SOURCES OF THE GREAT MODERATION: SHOCKS, FRICTIONS, OR MONETARY POLICY?

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Abstract. We study the sources of the Great Moderation by estimating a variety of medium-scale DSGE models that incorporate regime switches in shock variances and in the inflation target. The best-fit model, the one with two regimes in shock variances, gives quantitatively different dynamics in comparison with the benchmark constant-parameter model. Our estimates show that three kinds of shocks accounted for most of the Great Moderation and business-cycle fluctuations: capital depreciation shocks, neutral technology shocks, and wage markup shocks. In contrast to the existing literature, we find that changes in the inflation target or shocks in the investment-specific technology played little role in macroeconomic volatility. Moreover, our estimates indicate much less nominal rigidities than those suggested in the literature.

I. Introduction

We reexamine, in this paper, the sources of the Great Moderation by estimating a large set of dynamic stochastic general equilibrium (DSGE) models, along the lines of Altig, Christiano, Eichenbaum, and Linde (2004), Smets and Wouters (2007), and Justiniano and Primiceri (2006).[1] We use modern Bayesian techniques to study a constant-parameter model commonly used in the literature, a model that allows shock variances to switch regimes according to a Markov-switching process, a model that

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[1]Works by Levin, Onatski, Williams, and Williams (2006) and Del Negro, Schorfheide, Smets, and Wouters (2007) also offer useful references to large DSGE modeling.

allows the inflation target to switch regimes over time, models that allow both the inflation target and the shock variances to change regimes in a number of different ways, and models with different assumptions about shock processes. Our methodology allows us to incorporate different DSGE models in a unified framework to systematically examine the sources of the Great Moderation.

We study changes in the inflation target instead of changes in monetary policy's response to inflation mainly for computational reasons. When agents take into account changes in monetary policy's response to inflation in forming their expectations, a solution method to the model is nonstandard (Liu, Waggoner, and Zha, 2009) and it becomes computationally infeasible to estimate a large set of DSGE models like ours as the solution requires an iterative algorithm that can be time-consuming in Monte Carlo simulations.[2] Following Schorfheide (2005) and Ireland (2005), we examine instead changes in the inflation target; in this case, the standard method of solving linear rational expectations models can be directly used in our regime-switching framework, as will be shown in Section V.

Our study sheds new light on the sources of the Great Moderation. First, we find strong empirical evidence in favor of the DSGE model with two regimes in shock variances and with synchronized regime shifts in the variances. The model with independent regime shifts in shock variances does not fit to the data as well. Second, wage markup shocks, depreciation shocks, and neutral technology shocks are most important in accounting for the volatilities of output, inflation, and other macroeconomic variables in both regimes. Third, there is little empirical evidence in favor of regime changes in the inflation target. This conclusion is robust to a variety of model specifications and different assumptions about the shock persistence and consistent with other works' conclusions about changes in monetary policy in general (Stock and Watson, 2003; Canova and Gambetti, 2004; Cogley and Sargent, 2005; Primiceri, 2005; Sims and Zha, 2006). Fourth, our posterior estimates imply more frequent re-optimizations in price setting and nominal wage setting decisions than those obtained in other studies (Smets and Wouters, 2007). The marginal posterior distributions assign little probability to the Calvo price stickiness parameter above 0.6 and the wage stickiness parameter

[2]Previous DSGE studies have split the sample into two sub-samples (the pre-Volcker and post-Volcker periods) to address monetary policy changes of this type (Clarida, Galí, and Gertler, 2000; Lubik and Schorfheide, 2004; Boivin and Giannoni, 2006).

above 0.4, implying a large probability that price and wage contracts last no more than 2 quarters on average.[3]

Neutral technology shocks play a much more important role in driving business cycle fluctuations than do investment-specific technology shocks, a result similar to that found in Arias, Hansen, and Ohanian (2006). Wage markup shocks, along with the distortions associated with wage and price stickiness, captures the wedge between the intra-temporal marginal rate of substitution (MRS) and the marginal product of labor, which, as argued by Chari, Kehoe, and McGrattan (2007), plays an important role in accounting for the business cycle fluctuations. The depreciation shock, on the other hand, acts as a wedge in the intertemporal capital accumulation decision, which is also an important source of the business cycle fluctuations. Time variation in the depreciation rate reflects the difference between economic depreciation and physical depreciation.

The investment-specific technology shock also enters the intertemporal capital accumulation decisions. We find, however, that this biased technology shock does not account for much of the business-cycle fluctuations. This result is different from what Justiniano, Primiceri, and Tambalotti (2008) find mainly because we use direct observations on the biased technology shock in our estimation while they do not.

II. Related literature

Our approach differs from that employed in the literature in several aspects. First, we aim at fully characterizing the uncertainty across different models by examining several different versions of the DSGE model to check our results and substantiate our conclusion. Although estimating a large set of models has not been performed in the literature and pushes the limits of what our computational and analytical capacity can handle, it is necessary to examine the robustness of a conclusion like ours about potential sources of the Great Moderation.

Second, our approach does not require splitting the sample to examine changes in monetary policy, although it nests sampling-splitting as a special case.

Third and methodologically, for fairly large DSGE models, especially for regime-switching DSGE models, the posterior distribution tends to be very non-Gaussian, making it very challenging to search for the global peak. We improve on earlier works such as Cogley and Sargent (2005) and Justiniano and Primiceri (2006) by obtaining

[3]There often exist local posterior peaks at which the values of stickiness parameters are much higher, but these peaks are much lower than the posterior mode (see Section VII.3 for a concrete example).

our estimates at the posterior mode for each model that we study. We show that economic implications can be seriously distorted if the estimates are based on a lower posterior peak.[4]

Fourth, the DSGE models that we study are larger than those used by Schorfheide (2005) and Ireland (2005). Studying a medium-scale DSGE model like ours is necessary to avoid potential mis-specifications. Finally, we use three new methods for computing marginal data densities in model comparison. Since these methods were developed from completely different concepts, it is essential that all these methods give a numerically similar result so that the estimate of a marginal data density is unbiased and accurate (Sims, Waggoner, and Zha, 2008).

There is also a large strand of literature that emphasizes changes in the inflation target as a representation of important shifts in the conduct of U.S. monetary policy (for example, Favero and Rovelli (2003); Erceg and Levin (2003)). Unlike earlier works, we study a variety of fairly large DSGE models to determine whether the Federal Reserve's inflation target in the post-war period has changed.

As implied by Schorfheide (2005), with the inflation target switching regimes, the model is likely to rely less on shock volatilities to generate the 1970s observations of the dynamics of inflation, output, and other macroeconomic variables.[5] Unlike Sims and Zha (2006) where the number of VAR parameters is relatively large and the inflation target is implicit, our way of modeling policy changes takes the inflation target explicitly and gives a tightly parameterized model that has the best potential to find the importance of policy changes, if it exists, in generating business-cycle fluctuations.

III. The Model

The model economy is populated by a continuum of households, each endowed with a unit of differentiated labor skill indexed by $i \in [0, 1]$; and a continuum of firms, each producing a differentiated good indexed by $j \in [0, 1]$. The monetary authority follows a feedback interest rate rule, under which the nominal interest rate is set to respond to its own lag and deviations of inflation and output from their targets. The policy regime s_t represented by the time-varying inflation target switches between a finite number of regimes contained in the set $\mathcal{S}$, with the Markov transition probabilities summarized by the matrix $Q = [q_{ij}]$, where $q_{ij} = Prob(s_{t+1} = i|s_t = j)$ for $i, j \in \mathcal{S}$. The economy

[4]The importance of finding the posterior mode for Bayesian estimation is discussed in Sims, Waggoner, and Zha (2008).

[5]Econometrically, Choi (2002) and Beyer and Farmer (2005) argue that allowing regime shifts can potentially aid identification of other parameters in the model.

is buffeted by several sources of shocks. The variance of each shock switches between a finite number of regimes denoted by $s_t^* \in \mathcal{S}^*$ with the transition matrix $Q^* = [q_{ij}^*]$.

III.1. **The aggregation sector.** The aggregation sector produces a composite labor skill denoted by L_t to be used in the production of each type of intermediate goods and a composite final good denoted by Y_t to be consumed by each household. The production of the composite skill requires a continuum of differentiated labor skills $\{L_t(i)\}_{i\in[0,1]}$ as inputs, and the production of the composite final good requires a continuum of differentiated intermediate goods $\{Y_t(j)\}_{j\in[0,1]}$ as inputs. The aggregation technologies are given by

$$L_t = \left[\int_0^1 L_t(i)^{\frac{1}{\mu_{wt}}} di\right]^{\mu_{wt}}, \quad Y_t = \left[\int_0^1 Y_t(j)^{\frac{1}{\mu_{pt}}} dj\right]^{\mu_{pt}}, \tag{1}$$

where μ_{wt} and μ_{pt} determine the elasticity of substitution between the skills and between the goods, respectively. Following Smets and Wouters (2007), we assume that

$$\ln \mu_{wt} = (1-\rho_w)\ln \mu_w + \rho_w \ln \mu_{w,t-1} + \sigma_{wt}\varepsilon_{wt} - \phi_w \sigma_{w,t-1}\varepsilon_{w,t-1} \tag{2}$$

and that

$$\ln \mu_{pt} = (1-\rho_p)\ln \mu_p + \rho_p \ln \mu_{p,t-1} + \sigma_{pt}\varepsilon_{pt} - \phi_p \sigma_{p,t-1}\varepsilon_{p,t-1}, \tag{3}$$

where, for $j \in \{w,p\}$, $\rho_j \in (-1,1)$ is the AR(1) coefficient, ϕ_j is the MA(1) coefficient, $\sigma_{jt} \equiv \sigma_j(s_t^*)$ is the regime-switching standard deviation, and ε_{jt} is an i.i.d. white noise process with a zero mean and a unit variance. We interpret μ_{wt} and μ_{pt} as the wage markup and price markup shocks.

