth rates of neutral and investment-specific technology shocks follow an AR(1) process around deterministic growth rates. The third type is specified in (1.8). As is commonly adopted in DSGE empirical studies, price and wage markup shocks in the logarithm follow an autoregressive of order one with a first-order moving average (ARMA(1,1)) process around their steady-state values.[10] The ARMA process is suitable to capture the volatile fluctuations in price and wage inflations.

$$\log\left(x_t\right) \;=\; \left(1-\rho_x\right)\log\left(\bar{x}\right) + \rho_x \log\left(x_{t-1}\right) + \eta_{x,t}, \;\; x \in \{\zeta, \theta, \varphi, \nu, mp, g\},$$

$$\tag{1.6}$$

$$\Delta \log\left(A_t^x\right) \;=\; \left(1-\rho_x\right)\Delta\log\left(\bar{A}^x\right) + \rho_x \Delta\log\left(A_{t-1}^x\right) + \eta_{x,t}, \;\; x \in \{n, i\}, \tag{1.7}$$

$$\log\left(\epsilon_{x,t}\right) \;=\; \left(1-\rho_x\right)\log\left(\bar{\epsilon}_x\right) + \rho_x \log\left(\epsilon_{x,t-1}\right) + \eta_{x,t} - \theta_x \eta_{x,t-1}, \;\; x \in \{p, w\}. \tag{1.8}$$

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[10]Following conventions in the literature (e.g., Smets and Wouters (2007)), we normalize the price and wage markup shock to be a unit coefficient in the linearized price and wage Eular equations, respectively.

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1.2.7 Market clearing

All markets clear in equilibrium. Market clearing conditions for goods, labor, land, and bonds are denoted as follows:

$$
\begin{aligned}
Y_t &= C_t + I_t / A_t^i + G_t, \\
N_t &= N_t^d, \\
\bar{L} &= L_{h,t} + L_{c,t}, \\
B_t &= B_t^d
\end{aligned}
$$

where $\bar{L}$ is the total supply of land.

Because levels of neutral and investment-specific technologies introduce non-stationarities into the model, we render variables stationary by detrending their respective stochastic trends. Equilibrium conditions are then log-linearized. Finally, the linearized system of rational expectations is solved into state-space representation and estimated.

1.3 Estimation method and data

We employ Bayesian methods to estimate posterior distributions of the model's structural parameters.[11] The likelihood function and priors are incorporated using the Bayes formula, and the resulting conditional distributions of parameters are posterior distributions.

We calibrate some parameters to values that are conventional in the literature. Specifically, households' discount factor is 0.9925, which is equivalent to a 1 percent discount rate per annum. Capital owners' discount factor is

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[11] An and Schorfheide (2007) provide a survey of Bayesian estimation of DSGE models. For estimation, we use Dynare toolbox (Adjemian et al. (2011)).

TABLE 1.1: Parameter calibration

Parameters	Description	Calibrated values
β	Households' discount factor	0.9925
$\hat{\beta}$	Capital owners' discount factor	0.97
$1 - \alpha$	Labor share	0.65
$\bar{\theta}$	LTV ratio	0.75
$(\epsilon_p - 1)/\epsilon_p$	Steady state price markup	0.85
$(\epsilon_w - 1)/\epsilon_w$	Steady state wage markup	0.85
$\bar{q}_l \bar{L}_h / \bar{Y}$	Households' landholdings over GDP at annual frequency	1.45
$\bar{q}_l \bar{L}_e / \bar{Y}$	Capital owners' landholdings over GDP at annual frequency	0.65
$\bar{G}/\bar{Y}$	Government expenditure to GDP	0.22
$\bar{I}/\bar{K}$	Investment over Capital	0.21
$\bar{K}/\bar{Y}$	Capital to GDP at annual frequency	1.15

0.97. This value is used in Iacoviello and Neri (2010).[12] The share parameter of labor in production is 0.65. We set the steady-state LTV ratio $\bar{\theta}$ as 0.75 to be consistent with Liu, Wang, and Zha (2013). Given this calibration, the credit to GDP ratio (B/Y) at the steady state can be approximated to the historical average at annual frequency. The average markup ratios of price and wage are 15 percent. Land-holdings to GDP of households and capital owners are equivalent to those of Liu, Wang, and Zha (2013). The other values are selected to be consistent with historical averages. Some parameters are implicitly calculated from the steady state relationships. For example, the relative factor share of land to capital in the production function ϕ is calculated as $\phi = \frac{\bar{q}_l \bar{L}_e / \bar{Y}}{\hat{\beta} \alpha (\epsilon_p - 1)/\epsilon_p} = 0.124$.

Most prior distributions of parameters in Table 1.2 are in line with those in previous studies. The prior of persistent parameters is a Beta distribution with mean 0.6 and standard deviation 0.15. The only exception is monetary policy shocks. We assign a less persistent prior mean, 0.2, to clearly identify between the policy-rule's inertia and the persistence of discretionary policy shocks. Priors on the standard deviation of innovations are quite diffuse.

The model is estimated using 10 U.S. quarterly time series data items:

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[12]We re-estimated the model with alternative calibration ($\hat{\beta} = 0.985$) and found that results are almost similar to those with the baseline calibration.

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logarithmic first differences of private consumption, private business invest-
ments, land prices, credits, the inverse of the relative price of investment
goods, real wages, and GDP, the number of labor hours, the nominal inflation
of the consumption deflator, and the nominal effective federal funds rate. We
remove the sample means from all data to focus on the dynamics at business
cycle frequencies, as in Christiano, Motto, and Rostagno (2014).

The details of the datasets are as follows. Consumption is personal con-
sumption expenditures on non-durables and services. Investments represent
the sum of personal consumption expenditures on durables and gross private
domestic investments, including inventory investments. Labor input is the
log of total hours per person in the non-farm business sector. Credit is debt of
non-financial corporations. Land price is the FHFA based liquidity-adjusted
price index for residential land and is developed by Davis and Heathcote
(2007) and updated by Morris A. Davis. Following Justiniano, Primiceri, and
Tambalotti (2011), the consumption deflator is a chain-weighted price index
of personal consumption expenditures on non-durables and services. The
relative price of an investment is a chain-weighted price index of the pre-
viously described investments divided by the consumption deflator. Con-
sumption, investments, credits, GDP, real wages, and land prices are deflated
by the consumption deflator and, except for land prices, divided by the num-
ber of persons older than age 16 years in the population. The sample covers
1975/1Q to 2009/1Q. To make our results comparable to Justiniano, Prim-
iceri, and Tambalotti (2011) and avoid the effects of a zero bound on nominal
interest rates, the end of the sample is 2009/1Q.[13]

Our model and dataset encompass those of Liu, Wang, and Zha (2013)
and Justiniano, Primiceri, and Tambalotti (2011). Specifically, we add price
and wage inflations, policy rate, and GDP to the dataset of Liu, Wang, and

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[13]Hirose and Inoue (2016) point out that the zero lower bound on nominal interest rates
causes biased estimates of structural shocks even if estimated parameters are virtually unbi-
ased. The results are almost unchanged even if the end of the sample is 2008/4Q.

Zha ([2013](#)), who estimate a flexible-price RBC model with collateral constraints. We add land prices and credits to the dataset of Justiniano, Primiceri, and Tambalotti ([2011](#)), who estimate a standard medium-scale DSGE model with price and wage stickiness but without collateral constraints.

For the posterior distribution, we create two chains of 200,000 draws using the Metropolis-Hastings algorithm, and discarded the first 50 percent of these draws. The acceptance ratios of the Markov Chain Monte Carlo simulation are 37.82 and 37.63 percent in the respective chains. The multivariate and univariate diagnostics of Brooks and Gelman ([1998](#)) suggest that the estimation has converged.

1.4 Estimation results

Table [1.2](#) presents the posteriors of the parameters. Tight credible intervals suggest that the parameters are firmly estimated.[14]

Posterior parameters are within variations in previous DSGE estimations. The inverse Frisch elasticity (4.056), which is assumed to be zero in Liu, Wang, and Zha ([2013](#)), is statistically significant and similar to that of Justiniano, Primiceri, and Tambalotti ([2011](#)) (4.444). One of the controversial parameters is the investment adjustment cost. Ours (0.552) is in the midrange of these studies: 0.175 for Liu, Wang, and Zha ([2013](#)), 2.657 for Justiniano, Primiceri, and Tambalotti ([2011](#)), and 5.74 for Smets and Wouters ([2007](#)). Regarding the other major parameters, consumption habit persistence is 0.775 for households and 0.477 for capital owners. Both are similar to values in previous studies such as Smets and Wouters ([2007](#)) (0.71) and Liu, Wang, and Zha ([2013](#)) (0.500-0.658). They are slightly lower than the value in Justiniano, Primiceri, and Tambalotti ([2011](#)) (0.859). Price and wage reset probabilities

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[14]We check the estimated Lagrange multiplier on collateral constraint. It is fluctuating but is significantly away from zero. As suggested in Jermann and Quadrini ([2012](#)), this result implies the collateral constraint was binding during the period.

TABLE 1.2: Prior and posterior distributions of parameters

		Prior			Posterior		
		Distribution	Mean	S.D.	Mean	95% interval	
Panel I: structural parameters							
γ_l	Habit formation (HH)	**B**	0.60	0.15	0.775	0.721	0.828
γ_b	Habit formation (C)	**B**	0.60	0.15	0.477	0.302	0.650
ξ_p	Calvo (price)	**B**	0.60	0.15	0.810	0.741	0.882
ξ_w	Calvo (wage)	**B**	0.60	0.15	0.805	0.674	0.936
ι_p	Price indexation	**B**	0.60	0.15	0.195	0.080	0.307
ι_w	Wage indexation	**B**	0.60	0.15	0.256	0.149	0.365
Ω	Investment adjustment cost	**Γ**	5.00	3.00	0.552	0.316	0.775
χ	Inverse Frisch elasticity	**Γ**	2.00	0.75	4.056	2.670	5.383
$F/\bar{Y}$	Fixed cost per output	**B**	0.15	0.05	0.088	0.045	0.127
ϕ_π	Policy rule (inflation)	**Γ**	1.50	0.15	1.411	1.203	1.624
ϕ_y	Policy rule (output)	**Γ**	0.20	0.10	0.073	0.043	0.102
ϕ_{dy}	Policy rule (output growth)	**Γ**	0.20	0.10	0.466	0.363	0.568
ρ_r	Policy rule (policy inertia)	**B**	0.60	0.15	0.768	0.707	0.827
Panel II: autocorrelations and moving-averages of shocks							
ρ_v	Preference	**B**	0.60	0.15	0.621	0.502	0.746
ρ_n	Neutral technology	**B**	0.60	0.15	0.288	0.201	0.375
ρ_i	Investment-specific technology	**B**	0.60	0.15	0.249	0.159	0.332
ρ_ϕ	Housing demand	**B**	0.60	0.15	0.995	0.991	0.998
ρ_θ	LTV	**B**	0.60	0.15	0.969	0.958	0.981
ρ_ζ	MEI	**B**	0.60	0.15	0.721	0.658	0.780
ρ_p	Price markup	**B**	0.60	0.15	0.917	0.873	0.966
θ_p	Price markup (MA)	**B**	0.50	0.15	0.727	0.598	0.865
ρ_w	Wage markup	**B**	0.60	0.15	0.804	0.610	0.976
θ_w	Wage markup (MA)	**B**	0.50	0.15	0.760	0.551	0.960
ρ_{mp}	Monetary policy	**B**	0.20	0.05	0.210	0.132	0.287
ρ_g	Government	**B**	0.60	0.15	0.909	0.878	0.940
Panel III: standard deviations of shocks							
σ_v	Preference	**Γ^{-1}**	0.50	1.00	2.141	1.696	2.595
σ_n	Neutral technology	**Γ^{-1}**	0.10	1.00	0.657	0.589	0.724
σ_i	Investment-specific technology	**Γ^{-1}**	0.10	1.00	0.547	0.494	0.601
σ_ϕ	Housing demand	**Γ^{-1}**	0.50	1.00	6.737	4.650	8.655
σ_θ	LTV	**Γ^{-1}**	0.50	1.00	1.474	1.320	1.626
σ_ζ	MEI	**Γ^{-1}**	0.50	1.00	2.201	1.774	2.606
σ_p	Price markup	**Γ^{-1}**	0.50	1.00	0.259	0.215	0.302
σ_w	Wage markup	**Γ^{-1}**	0.10	1.00	0.352	0.297	0.405
σ_{mp}	Monetary policy	**Γ^{-1}**	0.10	1.00	0.338	0.281	0.394
σ_g	Government	**Γ^{-1}**	0.50	1.00	1.601	1.440	1.766
	Log marginal likelihood					-1847.235	

Note: Habit formation(HH) and Habit formation(C) represent the degree of consumption habit formation of households and capital owners, respectively. MA represents a moving-average parameter. **B**, **Γ**, and **Γ^{-1}** correspond to the beta, gamma, and inversed gamma distributions.

and the degrees of indexation resemble those in Justiniano, Primiceri, and Tambalotti (2011), although these nominal parameters are not estimated in Liu, Wang, and Zha (2013).

To ensure the identification between housing demand and investment shocks, we check the correlations between the draws from marginal posterior distributions of related parameters. One is the standard deviations of the housing demand and investment shocks and the other is the autoregressive parameters of these shocks. Further, we execute the same exercise with respect to the LTV and investment shocks. Table 1.3 suggests that investment shocks and housing demand (and LTV) shocks are clearly identified, showing that all the correlation coefficients are small and less than or equal to 10%.

TABLE 1.3: Identification between the investment and collateral-related shocks

Investment versus housing demand shocks		Investment versus LTV shocks	
S.D.	AR(1)	S.D.	AR(1)
0.043	-0.016	0.103	-0.034

Note: Table shows the correlation coefficients between the draws from marginal posterior distributions.

Next, we evaluate the cyclical properties of the model and data. Business cycles are fluctuations of aggregate economic activities occurring at approximately the same time in many variables. Figure 1.1 displays cross correlations between output and other variables to examine whether the model is successful in capturing business cycle co-movements. The shaded areas are the 95 percent confidence intervals of empirical cross correlations and the solid lines are theoretical cross correlations of the baseline model. The figure shows that our model can generate procyclical co-movements among important variables. In particular, the figure well captures the cross correlation of investments, which is our primary focus. The figure also indicates that there still remains a further room for improvements in terms of the empirical fit.

An introduction of adjustment costs in land transactions and financial contracts may help to improve the cross correlations of land prices and credits.

FIGURE 1.1: Cyclicalities of selected variables: data and model
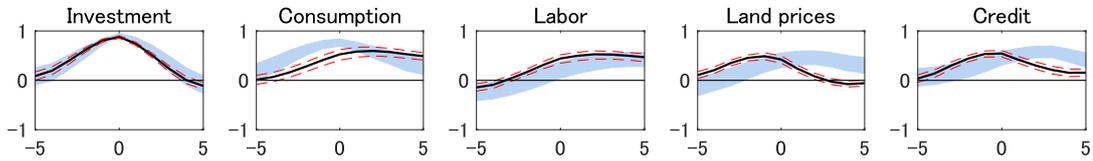
Note: Figure 1.1 displays cross correlations of selected variables with contemporaneous GDP. The solid and dotted lines represent the cross correlations calculated from the baseline model and 95 percent credible intervals, respectively. The shaded areas are the 95 percent intervals of the correlation coefficients of the data. All data are transformed into year-on-year growth rates.

1.4.1 Which shock is important at business cycle frequencies?

This subsection addresses our main question: what is the major source of business cycle fluctuations? Table 1.4 presents the contribution of each shock to the variance of the variables at business cycle frequencies. Following Stock and Watson (1999), we define business cycles as cycles between 6 and 32 quarters.[15]

First of all, Table 1.4 reports that housing demand shocks account for 74.9 percent of land-price fluctuations. Housing demand shocks determine most of land-price fluctuations. Second, Table 1.4 suggests that neither housing demand shocks nor investment shocks are the major determinant of business cycle fluctuations,[16] indicating that the primary driver of business cycles is the technology shocks that account for 44.9 percent of output fluctuations.

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[15]We split the whole sample period into the first and second half, and re-estimate the model in these subsamples. Specifically, the first and second half of sample periods covers 1975/1Q to 1992/4Q and 1993/1Q to 2009/1Q, respectively. Our results are robust to these subsample estimations. See the Appendix A for the detail.

[16]To check whether our results have an issue of weak identification, we compare prior and posterior densities of the share of variance in variables due to housing demand shocks and confirm that posterior density differs from prior density, indicating the likelihood information is used for the posterior variance decomposition.

Housing demand shocks account for 14.8 percent of output fluctuations and 23.0 percent of investment fluctuations. These results are different from those reported in Liu, Wang, and Zha (2013), in which 28.32 and 38.31 percent of output and investment variations, respectively, are attributed to housing demand shocks.[17] Furthermore, MEI shocks play a minor role in business cycles. They account for only 2.6 percent of fluctuations in output and 6.7 percent of fluctuations in investments.