The representative firm in the aggregation sector faces perfectly competitive markets for the composite skill and the composite good. The demand functions for labor skill i and for good j resulting from the optimizing behavior in the aggregation sector are given by

$$L_t^d(i) = \left[\frac{W_t(i)}{\bar{W}_t}\right]^{-\frac{\mu_{wt}}{\mu_{wt}-1}} L_t, \quad Y_t^d(j) = \left[\frac{P_t(j)}{\bar{P}_t}\right]^{-\frac{\mu_{pt}}{\mu_{pt}-1}} Y_t, \tag{4}$$

where the wage rate $\bar{W}_t$ of the composite skill is related to the wage rates $\{W_t(i)\}_{i\in[0,1]}$ of the differentiated skills by $\bar{W}_t = \left[\int_0^1 W_t(i)^{1/(1-\mu_{wt})}di\right]^{1-\mu_{wt}}$ and the price $\bar{P}_t$ of the composite good is related to the prices $\{P_t(j)\}_{j\in[0,1]}$ of the differentiated goods by $\bar{P}_t = \left[\int_0^1 P_t(j)^{1/(1-\mu_{pt})}dj\right]^{1-\mu_{pt}}$.

III.2. **The intermediate good sector.** The production of a type j good requires labor and capital inputs. The production function is given by

$$Y_t(j) = K_t^f(j)^{\alpha_1}[Z_t L_t^f(j)]^{\alpha_2}, \tag{5}$$

where $K_t^f(j)$ and $L_t^f(j)$ are the inputs of capital and the composite skill and the variable Z_t denotes a neutral technology shock, which follows the stochastic process

$$Z_t = \lambda_z^t z_t, \quad \ln z_t = (1-\rho_z)\ln z + \rho_z \ln z_{t-1} + \sigma_{zt}\varepsilon_{zt}, \tag{6}$$

where $\rho_z \in (-1,1)$ measures the persistence, $\sigma_{zt} \equiv \sigma_z(s_t^*)$ denotes the regime-switching standard deviation, and ε_{zt} is an i.i.d. white noise process with a zero mean and a unit variance. The parameters α_1 and α_2 measure the cost shares the capital and labor inputs. Following Chari, Kehoe, and McGrattan (2000), we introduce some real rigidity by assuming the existence of some firm-specific factors (such as land), so that $\alpha_1 + \alpha_2 \leq 1$.

Each firm in the intermediate-good sector is a price-taker in the input market and a monopolistic competitor in the product market where it sets a price for its product, taking the demand schedule in (4) as given. We follow Calvo (1983) and assume that pricing decisions are staggered across firms. The probability that a firm cannot adjust its price is given by ξ_p. Following Woodford (2003), Christiano, Eichenbaum, and Evans (2005), and Smets and Wouters (2007), we allow a fraction of firms that cannot re-optimize their pricing decisions to index their prices to the overall price inflation realized in the past period. Specifically, if the firm j cannot set a new price, its price is automatically updated according to

$$P_t(j) = \pi_{t-1}^{\gamma_p}\pi^{1-\gamma_p}P_{t-1}(j), \tag{7}$$

where $\pi_t = \bar{P}_t/\bar{P}_{t-1}$ is the inflation rate between $t-1$ and t, π is the steady-state inflation rate, and γ_p measures the degree of indexation.

A firm that can renew its price contract chooses $P_t(j)$ to maximize its expected discounted dividend flows given by

$$\mathrm{E}_t \sum_{i=0}^{\infty} \xi_p^i D_{t,t+i}[P_t(j)\chi_{t,t+i}^p Y_{t+i}^d(j) - V_{t+i}(j)], \tag{8}$$

where $D_{t,t+i}$ is the period-t present value of a dollar in a future state in period $t+i$, $V_{t+i}(j)$ is the cost function, and the term $\chi_{t,t+i}^p$ comes from the price-updating rule (7) and is given by

$$\chi_{t,t+i}^p = \begin{cases} \Pi_{k=1}^i \pi_{t+k-1}^{\gamma_p}\pi^{1-\gamma_p} & \text{if } i \geq 1 \\ 1 & \text{if } i = 0. \end{cases} \tag{9}$$

In maximizing its profit, the firm takes as given the demand schedule $Y^d_{t+i}(j) = \left(\frac{P_t(j)\chi^p_{t,t+i}}{\bar{P}_{t+i}}\right)^{-\frac{\mu_{p,t+i}}{\mu_{p,t+i}-1}} Y_{t+i}$. The first order condition for the profit-maximizing problem yields the optimal pricing rule

$$\mathrm{E}_t \sum_{i=0}^{\infty} \xi_p^i D_{t,t+i} Y^d_{t+i}(j) \frac{1}{\mu_{p,t+i}-1} \left[\mu_{p,t+i}\Phi_{t+i}(j) - P_t(j)\chi^p_{t,t+i}\right] = 0, \tag{10}$$

where $\Phi_{t+i}(j) = \partial V_{t+i}(j)/\partial Y^d_{t+i}(j)$ denotes the marginal cost function. In the absence of markup shocks, μ_{pt} would be a constant and (10) implies that the optimal price is a markup over an average of the marginal costs for the periods in which the price will remain effective. Clearly, if $\xi_p = 0$ for all t, that is, if prices are perfectly flexible, then the optimal price would be a markup over the contemporaneous marginal cost.

Cost-minimizing implies that the marginal cost function is given by

$$\Phi_t(j) = \left[\tilde{\alpha}(\bar{P}_t r_{kt})^{\alpha_1}\left(\frac{\bar{W}_t}{Z_t}\right)^{\alpha_2}\right]^{\frac{1}{\alpha_1+\alpha_2}} Y_t(j)^{\frac{1}{\alpha_1+\alpha_2}-1}, \tag{11}$$

where $\tilde{\alpha} \equiv \alpha_1^{-\alpha_1}\alpha_2^{-\alpha_2}$ and r_{kt} denotes the real rental rate of capital input. The conditional factor demand functions imply that

$$\frac{\bar{W}_t}{\bar{P}_t r_{kt}} = \frac{\alpha_2}{\alpha_1}\frac{K^f_t(j)}{L^f_t(j)}, \quad \forall j \in [0,1]. \tag{12}$$

III.3. **Households.** There is a continuum of households, each endowed with a differentiated labor skill indexed by $h \in [0,1]$. Household h derives utility from consumption and leisure. We assume that there exists financial instruments that provide perfect insurance for the households in different wage-setting cohorts, so that the households make identical consumption and investment decisions despite that their wage incomes may differ due to staggered wage setting.[6] In what follows, we impose this assumption and omit the household index for consumption and investment.

The utility function for household $h \in [0,1]$ is given by

$$\mathrm{E}\sum_{t=0}^{\infty}\beta^t A_t\left\{\ln(C_t - bC_{t-1}) - \frac{\Psi}{1+\eta}L_t(h)^{1+\eta}\right\}, \tag{13}$$

[6] To obtain complete risk-sharing among households in different wage-setting cohorts does not rely on the existence of such (implicit) financial arrangements. As shown by Huang, Liu, and Phaneuf (2004), the same equilibrium dynamics can be obtained in a model with a representative household (and thus complete insurance) consisting of a large number of worker members. The workers supply their homogenous labor skill to a large number of employment agencies, who transform the homogenous skill into differentiated skills and set nominal wages in a staggered fashion.

where $\beta \in (0,1)$ is a subjective discount factor, C_t denotes consumption, $L_t(h)$ denotes hours worked, $\eta > 0$ is the inverse Frish elasticity of labor hours, and b measures the importance of habit formation. The variable A_t denotes a preference shock, which follows the stationary process

$$\ln A_t = (1-\rho_a)\ln A + \rho_a \ln A_{t-1} + \sigma_{at}\varepsilon_{at}, \tag{14}$$

where $\rho_a \in (-1,1)$ is the persistence parameter, $\sigma_{at} \equiv \sigma_a(s_t^*)$ is the regime-switching standard deviation, and ε_{at} is an i.i.d. white noise process with a zero mean and a unit variance.