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[17]Since Liu, Wang, and Zha (2013) provide variance decompositions only in time domain, we pick these numbers from the results of variance decompositions at eight quarters.

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TABLE 1.4: Variance decomposition at business cycle frequencies: baseline case

	Housing demand	LTV	MEI	Supply				Other demand		
				Technologies		Markups				
				Neutral	IS	Price	Wage	Pati-ence	Monetary policy	Gov't
Y_{obs}	14.8	13.9	2.6	43.8	1.1	2.9	1.3	1.3	16.6	0.3
	[11.2,19.3]	[10.2,18.5]	[1.4,4.6]	[35.4,53.4]	[0.7,1.7]	[1.4,5.4]	[0.6,2.8]	[0.7,2.1]	[12.2,22.4]	[0.2,0.5]
I_{obs}	23.0	18.8	6.7	17.2	1.0	3.7	1.0	7.9	17.0	2.3
	[18.5,28.2]	[14.8,23.7]	[4.3,9.8]	[12.9,22.7]	[0.6,1.5]	[2.1,6.4]	[0.4,2.2]	[5.2,11.8]	[12.9,22.1]	[1.5,3.5]
C_{obs}	5.9	9.4	4.7	41.0	3.3	1.3	2.4	13.0	13.3	3.6
	[3.7,8.4]	[6.5,12.8]	[2.5,7.8]	[32.8,50.2]	[2.3,4.8]	[0.6,2.7]	[0.8,5.7]	[8.2,19.5]	[7.9,20.9]	[2.2,5.7]
N_{obs}	13.2	6.5	17.1	10.8	0.4	11.8	7.4	0.4	29.5	0.4
	[9.1,18.1]	[3.2,10.7]	[11.7,24.1]	[7.2,15.4]	[0.2,0.8]	[7.0,18.9]	[4.0,13.4]	[0.1,1.0]	[21.0,41.7]	[0.2,0.6]
$Q_{l,obs}$	74.9	3.2	2.9	9.3	1.2	0.3	0.7	2.0	3.6	1.2
	[69.6,79.8]	[2.3,4.5]	[1.9,4.3]	[6.7,12.9]	[0.8,1.8]	[0.1,0.7]	[0.3,1.6]	[1.1,3.5]	[2.0,5.6]	[0.8,1.8]
B_{obs}	25.5	47.0	10.7	2.6	3.9	1.1	0.5	2.2	5.1	0.7
	[21.0,30.9]	[41.1,53.3]	[7.7,14.8]	[1.8,3.6]	[2.9,5.4]	[0.4,2.2]	[0.2,0.8]	[1.4,3.2]	[3.8,6.9]	[0.5,1.0]

Note: Variance decomposition to periodic components with cycles between 6 and 32 quarters is presented using the spectrum of the linearized model. The spectrum density is computed from the state space representation of the model with 3,000 bins for frequency covering that range of periodicities. To reconstruct the levels of output, investments, consumption, and land prices, we apply an inverse first difference filter. 95 percent credible intervals are denoted in respective parenthesis under the mean estimates.

1.4.2 Why are housing demand shocks not important?

Compared with the empirical exercises in Liu, Wang, and Zha (2013) that claims housing demand shocks are the primary driving force of business cycles, our model is different in two respects. One is the nominal rigidities and the other is the finite labor supply elasticity. The latter is key to our conclusion.

TABLE 1.5: Variance decomposition at business cycle frequencies: hypothetical cases I

		Housing demand	LTV	MEI	Tech-nologies	Mark-ups	Other demands
Y_{obs}	baseline case	14.8	13.9	2.6	44.8	4.1	18.2
	infinite Frisch elasticity	28.2	15.8	4.9	23.8	1.9	24.2
	drop nominal frictions	14.5	15.4	0.1	59.1	0.0	10.2
I_{obs}	baselinecase	23.0	18.8	6.7	18.1	4.7	27.2
	infinite Frisch elasticity	30.5	17.6	7.9	9.4	1.3	32.3
	drop nominal frictions	24.9	22.0	1.9	23.9	0.0	25.8
C_{obs}	baseline case	5.9	9.4	4.7	44.3	3.7	29.8
	infinite Frisch elasticity	17.0	10.0	2.9	43.4	3.4	21.8
	drop nominal frictions	5.1	9.1	5.4	47.9	0.0	31.4
$Q_{l,obs}$	baseline case	74.9	3.2	2.9	10.5	1.0	6.7
	infinite Frisch elasticity	76.3	3.3	1.2	8.6	0.7	9.4
	drop nominal frictions	78.3	2.4	5.6	8.2	0.0	4.8
B_{obs}	baseline case	25.5	47.0	10.7	6.5	1.5	7.9
	infinite Frisch elasticity	32.6	41.7	2.9	5.0	0.9	16.0
	drop nominal frictions	14.5	15.4	0.1	59.1	0.0	10.2

Note: "Other demands", "Technologies", and "Markups" correspond to the contributions of "patience", "monetary policy", and "government expenditure" shocks, those of "neutral" and "investment-specific" technology shocks, and those of "price" and "wage" markup shocks, respectively. For computational details, see also the Note for Table 1.4. In the *infinite Frisch elasticity* case, the model and parameters are same as the baseline case except for inverse Frisch elasticity $\chi = 0$. In the *drop nominal frictions* case, the model and the parameters are the same as the baseline case except for the four parameters $\{\xi_x, \iota_x\}$ for $x = p, w$. The Calvo probabilities for price and wage changes are calibrated at 0.90 and the price and wage indexations are calibrated at 0.0.

To analyze the role of these differences in specifications, Table 1.5 presents variance decompositions in hypothetical economies with an infinite labor supply elasticity and without nominal rigidities. The *infinite Frisch elasticity* rows show that spillovers from housing demand becomes a major source

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of business cycles when the Frisch elasticity of labor supply is calibrated at infinite as in Liu, Wang, and Zha (2013). Specifically, housing demand shocks can account for 28.2 percent of output variations and 30.5 percent of investment variations. The contributions of housing demand shocks approach to the results reported in Liu, Wang, and Zha (2013): 28.3 percent for output variations and 38.7 percent for investment variations. In contrast, the *drop nominal frictions* rows report that the contributions of housing demand shocks are similar to those in the baseline case even when nominal price and wage stickinesses are almost muted.[18] These decompositions clearly indicate that shifting housing demand matters for business cycles only when the labor supply elasticity is infinitely high.

The higher Frisch elasticity leads to the greater substitution effects. A positive housing demand shock, which increases the land prices and available funds by relaxing the collateral constraint, will strengthen the amplification effect of the shock. In contrast, the lower Frisch elasticity, which is consistent with micro evidence and estimated medium-scale DSGE models, leads to the greater income effects. In this case, a shock amplification upon a positive housing demand shock is limited even if rising collateral values increases available funds through the relaxation of collateral constraint.

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[18]Specifically, we set Calvo parameters of price and wage changes are 0.9 and indexation parameters of price and wage are 0.0, as in the similar exercises of Smets and Wouters (2007).

FIGURE 1.2: Impulse responses to a housing demand shock and an MEI shock
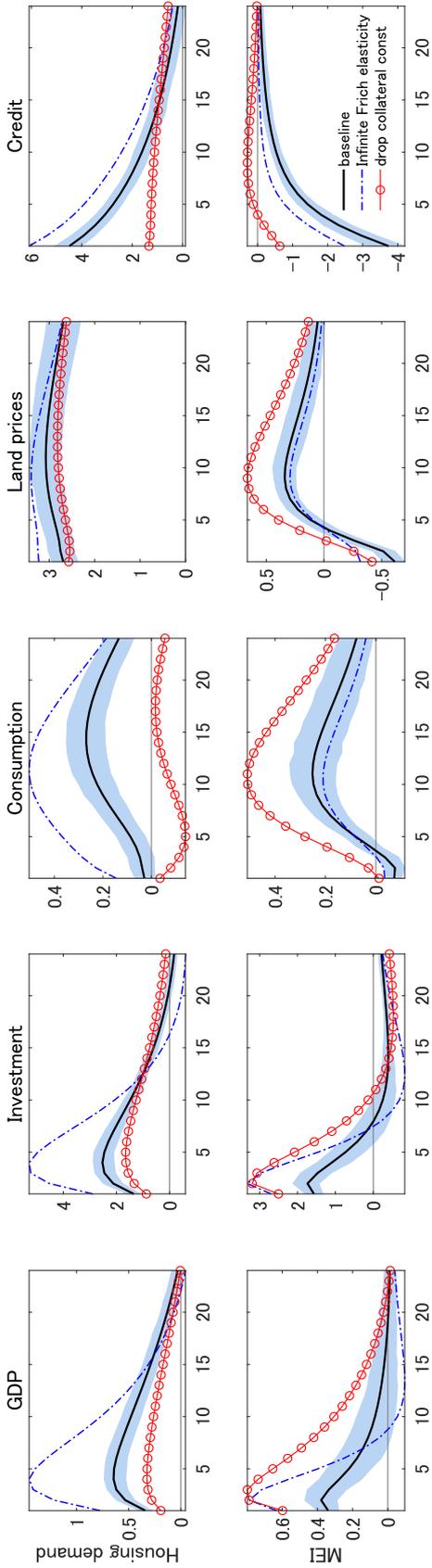
Note:The upper and lower panels are impulse responses to one standard deviation of housing demand and MEI shocks, respectively. The solid lines are the medians, whereas the shaded areas represent the 95th percentile intervals in the baseline model. The broken lines and marker lines are responses in hypothetical economy with infinite Frisch elasticity and without collateral constraints, respectively.

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The upper panels of Figure 1.2 assist in understanding this point, by displaying the impulse responses of selected variables to a positive housing demand shock. Thick and broken lines correspond to the baseline and *infinite Frisch elasticity* cases, respectively. They show that output, investments, and consumption move in tandem in a hump-shared pattern. Land prices and credits also co-move procyclically. However, the amplification effects of housing demand shocks are greater in the *infinite Frisch elasticity* case. The peak responses of output and investments are approximately three times greater that those in the baseline case. These responses are reflections of amplification effects of the higher Frisch elasticity.

1.4.3 Why are investment shocks not important?

Compared with the empirical exercises in Justiniano, Primiceri, and Tambalotti (2011) that claim MEI shocks are the primary driving force of business cycles, we impose a collateral constraint on capital owners' funding and add land prices and credits to the dataset for estimation.

To understand the roles of collateral constraint, the lower panels of Figure 1.2 presents the impulse responses of variables to an MEI shock. An MEI shock cannot reproduce the procyclical responses of land prices and credits in the data shown in Figure 1.1 although this shock successfully generates co-movements in output, investments, and consumption. In particular, the response of credits is completely opposite for entire simulation periods.

TABLE 1.6: Variance decomposition at business cycle frequencies: hypothetical cases II

		Housing demand	LTV	MEI	Tech-nologies	Mark-ups	Other demands
Y_{obs}	baseline case	14.8	13.9	2.6	44.8	4.1	18.2
	drop collateral const.	5.7	0.0	22.7	42.4	10.1	17.1
	drop collateral const. and B_{obs} & $Q_{l,obs}$	0.0	0.0	44.7	37.4	9.7	6.4
I_{obs}	baseline case	23.0	18.8	6.7	18.1	4.7	27.2
	drop collateral const.	14.8	0.0	39.4	15.3	11.1	17.7
	drop collateral const. and B_{obs} & $Q_{l,obs}$	0.0	0.0	73.6	11.8	7.1	6.2
C_{obs}	baseline case	5.9	9.4	4.7	44.3	3.7	29.8
	drop collateral const.	2.1	0.0	20.2	39.5	7.8	27.7
	drop collateral const. and B_{obs} & $Q_{l,obs}$	0.0	0.0	32.8	30.9	9.5	24.0
$Q_{l,obs}$	baseline case	74.9	3.2	2.9	10.5	1.0	6.7
	drop collateral const.	71.7	0.0	7.6	10.4	2.1	7.3
	drop collateral const. and B_{obs} & $Q_{l,obs}$	0.0	0.0	36.1	29.4	9.8	21.1
B_{obs}	baseline case	25.5	47.0	10.7	6.5	1.5	7.9
	drop collateral const.	39.8	39.9	5.3	7.5	2.3	4.4
	drop collateral const. and B_{obs} & $Q_{l,obs}$	0.0	1.2	46.5	22.7	7.2	16.8

Note: For computational details, see also the Note for Table 1.4. In the *drop collateral const.* case, the model and the parameters are the same as the baseline case except for $\bar{\theta} = 0.001$. In the *drop collateral const. and B_{obs} & $Q_{l,obs}$* case, the model is re-estimated with calibrated at $\bar{\theta} = 0.001$ and without using credits and land prices data. Respective shocks are the same as those in Table 1.5.

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Contrasting credits' responses are due to the combination of collateral constraints and stock price responses. MEI shocks are supply shocks that shift the marginal cost curve for building capital. For this reason, an MEI shock lowers stock prices, which is the price of capital, while it has an expansionary impact on production, investments, and consumption. Justiniano, Primiceri, and Tambalotti (2011) admit this decline in stock prices during a boom as a shortcoming of an MEI shock. Stock price movements are transmitted into credit responses through the collateral constraint. The marked line in the lower panel of Figure 1.2 illustrates the negative response of credits almost disappears once the collateral constraint is dropped.

Table 1.6 presents variance decompositions in a hypothetical economy without collateral constraints. The *drop collateral constraints* rows show that spillovers from collateral-related shocks (i.e. housing demand and LTV shocks) become smaller than those in the baseline case and MEI shocks become an important driver of business cycles instead. Specifically, MEI shocks account for 22.7 percent of output variations and 39.4 percent of investment variations, whereas housing demand shocks account for 5.7 percent of output variations and 14.8 percent of investment variations.

In addition, we re-estimate the model without collateral constraint and with dropping land prices and credits data.[19] This alternative formulation is similar to that of Justiniano, Primiceri, and Tambalotti (2011). The *drop collateral const. and B_{obs} & $Q_{l,obs}$* rows in Table 1.6 report that MEI shocks account for 44.7 and 73.6 percent of output and investment variations. The contribution of MEI shocks increases and approximates to the results reported in Justiniano, Primiceri, and Tambalotti (2011).

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[19]To check the robustness of the results, we generate hypothetical data from the baseline model with posterior mean of parameters and execute the same exercise. The variance decompositions are similar in the exercise with actual data and with hypothetical data.

1.4.4 Robustness check: unconditional variance decomposition

For the exercises in Tables 1.5 and 1.6, we change one feature of the model and keep all other parameters fixed at their estimated values. The purpose of this exercise is to identify the effects of certain features "conditional on the baseline estimation". However, once one parameter is changed, the other parameters could be affected in estimation. Then, this "conditional" variance decomposition may not be the same as the "unconditional" one. Therefore, we re-estimate parameters with an infinite Frisch elasticity and without collateral constraint, and calculate variance decompositions "unconditionally".[20]

Table 1.7 reports that unconditional variance decompositions are about the same as the conditional variance decompositions presented in Table 1.5 and 1.6. It suggests that our conclusion is robust even after we re-estimate the baseline model.

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[20]We do not calculate the case without nominal frictions because it is hard to fit the model to the dataset that includes price and wage inflations without nominal frictions.

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TABLE 1.7: Variance decomposition at business cycle frequencies: unconditional comparison

		Housing demand	LTV	MEI	Technologies	Markups	Other demands
Y_{obs}	baseline case	14.8	13.9	2.6	44.8	4.1	18.2
	infinite Frisch elasticity	27.8	18.5	4.5	21.0	6.4	20.4
	drop collateral constraint	6.8	0.0	35.4	36.2	9.5	10.1
I_{obs}	baseline case	23.0	18.8	6.7	18.1	4.7	27.2
	infinite Frisch elasticity	31.2	20.7	7.8	9.5	4.0	25.6
	drop collateral constraint	13.9	0.0	57.0	12.0	7.8	7.5
C_{obs}	baseline case	5.9	9.4	4.7	44.3	3.7	29.8
	infinite Frisch elasticity	17.0	12.3	5.5	31.8	12.6	19.2
	drop collateral constraint	1.2	0.0	25.9	34.7	10.0	25.7
$Q_{l,obs}$	baseline case	74.9	3.2	2.9	10.5	1.0	6.7
	infinite Frisch elasticity	76.6	3.6	1.8	7.0	2.7	7.6
	drop collateral constraint	73.3	0.0	8.6	9.1	2.8	5.5
B_{obs}	baseline case	25.5	47.0	10.7	6.5	1.5	7.9
	infinite Frisch elasticity	31.4	43.3	4.4	5.8	0.4	14.1
	drop collateral constraint	34.7	49.3	4.6	5.6	1.6	3.2

Note: For computational details, see also the Note for Table 1.4. In the *infinite Frisch elasticity* case, the model is re-estimated with calibrated at $\chi = 0$. In the *drop collateral const.* case, the model is re-estimated with calibrated at $\bar{\theta} = 0.001$. Respective shocks are the same as those in Table 1.5.

1.5 In Closing

Studies like that of Liu, Wang, and Zha (2013) argue that spillovers from land-price fluctuations is the major determinant of output and investment movements at business cycle frequencies. Other studies such as Justiniano, Primiceri, and Tambalotti (2010) stress the importance of investment shocks as a determinant of business cycles. To compare these views within one unified framework, this study introduces land as a collateral asset in investment financing in a standard New Keynesian DSGE model, estimates it, and identifies the major source of U.S. business cycle fluctuations.

The implications are as follows. First, neither housing demand shocks, which is the major determinant of land-price fluctuations, nor MEI shocks are the major source of business cycle fluctuations. Our model suggests that technology shocks are the primary determinant of business cycles. Second, we clarify that the main findings of Liu, Wang, and Zha (2013) crucially depends on the specification of households' utility function. Third, MEI shocks play a minor role in business cycles. Since MEI shocks fail to reproduce business cycle co-movements between output and credits in the model with collateral constraint, they cannot be the principle determinant of business cycles when identified with a model of collateral constraint and credits data.

We raise several caveats. First of all, our model abstracts housing expenditure in construction, following Liu, Wang, and Zha (2013) for the purpose of making comparison easier. This simplification may be justifiable because most of the housing price movements are attributable to the land price movements. However, as suggested in Davis and Heathcote (2007), the importance of housing investments at business cycle frequency is more than non-negligible. Studies in the model with land prices, residential investments in structure, and collateral constraint are the important subject. Second, our

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Chapter 1. What is the Major Source of Business Cycles: Spillovers from Land Prices, Investment Shocks, or Anything Else?

results find that exogenous LTV shocks are also the important factor for output and investment fluctuations, implying that financial intermediaries play a certain role in business cycles. Recent studies such as Justiniano, Primiceri, and Tambalotti (2016) challenge to clarify this role of financial intermediaries in a DSGE model with a housing sector. This line of research is important and promising. Third, we assumed that the collateral constraint always binds. As Guerrieri and Iacoviello (2017) suggest, an occasionally binding constraint creates asymmetric responses and might deliver different results concerning the source of business cycles. This issue is also a promising avenue for future research.

Chapter 2

Flattening of the Phillips Curve under Low Trend Inflation

[1]

2.1 Introduction

It is a conventional view that the output-inflation correlation, i.e., the Phillips curve, is flatter under low trend inflation. Ball, Mankiw, and Romer (1988) (hereafter BMR) suggest that the slope of the Phillips curve becomes *flatter* when the average rate of inflation is low. Benati (2007) has statistically verified BMR's argument using data from OECD countries.

However, standard sticky price models, which occupy the predominant position in recent monetary policy analyses,[2] fail to account for these empirical facts. Notably, Bakhshi et al. (2007) demonstrate that the slope of the new Keynesian Phillips curve (NKPC) becomes *steeper* under lower trend inflation.[3] This theoretical implication of trend inflation is not consistent with the empirical facts.

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[1]The chapter is the revised version of the article in *Economics Letters*, vol.132 (c).

[2]Sticky price models with the Calvo (1983) type infrequent price adjustments and monopolistic competition are widely used in this literature (*e.g.* Woodford (2003)) and policy analysis (*c.f.* Linde, Smets, and Wouters (2016).

[3]Ascari (2004) derives the New Keynesian Phillips curve under non-zero trend inflation. Recent developments in this field are summarized in Ascari and Sbordone (2014)

This study demonstrates how to resolve this discrepancy between empirical findings and the implications derived from standard models. Here, what we consider important is the curvature of the demand curve.

Let's consider a price-setting problem. If firms cannot reset their prices every period, they have to think about not only the present demand schedule but also the future demand schedule. This issue is more troublesome under the positive trend inflation because their relative prices go down while firms cannot reset prices. Now, suppose that firms face a constant elasticity of substitution (CES) demand aggregator, which is most commonly used in standard sticky price models. In this situation, the demand curve becomes steeper as relative prices decline. Then, it is optimal for firms to be more forward-looking under higher trend inflation. Hence, reset prices are less sensitive to current economic conditions and the slope of the Phillips curve becomes flatter.

Suppose that price-setting firms can reset prices only infrequently and face a constant elasticity of substitution (CES) demand curve, which is most commonly used in standard sticky price models. In this situation, demand becomes more price sensitive as the relative price declines. Then, firms are more forward-looking under higher trend inflation. Hence, reset prices are less sensitive to current economic conditions and the slope of the Phillips curve becomes flatter.

In contrast, if firms face a kinked demand aggregator, which was first formulated by Sweezy (1939) and revived by Kimball (1995) in the context of modern dynamic stochastic equilibrium models, the demand curve becomes flatter as relative prices decline. Then, it is optimal for firms to be less forward-looking under higher trend inflation and the slope of the Phillips curve becomes steeper as trend inflation increases.

Concerning the flatter slope of the Phillips curve under lower inflation,

past literature has emphasized the role of time-varying price rigidities.[4] BMR and Romer (1990) claim that the frequency of price adjustments is lower in an environment of low inflation. Bakhshi, Khan, and Rudolf (2007) apply Romer (1990)'s concept to the typical sticky price model and derive the flatter slope of the Phillips curve under lower inflation. As an alternative argument, Tobin (1972) and Akerlof, Dickens, and Perry (1996) claim that the unemployment rate is apt to increase during a low-inflation period because nominal prices and nominal wages tend to be more rigid downwards than upwards. Consequently, the Phillips curve flattens when the inflation rate is near zero. Further, some studies regard monetary policy credibility as an important factor. For example, Boivin, Kiley, and Mishkin (2010) argue that the Phillips curve becomes flat because of changes in monetary policy behavior and effect of these changes on expectations.

Our approach complements these lines of research, however, differs from them in that we focus on demand behavior instead of price-setting friction, wage-setting behavior, or monetary policy credibility.

For the ease of explanation, we first consider the pricing decision of firms in a partial equilibrium setting and indicate that the curvature of demand curve has important implications for firms' pricing behavior under trend inflation. Further, we extend the analysis to the general equilibrium setting and perform stochastic simulations. By doing so, we demonstrate that the Phillips curve is flatter under lower trend inflation if the demand curve is kinked; however, it is steeper if the demand curve is CES.

---

[4]Some studies consider the recent flattening of the Phillips curve observed in industrial countries is attributable to the globalization and increased competition (*e.g.*, Sbordone (2009)). However, the evidence based on the micro data is not necessarily supportive for this hypothesis. For example, Gaiotti (2010) reports that the link between capacity utilization and prices is not necessarily strong for firms that are more exposed to foreign competition.

2.2   A two-period sticky price setting with positive inflation: The partial equilibrium approach

Consider a two-period version of a price setting problem. A fraction of monopolistic competitive firms indexed as $z \in (0,1)$ pick prices $P(z)$. The firms cannot change their prices for two periods.[5]

Now, we will consider the demand curve that pricing firms face. Let an increasing concave function $D(\cdot)$ be a homothetic demand aggregator. Households solve a expenditure minimization problem: $min_{C(z)} \int_0^1 P(z)C(z)dz$ subject to $\int_0^1 D(C(z)/C)dz = 1$, where C is the total consumption implicitly defined by the demand aggregator D. Kimball (1995) presumes a function $D(\cdot)$ suffices $D(1) = 1$, $D(\cdot)' > 0$, and $D(\cdot)'' < 0$. The aggregate price level, P, is implicitly defined by $\int_0^1 (\frac{P(z)}{P})(\frac{C(z)}{C})dz = 1$. The expenditure minimization problem can be solved to obtain the following demand curve: $\frac{C(z)}{C} = d(\frac{P(z)}{\lambda})$, where λ is a Lagrange multiplier on the constraint. Dotsey and King (2005) give a specific function form of $D(\cdot)$ as

$$D\left(\frac{C_t(z)}{C_t}\right) = \frac{1}{(1+\psi)\gamma}\left[(1+\psi)\left(\frac{C_t(z)}{C_t}\right) - \psi\right]^{\gamma} - \left[1 + \frac{1}{(1+\psi)\gamma}\right],$$

where $\gamma \equiv [\epsilon(1+\psi) - 1]/[\epsilon(1+\psi)]$; ϵ is the parameter of demand elasticity and assumed to be greater than one; ψ is the parameter of curvature of demand curve. In this function form, we have one additional parameter, ψ, compared to the CES demand aggregator. This parameter determines the curvature of the demand curve.

---

[5]Ascari (2000) employs a similar two-period model and analyzes how sensitivities of new reset wages depend on trend inflation.

Solving the cost minimization problem, we obtain the following demand curve,

$$\frac{C_t(z)}{C_t} = \frac{1}{1+\psi} \left[\left(\frac{P_t(z)}{\lambda_t} \right)^{-\epsilon(1+\psi)} + \psi \right]. \tag{2.1}$$

$$\frac{\lambda_t}{P_t} = \left[\int_0^1 \left(\frac{P_t(z)}{P_t} \right)^{\frac{\gamma}{\gamma-1}} dz \right]^{\frac{\gamma-1}{\gamma}}.$$

When $\psi = 0$, a demand curve exhibits constant elasticity, as the CES formulation; When $\psi < 0$, each firm faces a quasi-kinked demand curve, á la Kimball (1995).

Figure 2.1 presents the demand curve under respective parameter values. In the case of $\psi = 0$, the demand curve is equivalent to the CES. In the cases of $\psi = -2, -8.4, -16$, the curvature of the demand curve overturns, reflecting the kinked demand property of the Kimball-Dotsey-King type demand aggregator.

FIGURE 2.1: Demand curve: CES versus Kink
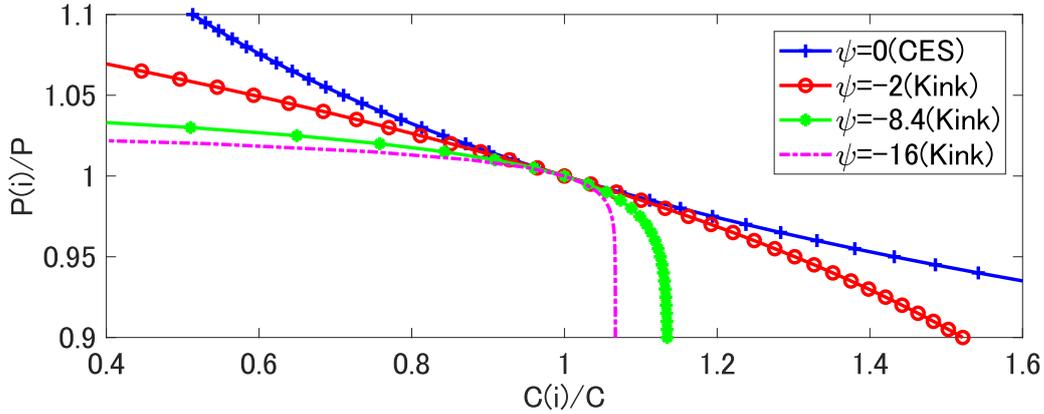
The Dotsey-King's specification has a nice property. The aggregate price index has a specified function form as following,

$$P_t = \frac{1}{1+\psi} \left[\int_0^1 P_t(z)^{\frac{\gamma}{\gamma-1}} dz \right]^{\frac{\gamma-1}{\gamma}} + \frac{\psi}{1+\psi} \int_0^1 P_t(z) dz. \tag{2.2}$$

(2.2) shows that the aggregate price index is expressed as a linear combination of the price index that corresponds to the CES demand aggregator and the simple average of individual prices.

Given the demand curve defined above, we will examine the firms' pricing problem. Specifically, a firm z choose $P_t(z)$ to maximize the following profits over two periods:

$$
\left(\frac{P_t(z)}{P_t} - \frac{MC_t^n}{P_t} \right) d \left(\frac{P_t(z)}{P_t} Q_t \right) Y_t
$$
$$
+ \beta E_t \left[\Lambda_{t,t+1} \left(\frac{P_t(z)}{P_{t+1}} - \frac{MC_{t+1}^n}{P_{t+1}} \right) d \left(\frac{P_t(z)}{P_t} \frac{Q_{t+1}}{\pi_{t+1}} \right) Y_{t+1} \right], \tag{2.3}
$$

where $Q_{t+n} \equiv P_{t+n}/\lambda_{t+n}$, $\pi_{t+1} \equiv P_{t+1}/P_t$, and β is a discount factor ($\beta < 1$). MC_{t+n}^n, Y_{t+n}, and $\Lambda_{t,t+n}$ are the nominal marginal cost, aggregated output, and stochastic discount factor at time $t + n$, respectively. $E_t[\cdot]$ is an expectation operator based on the information set at time t.

Assuming that the utility function is specified as $U_t = \log(C_t)$ and $C_t = Y_t$, the first-order condition of a firm z can be summarized as follows:

$$
\frac{P_t^*}{P_t} = \Theta_t \underbrace{(MC_t - \eta_t)}_{\text{variables at } t} + (1 - \Theta_t) E_t \underbrace{[\pi_{t+1} (MC_{t+1} - \eta_{t+1})]}_{\text{variables at } t+1}, \tag{2.4}
$$

where P_t^* is the optimal price and $MC_t = MC_t^n/P_t$. η_{t+n} is the inversed price sensitivity of demand: $\eta_{t+n} \equiv \frac{d_t}{d_t'}$ and $d_{t+n}' = \partial d(x_{t+n})/\partial(P_t(z)/P_t)$. The inter-temporal weight in (2.4), takes the following form: $\Theta_t \equiv d_t'/[d_t' + E_t(\frac{\beta}{\pi_{t+1}} d_{t+1}')]$.

(2.4) suggests that the optimal relative price is the weighted sum of the current and future variables. Furthermore, the concurrent relationship between the marginal cost and optimal prices depends on the weight, Θ_t. It is clearer when we log-linearize (2.4) around the steady state and derive the coefficient of the optimal price to changes in marginal costs: $\frac{d(P_t^*/P_t)}{\bar{MC} \cdot d\hat{mc}_t} = \bar{\Theta}$, where $\hat{x}_t$ represents a log-deviation of x from the steady state, $\bar{x}$.

Using the specific form of the demand curve in (2.1), we obtain

$$\bar{\Theta} = \frac{1}{1 + \beta \bar{\pi}^{[\epsilon(1+\psi)-2]}}. \tag{2.5}$$

(2.5) means that the optimal price's responsiveness to marginal costs are determined by trend inflation, two parameters of the demand curve, and discount rate. Specific implications of (2.5) can be summarized as follows.

If the demand curve is CES ($\psi = 0$), then the optimal price is more responsive to changes in current marginal cost under lower trend inflation as long as the demand elasticity is $\epsilon > 2$; this condition is quite wide since the steady-state demand elasticity is calibrated as around 7 in many previous works. In contrast, if the demand curve is kinked ($\psi < 0$), the optimal price is less responsive to changes in current marginal costs under lower trend inflation as long as $\epsilon(\psi + 1) < 2$, which is also consistent with wide range of realistic parameter values.

Figure 2.2 presents a graphical interpretation of the above results. The inter-temporal weight, Θ_t, comprises the demand curve's current and future slope. If current demand is more price sensitive than inflation-adjusted future demand, the inter-temporal weight increases. As illustrated in the left-hand side of Figure 2.2, when firms face a kinked demand curve, they expect less price sensitive demand in the future ($|d'_{t+1}/\pi_{t+1}| < |d'_t|$) under higher trend inflation. Hence, in case of the kinked demand, the reset price is more responsive to changes in current marginal costs under lower trend inflation.

Pricing behavior is different when firms face a CES demand curve. As illustrated in the right-hand side of Figure 2.2, the higher trend inflation could result in more forward-looking pricing ($|d'_{t+1}/\pi_{t+1}| > |d'_t|$). In case of CES demand, the reset price is less responsive to changes in current marginal costs under lower trend inflation.