In each period t, the household faces the budget constraint

$$\begin{aligned} \bar{P}_t C_t + \frac{\bar{P}_t}{Q_t}[I_t + a(u_t)K_{t-1}] + \mathrm{E}_t D_{t,t+1} B_{t+1} \leq \\ W_t(h) L_t^d(h) + \bar{P}_t r_{kt} u_t K_{t-1} + \Pi_t + B_t + T_t. \end{aligned} \tag{15}$$

In the budget constraint, I_t denotes investment, B_{t+1} is a nominal state-contingent bond that represents a claim to one dollar in a particular event in period $t+1$, and this claim costs $D_{t,t+1}$ dollars in period t; $W_t(h)$ is the nominal wage for h's labor skill, K_{t-1} is the beginning-of-period capital stock, u_t is the utilization rate of capital, Π_t is the profit share, and T_t is a lump-sum transfer from the government. The function $a(u_t)$ captures the cost of variable capital utilization. Following Altig, Christiano, Eichenbaum, and Linde (2004) and Christiano, Eichenbaum, and Evans (2005), we assume that $a(u)$ is increasing and convex. The term Q_t denotes the investment-specific technological change. Following Greenwood, Hercowitz, and Krusell (1997), we assume that Q_t contains a deterministic trend and a stochastic component. In particular,

$$Q_t = \lambda_q^t q_t, \tag{16}$$

where λ_q is the growth rate of the investment-specific technological change and q_t is an investment-specific technology shock, which follows a stationary process given by

$$\ln q_t = (1-\rho_q)\ln q + \rho_q \ln q_{t-1} + \sigma_{qt}\varepsilon_{qt}, \tag{17}$$

where $\rho_q \in (-1,1)$ is the persistence parameter, $\sigma_{qt} \equiv \sigma_q(s_t^*)$ is the regime-switching standard deviation, and ε_{qt} is an i.i.d. white noise process with a zero mean and a unit variance. The importance of investment-specific technological change is also documented in Fisher (2006) and Fernandez-Villaverde and Rubio-Ramirez (Forthcoming).

The capital stock evolves according to the law of motion

$$K_t = (1-\delta_t)K_{t-1} + [1 - S(I_t/I_{t-1})]\, I_t, \tag{18}$$

where the function $S(\cdot)$ represents the adjustment cost in capital accumulation. We assume that $S(\cdot)$ is convex and satisfies $S(\lambda_q \lambda_*) = S'(\lambda_q \lambda^*) = 0$, where $\lambda^* = (\lambda_q^{\alpha_1} \lambda_z^{\alpha_2})^{\frac{1}{1-\alpha_1}}$ is the steady-state growth rate of output and consumption. The term δ_t denotes the depreciation rate of the capital stock and follows the stationary stochastic process

$$\ln \delta_t = (1 - \rho_d) \ln \delta + \rho_d \ln \delta_{t-1} + \sigma_{dt} \varepsilon_{dt}, \tag{19}$$

where $\rho_e \in (-1, 1)$ is the persistence parameter, $\sigma_{dt} \equiv \sigma_d(s_t^*)$ is the regime-switching standard deviaiton, and ε_{dt} is the white noise innovation with a zero mean and a unit variance. We introduce this time variation in the depreciation rate to capture the difference between economic depreciation (reflecting in part an unobserved quality improvement in equipment) and physical depreciation.

The household takes prices and all wages but its own as given and chooses C_t, I_t, K_t, u_t, B_{t+1}, and $W_t(h)$ to maximize (13) subject to (15) - (18), the borrowing constraint $B_{t+1} \geq -\underline{B}$ for some large positive number $\underline{B}$, and the labor demand schedule $L_t^d(h)$ described in (4).

The wage-setting decisions are staggered across households. In each period, a fraction ξ_w of households cannot re-optimize their wage decisions and, among those who cannot re-optimize, a fraction γ_w of them index their nominal wages to the price inflation realized in the past period. In particular, if the household h cannot set a new nominal wage, its wage is automatically updated according to

$$W_t(h) = \pi_{t-1}^{\gamma_w} \pi^{1-\gamma_w} \lambda_{t-1,t}^* W_{t-1}(h), \tag{20}$$

where $\lambda_{t-1,t}^* \equiv \frac{\lambda_t^*}{\lambda_{t-1}^*}$, with $\lambda_t^* \equiv (Q_t^{\alpha_1} Z_t^{\alpha_2})^{\frac{1}{1-\alpha_1}}$ denoting the trend growth rate of aggregate output (and the real wage). If a household $h \in [0, 1]$ can re-optimize its nominal wage-setting decision, it chooses $W(h)$ to maximize the utility subject to the budget constraint (15) and the labor demand schedule in (4). The optimal wage-setting decision implies that

$$\mathrm{E}_t \sum_{i=0}^{\infty} \xi_w^i D_{t,t+i} L_{t+i}^d(h) \frac{1}{\mu_{w,t+i} - 1} [\mu_{w,t+i} MRS_{t+i}(h) - W_t(h) \chi_{t,t+i}^w] = 0, \tag{21}$$

where $MRS_t(h)$ denotes the marginal rate of substitution between leisure and income for household h and $\chi_{t,t+i}^w$ is defined as

$$\chi_{t,t+i}^w \equiv \begin{cases} \Pi_{k=1}^i \pi_{t+k-1}^{\gamma_w} \pi^{1-\gamma_w} \lambda_{t,t+i}^* & \text{if } i \geq 1 \\ 1 & \text{if } i = 0. \end{cases}, \tag{22}$$

where $\lambda_{t,t+i}^* \equiv \frac{\lambda_{t+i}^*}{\lambda_t^*}$. In the absence of wage-markup shocks, μ_{wt} would be a constant and (21) implies that the optimal wage is a constant markup over a weighted average of the marginal rate of substitution for the periods in which the nominal wage remains effective. If $\xi_w = 0$, then the nominal wage adjustments are flexible and (21) implies that the nominal wage is a markup over the contemporaneous marginal rate of substitution. We derive the rest of the household's optimizing conditions in a technical appendix available upon request.

III.4. **The government and monetary policy.** The government follows a Ricardian fiscal policy, with its spending financed by lump-sum taxes so that $\bar{P}_t G_t = T_t$, where G_t denotes the government spending in final consumption units. Denote by $\tilde{G}_t \equiv \frac{G_t}{\lambda_t^*}$ the detrended government spending, where

$$\lambda_t^* \equiv \left(Z_t^{\alpha_2} Q_t^{\alpha_1}\right)^{\frac{1}{1-\alpha_1}}. \tag{23}$$

We assume that $\tilde{G}_t$ follows the stationary stochastic process

$$\ln \tilde{G}_t = (1-\rho_g)\ln \tilde{G} + \rho_g \ln \tilde{G}_{t-1} + \sigma_{gt}\varepsilon_{gt} + \rho_{gz}\sigma_{zt}\varepsilon_{zt}, \tag{24}$$

where we follow Smets and Wouters (2007) and assume that the government spending shock responds to productivity shocks.

Monetary policy is described by a feedback interest rate rule that allows the possibility of regime switching in the inflation target. The interest rate rule is given by

$$R_t = \kappa R_{t-1}^{\rho_r}\left[\left(\frac{\pi_t}{\pi^*(s_t)}\right)^{\phi_\pi}\left(\frac{Y_t}{\lambda_t^*}\right)^{\phi_y}\right]^{1-\rho_r} e^{\sigma_{rt}\varepsilon_{rt}}, \tag{25}$$

where $R_t = [\mathrm{E}_t D_{t,t+1}]^{-1}$ denotes the nominal interest rate and $\pi^*(s_t)$ denotes the regime-dependent inflation target. The constant terms κ, ρ_r, ϕ_π, and ϕ_y are policy parameters. The term ε_{rt} denotes the monetary policy shock, which follows an i.i.d. normal process with a zero mean and a unit variance. The term $\sigma_{rt} \equiv \sigma_r(s_t^*)$ is the regime-switching standard deviation of the monetary policy shock. We assume that the 8 shocks ε_{wt}, ε_{pt}, ε_{zt}, ε_{qt}, ε_{dt}, ε_{at}, ε_{rt}, and ε_{gt} are mutually independent.

III.5. **Market clearing and equilibrium.** In equilibrium, markets for bond, composite labor, capital stock, and composite goods all clear. Bond market clearing implies that $B_t = 0$ for all t. Labor market clearing implies that $\int_0^1 L_t^f(j)dj = L_t$. Capital market clearing implies that $\int_0^1 K_t^f(j)dj = u_t K_{t-1}$. Composite goods market clearing implies that

$$C_t + \frac{1}{Q_t}[I_t + a(u_t)K_{t-1}] + G_t = Y_t, \tag{26}$$

where aggregate output is related to aggregate primary factors through the aggregate production function

$$G_{pt} Y_t = (u_t K_{t-1})^{\alpha_1} (Z_t L_t)^{\alpha_2}, \tag{27}$$

with $G_{pt} \equiv \int_0^1 \left(\frac{P_t(j)}{\bar{P}_t}\right)^{-\frac{\mu_{pt}}{\mu_{pt}-1}\frac{1}{\alpha_1+\alpha_2}} dj$ measuring the price dispersion.

Given fiscal and monetary policy, an *equilibrium* in this economy consists of prices and allocations such that (i) taking prices and all nominal wages but its own as given, each household's allocation and nominal wage solve its utility maximization problem; (ii) taking wages and all prices but its own as given, each firm's allocation and price solve its profit maximization problem; (iii) markets clear for bond, composite labor, capital stock, and final goods.