FIGURE 2.2: Demand schedule under non-zero trend inflation
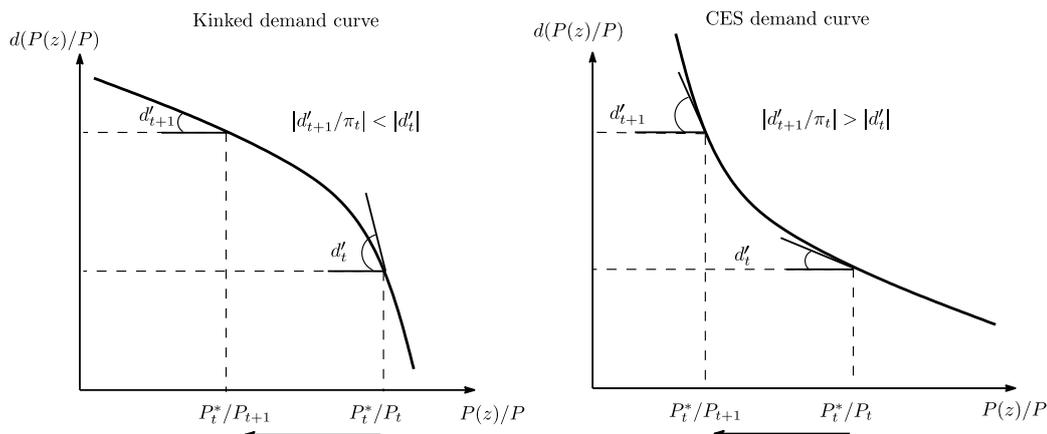
2.3   An infinite-period sticky price model with positive inflation: General equilibrium approach

This section studies the slope of the reduced-form Phillips curve under different trend inflation by simulation, using a standard New Keynesian type dynamic stochastic general equilibrium model. The brief description of the model is as follows.

2.3.1   The Model

We assume that any price-setter indexed by $z \in [0,1]$ is a monopolistic competitor that produces a differentiated intermediate good z. A wholesaler produces a final good, using differentiated intermediate goods as inputs and sells it to households in a perfectly competitive market. The production function of the wholesaler is equivalent to the consumption aggregator of D in the previous section.

Households

A representative household's objective function is defined as follows:

$$E_t \sum_{j=0}^{\infty} \beta^j \ln(C_{t+j}) - N_{t+j},$$

where N_t is labor input.

The contemporaneous budget constraint for the representative household is

$$P_t C_t + B_t \leq W_t N_t + \Pi_t + R_{t-1} B_{t-1},$$

where R_t, B_t, W_t, and Π_t are a price of one period contingent claim bond, amount of the bond, nominal wage, and lump-sum transfer and firms profits, respectively.

Producers

A monopolistically competitive producer sets its price in a Calvo (1983) fashion such that when a producer gets an opportunity to reset the price at time t, the producer can choose the optimal price to maximize the discounted sum of future profits, as in (2.6). The price-reset probability is denoted as $0 < 1 - \alpha < 1$.

$$E_t \sum_{j=0}^{\infty} (\alpha \beta)^j \Lambda_{t,t+j} \left[\left(\frac{P_t(i)}{P_{t+j}} - \frac{W_{t+j}(i)}{P_{t+j}} \right) \right] Y_{t+j}(i) \qquad (2.6)$$

The production function is linear in labor input: $Y_t(i) = N_t(i)$. Market clearing condition holds: $Y_t = C_t$.

Monetary Authority

The monetary authority follows a Taylor-type policy rule with inertia, that is, the monetary authority gradually adjusts the nominal interest rate in response to the deviation of inflation and output from steady-state values.

$$
\frac{R_t^n}{\bar{R}^n} = \left(\frac{R_{t-1}^n}{\bar{R}^n} \right)^\rho \left[\left(\frac{\pi_t}{\bar{\pi}} \right)^{\phi_\pi} \left(\frac{Y_t}{\bar{Y}} \right)^{\phi_y} \right]^{1-\rho}, \tag{2.7}
$$

where $\bar{X}$ denotes the steady state value of X.

2.3.2   Simulation

After solving the agents' optimization problems and log-linearizing equilibrium conditions, we generate hypothetical equilibrium paths of 500 periods, in which the only source of equilibrium dynamics is the exogenous monetary policy shock. For each simulation, we change the combination of the trend inflation({0%, 4%, 8%}) and type of demand function ({ *CES*, *Kink*}).

The other parameters are calibrated as follows. The subjective discount factor is $\beta = 0.99$. The probability of no price change is $\alpha = 0.6$. Following Levin, Lopez-Salido, and Yun (2007), the parameters of demand elasticity and demand curvature are set as $\epsilon = 7$ and $\psi = -8.4$, respectively. Finally, the monetary policy rule's coefficients on output and inflation are $\phi_y = 0.5$ and $\phi_\pi = 1.5$, respectively. The lag coefficient of the policy rule is $\rho = 0.8$.

Figure 2.3 indicates the scatter plots of simulated values of inflation and output, that is, the simulated Phillips curves. The left-hand and right-hand side panels correspond to the cases that employ the CES demand curve and the kinked demand curve, respectively. Three types of scatter plots in each panel correspond to the cases of different trend inflation: 0, 4, and 8% per annum.

FIGURE 2.3: The reduced-form Phillips curve
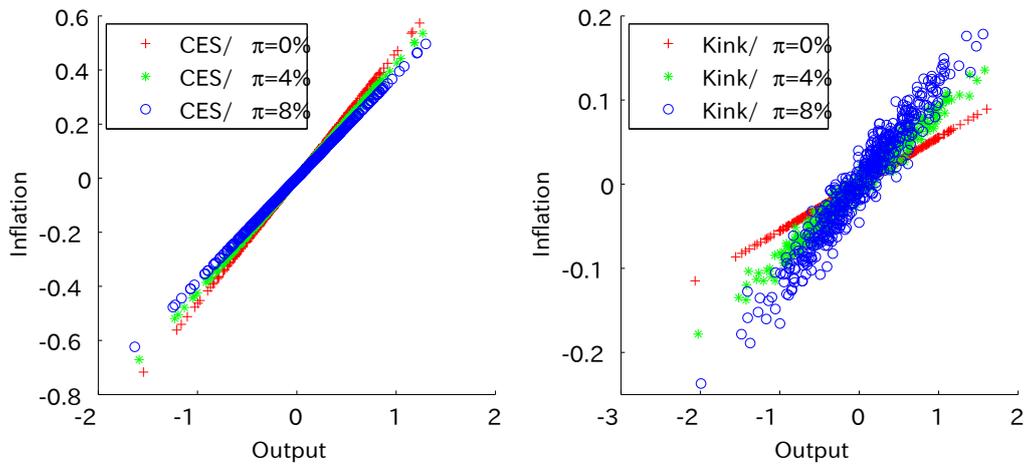
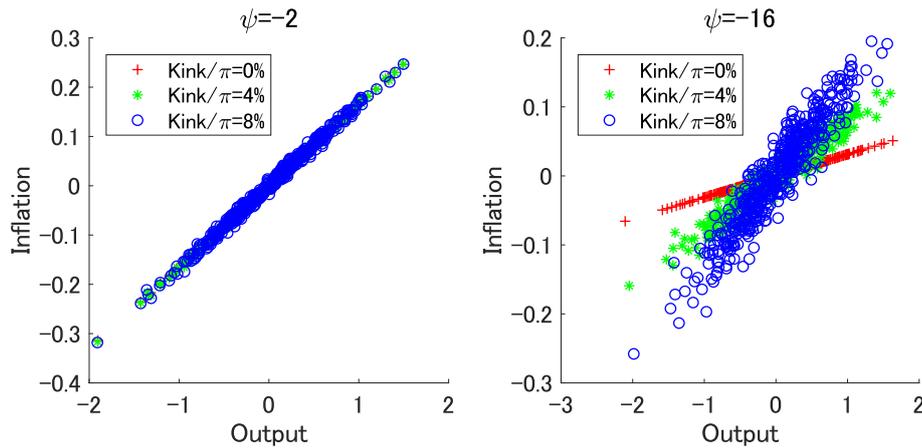Note: Inflation and output are log-deviations from respective steady states.

In the figure, we can see the clear difference between CES and kinked demand cases. In the CES demand cases, the Phillips curve becomes *steeper* as trend inflation decreases. In contrast, in the kinked demand cases, the Phillips curve becomes *flatter* as trend inflation decreases. The results that use kinked demand curve are consistent with the empirical work by Benati (2007).

As suggested in Bakhshi et al. (2007), the canonical sticky price model cannot explain this flatter slope of the Phillips curve under lower inflation. Our analysis is successful in explaining this discrepancy between the standard sticky price models and the empirical evidence. Notably, the mechanism behind our results is different from Bakhshi, Khan, and Rudolf (2007), which stress the role of time-varying nominal rigidities in the spirit of BMR or Romer (1990). We have indicated that the kinked demand can also explain the flatter slope of the Phillips curve under lower trend inflation.

Figure 2.4 presents the simulated Phillips curve under different parameter values of demand curvature $\psi = -2$ and $\psi = -16$. The left-hand size panel suggests that the *steeper* Phillips curve under lower trend inflation, which is

a problematic feature of standard sticky price models, will be fixed only if we postulate a small degree of non-constant elasticity $\psi = -2$. Further, our main result and two panels in this Figure show that the curvature of demand curve can be the crucial factor to determine the slope of the Phillips curve under variable trend inflation rates.

FIGURE 2.4: The reduced-form Phillips curve: alternative ψ

Note: Inflation and output are log-deviations from respective steady states.

2.4   In Closing

This study challenges to fill the gap between the implications of standard sticky price models and empirical facts regarding the Phillips curve under low trend inflation. We demonstrate that introducing the "smoothed out kinked" demand curve (Kimball (1995)) can offer an explanation of the flattened Phillips curve under conditions of lower trend inflation. In the case of the kinked demand curve, the elasticity of substitution is non-constant. Under positive trend inflation, forward-looking firms expect that the demand would be price sensitive in the future and their pricing behavior become front loading. Consequently, the inflation is less sensitive to current economic activities and more exerted by the prospect of the future economy.

There still remains much room for further exploration. This study takes a time-dependent nominal friction as given. However, nominal frictions are not limited to the time–dependent ones. It is still ambiguous whether the conclusion set forth in this study holds for model with other types of nominal frictions such as menu-cost pricing. It would be an interesting topic for future research to study the effect of the demand curvature and trend inflation under different nominal frictions.

Much room is also left for empirical exploration. In the simulation section, this study uses a simple three-equation model and calibrates parameters to focus on the theoretical possibilities. As a next step, it would be interesting to expand the model to a medium-scale model that can capture the actual business cycle dynamics and to estimate parameters using actual data.

Chapter 3

Shock Size Matters for US Monetary policy: Menu-cost Pricing, Information Effect, or Selective Gradualism?

3.1 Introduction

Sometimes, central banks initiate major policy changes. Is a big monetary policy change more powerful than an incremental one? This study investigates whether shock size matters for the US monetary policy.

It is unobvious that a large monetary policy shock is more effective than a small shock. For instance, typical menu-cost models imply that a large monetary policy shock is less powerful than a small shock. In these models, most firms reset prices after a large monetary policy shock; thus, the impacts on economic fundamentals would be small.[1] In contrast, some theoretical

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[1]Golosov and Lucas (2007) employed a menu cost model with normally distributed idiosyncratic shocks and indicated that monetary policy slightly impacts economic fundamentals. Midrigan (2011) used a menu cost model with a fat-tailed distribution of idiosyncratic shocks and claimed that monetary policy is considerably non-neutral. Both researchers have assumed that monetary policy shocks are small.

studies such as those by Diamond (1982) have inferred that an active policy intervention stimulates aggregate economic activities and leads to better equilibrium outcomes. Although this topic has potential implications for understanding the hidden economic structure, it has not been thoroughly studied.

To address this issue, this study employs the local projection method of Jorda (2005) and estimates the impulse response function, allowing for parameters to depend on the size of shocks. The monetary policy shocks are identified following the study by Romer and Romer (2004). The estimated impacts on major economic variables clearly demonstrate that the shock size matters for the US monetary policy effects.

This study's findings are summarized as follows. First, the main result of the analysis indicates that a large monetary policy shock is less effective than a small shock. The finding is relevant for the classification of large and small shocks, outliers, and market disruptions during the Volker's chairmanship as well as the distribution of contractionary and expansionary shocks.

Second, this study examines three hypotheses concerning the asymmetric responses to large and small shocks. It finds that the monetary policy design is the relevant source of the phenomenon. The first hypothesis to be examined is with regard to menu cost pricing. As described above, typical menu cost models suggest that a large monetary policy shock considerably impacts aggregate prices; however, the impact on economic fundamentals is almost neutral because most firms find it optimal to adjust prices. However, our result contradicts the theoretical prediction of menu cost models, indicating that a large shock has a weak impact on economic fundamentals and inflation. The second hypothesis concerns the information effect. As indicated by Romer and Romer (2000), the monetary policy shock conveys information about the future prospects of monetary policy and other economic fundamentals. If households and firms update their beliefs about

potential growth rates with greater sensitivity to a larger monetary policy shock, then monetary policy effects would be asymmetric according to the shock size. However, our regression analysis using survey expectations denies this possibility. Finally, the third hypothesis covers the selective gradualism of monetary policy. The Federal Reserve basically adjusts policy rates gradually, but it selectively deviates from a gradualist approach if necessary. As stressed by Woodford (2003), a commitment to gradual interest rate adjustment can significantly impact long-term interest rates and economic fundamentals through the expectations channel, while a monetary policy shock that is perceived to be temporary cannot. By performing impulse response matching with a standard medium-scale dynamic stochastic general equilibrium (DSGE) model, this study suggests that the main result is consistent with the "selective" gradualism of the Federal Reserve.

Third, this study revisits several state dependencies of monetary policy effects through the lens of shock size distribution. One is the dependency on uncertainty. Real option effects on business investments (Dixit and Pindyck (1994) and Bloom (2009)), households' precautionary savings (Deaton (1991) and Carroll (1992)), and financial institutions' behavior (Christiano, Motto, and Rostagno (2014)) suggest that increased uncertainty reduces firms' and households' responsiveness to exogenous shocks. Aastveit, Natvik, and Sola (2017) and Castelnuovo and Pellegrino (2018) provide evidence that the effect of monetary policy is asymmetric and less powerful under higher uncertainty. Our result reveals that the asymmetric effect appears only when all the monetary policy shocks are included in the empirical analysis but disappears once a small number of huge monetary policy shocks are excluded. This conclusion stresses the importance of controlling the shock size distribution in the empirical analysis of the monetary policy effect.

Another state dependency re-examined here is that on economic growth

rates. It is a conventional wisdom among practitioners that monetary policy is more effective during an expansionary phase of the economy. Previous studies on this and adjacent matters[2] have found mixed results. In line with the recent studies by Tenreyro and Thwaites (2016), we find that the monetary policy is effective when the economic growth rate is high, and this conclusion is robust even after controlling for the shock size.

This study is a part of the literature that uncovers nonlinearity of the monetary policy effects but differs from previous studies in that its focus is on the shock size. Among others, our study is close to that by Ravn and Sola (2004). Ravn and Sola (2004) use a time series procedure related to that of Barro (1977) and Mishkin (1982). They examine the contemporaneous impact of monetary policy shocks on output and find that only a small negative shock on the federal funds rate has a real effect. Furthermore, they conjecture that a menu cost model can offer a reasonable explanation regarding their finding. Our study extends the findings of the study by Ravn and Sola (2004) in several dimensions. First, employing a variant of the local projection method of Jorda (2005), it estimates dynamic impulse responses over long horizons, which are more common and pertain to the central issue discussed in the literature.[3] Second, this study estimates impulse responses of the output (production) and other important variables such as inflation and term spreads of interest rates. This point enables us to explore the specific mechanism behind the asymmetry and helps discover that the relevant mechanism is not menu cost pricing but the monetary policy framework. The hypothesis concerning the information effects of Romer and Romer (2000), Nakamura and Steinsson (2013), and Jarocinski and Karadi (2018) are checked as a potential cause

---

[2]*e.g.* Evans (1986), Weise (1999),Thoma (1994),Lo and Piger (2005),Garcia and Schaller (2002), and Tenreyro and Thwaites (2016).

[3]Compared with a structural vector autoregression model frequently used to estimate impulse responses in the monetary policy analysis, the local projection adopted in this article has several advantages: it does not impose any restrictions on the functional form of dynamic shock propagation and requires only a small number of parameters to be estimated.

of the asymmetry. Another related study is that by Tenreyro and Thwaites (2016), which suggests the possibility that monetary policy effects might be different depending on the shock size. However, their primary interest is the state dependency on the economic growth rate. Our analysis expands their work and explores a suggested direction intensively.

The remainder of this paper is organized as follows. Section 3.2 presents the econometric framework of this study. Section 3.3 outlines the main result and robustness checks. Section 3.4 investigates the cause of shock size dependency. Section 3.5 reconsiders other state dependencies of monetary policy effects through the lens of shock size. Section 3.6 presents the conclusion.

3.2 Econometric framework

3.2.1 The model

The empirical methodology is based on the local projection model of Jorda (2005). We expand it to estimate parameters separately for large shock and small shock states.[4] In this framework, we first identify monetary policy shocks, and then, estimate impulse responses of target variables.

Linear and regime-switching Romer regression

Romer and Romer (2004) propose a new measure of monetary policy shocks as residuals of the following monetary policy reaction function:

$$\Delta FF_t = \kappa' X_t + \epsilon_t. \tag{3.1}$$

---

[4]Similar framework has been employed by Auerbach and Gorodnichenko (2012), Ramey and Zubairy (2018), and Tenreyro and Thwaites (2016) to investigate the state-dependent effects of fiscal and monetary policies.

where FF_t denotes an intended federal funds rate derived narratively by Romer and Romer (2004), and the covariate matrix X_t includes Federal Reserve's internal forecasts prepared for the Federal Open Market Committee (FOMC). Intended funds rates enable us to identify consistent policy shocks regardless of the policy instrument in effect at each particular time. Further, the Fed's internal forecasts help to bleach the systematic responses of monetary policy to the current and future prospect of the economy.

The hypothesis to be examined in this study is that the economy responds differently to large and small shocks. Accordingly, this study adopts two types of policy reaction functions. One is Romer's original linear regression model of (3.1). After obtaining monetary policy shocks, this study stratifies them into large and small shocks by setting a certain threshold. For convenience, this study introduces a binary state variable s_t that represents the current state of the shock size: $s_t = 0$ for small shocks and $s_t = 1$ for large ones.

Another policy reaction function is a regime-switching one. Monetary policy shocks may switch between high and low volatility processes. Then, economic agents would change their behavior under high and low volatility regimes. Consequently, economic responses to large and small shocks could be observed differently. As a specific functional form, this study adopts the following regime-switching (RS) Romer regression model,

$$
\begin{aligned}
\Delta FF_t &= \kappa(s_t)' X_t + \tilde{\epsilon}_t, \ s_t = \{0, 1\}, \\
\tilde{\epsilon}_t &\sim N\left(0, \sigma_{\tilde{\epsilon}}(s_t)\right), \\
p &= \begin{bmatrix} p_{0,0} & 1 - p_{1,1} \\ 1 - p_{0,0} & p_{1,1} \end{bmatrix},
\end{aligned}
\tag{3.2}
$$

where parameters $\{\kappa(s_t), \sigma_{\tilde{\epsilon}}(s_t)\}$ are different depending on the state s_t; p denotes the matrix of state transition probabilities. Hereafter, we call ϵ_t and

$\tilde{\epsilon}_t$ linear and RS Romer shocks, respectively.

Impulse response function

The impulse response of variable z_t at h periods ahead in state $s = \{0, 1\}$ to an exogenous monetary policy shock is estimated as β_h^s,

$$
z_{t+h} = \begin{cases}
\delta\tau + I\left(s_t\right)\left(\alpha_h^0 + \beta_h^0 \epsilon_t + \gamma^{0\prime} x_t\right) \\
\quad + \left[1 - I\left(s_t\right)\right]\left(\alpha_h^1 + \beta_h^1 \epsilon_t + \gamma^{1\prime} x_t\right) + \eta_t \quad \textit{(linear Romer shock)}, \\
\delta\tau + q\left(s_t\right)\left(\alpha_h^0 + \beta_h^0 \tilde{\epsilon}_t + \gamma^{0\prime} x_t\right) \\
\quad + \left[1 - q\left(s_t\right)\right]\left(\alpha_h^1 + \beta_h^1 \tilde{\epsilon}_t + \gamma^{1\prime} x_t\right) + \tilde{\eta}_t \quad \textit{(RS Romer shock)},
\end{cases}
\tag{3.3}
$$

where $I(s_t)$ is an indicator function of small shocks that takes a value of 1 when the shock size is small and 0 otherwise; $q(s_t)$ is a probability of low volatility regime; τ denotes a time trend; α_h^s is a constant; and x_t is the vector of covariates. In (3.3), the coefficients of large shocks and small shocks are estimated separately.

We stuck the local projection equation of (3.3) for $h = 0, 1, ...H$ and apply the seemingly unrelated regression (SUR) to calculate the smoothed impulse response functions.[5] The dependent variables are industrial production, housing, real consumption, inflation, and interest rates (i.e., term spreads).

One caveat when performing time series analysis using Romer and Romer (2004)-type monetary policy shocks is that the identified shocks are available only for the months with FOMC meetings, which "Greenbook" is prepared for[6]. Intermittent data is not suitable for standard time series analysis, such as the estimation of (3.3).

---

[5]Although the SUR does not improve the efficiency of (3.3) because the regressors are identical for each equation, it is useful to calculate the distribution of functions of smoothed parameters.

[6]Romer and Romer (2004) fill the shocks with zero for the months without FOMC meetings. Tenreyro and Thwaites (2016) avoid this issue by converting monthly data to quarterly data.

To cope with the discrepancy between the model and the data, this study constructs dataset in a panel format, in which t represents intermittent months of FOMC meetings and h represents H consecutive months after a period t (c.f. Table 3.1). By splitting intermittent t and continuous h, we can estimate the model in a consistent manner. Hereafter, the left-hand side variable of (3.3) is denoted as $z_{t,h}$ instead of z_{t+h}.

TABLE 3.1: Illustrative example: panel structure of dataset

Date of FOMC meeting	ϵ_t	z_t	$z_{t,1}$	$z_{t,2}$	$\cdots$	$z_{t,H}$	x_t
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
December 21, 1999	.	.	.	.	.	.	.
February 2, 2000	.	.	.	.	.	.	.
March 21, 2000	.	.	.	.	.	.	.
May 16, 2000	.	.	.	.	.	.	.
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$

The panel-formatted dataset also enables us to utilize stratification in estimation. Traditional time series analysis (e.g., vector autoregression models) requires a continuous time series of data and has difficulties estimating a model when some of the consecutive time series data are excluded. However, the local projection method is easy to accommodate with stratification in estimation when combined with a panel-formatted dataset. We will use this benefit in the latter section.

3.2.2 Data source and sample period

This study estimates the impulse responses of industrial production, housing construction, real consumption, inflation rate, and term spreads. The data is downloaded through the FRED API provided by the Federal Reserve Bank of St. Louis. Inflation is the monthly change in the personal consumer expenditure (PCE) core deflator. Term spreads are the differentials between 10-year government bond yields and effective federal funds rates. Housing is the

logarithm of housing starts. Industrial production and real consumption are also in logarithm. As for the policy reaction function, this study employs the dataset originally developed by Romer and Romer (2004) and extended and shared by Tenreyro and Thwaites (2016).

The sample period spans March 1969 to December 2007.[7] It does not include the crisis period around the collapse of Lehman Brothers because the impact of monetary policy during this period could have been different from those of monetary policies during other normal periods.

3.3 Shock Size and Monetary Policy Effects

This section first outlines the estimated monetary policy shocks and our main results. Thereafter, it examines their robustness.

3.3.1 Estimated monetary policy shocks

Figure 3.1 presents the estimated monetary policy shocks.[8] Linear and RS Romer shocks move in tandem. The correlation between these shocks is 0.954. Both shocks fluctuate around zero, by definition, but show large spikes at certain times. Huge shocks were concentrated during the early part of Chairman Volker's monetary targeting periods.

The descriptive statistics in Table 3.2 report that 27 shocks have standard deviation greater than 1.5 over the entire sample period. In the following empirical exercises featuring linearly identified Romer shocks, this study defines large shocks as those with standard deviation greater than 1.5, considering the balance between relative shock size and the number of observations. The robustness of this definition will be examined in the following section.

---

[7]Since the length of impulse responses is 60 months, the monetary policy shocks end in December 2002.

[8]Our linearly identified Romer shocks are quite similar to Romer and Romer (2004)'s shocks. The correlation between the Romer's shocks and those in this study is 0.979. The correlation is calculated using estimated shocks from March 1969 to December 1996.

In the exercises featuring RS Romer shocks, 85 shocks are estimated to have been in the large shock (high volatility) regime.[9] The standard deviations of shocks are 0.368 for linear Romer shocks and 0.357 for RS Romer shocks. The Federal Reserve tends to change policy rates by 0.25 or 0.50 percent. The estimated standard deviations lie in the midst of these values.

Contractionary shocks are considered to be more powerful than expansionary ones, as implied in the famous phrase, "cannot push on a string". If these shocks are more common in either small or large shocks, our estimated results could be biased. However, the 5th column of Table 3.2 shows that the number of positive and negative shocks are almost equivalent in both large and small shock clusters. It is unlikely to be a source of asymmetry between large and small shocks.

FIGURE 3.1: Romer and Romer [2004] type monetary policy shocks
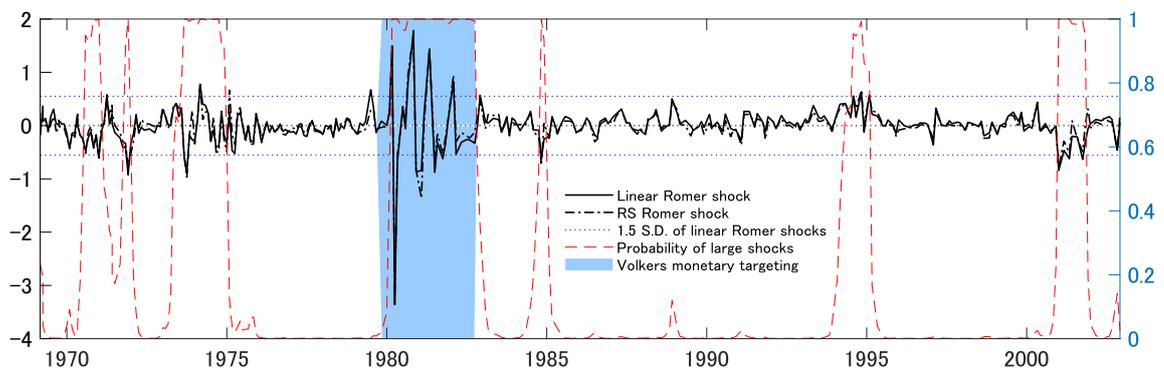
Note: The probability of large shocks is right-hand-side scaled. Shaded area denotes Volcker's monetary targeting period between October 1979 and October 1982.

3.3.2 Main results: the shock size matters for monetary policy effects

Figure 3.2 reports impulse responses to monetary policy shocks. Solid and broken lines represent the cases of linear and RS Romer shocks, respectively.

---

[9]Specifically, the probability of the high volatility regime exceeds 50%.

TABLE 3.2: Descriptive statistics of monetary policy shocks

|	N	$N_{2\sigma_\epsilon \leq |\epsilon|}$	$N_{3\sigma_\epsilon \leq |\epsilon|}$	Positive shocks (% of total)	Mean	S.D.	Max	Min
Linear Romer shocks								
Overall	314	14	5	50.0	-0.008	0.368	1.783	-3.361
Small shocks	287	-	-	50.2	-0.005	0.191	0.502	-0.534
Large shocks	27	14	5	48.2	-0.036	1.106	1.783	-3.361
RS Romer shocks								
Overall	314	13	6	51.0	-0.007	0.357	1.490	-3.212
Small shocks	229	-	-	52.0	0.006	0.156	0.673	-0.465
Large shocks	85	13	6	48.2	-0.041	0.637	1.490	-3.212

Note: Large shocks are shocks greater than 1.5 σ_ϵ for linear Romer shocks and shocks in the large shock regime (probability is greater than 50%) for RS Romer shocks.

The first column provides the estimated responses without making a distinction between large and small shocks. The second and third columns report the responses to small and large shocks, respectively. The fourth column is the differential between the second and third columns. The impulse responses are three-horizon centered moving averages and are normalized to generate an initial 1 percentage point rise in the federal funds rate.

The first three rows of Figure 3.2 report that production, housing, and consumption decline following a positive monetary policy shock. In the linear model that does not distinguish between large and small shocks, the production hits the bottom approximately after two years, as suggested in previous studies (e.g., Christiano, Eichenbaum, and Evans (1999) and Romer and Romer (2004)). Production responses to contractionary shocks after two years are -3.72 percent (linear Romer shocks) and -3.29 percent (RS Romer shocks). These values are similar to those in the study by Romer and Romer (2004) (-4.3 percent) even though the sample periods of both the studies are different.

The second and third columns clearly indicate that the impacts of large shocks are significantly attenuated. The bottom of production responses to large shocks is less than one-half of those made to small shocks. As for linear Romer shocks, production responses to small shocks are -8.08 percent and

FIGURE 3.2: Impulse responses to a monetary policy shock
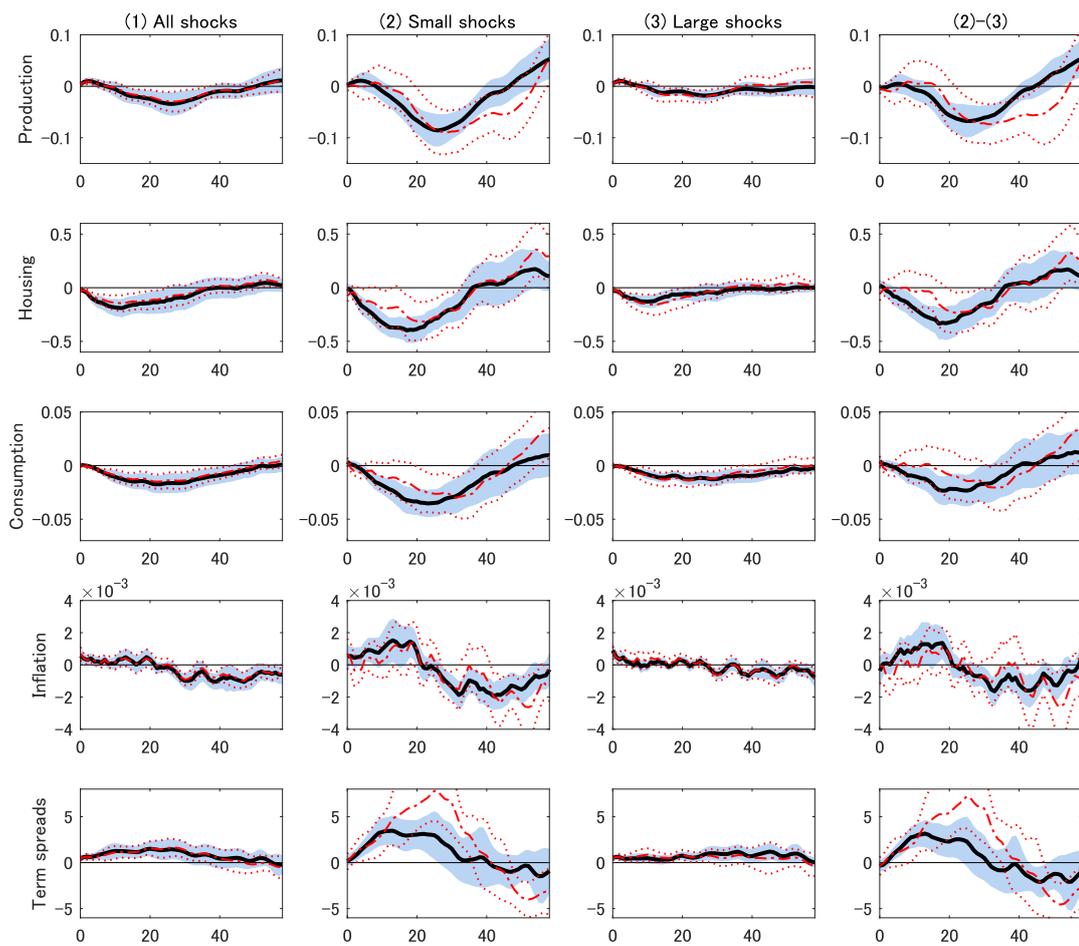
Note: Impulse responses to a contractionary monetary policy shock are presented with 90 percent confidence intervals. Thick and broken lines correspond to linear and RS Romer shocks.

those to large shocks are -2.00 percent after two years. The difference between large and small shocks in the fourth column is significant around the bottom of the responses. In the case of RS Romer shocks, the quantitative impacts on production are quite similar. The contrasts between large and small shocks are evident in housing and consumption; however, the confidence intervals are wider in the case of RS Romer shocks.

For inflation and interest rates provided in the fourth and fifth rows, the impulse responses to large shocks are also weak. Inflation starts to turn significantly negative after 1.5 to 2 years for all shocks in the first column and for small shocks in the second column. This pattern is consistent with that in the aforementioned previous studies. However, inflation responses to large shocks are indistinct and remain close to zero. Term spreads increase to around 2 (6) percent after 2 years in the case of small linear (RS) Romer shocks but stay under 0.5 percent in the case of large shocks. We will discuss the implications of both inflation and term-spread reactions in the next section.

3.3.3 Robustness check: Volker's chairmanship, outliers, and other factors

Several concerns could be raised regarding the main results. First, large shocks are concentrated in the early period of the Chairperson Volker's monetary-targeting regime. Large shocks may not be the source of ineffective monetary policy but rather outcomes of an alternative monetary policy regime. To check the robustness of the main results, the model is re-estimated after excluding observations from October 1979 to May 1981, which is the same as the period of Romer and Romer (2004)'s robustness check. Our panel-formatted dataset can easily accommodate partial exclusions within

the dataset. Thick lines in Figure 3.2 indicate that small shocks have a significantly greater impact on production. The conclusions are basically unchanged even after considering the extraordinary periods during Volker's Chairmanship.