IV. Equilibrium Dynamics

IV.1. **Stationary equilibrium and the deterministic steady state.** We focus on a stationary equilibrium with balanced growth. On a balanced growth path, output, consumption, investment, capital stock, and the real wage all grow at constant rates, while hours remain constant. Further, in the presence of investment-specific technological change, investment and capital grow at a faster rate. To induce stationarity, we transform variables so that

$$\tilde{Y}_t = \frac{Y_t}{\lambda_t^*}, \quad \tilde{C}_t = \frac{C_t}{\lambda_t^*}, \quad \tilde{w}_t = \frac{W_t}{\bar{P}_t \lambda_t^*}, \quad \tilde{I}_t = \frac{I_t}{Q_t \lambda_t^*}, \quad \tilde{K}_t = \frac{K_t}{Q_t \lambda_t^*},$$

where λ_t^* is the underlying trend for output, consumption, and the real wage given by (23).

Along the balanced growth path, as noted by Greenwood, Hercowitz, and Krusell (1997), the real rental price of capital keeps falling since the capital-output ratio keeps rising. The rate at which the rental price is falling is given by λ_q. Thus, the transformed variable $\tilde{r}_{kt} = r_{kt} Q_t$, that is, the rental price in consumption unit, is stationary. Further, the marginal utility of consumption is declining, so we define $\tilde{U}_{ct} = U_{ct} \lambda_t^*$ to induce stationarity.

The steady state in the model is the stationary equilibrium in which all shocks are shut off, including the "regime shocks" to the inflation target. To derive the steady state, we represent the finite Markov switching process with a vector AR(1) process (Hamilton, 1994). Specifically, the inflation target can be written as

$$\pi^*(s_t) = [\pi^*(1),\ \pi^*(2)] e_{s_t}, \tag{28}$$

where $\pi^*(j)$ is the inflation target in regime $j \in \{1, 2\}$ and

$$e_{s_t} = \begin{bmatrix} \mathbf{1}\{s_t = 1\} \\ \mathbf{1}\{s_t = 2\} \end{bmatrix}, \tag{29}$$

with $\mathbf{1}\{s_t = j\} = 1$ if $s_t = j$ and 0 otherwise. As shown in Hamilton (1994), the random vector e_{s_t} follows an AR(1) process:

$$e_{s_t} = Qe_{s_{t-1}} + v_t, \tag{30}$$

where Q is the transition matrix of the Markov switching process and the innovation vector has the property that $\mathrm{E}_{t-1}v_t = 0$. In the steady state, $v_t = 0$ so that (30) defines the ergodic probabilities for the Markov process and, from (28), the steady-state inflation π is the ergodic mean of the inflation target. Given π, the derivations for the rest of the steady-state equilibrium conditions are straightforward.

IV.2. **Linearized equilibrium dynamics.** To solve for the equilibrium dynamics, we log-linearize the equilibrium conditions around the deterministic steady state. We use a hatted variable $\hat{x}_t$ to denote the log-deviations of the stationary variable X_t from its steady-state value (i.e., $\hat{x}_t = \ln(X_t/X)$).

Linearizing the optimal pricing decision rule implies that[7]

$$\hat{\pi}_t - \gamma_p\hat{\pi}_{t-1} = \frac{\kappa_p}{1 + \bar{\alpha}\theta_p}(\hat{\mu}_{pt} + \hat{mc}_t) + \beta\mathrm{E}_t[\hat{\pi}_{t+1} - \gamma_p\hat{\pi}_t], \tag{31}$$

where $\theta_p \equiv \frac{\mu_p}{\mu_p - 1}$, $\kappa_p \equiv \frac{(1-\beta\xi_p)(1-\xi_p)}{\xi_p}$, $\bar{\alpha} \equiv \frac{1-\alpha_1-\alpha_2}{\alpha_1+\alpha_2}$, and

$$\hat{mc}_t = \frac{1}{\alpha_1 + \alpha_2}[\alpha_1\hat{r}_{kt} + \alpha_2\hat{w}_t] + \bar{\alpha}\hat{y}_t. \tag{32}$$

This is the standard price Phillips-curve relation generalized to allow for partial dynamic indexation. In the special case without indexation (i.e., $\gamma_p = 0$), this relation reduces to the standard forward-looking Phillips curve relation, under which the price inflation depends on the current-period real marginal cost and the expected future inflation. In the presence of dynamic indexation, the price inflation also depends on its own lag.

Linearizing the optimal wage-setting decision rule implies that

$$\hat{w}_t - \hat{w}_{t-1} + \hat{\pi}_t - \gamma_w\hat{\pi}_{t-1} = \frac{\kappa_w}{1 + \eta\theta_w}(\hat{\mu}_{wt} + \hat{mrs}_t - \hat{w}_t) + \beta\mathrm{E}_t[\hat{w}_{t+1} - \hat{w}_t + \hat{\pi}_{t+1} - \gamma_w\hat{\pi}_t], \tag{33}$$

where $\hat{w}_t$ denotes the log-deviations of the real wage, $\hat{mrs}_t = \eta\hat{l}_t - \hat{U}_{ct}$ denotes the marginal rate of substitution between leisure and consumption, $\theta_w \equiv \frac{\mu_w}{\mu_w - 1}$, and $\kappa_w \equiv$

[7]Derivations of the linearized equilibrium conditions are available upon request.

$\frac{(1-\beta\xi_w)(1-\xi_w)}{\xi_w}$ is a constant. To help understand the economics of this equation, we rewrite this relation in terms of the nominal wage inflation:

$$\hat{\pi}_t^w - \gamma_w \hat{\pi}_{t-1} = \frac{\kappa_w}{1+\eta\theta_w}(\hat{\mu}_{wt} + \hat{mrs}_t - \hat{w}_t) + \beta \mathrm{E}_t(\hat{\pi}_{t+1}^w - \gamma_w \hat{\pi}_t)$$
$$+ \frac{1}{1-\alpha_1}[\alpha_1(\Delta \hat{z}_t - \beta \mathrm{E}_t \Delta \hat{z}_{t+1}) + \alpha_2(\Delta \hat{q}_t - \beta \mathrm{E}_t \Delta \hat{q}_{t+1})]. \quad (34)$$

where $\hat{\pi}_t^w = \hat{w}_t - \hat{w}_{t-1} + \hat{\pi}_t + \Delta \hat{\lambda}_t^*$ denotes the nominal wage inflation. This nominal-wage Phillips curve relation parallels that of the price-Phillips curve and has similar interpretations.

The rest of the linearized equilibrium conditions are summarized below:

$$\begin{aligned}
\hat{q}_{kt} &= S''(\lambda_I)\lambda_I^2 \Big\{ \Delta \hat{i}_t - \beta \mathrm{E}_t \Delta \hat{i}_{t+1} \\
&\quad + \frac{1}{1-\alpha_1}\left[\alpha_2(\Delta \hat{z}_t - \beta \mathrm{E}_t \Delta \hat{z}_{t+1}) + \Delta \hat{q}_t - \beta \mathrm{E}_t \Delta \hat{q}_{t+1}\right] \Big\}, && (35) \\
\hat{q}_{kt} &= \mathrm{E}_t \Big\{ \Delta \hat{a}_{t+1} + \Delta \hat{U}_{c,t+1} - \frac{1}{1-\alpha_1}\left[\alpha_2 \Delta \hat{z}_{t+1} + \Delta \hat{q}_{t+1}\right] \\
&\quad + \frac{\beta}{\lambda_I}\left[(1-\delta)\hat{q}_{k,t+1} - \delta \hat{\delta}_{t+1} + \tilde{r}_k \hat{r}_{k,t+1}\right] \Big\}, && (36) \\
\hat{r}_{kt} &= \sigma_u \hat{u}_t, && (37) \\
0 &= \mathrm{E}_t \left[\Delta \hat{a}_{t+1} + \Delta \hat{U}_{c,t+1} - \frac{1}{1-\alpha_1}\left[\alpha_2 \Delta \hat{z}_{t+1} + \alpha_1 \Delta \hat{q}_{t+1}\right] + \hat{R}_t - \hat{\pi}_{t+1} \right], && (38) \\
\hat{k}_t &= \frac{1-\delta}{\lambda_I}\left[\hat{k}_{t-1} - \frac{1}{1-\alpha_1}(\alpha_2 \Delta \hat{z}_t + \Delta \hat{q}_t)\right] - \frac{\delta}{\lambda_I}\hat{\delta}_t + \left(1 - \frac{1-\delta}{\lambda_I}\right)\hat{i}_t, && (39) \\
\hat{y}_t &= c_y \hat{c}_t + i_y \hat{i}_t + u_y \hat{u}_t + g_y \hat{g}_t, && (40) \\
\hat{y}_t &= \alpha_1 \left[\hat{k}_{t-1} + \hat{u}_t - \frac{1}{1-\alpha_1}(\alpha_2 \Delta \hat{z}_t + \Delta \hat{q}_t)\right] + \alpha_2 \hat{l}_t, && (41) \\
\hat{w}_t &= \hat{r}_{kt} + \hat{k}_{t-1} + \hat{u}_t - \frac{1}{1-\alpha_1}(\alpha_2 \Delta \hat{z}_t + \Delta \hat{q}_t) - \hat{l}_t, && (42)
\end{aligned}$$

where (35) is the linearized investment decision equation with $\hat{q}_{kt}$ denoting the shadow value of existing capital (i.e., Tobin's Q) and the Δ denoting the first-difference operator (so that $\Delta x_t = x_t - x_{t-1}$); (36) is the linearized capital Euler equation; (37) is the linearized capacity utilization decision equation with $\sigma_u \equiv \frac{a''(1)}{a'(1)}$ denoting the curvature the function $a(u)$ evaluated at the steady state; (38) is the linearized bond Euler equation; (39) is the linearized law of motion for the capital stock; (40) is the linearized aggregate resource constraint, with the steady-state ratios given by $c_y = \frac{\tilde{C}}{\tilde{Y}}$, $i_y = \frac{\tilde{I}}{\tilde{Y}}$, $u_y = \frac{\tilde{r}_k \tilde{K}}{\tilde{Y}\lambda_I}$, and $g_y = \frac{\tilde{G}}{\tilde{Y}}$; (41) is the linearized aggregate production function; and (42) is the linearized factor demand relation.