Another concern is that large shocks might be affected by a few outliers.[10] In Figure 3.3, the model is re-estimated after excluding observations greater than 3 standard deviations. Figure 3.3 suggests that the monetary policy effect on production is weaker for large shocks even after excluding inordinately large shocks.

FIGURE 3.3: Exclusion of early periods of Volker's chairmanship and extraordinary shocks
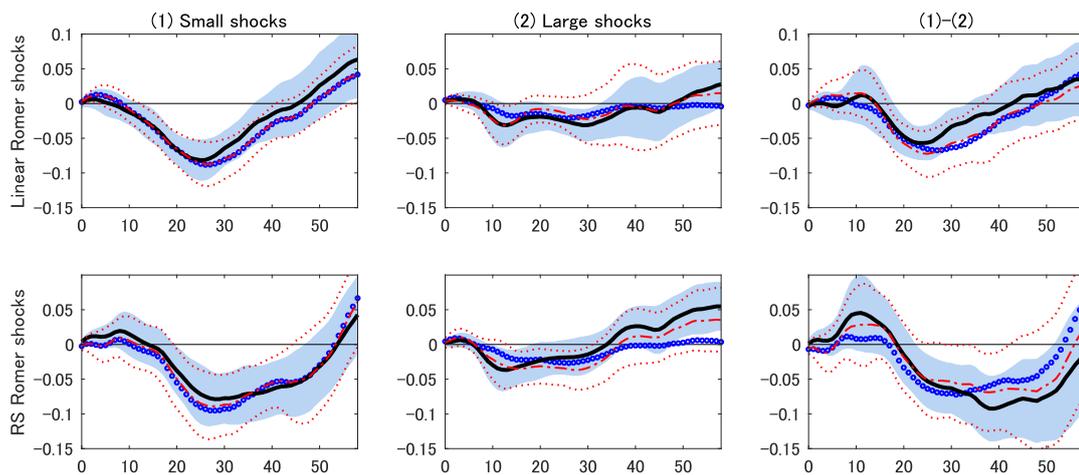
Note: Thick lines and shaded areas show impulse responses and 90 percent confidence intervals estimated after excluding Chairman Volcker's earlier monetary targeting periods from October 1979 to May 1981. Broken lines with dotted lines are impulse responses and 90 percent confidence intervals after excluding shocks greater than 3 standard deviations. Circles represent impulse responses of the main results, for reference.

Table 3.3 summarizes other robustness checks. The upper and lower panel of Table 3.3 are impulse responses to linear Romer shocks and RS Romer shocks under alternative specifications, respectively.

---

[10]Another potential concern might be that large shocks are measurement errors. However, significant impulse responses of economic fundamentals suggest that the measurement error hypothesis is less likely.

Linear Romer shocks used in the main results are stratified into large and small shocks at a certain threshold value: 1.5 standard deviations. Column (1-b) presents the results under alternative stratifications. The alternative threshold value between large and small shocks is 2 standard deviations instead of 1.5 standard deviations. The peak response of production to small shocks is still significantly greater than that under large shocks although the quantitative impact weakens from -8.4% to -5.3%. Column (1-c) estimates impulse responses with regard to shocks greater than 2 standard deviations as outliers. This exercise is more conservative than the robustness check in Figure 3.3. The quantitative impacts from a one-unit shock are almost identical to the main results, and the differences between large and small shocks are still significant.

Next, the RS Romer shocks used in the main results are identified as residuals of the reaction function, in which both parameters and standard deviation of the shocks are regime-switching. Column (2-b) shows the impulse response to an alternative RS Romer shock that is identified with a model in which only the standard deviation of shocks is regime-switching. The peak responses of -8.4 and -2.5 percent at $h = 30$ for small and large shocks are quite similar to -9.5 and -2.6 percent of the main results. The difference between large and small shocks remains significant.

Column (2-c) reports the estimated impulse responses under alternative regime transition process. Following Granger and Terasvirta (1993) and Tenreyro and Thwaites (2016), this study employs the logistic function to describe a smooth transition process between the states instead of a Markov switching process.

$$\hat{q}\left(s_t\right) = 1 - \frac{e^{\theta \frac{|\epsilon_t| - c}{\sigma_\epsilon}}}{1 + e^{\theta \frac{|\epsilon_t| - c}{\sigma_\epsilon}}},$$

where θ denotes a parameter to control transition smoothness and is set to 3 to give an intermediate degree of intensity to the regime-switching, as in

the study by Tenreyro and Thwaites (2016); c is an arbitrary constant used to determine what proportion of observations the economy spends in a large shock state.[11] Column (2-c) clearly shows that the results are almost identical to the main results.

Finally, the "Calender dates" columns of (1-d) and (2-d) suggest that the main results are robust even if the monetary policy shocks of non FOMC months are imputed with zero values. In summary, our main results are robust to other shock size classifications, specifications, and treatments of missing observations.

---

[11]In this exercise, we set c so that the top 20 percent of shocks are classified as large shocks.

TABLE 3.3: Responses of industrial production: robustness checks

Linear Romer shocks

	(1-a) Main results			(1-b) Alternative size 1			(1-c) Alternative size 2			(1-d) Calender dates		
h	Small shocks	Large shocks	Diff. t-value	Small shocks	Large shocks	Diff. t-value	Small shocks	Large shocks	Diff. t-value	Small shocks	Large shocks	Diff. t-value
6	0.011	0.002	0.838	0.007	-0.001	1.078	0.011	0.011	0.028	0.010	0.005	0.465
12	-0.014	-0.011	-0.281	-0.012	-0.014	0.182	-0.013	-0.007	-0.316	-0.014	-0.006	-0.693
18	-0.048	-0.015	-2.488	-0.028	-0.023	-0.529	-0.047	0.016	-3.295	-0.048	-0.011	-2.679
24	-0.081	-0.020	-3.521	-0.048	-0.026	-1.764	-0.079	0.010	-3.911	-0.080	-0.016	-3.607
30	-0.084	-0.019	-4.057	-0.053	-0.019	-1.992	-0.082	-0.011	-2.633	-0.080	-0.017	-4.238
36	-0.058	-0.008	-3.851	-0.037	-0.004	-1.745	-0.056	-0.015	-1.119	-0.053	-0.007	-4.301

RS Romer shocks

	(2-a) Main results			(2-b) Alternative specification			(2-c) Alternative regime			(2-d) Calender dates		
h	Small shocks	Large shocks	Diff. t-value	Small shocks	Large shocks	Diff. t-value	Small shocks	Large shocks	Diff. t-value	Small shocks	Large shocks	Diff. t-value
6	-0.001	0.003	-0.273	0.008	0.007	0.064	0.001	0.005	-0.303	-0.001	0.005	-0.350
12	-0.003	-0.011	0.289	0.004	-0.010	0.552	-0.015	-0.014	-0.046	-0.002	-0.007	0.176
18	-0.024	-0.022	-0.066	-0.016	-0.022	0.324	-0.049	-0.020	-1.178	-0.022	-0.017	-0.179
24	-0.080	-0.026	-2.032	-0.065	-0.028	-1.509	-0.090	-0.022	-1.588	-0.073	-0.019	-2.039
30	-0.095	-0.024	-2.746	-0.084	-0.025	-2.661	-0.097	-0.018	-2.238	-0.089	-0.017	-3.074
36	-0.075	-0.010	-2.598	-0.077	-0.010	-2.569	-0.082	0.002	-2.756	-0.074	-0.005	-3.056

Note: The left column denotes the months after a contractionary monetary policy shock. In (1-b), large (small) shocks are defined as $|\epsilon| > (\leq)2\sigma_\epsilon$. In (1-c), shocks greater than $2\sigma_\epsilon$ are excluded and large (small) shocks are defined as $|\epsilon| > (\leq)1.5\sigma_\epsilon$. In (1-d), shocks in non FOMC months are imputed with zero. In (2-b), only the standard deviation of the error term follows Markov switching. In (2-c), the stated transition function is logistic. See main text for details.

3.4 Why does the shock size matter?

This section examines several hypotheses pertaining to why shock size matters for monetary policy effects.

3.4.1 Menu cost pricing

The first hypothesis is that the lumpy price adjustments implied by models with menu costs of price adjustments[12] cause asymmetric responses to large and small shocks. In the presence of menu costs, (small) monetary policy shocks are non-neutral to economic fundamentals because a considerable fraction of prices remain unchanged. However, large shocks slightly influence economic activities because the majority of firms find it optimal to adjust prices. Consequently, standard menu cost models suggest smaller output responses and larger price responses to large monetary policy shocks.[13]

The impulse responses presented in Figure 3.2 contradict the theoretical prediction of standard menu cost models. Specifically, output and price responses are weaker for large monetary policy shocks. We can conclude that menu cost pricing is not the relevant hypothesis for the shock size dependency of monetary policy effects.[14]

3.4.2 Information effect

The second hypothesis concerns the information effect. Romer and Romer (2000) mentioned that a monetary policy surprise conveys information about

---

[12]Among others, see Ball and Mankiw (1994), Golosov and Lucas (2007), and Midrigan (2011).

[13]Using a menu cost model, Karadi and Reiff (2014) analyzed the impact of large tax shocks.

[14]To be clear, this study did not test menu cost pricing. It just argues that menu cost pricing cannot provide quantitative explanation for the impulse responses in Figure 3.2. In the later section, we discuss other hypotheses consistent with menu cost pricing.

Federal Reserve's assessment of the economic outlook.[15] For ease of explanation about conventional interest rate channels and information effects, this study considers an intertemporal Euler equation and solves it in forward,

$$
\begin{aligned}
y_t &= E_t y_{t+1} - (i_t - E_t \pi_{t+1} - r_t^*), \\
&= -E_t \sum_{i=0}^{\infty} (i_{t+i} - \pi_{t+1+i} - r_{t+i}^*),
\end{aligned}
$$

where y_t, i_t, π_t, and r_t^* are output, nominal interest rates, inflation, and natural rates of interest, respectively. In standard models, a positive monetary policy shock increases the real interest rate $i_t - E_t \pi_{t+1}$ and creates contractionary impacts on the economy.

When we consider the information revealed through the monetary policy action, the effect of a policy surprise is not limited to a depressing effect through the real interest rate. As suggested by Romer and Romer (2000) and Nakamura and Steinsson (2013), the policy surprise may also increase the prospects of future natural rates r_{t+i}^* because economic agents regard that the Fed is more optimistic about the path for potential output.[16] Specifically, agents infer that the Fed has private information that supports the increased natural rate of interest in the future. The information effects mitigate the depressive effects impelled by increases in real interest rates.

If large shocks have stronger effects on agents' beliefs about future natural rates, monetary policy effects become asymmetric to large and small shocks.

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[15]Recently, Nakamura and Steinsson (2013) and Jarocinski and Karadi (2018) identify the information effects of monetary policy in high-frequency domains.

[16]Fujiwara et al. (2005) examine the monetary policy in a liquidity trap when the perception of natural rate could be updated.

To check the shock size dependency of the information effect, this study estimates the following state transition model using survey expectations:

$$
\Delta y_{t,t+1}^{bc} = \begin{cases} I\left(s_t\right)\left(\mu^0 + \lambda^0 \epsilon_t\right) + \left[1 - I\left(s_t\right)\right]\left(\mu^1 + \lambda^1 \epsilon_t\right) & \textit{(linear Romer shock),} \\ q\left(s_t\right)\left(\mu^0 + \lambda^0 \tilde{\epsilon}_t\right) + \left[1 - q\left(s_t\right)\right]\left(\mu^1 + \lambda^1 \tilde{\epsilon}_t\right) & \textit{(RS Romer shock),} \end{cases}
$$
(3.4)

where Δy_{t+i}^{bc} is the consensus forecasts of economic growth rate to the next year compiled by Blue chip economic indicators.[17]

TABLE 3.4: Response of survey expectations to a monetary policy shock

	Linear Romer shocks		RS Romer shocks		Linear model (for reference)
	Small shock λ^0	Large shock λ^1	Small shock λ^0	Large shock λ^1	$\lambda^0 = \lambda^1$
Coefficient	0.2634	0.0477	0.0668	0.0705	0.0819
S.E.	0.1122	0.0214	0.0159	0.0263	0.0297
t-value	2.3476	2.2234	4.1979	2.6797	2.9617
Wald test: $H_0 : \lambda^0 = \lambda^1$	2.6827		0.0194		-
p-value	0.1029		0.8893		-

Note: S.E. is the HAC standard error.

The positive coefficient of monetary policy shocks supports the information effect. The results in Table 3.4 show that the estimated parameters for small and large shocks are both positive, suggesting that a contractionary monetary policy shock increases expectations about output growth. However, the coefficients of small and large monetary policy shocks are statistically indifferent in cases of either linear and RS Romer shocks. An interpretation of this evidence is that private agents update their beliefs proportionally to the shock size when they face large or small monetary policy surprises. In conclusion, the information effect is unlikely to be a relevant hypothesis that can explain our main results.

---

[17]For each year, the economic forecast is the GDP growth rate of the year until the May survey and those of the next year after the June survey. We switch the forecast horizon at June survey mainly due to data limitations of early surveys. This treatment is reasonable because the survey is conducted during the first week of each month and the quick estimates of first quarter's GDP is released in mid-May.

3.4.3   Selective gradualism of monetary policy

A clue that might explain the shock-size dependent effects of monetary policy is the distinct responses of term spreads. In the main results, responses of term spreads to small shocks are significantly positive and exceed 2 percent for linear Romer shocks and 5 percent for RS Romer shocks at the peak, but its response to large shocks is weak and remains less than 0.5 percent for two years after the shock. Term spreads reflect views on future monetary policy. The increase in term spreads suggests that economic agents expect the continuation of monetary tightening, whereas stable term spreads suggest that economic agents regard a monetary policy surprise as being merely temporary. Such expectations are relevant for the spending and investment decisions made by households and firms.

Term spreads increase after monetary tightening due to the Federal Reserve's gradualism. As described in the address of Chairman Bernanke[18], a central bank that takes a gradualist approach "tends to adjust interest rates incrementally, in a series of small or moderate steps in the same direction." From a theoretical perspective, Woodford (2003) argues that a commitment to gradual interest rate adjustment is optimal and gives central banks more control over term spreads through the expectations channel. Our empirical results are consistent with the view that the Federal Reserve follows a gradualist approach after small shocks.

At the same time, the Federal Reserve does not always take a gradualist approach. It prefers to rapidly respond to certain episodes for some time. In the same address mentioned above, Chairman Bernanke argued that the Federal Reserve has undertaken aggressive strategies when "the risk of doing too little appeared to exceed the risk of too much". Some theoretical studies (*c.f.*

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[18]"Gradualism," speech delivered at an economics luncheon co-sponsored by the Federal Reserve Bank of San Francisco (Seattle Branch) and the University of Washington, Seattle, Washington, May 20, https://www.federalreserve.gov/boarddocs/speeches/2004/200405202/default.htm.

Soderstrom ([2002])) have clarified that the optimality of a gradualist approach depends on the model specification and sources of uncertainty. During large shocks, the Federal Reserve may deviate from its gradualist approach and take a short-lived aggressive approach.

Gradualism with some exceptions, which we call "selective" gradualism, can be specified by the following monetary policy rule:

$$i_t = i_{g,t} + i_{a,t}, \tag{3.5}$$

$$i_{g,t} = \rho_g i_{g,t-1} + (1 - \rho_g) \left[\tau_\pi \pi_t + \tau_y y_t \right] + \epsilon_{g,t},$$

$$i_{a,t} = \rho_a i_{a,t-1} + \epsilon_{a,t}, \tag{3.6}$$

where $i_{g,t}$ and $i_{a,t}$ are gradual and aggressive components of the policy rate i_t; $\epsilon_{g,t}$ and $\epsilon_{a,t}$ are respective monetary policy shocks that follow *i.i.d* normal processes of $N(0, \sigma_{x \in \{g,a\}})$; and π_t and y_t are inflation and logarithmic deviations of output from its steady state.

The gradual component, $i_{g,t}$, captures that the central bank eventually reflects the changes in inflation, output, and monetary policy shock $\epsilon_{g,t}$ to the policy rate. ρ_g represents the degree of gradualism. However, the aggressive component, $i_{a,t}$ captures that the central bank can respond to some unobserved events with different lengths of persistence.

If the selective gradualism is the source of differences between large and small shocks, the persistence of aggressive shocks will be lower than that of a gradualist monetary policy shock: $\rho_g > \rho_a$. To estimate these persistence parameters, this study employs impulse response matching as in the study by Blanchard and Perotti ([2002]). Specifically, it searches ρ_g and ρ_a that minimize the distance between impulse responses of our main results and those generated by a medium-scale DSGE model of Christiano, Eichenbaum, and Evans ([2005]), in which the monetary policy rule is replaced by ([3.5]). Other

parameters are calibrated as standard values in the literature.[19]

TABLE 3.5: Estimated parameters: interest rate smoothing versus shock inertia

	Persistence		Standard deviations	
	ρ_g: gradualism	ρ_a: aggressive	σ_g	σ_a
Linear Romer shock	0.7002	0.4087	0.0159	0.0101
RS Romer shock	0.8460	0.5910	0.0235	0.0096

The results of impulse response matching also support the selective gradualism hypothesis. Table 3.5 reports that the parameters of interest rate smoothing, $\rho_g = 0.70$ for linear Romer shocks and $\rho_g = 0.85$ for RS Romer shocks, are greater than those of the aggressive shock persistence, $\rho_a = 0.41$ and $\rho_a = 0.59$, for respective cases.[20] The analyses so far suggest that selective gradualism is the source of size-dependent effects of the monetary policy.

3.5 Revisiting state-dependent effects of monetary policy through the lens of shock size

This section revisits some other state-dependent effects of monetary policy reported in previous studies. Specifically, it examines the following hypothesis before and after controlling the shock size: (1) high uncertainty reduces the monetary policy effects, and (2) monetary policy effects are less powerful during low growth periods.

In the analyses below, this study first replicates each hypothesis using a standard state-transition local projection model. Then, it re-estimates the impulse responses after stratifying shocks according to the shock size. To avoid the potential overlap between shock size distribution and other economic

---

[19]Appendix explains about impulse response matching in details.

[20]The estimated parameters of interest rate smoothing are similar to or slightly lower than values in other previous estimates (*c.f* Coibion and Gorodnichenko (2012) 0.82; Smets and Wouters (2007) 0.81).

states, the study classifies monetary policy shocks into the small number of large shocks greater than 2 standard deviations and other shocks.

3.5.1 Dependency on economic uncertainty

Aastveit, Natvik, and Sola (2017) and Castelnuovo and Pellegrino (2018) employ nonlinear vector autoregression models and report that the US monetary policy is less powerful under higher uncertainty.[21] To re-examine these results in previous studies, this study estimates a state-dependent local projection model, which is the same model as in the previous section except for two points. First, this study modifies the identification of monetary policy shocks. Instead of a policy reaction function used in the analysis so far, this study estimates the state-dependent policy reaction function, which allows for coefficients to be different for high and low uncertainty states.

$$\Delta FF_t = F\left(v_t\right) \boldsymbol{\kappa^{high'}} \boldsymbol{X_t} + \left[1 - F\left(v_t\right)\right] \boldsymbol{\kappa^{low'}} \boldsymbol{X_t} + \hat{\epsilon}_t, \tag{3.7}$$

where v_t represents the state of the economy in general and is a measure of uncertainty in this case, and $F(\cdot)$ represents the probability of high uncertainty. Considering the smooth transition from one state to the other, this study employs the logistic function as in the previous section. The proxy of macroeconomic uncertainty is a six-month moving average of an indicator developed by Jurado, Ludvigson, and Ng (2015), which is adopted in the aforementioned studies.

Estimated monetary policy shocks in Figure 3.4 are quite similar to those of linear Romer shocks: the correlation between linear and uncertainty-dependent Romer shocks is 0.941. Although the transition probability $F(v_t)$ switches

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[21]Real option effects on business investments (Dixit and Pindyck (1994) and Bloom (2009)), households' precautionary savings (Deaton (1991) and Carroll (1992)), and financial institutions' behavior (Christiano, Motto, and Rostagno (2014)) are potential sources of this phenomenon.

several times during the sample period, it is maintained low during the "great moderation" periods.

FIGURE 3.4: Uncertainty and monetary policy shocks
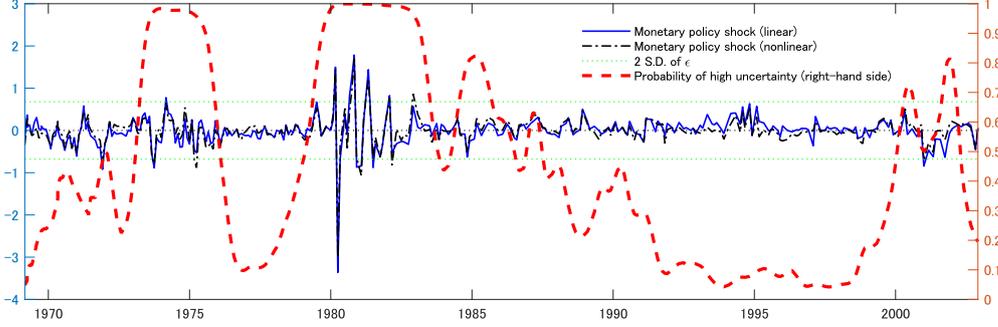
Descriptive statistics in Table 3.6 suggest that large shocks are more frequent under high-uncertainty regimes. Fourteen shocks greater than 2 standard deviations occurred under a high-uncertainty regime but just once under a low-uncertainty regime.

TABLE 3.6: Monetary policy shocks under high and low uncertainty

	N	$N_{2\sigma_\epsilon \leq |\epsilon|}$	$N_{3\sigma_\epsilon \leq |\epsilon|}$	Positive shocks (% of total)	Mean	S.D.	Max	Min
Overall	314	15	5	51.3	-0.005	0.346	1.737	-3.114
High uncertainty	113	14	5	55.8	0.004	0.529	1.737	-3.114
Low uncertainty	201	1	0	48.8	-0.011	0.177	0.564	-0.706

Note: High (low) uncertainty periods in this table are defined as the periods of $F(v_t) > (\leq)0.5$

Next, we specify the impulse response function that allows for parameters to be different depending on the state of uncertainty as follows:

$$
\begin{aligned}
z_{t,h} \;=\; & \delta\tau + F\left(v_t\right)\left\{\alpha_h^{high} + \beta_h^{0,high} I\left(s_t\right)\hat{\epsilon}_t + \beta_h^{1,high}\left[1 - I\left(s_t\right)\right]\hat{\epsilon}_t + \gamma^{high\prime} x_t\right\} \\
& + \left[1 - F\left(v_t\right)\right]\left\{\alpha_h^{low} + \beta_h^{0,low} I\left(s_t\right)\hat{\epsilon}_t + \beta_h^{1,low}\left[1 - I\left(s_t\right)\right]\hat{\epsilon}_t + \gamma^{low\prime} x_t\right\} + \zeta_t,
\end{aligned}
$$

$$(3.8)$$

where impulse responses at horizon h comprise the combination of two economic states and two shock sizes: $\beta_h^{0,high}$ (small shocks, high uncertainty),

$\beta_h^{1,high}$ (large shocks, high uncertainty), $\beta_h^{0,low}$ (small shocks, low uncertainty), and $\beta_h^{1,low}$ (large shocks, low uncertainty).

The first row of Figure 3.5 presents the responses of the economy under high and low uncertainty regimes estimated without controlling for the shock size. The monetary policy effects on production are less effective under higher uncertainty, as reported in previous studies. The difference of the effects under high uncertainty and low uncertainty is significantly positive at the bottom around 24 months after a shock.

However, these asymmetric responses disappear once the shock size is controlled. The second row of Figure 3.5 shows impulse responses to all monetary policy shocks except for a small number of huge shocks. A monetary policy shock under high uncertainty is just as effective as the one under low uncertainty. The difference between these two presented in the third column stays around zero and is insignificant. The responses to large shocks in the third row suggest that large shocks significantly impact production under high uncertainty regime though the quantitative impact is nearly zero. In summary, except for a small number of huge shocks, a monetary policy shock has a similar effect under either high or low uncertainty regime. This finding stresses the importance of controlling for the shock size distribution in the empirical analysis of any monetary policy effect.

3.5.2 Dependency on economic growth rates

Thoma (1994) and Tenreyro and Thwaites (2016) argue that the monetary policy is more effective under high growth rates. Now, this study examines the dependency on economic growth rates by estimating those similar to (3.8) but different in the state variable. At this time, the state variable v_t

FIGURE 3.5: Impulse responses of production: high uncertainty
versus low uncertainty
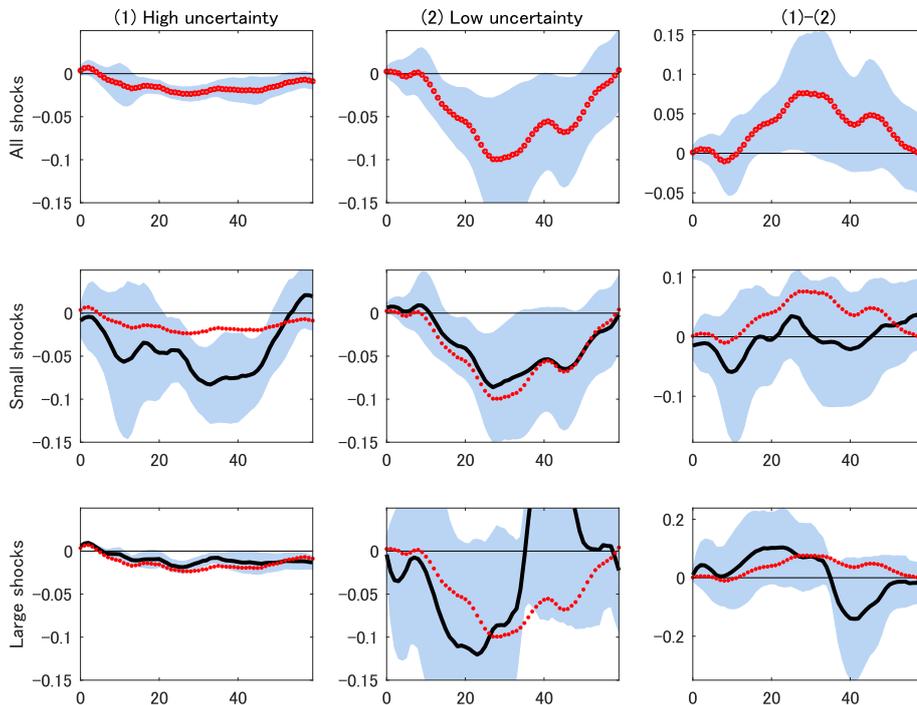
Note: Shaded area denotes the 90 percent confidence interval.

is the two-year moving average of economic growth rates rather than a measure of uncertainty.[22] To obviate the state dependency of the policy reaction function, Romer shocks are estimated using a nonlinear function of economic growth rates as (3.7).

Figure 3.6 reports that the estimated monetary policy shocks are similar to the linear Romer shocks.[23] Descriptive statistics in Table 3.7 report that large shocks occurred more frequently during the high-growth state.

Figure 3.7 suggests that empirical results on growth rate dependency are robust even if a small number of huge shocks are excluded. First, impulse responses in the first row show that a positive shock to the policy rate significantly negatively impacts production when the economy is expanding.

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[22]Tenreyro and Thwaites (2016) calculate the smooth transition function in the same manner.

[23]The correlation between these two shocks is 0.939. The transition probability of the high-growth and low-growth states is also similar to the ones in the study by Tenreyro and Thwaites (2016).

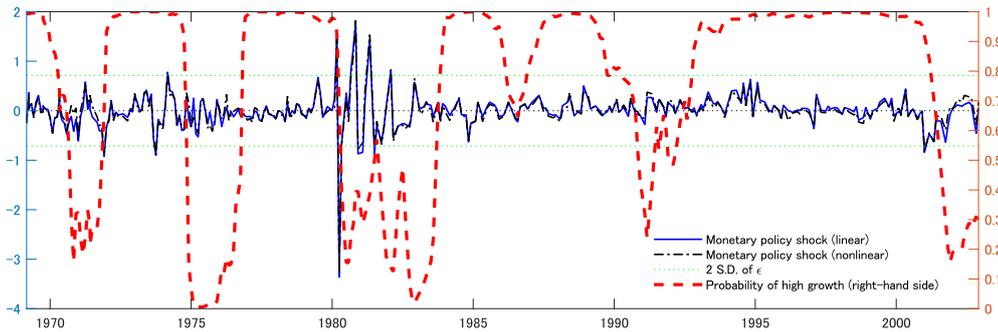FIGURE 3.6: Economic growth and monetary policy shocks

TABLE 3.7: Monetary policy shocks in high and low-growth states

	N	$N_{2\sigma_\epsilon \leq |\epsilon|}$	$N_{3\sigma_\epsilon \leq |\epsilon|}$	Positive shocks (% of total)	Mean	S.D.	Max	Min
Overall	314	12	5	47.1	-0.007	0.357	1.829	-3.291
High growth	248	10	4	45.6	-0.014	0.365	1.829	-3.291
Low growth	66	2	1	53.0	0.019	0.330	1.158	-0.653

Note: High (low) growth periods are the periods of $F(v_t) > (\leq)0.5$.

On the contrary, the same shock has only insignificant effects on production when the economy is contracting. The responses in the second row present that this pattern holds true after excluding large shocks. As for a small number of large shocks in the third row, a monetary policy does not significantly impact production in expansionary periods. It has a significant but weak effect in contractionary periods. The phrase " cannot push on a string" is still relevant even after controlling for the shock size.

Although our conclusions are in line with those of Tenreyro and Thwaites (2016), the economic interpretation is different. With reference to the study by Vavra (2014), Tenreyro and Thwaites (2016) conjecture that recessions are often characterized by high uncertainty and thus frequent price changes, which leads to a steep Phillips curve and ineffective monetary policy. However, as in the previous subsection, high uncertainty is not the source of asymmetric monetary policy effects except for periods of large shocks. Theoretical exploration of this issue is an interesting topic for future studies.

FIGURE 3.7: Impulse responses of production: high growth versus low growth
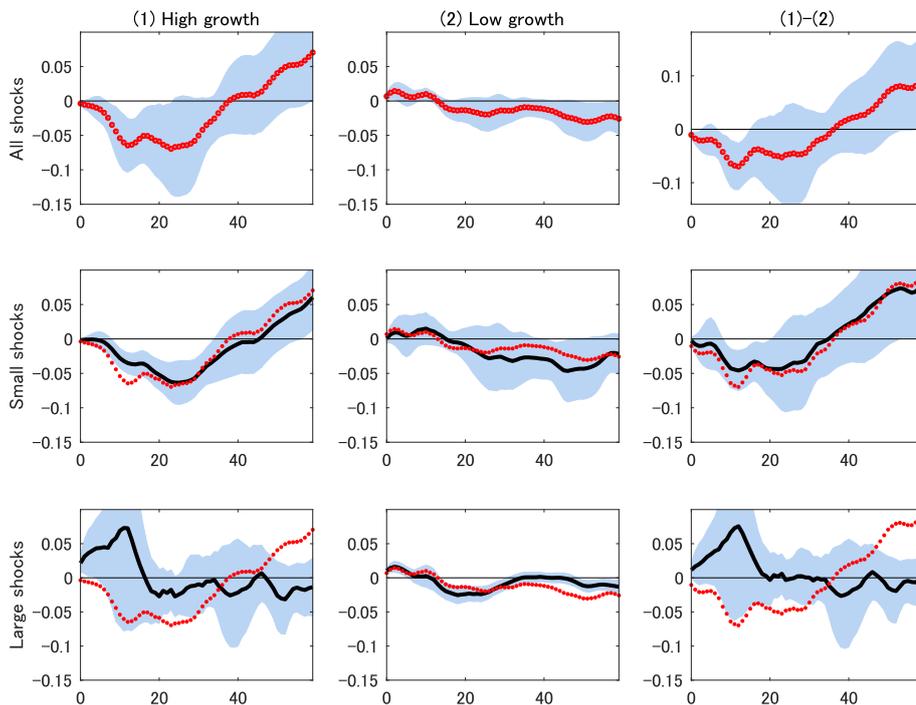
Note: Shaded area is the 90 percent confidence interval.

3.6 In Closing

This study empirically examines whether shock size matters for US monetary policy effects. Using the nonlinear local projection method, this study finds that large shocks are less powerful than small shocks. This study suggests that the monetary policy design, rather than menu cost pricing and information effects, is the relevant cause of the differences in policy effects between large and small shocks. Finally, it clarifies that large monetary policy shocks are crucial for identifying uncertainty dependency of monetary policy effects, which is indicated in recent studies.

Appendix A

Sensitivity Checks on the Major Determinant of Business Cycles

A.1 The alternative end of sample

In our estimation, the end of the sample periods is 2009/1Q that is consistent with Justiniano, Primiceri, and Tambalotti (2011) and suitable to avoid the distorting effects caused by a zero boundary on nominal interest rates. Here, we show that the variance decompositions are almost unchanged even when the end of sample is 2008/4Q.