Finally, the linearized interest rate rule is given by

$$\hat{R}_t = \rho_r \hat{R}_{t-1} + (1-\rho_r)\left[\phi_\pi(\hat{\pi}_t - \hat{\pi}^*(s_t)) + \phi_y \hat{y}_t\right] + \sigma_{rt}\varepsilon_{rt}, \tag{43}$$

where the term $\hat{\pi}^*(s_t) \equiv \log \pi^*(s_t) - \log \pi$ denotes the deviations of the inflation target from its ergodic mean.

V. Estimation Approach

We estimate the parameters in our model using the Bayesian method. We describe a general empirical strategy so that the method can be applied to other regimes-switching DSGE models. As shown in the appendices, our model contains twenty seven variables. Adding the five lagged variables $\hat{y}_{t-1}, \hat{c}_{t-1}, \hat{i}_{t-1}$, $\hat{w}_{t-1}$, and $\hat{q}_{t-1}$ to the list gives a total of thirty three variables. We denote all these state variables by the vector f_t where f_t is so arranged that the first eight variables are $\hat{y}_t, \hat{c}_t, \hat{i}_t, \hat{w}_t, \hat{q}_t, \hat{\pi}_t, \hat{\ell}_t$, and $\hat{R}_t$ and the last five variables are $\hat{y}_{t-1}, \hat{c}_{t-1}, \hat{i}_{t-1}$, $\hat{w}_{t-1}$, and $\hat{q}_{t-1}$.

We apply the relation (28) to the policy rule (43), where the vector e_{s_t} defined in (29) follows a vector AR(1) process described in (30). Expanding the log-linearized system with the additional variables represented by e_{s_t} maintains the log-linear form in which all coefficients are constant (i.e., independent of regime changes). A standard solution technique, such as the method proposed by Sims (2002), can be directly utilized to solve our DSGE model. The solution leads to the following VAR(1) form of state equations

$$f_t = c(s_t, s_{t-1}) + F f_{t-1} + C(s_t^*)\epsilon_t, \tag{44}$$

where $\epsilon_t = [\epsilon_{rt},\ \epsilon_{pt},\ \epsilon_{wt},\ \epsilon_{gt},\ \epsilon_{zt},\ \epsilon_{at},\ \epsilon_{dt},\ \epsilon_{qt}]'$, and $c(s_t)$ is a vector function of the inflation targets $\pi^*(s_t)$ and $\pi^*(s_{t-1})$ and the elements in the transition matrix Q, and $C(s_t^*)$ is a matrix function of $\sigma_{rt}(s_t^*)$, $\sigma_{pt}(s_t^*)$, $\sigma_{wt}(s_t^*)$, $\sigma_{gt}(s_t^*)$, $\sigma_{zt}(s_t^*)$, $\sigma_{at}(s_t^*)$, $\sigma_{dt}(s_t^*)$, and $\sigma_{qt}(s_t^*)$.

It follows from (44) that the solution to our DSGE model depends on the composite regime (s_t, s_{t-1}, s_t^*). If s_t^* is assumed to be the same as (s_t, s_{t-1}) (see Schorfheide (2005)), then the composite regime collapses to s_t. To simplify our notation and keep analytical expressions tractable, we use s_t to represent a composite regime that includes (s_t, s_{t-1}, s_t^*) as a special case for the rest of this section.

Our estimation is based on the 1959:I-2007:IV quarterly time-series observations on 8 U.S. aggregate variables: real per capita GDP (Y_t^{Data}), real per capita consumption (C_t^{Data}), real per capita investment (I_t^{Data}), real wage (w_t^{Data}), the investment-specific technology (i.e., the biased technology Q_t), the quarterly GDP-deflator inflation rate

(π_t^{Data}), per capita hours (L_t^{Data}), and the (annualized) federal funds rate ($\text{FFR}_t^{\text{Data}}$). Note that I_t^{Data} corresponds to $\frac{I_t}{Q_t}$ in the model (i.e., investment measured in units of consumption goods); a detailed description of the data is in Appendix A. These data are represented by the following vector of observable variables:

$$y_t = \left[\Delta \ln Y_t^{\text{Data}}, \Delta \ln C_t^{\text{Data}}, \Delta \ln I_t^{\text{Data}}, \Delta \ln w_t^{\text{Data}}, \ln \pi_t^{\text{Data}}, \Delta \ln Q_t^{\text{Data}}, \ln L_t^{\text{Data}}, \frac{\text{FFR}_t^{\text{Data}}}{400}\right]'.$$

The observable vector is connected to the model (state) variables through the measurement equations

$$y_t = a + H f_t,$$

where

$$a = \left[\ln \lambda_*, \ln \lambda_*, \ln \lambda_*, \ln \lambda_*, \ln \pi, \ln \lambda_q, \ln L, \ln R\right]'. \tag{45}$$

Give the aforementioned regime-switching state space form, one can estimate the model following the general estimation methodology of Sims, Waggoner, and Zha (2008).[8]

V.1. **Three methods for computing marginal data densities.** To evaluate the model's fit to the data and compare it to the fit of other models, one wishes to compute the marginal data density implied by the model. To keep the notation simple, let θ represent a vector of all model parameters except the transition matrix and Q be a collection of all free parameters in the transition matrix. The marginal data density is defined as

$$p(Y_T) = \int p(Y_T \mid \theta, Q) p(\theta)\, d\theta dQ, \tag{46}$$

where the likelihood function $p(Y_T \mid \theta, Q)$ can be evaluated recursively. For many empirical models, the modified harmonic mean (MHM) method of Gelfand and Dey (1994) is a widely used method to compute the marginal data density. The MHM method used to approximate (46) numerically is based on a theorem that states

$$p(Y_T)^{-1} = \int_\Theta \frac{h(\theta, Q)}{p(Y_T \mid \theta, Q) p(\theta, Q)} p(\theta, Q \mid Y_T) d\theta dQ, \tag{47}$$

where Θ is the support of the posterior probability density and $h(\theta, Q)$, often called a *weighting* function, is any probability density whose support is contained in Θ. Denote

$$m(\theta, Q) = \frac{h(\theta, Q)}{p(Y_T \mid \theta, Q) p(\theta, Q)}.$$

[8]The method details are also provided in an independent technical appendix to this article, which is available on http://home.earthlink.net/ tzha01/workingPapers/wp.html.

A numerical evaluation of the integral on the right hand side of (47) can be accomplished in principle through the Monte Carlo (MC) integration

$$\hat{p}(Y_T)^{-1} = \frac{1}{N}\sum_{i=1}^{N} m(\theta^{(i)}, Q^{(i)}), \tag{48}$$

where $(\theta^{(i)}, Q^{(i)})$ is the i^{th} draw of (θ, Q) from the posterior distribution $p(\theta, Q \mid Y_T)$. If $m(\theta, Q)$ is bounded above, the rate of convergence from this MC approximation is likely to be practical.

Geweke (1999) proposes a Gaussian function for $h(\cdot)$ constructed from the posterior simulator. The likelihood and posterior density functions for our medium-scale DSGE model turn out to be quite non-Gaussian and there exist zeros of the posterior pdf in the interior points of the parameter space. In this case, the standard MHM procedure tends to be unreliable as the MCMC draws are likely to be dominated by a few draws as the number of draws increase. Sims, Waggoner, and Zha (2008) proposes a truncated non-Gaussian weighting function for $h(\cdot)$ to remedy the problem. This weighting function seems to work well for the non-Gaussian posterior density.

In addition to the method of Sims, Waggoner, and Zha (2008), we use the unpublished method developed by Ulrich Müeller at Princeton University. To summarize Müeller's method for computing the marginal data density, we introduce the following notation. Let θ be an $n \times 1$ vector of random variables, $p(\theta)$ be the target pdf, whose probability density is of unknown form, and $p^*(\theta)$ be the target kernel where $p(\theta) = c^* p^*(\theta)$. Thus, our objective is to obtain an accurate estimate of the positive constant c^*. Let $h(\theta)$ be an approximate or weighting pdf and c be a positive real number. Define the function $f(c)$ as follows:

$$f(c) = E_h\left[\mathbf{1}\left\{\frac{cp^*(\theta)}{h(\theta)} < 1\right\}\left(1 - \frac{cp^*(\theta)}{h(\theta)}\right)\right] - E_g\left[\mathbf{1}\left\{\frac{h(\theta)}{cp^*(\theta)} < 1\right\}\left(1 - \frac{h(\theta)}{cp^*(\theta)}\right)\right].$$

One can show that this function has the following properties:

- $f(c)$ is monotonically decreasing in c;
- $f(0) = 1$ and $f(\infty) = -1$.

Given these properties, one can use a bisection method to find an estimate of c^* where $f(c^*) = 0$.

A third method we use is bridge sampling of Meng and Wong (1996). The bridge-sampling method has been often regarded as one of the most reliable methods for computing the Bayes factor. Since these three methods are developed from different mathematical relationships, we recommend using all these methods to ensure that the estimated value of the marginal data density is numerically similar across methods.

Because the posterior density function is very non-Gaussian and complicated in shape, it is all the more important to find the posterior mode via an optimization routine. The estimate of the mode not only represents the most likely value (and thus the posterior estimate) but also serves as a crucial starting point for initializing different chains of MCMC draws.

For various DSGE models studied in this paper, finding the mode has proven to be a computationally challenging task. The optimization method we use combines the block-wise BFGS algorithm developed by Sims, Waggoner, and Zha (2008) and various constrained optimization routines contained in the commercial IMSL package. The block-wise BFGS algorithm, following the idea of Gibbs sampling and EM algorithm, breaks the set of model parameters into subsets and uses Christopher A. Sims's `csminwel` program to maximize the likelihood of one set of the model's parameters conditional on the other sets.[9] Maximization is iterated at each subset until it converges. Then the optimization iterates between the block-wise BFGS algorithm and the IMSL routines until it converges. The convergence criterion is the square root of machine epsilon.

Thus far we have described the optimization process for only one starting point.[10] Our experience is that without such a thorough search, one can be easily misled to a much lower posterior value (e.g., a few hundreds lower in log value than the posterior peak). We thus use a set of cluster computing tools described in Ramachandran, Urazov, Waggoner, and Zha (2007) to search for the posterior mode. We begin with a grid of 100 starting points; after convergence, we perturb each maximum point in both small and large steps to generate additional 20 new starting points and restart the optimization process again; the posterior estimates attain the highest posterior density value. The other converged points typically have much lower likelihood values by at least a magnitude of hundreds of log values. For each DSGE model, the peak value of the posterior kernel and the mode estimates are reported.

[9]The `csminwel` program can be found on `http://sims.princeton.edu/yftp/optimize/`.

[10]For the no-switching (constant-parameter) DSGE model, it takes a couple of hours to find the posterior peak. While the model with two-regime shock variances takes about 20 hours to converge, the model with two-regime inflation targets and two-regime two-regime shock variances takes four times longer.

V.2. **Priors.** We set three parameters a priori. We set the steady-state government spending to output ratio at $g_y = 0.18$. We follow Justiniano and Primiceri (2006) and fix the persistence of the government spending shock process at $\rho_g = 0.99$. As noted by Smets and Wouters (2007), all these government parameter are difficult to estimate unless government spending is included in the set of measurement equations. Finally, we normalize and fix the steady-state hours worked at $L = 0.2$. We estimate all the remaining parameters. Tables 3 and 4 summarize the prior distributions for the structural parameters and the shock parameters.

Our priors are chosen to be more flexible and less tight than those in the previous literature. Specifically, instead of specifying the mean and the standard deviation, we use the 90% probability interval to back out the hyperparameter values of the prior distribution.[11] The intervals are generally set wide enough to allow the possibility of multiple posterior peaks (Del Negro and Schorfheide, 2008). Our approach is also necessary to deal with skewed distributions and allow for some reasonable hyperparameter values in certain distributions (such as the Inverse-Gamma) where the first two moments may not exist. The probability intervals reported in Table 3 cover the calibrated value of each parameter.

We begin with the preference parameters b, η, and β. Our prior for the habit-persistence parameter b follows the Beta distribution. We choose the 2 hyper-parameters of the Beta distribution such that the lower bound for b (0.05) has a cumulative probability of 5% and the upper bound (0.948) has a cumulative probability of 95%. This 90% probability interval for b covers the values used by most economists (for example, Boldrin, Christiano, and Fisher (2001) and Christiano, Eichenbaum, and Evans (2005)). Our prior for the inverse Frisch elasticity η follows the Gamma distribution. We choose the 2 hyper-parameters of the Gamma distribution such that the lower bound (0.2) and the upper bound (10.0) of η correspond to the 90% probability interval. This prior range for η implies that the Frisch elasticity lies between 0.1 and 5, a range broad enough to cover the values based on both microeconomic evidence (Pencavel, 1986) and macroeconomic studies (Rupert, Rogerson, and Wright, 2000). Our prior for the transformed subjective discount factor $\chi_\beta \equiv 100(\frac{1}{\beta} - 1)$ follows the Gamma distribution, with the hyper-parameters appropriately chosen such that the bounds for the 90% probability interval of χ_β are 0.2 and 4.0. The implied value of β lies in the range between 0.9615 and 0.998, which nests the values obtained by Smets

[11]The program for backing out the hyperparameter values of a given prior can be found in http://home.earthlink.net/ tzha02/ProgramCode/programCode.html.

and Wouters (2007) ($\beta = 0.9975$) and Altig, Christiano, Eichenbaum, and Linde (2004) ($\beta = 0.9926$).

Next, we discuss the prior distributions for the technology parameters α_1, α_2, λ_q, λ_*, σ_u, S'', and δ. Our priors for the labor share and capital share both follow the Beta distribution with the restriction $\alpha_1 + \alpha_2 \leq 1$ so that the production technology requires firm-specific factors (Chari, Kehoe, and McGrattan, 2000). Specifically, the bounds for the α_1 values in the 90% probability interval are 0.15 and 0.35 and those for α_2 are 0.35 and 0.75. With the restriction $\alpha_1 + \alpha_2 \leq 1$, however, the joint 90% probability region would be somewhat different. We assume that the priors for the (transformed) trend growth rates of the investment-specific technology and the neutral technology both follow the Gamma distribution, with the 5% and 95% bounds given by 0.1 and 1.5 respectively. These values imply that, with 90% probability, the prior values for the trend growth rates λ_q and λ_* lie in the range between 1.001 and 1.015 (corresponding to annual rates of 0.4% and 6%, respectively). We assume that the priors for the capacity utilization parameter σ_u and the investment adjustment cost parameter S'' both follow the Gamma distribution, with the lower bounds given by 0.5 and 0.1 and the upper bounds given by 3.0 and 5.0, respectively. These 90% probability ranges cover the values obtained, for example, by Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007). We assume that the prior for the average annualized depreciation rate follows the Beta distribution with the 90% probability range lying between 0.05 and 0.20.

Third, we discuss the prior distributions for the parameters that characterize price and nominal wage setting in the model. These include the average price markup μ_p, the average wage markup μ_w, the Calvo probabilities of non-adjustment in pricing ξ_p and in wage-setting ξ_w, and the indexation parameters γ_p and γ_w. The priors for the net markups $\mu_p - 1$ and $\mu_w - 1$ both follow the Gamma distribution with the 90% probability range covering the values between 0.01 and 0.5. This range covers most of the calibrated values of the markup parameters used in the literature (e.g., Basu and Fernald (2002), Rotemberg and Woodford (1997), Huang and Liu (2002)). The priors for the price and wage duration parameters ξ_p and ξ_w both follow the Beta distribution with the 90% probability range between 0.1 and 0.75. Under this prior distribution, the nominal contract durations vary, with 90% probability, between 1.1 quarters and 4 quarters. This range covers the values of the frequencies of price and wage adjustments used in the literature (e.g., Bils and Klenow (2004), Taylor (1999)). The priors for the indexation parameters γ_p and γ_w both follow the uniform distribution with the 90%

probability range lying between 0.05 and 0.95. In this sense, we have loose priors on these indexation parameters, the range of which covers those used in most studies (e.g., Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), and Woodford (2003)).

Finally, we discuss the coefficients in the monetary policy rule, including ρ_r, ϕ_π, and ϕ_y. The prior for the interest-rate smoothing parameter ρ_r follows the Beta distribution with the 90% probability range between 0.05 and 0.948. The prior for the inflation coefficient ϕ_π follows the Gamma distribution with the 90% probability range between 0.5 and 5.0. The prior for the output coefficient ϕ_y follows the Gamma distribution with the 90% probability range between 0.05 and 3.0. This range includes the values obtained by Clarida, Galí, and Gertler (2000) and others. These prior values allow for an indeterminacy region. When the equilibrium is indeterminate, we follow Boivin and Giannoni (2006) and use the MSV solution. In our estimation, however, there is practically little probability for the parameters to be in the indeterminate region.

Our priors for the AR(1) coefficients for the neutral and biased technology shocks ρ_q and ρ_z are uniformly distributed in the $[0, 1]$ interval. The AR(1) coefficients for all other shocks and the MA(1) coefficients for the price and wage markup shocks follow the Beta distribution with the 5%-95% probability range given by $[0.05, 0.948]$. The prior for the parameter ρ_{gz} follows the Gamma distribution with the 90% probability range given by $[0.2, 3.0]$. The standard deviations of each of the 8 shocks follow the Inverse Gamma distribution with the 90% probability range given by $[0.0005, 1.0]$. This probability range implies a more agnostic prior than Smets and Wouters (2007) and Justiniano and Primiceri (2006). Such an agnostic prior is needed to allow for possible large changes in shock variances across regimes, as found in Sims and Zha (2006).