TABLE A.1: Variance decomposition at business cycle frequencies: the sample covers between 1975Q1 and 2008Q4

| | Housing demand | LTV | MEI | Supply | | | | Otherdemand | | |
| | | | | Technologies | | Markups | | | | |
				Neutral	IS	Price	Wage	Patience	Monetary policy	Gov't
Y_{obs}	13.7 [10.2,17.7]	13.8 [10.2,18.0]	2.0 [0.9,3.6]	46.9 [38.7,56.4]	1.3 [0.8,1.9]	2.9 [1.5,5.2]	1.2 [0.7,2.6]	1.3 [0.8,2.1]	15.6 [11.6,20.5]	0.3 [0.2,0.6]
I_{obs}	23.1 [18.7,28.4]	20.1 [16.0,24.7]	6.7 [4.1,10.1]	17.4 [12.9,22.9]	1.2 [0.8,1.9]	4.0 [2.3,6.6]	1.3 [0.6,2.8]	6.8 [4.6,10.0]	15.3 [11.8,19.9]	2.8 [1.9,4.1]
C_{obs}	5.4 [3.5,7.7]	9.0 [6.3,12.1]	4.6 [2.4,7.7]	44.4 [36.2,53.6]	3.6 [2.5,5.2]	1.3 [0.6,2.6]	1.9 [0.7,4.9]	9.9 [6.6,15.2]	14.8 [9.1,21.3]	3.6 [2.3,5.5]
N_{obs}	11.2 [7.5,15.8]	5.8 [2.6,9.5]	16.8 [10.9,24.5]	11.8 [8.0,16.9]	0.4 [0.2,0.9]	14.6 [9.2,21.6]	7.9 [4.7,13.4]	0.4 [0.2,1.0]	28.7 [20.3,39.8]	0.3 [0.2,0.5]
$Q_{l,obs}$	75.6 [70.3,80.4]	3.1 [2.2,4.4]	3.3 [2.2,4.8]	9.5 [6.8,12.9]	1.3 [0.9,1.8]	0.3 [0.1,0.7]	0.5 [0.2,1.2]	1.3 [0.7,2.3]	3.5 [2.2,5.1]	1.1 [0.8,1.7]
B_{obs}	24.1 [20.0,29.1]	45.9 [40.4,52.0]	14.7 [10.8,19.3]	2.0 [1.4,2.8]	4.0 [2.9,5.6]	1.6 [0.8,2.7]	0.6 [0.3,1.0]	1.5 [0.9,2.4]	4.2 [2.9,5.7]	0.6 [0.4,0.9]

Note: Variance decomposition to periodic components with cycles between 6 and 32 quarters is presented using the spectrum of the linearized model. The spectrum density is computed from the state space representation of the model with 3,000 bins for frequency covering that range of periodicities. To reconstruct the levels of output, investments, consumption, and land prices, we apply an inverse first difference filter. 95 percent credible intervals are denoted in respective parenthesis under the median estimates.

A.2 Subsample estimations

To check the robustness of the results in the main text, we run subsample estimations by splitting the full sample periods into the first and second half. Table A.2 shows that our main conclusion is unchanged although the effects of housing demand shocks and monetary policy shocks, which are categorized in "Other demand", increase in the latter half of the sample periods (subsample II).

TABLE A.2: Variance decomposition at business cycle frequencies: Subsample estimations

		Housing demand	LTV	MEI	Tech- nologies	Markups	Other demands
Y_{obs}:	baseline case	14.8	13.9	2.6	44.8	4.1	18.2
	subsample I	13.7	12.9	2.6	48.2	4.1	16.7
	subsample II	16.4	9.0	1.6	46.6	5.0	19.5
I_{obs}:	baseline case	23.0	18.8	6.7	18.1	4.7	27.2
	subsample I	23.4	18.1	8.2	17.6	4.7	25.6
	subsample II	28.0	13.0	4.7	19.6	5.4	27.1
C_{obs}:	baseline case	5.9	9.4	4.7	44.3	3.7	29.8
	subsample I	5.2	8.1	3.3	49.1	3.1	28.5
	subsample II	4.7	5.5	3.0	44.7	2.9	36.2
$Q_{l,obs}$:	baseline case	74.9	3.2	2.9	10.5	1.0	6.7
	subsample I	75.4	2.6	3.0	11.1	0.8	6.1
	subsample II	74.8	1.9	1.5	10.6	0.8	9.3
B_{obs}:	baseline case	25.5	47.0	10.7	6.5	1.5	7.9
	subsample I	23.3	46.6	14.3	5.7	1.8	6.9
	subsample II	32.9	42.0	5.4	6.9	1.5	9.7

Note: *Subsample I* and *II* correspond 1975/1Q-1991/4Q and 1992/1Q-2009/1Q, respectively. Variance decomposition to periodic components with business cycles between 6 and 32 quarters is presented using the spectrum of the linearized model. The *drop credit and land price data* rows correspond to variance decomposition in the case that the baseline model is evaluated at the posterior mean of parameters alternatively estimated without using credits and land prices data. For computational details, see also the Note for Table A.1. "Other demands", "Technologies", and "Markups" correspond to the contributions of "patience", "monetary policy", and "government expenditure" shocks, those of "neutral" and "investment-specific" technology shocks, and those of "price" and "wage" markup shocks, respectively.

A.3 Estimation with hypothetical data

In Table 6 of the main text, we re-estimate the model without using B_{obs} and $Q_{l,obs}$. To check its robustness, we estimate the model with hypothetical data that are generated by the baseline model evaluated at the posterior means of parameters. The hypothetical data is a length of 100 periods. Table A.3 shows that the main conclusion are unchanged even if hypothetical data is used for estimation.

TABLE A.3: Variance decomposition at business cycle frequencies: actual data versus hypothetical data

		Housing demand	LTV	MEI	Tech-nologies	Mark-ups	Other demands
Y_{obs}	*actual data*	0.0	0.0	44.7	37.4	9.7	6.4
	hypothetical data	0.0	0.0	46.9	45.2	4.1	2.6
I_{obs}	*actual data*	0.0	0.0	73.6	11.8	7.1	6.2
	hypothetical data	0.0	0.0	83.3	12.0	2.5	1.4
C_{obs}	*actual data*	0.0	0.0	32.8	30.9	9.5	24.0
	hypothetical data	0.0	0.0	39.9	38.5	4.7	14.9
$Q_{l,obs}$	*actual data*	0.0	0.0	36.1	29.4	9.8	21.1
	hypothetical data	0.0	0.0	43.1	36.2	7.4	10.7
B_{obs}	*actual data*	0.0	1.2	46.5	22.7	7.2	16.8
	hypothetical data	0.0	1.2	52.9	26.9	6.5	7.9

Note: "Other demands", "Technologies", and "Markups" correspond to the contributions of "patience", "monetary policy", and "government expenditure" shocks, those of "neutral" and "investment-specific" technology shocks, and those of "price" and "wage" markup shocks, respectively. In this exercise, the baseline model is evaluated at the posterior mean of parameters re-estimated with calibrated at $\bar{\theta} = 0.001$ and without using credits and land prices data. For computational details, see also the main text. The *actual data* case corresponds to the *without collateral const. and B_{obs} & $Q_{i,obs}$* case in Table 6 of the main text. In the hypothetical data case, the data for estimation is generated by the model evaluated at the posterior mean of parameters of the baseline case.

A.4 Estimation diagnostics: baseline case

Figure A.1 suggests that the parameters are clearly identified by showing the prior and posterior distributions are different for most of parameters.
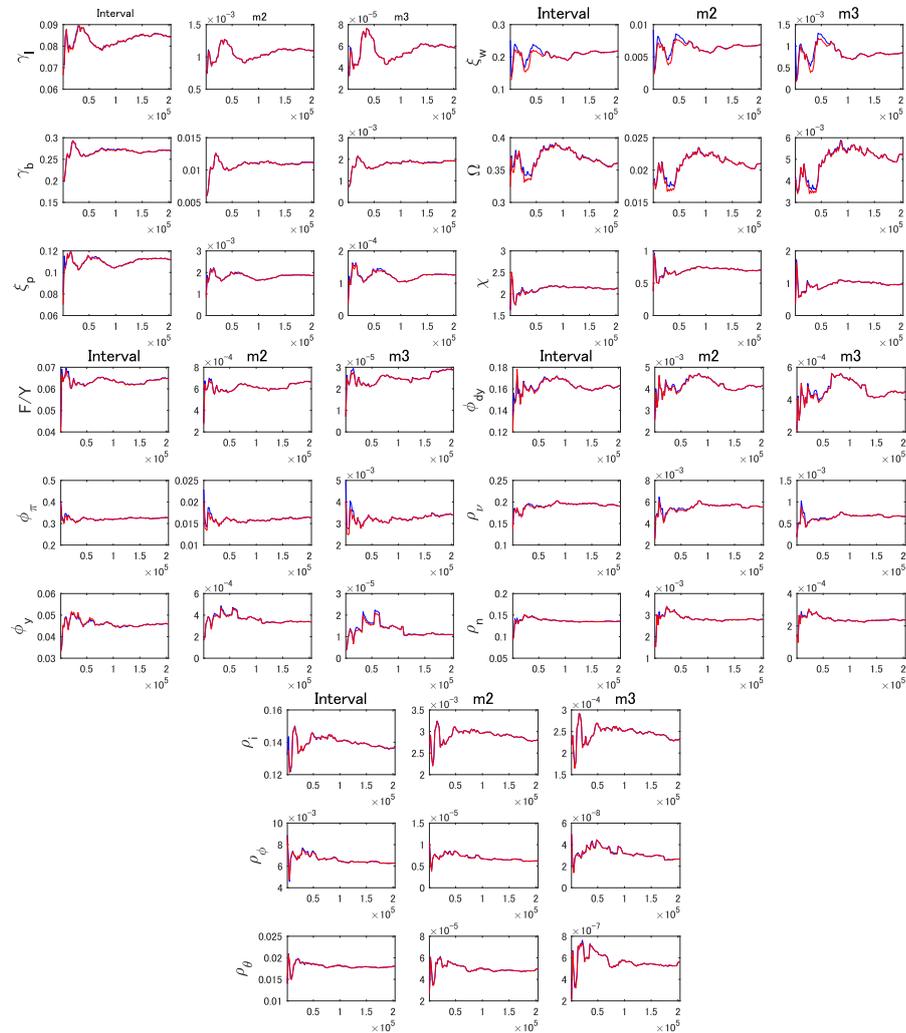
FIGURE A.1: Prior versus posterior distributions
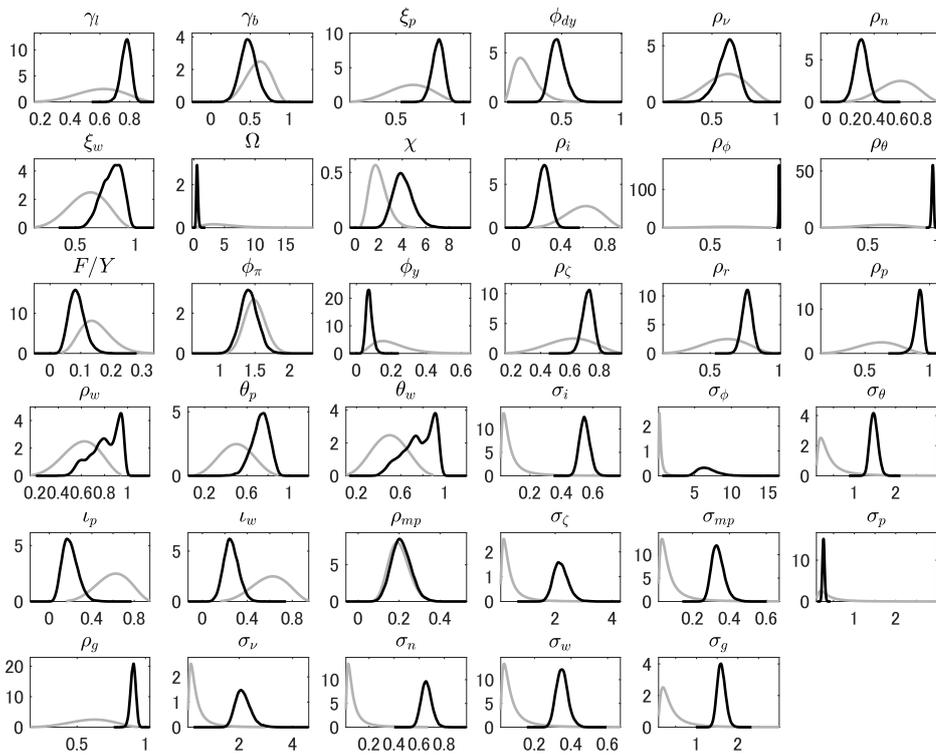
Note:Black and gray lines are posterior and prior distributions of parameters.
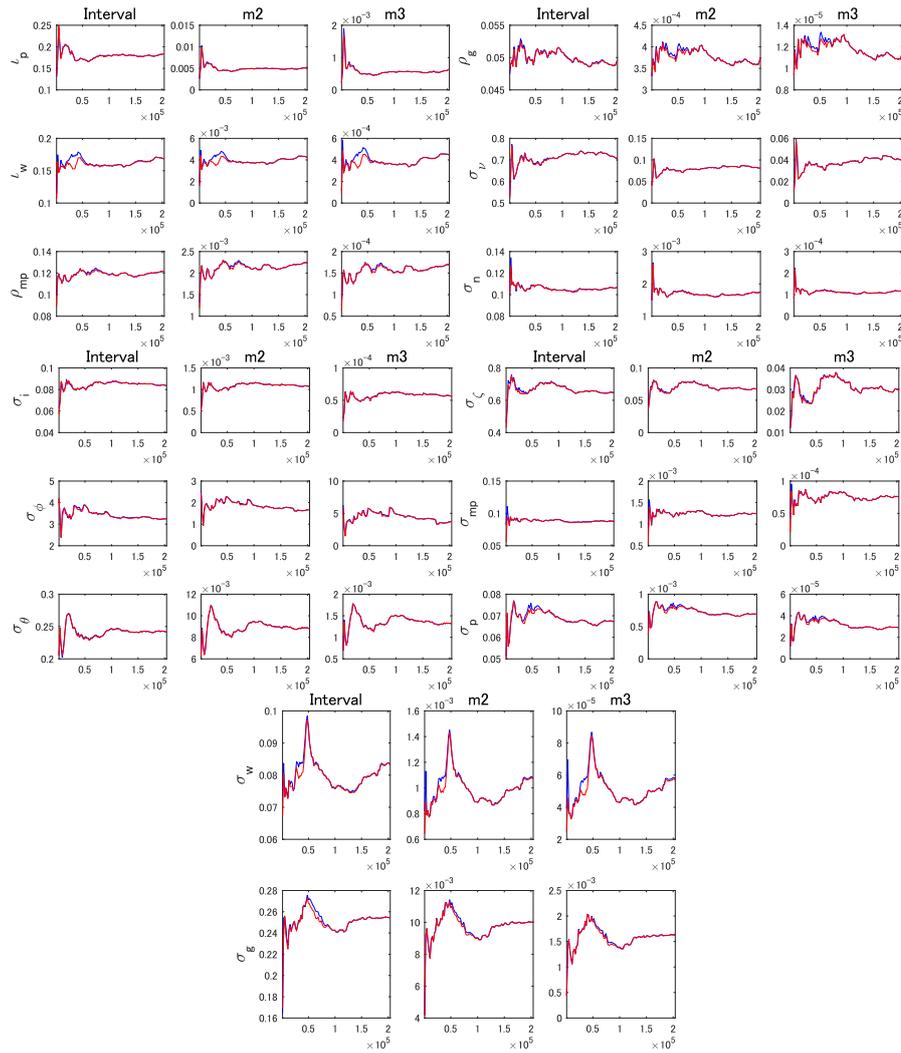
Figure A.2 and A.3 suggest the estimation converges by showing that Brooks and Gelman's convergence statistics.

FIGURE A.2: Convergence diagnostics (1)

Note:Gray and black lines are posterior draws of respective chains.

FIGURE A.3: Convergence diagnostics (2)

Note:Gray and black lines are posterior draws of respective chains.

Appendix B

Impulse response matching

In the impulse response matching exercise, this study uses the empirical impulse responses of production and policy rates to normalize large and small monetary policy shocks. The DSGE model is identical to that in the study by Christiano, Eichenbaum, and Evans (2005) except for the monetary policy rule. Since the frequency of Christiano, Eichenbaum, and Evans (2005) is quarterly, this study uses the monthly responses of production and Federal Funds rates every 3 months. To minimize the distance between the empirical and model's impulse responses, it employs the csminwel procedure developed by Chris Sims. Calibrated parameters are summarized as follows.

TABLE B.1: Calibrated parameters

Parameters	Calibrated values
Habit persistence of consumption	0.73
Subjective discount factor	$1.03^{-1/4}$
Marginal disutility of hours	1.00
Capital share	0.36
Capital depreciation rate	0.025
Calvo (wage)	0.64
Calvo (price)	0.60
Price elasticity of demand	6.00
Taylor rule (inflation)	1.50
Taylor rule (production)	0.50

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