We have experimented with different priors. In one alternative prior, we follow the literature and make a prior on the persistence parameters in shock processes much tighter towards zero, such as the Beta$(1, 2)$ probability density. Our conclusions hold true for these priors as well.

VI. Model Fit

The first set of results to discuss is measures of model fit, with the comparison based on maximum log posterior densities adjusted by the Schwarz criterion.[12] Table 1 reports Schwarz criteria for different versions of our DSGE model (the column "Baseline") and

[12]The Schwarz criterion is similar to the Laplace approximation used by Smets and Wouters (2007).

for models with the restriction that all the persistence parameters in both price markup and wage markup processes are set to zero (the column "Restricted").

Table 1 shows that the model with regime shifts in shock variances only (DSGE-2v) is the best-fit model, much better than the constant-parameter DSGE model (DSGE-con). The Schwarz criterion for the baseline DSGE-2v model is 5963.03, compared to 5859.71 for the DSGE-con model. When we allow the inflation target to switch regimes while holding the shock variances constant (DSGE-2c), the model's fit does not improve upon the constant-parameter DSGE model. When we allow both the inflation target and shock variances to switch regimes with the same Markov process (i.e., regime switching is synchronized), the model (DSGE-2cv) does better than the one with regime switching in the inflation target alone, but it does not improve upon the baseline DSGE-2v model with regime shifts in the shock variances only. When we relax the assumption that switches in the shock regime and those in the inflation target regime are synchronized and compute the Schwarz criterion for the model with the target regime and the shock regime independent of each other (DSGE-2c2v), we find that the model's fit does not improve relative to either the DSGE-2cv model with synchronized regime shifts in the inflation target and the shock variances or the baseline DSGE-2v model with synchronized regime shifts in shock variances only. We have also examined the possibility of 3 shock regimes instead of 2. We find that the 3-regime model (DSGE-3v) does not improve upon the baseline 2-regime model (DSGE-2v).

We have also estimated models with shock variances following independent Markov switching processes. This scenario approximates the stochastic volatility model of Uhlig (1997), where each shock variance has its own independent stochastic process (Tauchen, 1986; Sims, Waggoner, and Zha, 2008). In addition, we have grouped a subset of shock variances having the same Markov processes. None of these models fits to the data better than our baseline DSGE-2v model. For example, when we allow regimes associated with the variances of the two technology shocks to be independent of the regime switching processes of the other shock variances (DSGE-2v2v), we obtain a Schwarz criterion of 5958.18, which is lower than that of the baseline DSGE-2v model (5963.03). In short, the data favor the parsimoniously-parameterized model with shock variances switch regimes simultaneously.

The last column in Table 1 shows that the model with regime changes in shock variances only continues to dominate all the other models, when the persistence parameters in both price and wage markup shock processes are restricted to zero. In particular, the model with the target switching regimes (DSGE-2c) does not improve upon the constant-parameter model. Of course, all these restricted models fit to the data much worse than the corresponding baseline models, implying that persistent shock processes are important in fitting the data.

Finally, we have estimated a number of models with persistence parameters in other shock processes set to zero and with habit and indexation parameters set to zero. The model with synchronized regimes in shock variances continue to outperform other models in fitting the data.

The relative performance of the alternative DSGE models in fitting the data does not change when we look at the marginal data density (MDD). Table 2 reports the MDD for each of the alternative models. The table shows that the model with simultaneous regime shifts in shock variances (DSGE-2v) is the best-fit model not only in terms of the Schwarz criterion, but also in terms of the marginal data density. In particular, the DSGE-2v model's MDD is 5832.38, much higher than that of the DSGE-con model (whose MDD is 5741.24). The model with regime switching in the inflation target alone (DSGE-2c) slightly outperforms the constant parameter model, but substantially under-performs the DSGE-2v model. With regime shifts in shock variances, introducing regime shifts in the inflation target synchronized with regime shifts in shock variances (DSGE-2cv) or allowing the inflation target to follow a Markov switching process independent of shock regimes (DSGE-2c2v) does not improve the marginal data density relative to the DSGE-2v model.[13]

VII. Estimates of Structural Parameters

Because the constant-parameter model is a most often used model, we report the parameter estimates for the baseline DSGE-con model. We then compare them with the results in the existing literature and with the estimates for our best-fit model (i.e., the baseline DSGE-2v model). We also discuss the implications based on the estimates at a local (lower) posterior peak to show how the results can be seriously distorted. The results are reported in Tables 3 and 4. The last column labelled by "DSGE-con-lp" reports the results obtained at a local posterior peak for the constant-parameter DSGE model.

VII.1. **The constant-parameter model.** We first discuss the posterior estimates for the model with no regime shifts. This model is similar to that in Smets and Wouters

[13]The good fit represented by DSGE-2cv comes entirely from significant shifts in shock variances. The estimated inflation targets are 2.18% for one regime and 1.70% for the other regime and the difference between these two targets are statistically insignificant.

(2007), with five notable exceptions. First, we introduce a source of real rigidity in the form of firm-specific factors, which replaces the kinked demand curves considered by Smets and Wouters (2007). Second, we introduce trend growth in the investment-specific technological change to better capture the data, in which the relative price of investment goods (e.g., equipment and software) has been declining for most of the postwar period, while in Smets and Wouters (2007) the investment-specific technological changes have no trend component. We use the observed time series of biased technological changes in our estimation, while Smets and Wouters (2007) treat these changes as a latent variable. Third, we introduce the depreciation shock that acts as a wedge in the capital-accumulation Euler equation. Fourth, the preference shock in our model enters all intertemporal decisions, including choices of the nominal bond, the capital stock, and investment, while Smets and Wouters (2007) introduce a "risk-premium shock" that enters the bond Euler equation only and does not affect other intertemporal decisions. Finally, in the interest rate rule, we assume that the nominal interest rate responds to deviations of inflation from its target and detrended output, while in Smets and Wouters (2007) the interest rate rule targets inflation, output gap, and the growth rate of output gap. These distinctions may explain some of the differences between our estimated results and theirs.

We report the posterior estimates for our constant-parameter model (DSGE-con) in the fifth column (under "DSGE-con") of Table 3. The data are informative about many structural parameters, as will be discussed in Section VIII.3. The table shows that among the three preference parameters, the posterior mode for habit persistence is 0.88, which lies in the higher end of the 90% probability interval. The posterior mode for η is 2.24, implying a Frisch elasticity of about 0.45, consistent with most microeconomic studies. The estimate for the subjective discount factor implies that β is about 0.9989, which is similar to the value obtained by Smets and Wouters (2007) (0.9984).

Among the technology parameters, the posterior mode for α_1 (0.154) is close to the lower bound of the 90% probability interval for the prior distribution and is lower than the estimate obtained by by Smets and Wouters (2007) (0.19). Because of the constraint $\alpha_1 + \alpha_2 \leq 1$, the posterior mode for α_2 (0.837) lies inside the joint 90% prior probability region. These posterior estimates suggest that the data prefer a model specification with (near) constant-returns production technology. The estimated trend growth rate for the investment-specific technological change is about 4% per annum, which is slightly higher than the calibrated value obtained by Greenwood, Hercowitz, and Krusell (1997). The estimate for the trend growth rate of the neutral technological change is about 0.72% per annum. The curvature parameter in the utilization function (σ_u) is estimated at 2.266, which lies at the high end of the 90% prior probability range. This value is close to that estimated by Altig, Christiano, Eichenbaum, and Linde (2004) (2.02), although it is higher than that obtained by Smets and Wouters (2007) (1.174) and lower than that obtained by Justiniano and Primiceri (2006) (7.13). The investment adjustment cost parameter (S'') has a posterior mode of 1.525. This value is somewhat lower than those obtained in the literature. Unlike most studies in the literature that fix the value of the capital depreciation rate a priori, we allow the depreciation rate to follow a stationary stochastic process and we estimate the parameters in the process. The posterior estimate implies that the average annum depreciation rate is about 10.7%, which is remarkably close to the standard calibration value in the real business cycle literature.

Among the pricing and wage setting parameters, our posterior estimates show that the average price markup is about 1.002, which is consistent with the studies by Hall (1988), Basu and Fernald (1997), and Rotemberg and Woodford (1999), who argue that the pure economic profit is close to zero. It is also similar to the estimate obtained by Altig, Christiano, Eichenbaum, and Linde (2004), but much smaller than the value estimated by Justiniano and Primiceri (2006). Our estimate for the average wage markup is 1.07, which is lower than the calibrated value (Huang and Liu, 2002) and the estimated value (Justiniano and Primiceri, 2006) in the literature, but is similar to the value used by Christiano, Eichenbaum, and Evans (2005). The posterior estimates imply that the price contracts last on average for slightly more than 2 quarters and nominal wage contracts are very short (slightly more than 1 quarter). These estimated durations for the nominal contracts are very close to those obtained by Galí and Rabanal (in press). The price contract duration is also consistent with the microeconomic studies such as Bils and Klenow (2004). Our estimates suggest that dynamic indexation is not important for price setting but very important for nominal wage setting.

Our posterior estimates of the policy parameters suggest that interest-rate smoothing is important, with a posterior mode for ρ_r being 0.73. The response to deviations of inflation from its target in the interest rule is 1.186, but it does not respond much to detrended output. Finally, the inflation target is estimated at 1.98% per annum.

Our posterior estimates of shock variances reported in Table 4 reveal that all but the preference shock are very persistent, with the AR(1) coefficient at 0.9 or above.

The preference shock is almost i.i.d.. The MA(1) coefficients in the price markup and wage markup processes are both sizable, at 0.676 and 0.645 respectively. In addition, the government spending shock responds to the neutral technology shock, with the response coefficient being 1.446. Although we assume the same prior distribution for all the shock volatility parameters, we obtain very disperse posterior estimates for different types of shock variances. The estimates reveal that the depreciation shock and the wage markup shock have the largest variances, the monetary policy shock and the two types of technology shocks have the smallest variances, and the price markup shock, the preference shock, and the government spending shock lie somewhere in between.

VII.2. **The variances-changing model.** We now discuss the posterior estimates in the model with regime changes in shock variances, as reported in the sixth column (under "DSGE-2v") of Table 3.

Introducing regime shifts in shock variances does not significantly change the estimates of most structural parameters. It is worth noting a few differences compared to the estimates in the model with the constant regime. The estimated average duration of the price contracts becomes even shorter (1.7 quarters vs. 2.2 quarters); the average depreciation rate is slightly higher (13% vs. 11%); the interest-rate-smoothing parameter ρ_r is slightly larger (0.82 vs. 0.73); the response coefficient to inflation in the interest rate rule is considerably larger (1.66 vs. 1.19); and the inflation target is slightly higher (2.28 vs. 1.98).

The lack of price rigidity in our estimation is due to a strong strategic complementarity implied by our best-fit model. There is a tension between the demand elasticity and the returns to scale: with constant returns ($\bar{\alpha} = 0$), the demand elasticity drops out of the log-linearized pricing equation so that firms are not concerned about the size of the demand elasticity when they set prices; with decreasing returns ($\bar{\alpha} > 0$), however, the optimal price adjustment is smaller if the demand elasticity is larger. Despite near constant returns (the estimated value of $\alpha_1 + \alpha_2$ is 0.998), the very large demand elasticity (the estimated value of ν_p is 1.0001) implies a strong strategic complementarity such that firms are deterred from adjusting their relative prices when the demand curve is flat. Indeed, the estimated coefficient of the marginal cost in (31) is 0.076. This value implies that the value of the price rigidity parameter (ξ_p) would be $= 0.76$ if there were constant returns.

Regime changes in shock variances influence the estimation of shock processes, as shown in Table 4. Compared to the constant-parameter model (DSGE-con), the estimated AR(1) coefficient for the price markup shock becomes smaller (0.9491 vs. 0.9998); the estimated MA(1) coefficients in both price and wage markup shock processes are larger (0.699 and 0.750 vs. 0.676 and 0.645); the response of government spending to the neutral technology shock becomes smaller (0.894 vs. 1.446); and the AR(1) coefficient for the depreciation shock is slightly larger (0.934 vs. 0.899).

The estimates of shock variances are quite different from those for the constant-parameter model. The shock variances in the second regime are substantially smaller than those in the first regime. The sizes of shock variances for the constant-parameter model are somewhere between those in the first regime and those in the second regime. The estimates of the transition probabilities for shock regimes are summarized by the matrix

$$\hat{Q} = \begin{bmatrix} 0.8072 & 0.0598 \\ 0.1928 & 0.9402 \end{bmatrix}, \tag{49}$$

where the elements in each column sum to one. The second regime (i.e., the regime with low shock variances) is more persistent and, as shown in Figure 1, covers most periods after Greenspan became Chairman of the Federal Reserve Board.

VII.3. **Estimates based on a local posterior peak.** Because the likelihood is very non-Gaussian, there exist many local peaks of the posterior density function even for the constant-parameter model. The last column (under "DSGE-con-lp") of Tables 3 and 4 report a set of estimates of the structural parameters obtained at a local posterior peak for the constant-parameter model. This situation is likely to occur in the estimation of any DSGE model.

Compared to the mode estimates (in the DSGE-con column of Tables 3 and 4), the values of both price and wage stickiness parameters are higher; the habit parameter is smaller; the durations for the price and wage contracts are slightly longer; the wage indexation parameter is much smaller; the monetary policy response to inflation is modestly larger and the response to output is much larger. The trend growth rate for investment technology is 2.3% per annum. Furthermore, the estimated price and wage markup processes are less persistent and the indexation becomes less important than those implied by the estimates obtained at the posterior mode; the preference shock becomes much more persistent. The variances of the shocks are broadly similar to the mode estimates.

At this local peak, we get two distinct inflation targets: one is at 2.8% and the other is at 5.2%. These estimates, as well as the other estimates, seem to be all reasonable and in line with our a priori beliefs. But the posterior value is much smaller than the value at the posterior mode on the order of 100 in log value, implying an extremely poor fit to the data. As we will show in Section VIII.2, the variance decompositions under the estimates at the lower posterior peak are drastically different from those at the posterior mode.

VIII. Model Analysis

VIII.1. **Impulse responses.** To gain intuition about the model's transmission mechanisms, we analyze impulse responses of selected variables following some of the structural shocks. In particular, we focus on the dynamic effects of a wage markup shock, a neutral technology shock, and a depreciation shock on output, investment, the real wage, the inflation rate, hours, and the nominal interest rate. As we have discussed in Section VII, the wage markup shock and the depreciation shock have the largest variances among all eight structural shocks. The neutral technology shock is of considerable interest because of the debate in the recent literature on its dynamic effects on the labor market variables (e.g., Galí (1999), Christiano, Eichenbaum, and Vigfusson (2003), Uhlig (2004), and Liu and Phaneuf (2007)). The macroeconomic effects of the other five shocks, including the monetary policy shock, the price markup shock, the biased technology shock, the preference shock, and the government spending shock are similar to those in the literature (Smets and Wouters, 2007), so we do not report those results. Since the impulse responses display qualitatively similar patterns across the two shock regimes except the scaling effects, we focus on the responses in the second regime.

Figure 2 displays the impulse responses following a one-standard-deviation shock to the capital depreciation rate. The increase in the depreciation rate reduces the value of capital accumulation and thus investment falls. Since the expected stock of capital wealth declines, the negative wealth effect leads to a fall in consumption as well. Consequently, aggregate output falls. The decline in output leads to a decline in hours. The decline in hours and in consumption lowers the marginal rate of substitution between leisure and consumption, so that the households' desired wage falls. Thus, the equilibrium real wage declines as well. The fall in the real wage reduces the firms' marginal cost so that inflation declines. Through the Taylor rule, the nominal interest rate declines as well.

Figure 3 displays the impulse responses following a one-standard-deviation shock to the investment-specific technology. The biased shock raises the efficiency of investment, investment goods today become cheaper and current consumption becomes more expensive. This type of shock, unlike the depreciation shock or the neutral technology shock, shifts resources from consumption to investment. Consequently, investment rises and consumption declines for more than eight quarters. Hours declines initially due to the costly adjustment in investment, as well as the habit formation. After the second quarter, the increase in demand for investment gradually leads to a rise in hours and the real wage. The rise in labor hours helps produce more output. In contrast to the responses to the depreciation shock, the biased technology shock generates opposite movements in output and consumption in the short run.

Figure 4 displays the impulse responses following a one-standard-deviation shock to the neutral technology. The positive neutral technology shock raises output, consumption, investment, and the real wage. The shock lowers inflation and, through the Taylor rule, the nominal interest rate as well. The shock also leads to a decline in hours worked. The decline in hours here, however, is not a direct consequence of price stickiness. Even with much more frequent price adjustments, we find that the positive neutral technology shock leads to a decline in hours (not reported). Instead, the investment adjustment cost (as well as the habit formation to a less extent) plays an important role in generating the decline in hours. If the investment adjustment cost parameter is small, we find that the model generates an increase in hours following the neutral technology shock (not reported), regardless of whether prices are sticky or not. In this sense, our finding does not support the view that the contractionary effect of a neutral technology shock arises from the price stickiness. Our finding is consistent with Francis and Ramey (2005), who argue that a real business cycle model with habit persistence and investment adjustment cost can generate a decline in hours following a positive neutral technology shock.

Figure 5 displays the impulse responses following a one-standard-deviation shock to the wage markup. An increase in the wage markup raises the households' desired real wage. The households who can adjust their nominal wage raise their nominal wage. The increase in the nominal wage raises the firms' marginal cost so that inflation rises and real aggregate demand falls. It follows that aggregate output, investment, and hours decline. Through the interest-rate rule, the rise in inflation also leads to an increase in the nominal interest rate.

VIII.2. **Variance decompositions.**

VIII.2.1. *The lower peak case.* We first examine the variance decomposition results based on the parameter estimates obtained under the constant regime and at the lower posterior peak. The parameter values are reported in the last column of Tables 3 and 4. As we have discussed in Section VII, the parameter estimates at this lower posterior peak all seem reasonable. Yet, the variance decompositions reported in Table 7 indicate that most of the fluctuations in output are attributed to the neutral technology shock and those in inflation to the preference shock and the biased technology shock. In contrast to the variance decompositions reported in Tables 5 and 6, the estimated model at the lower posterior peak mistakenly suggests that the wage markup shock and the depreciation shock do not play much role in generating the fluctuations. These results suggest caution in searching for the posterior mode in Bayesian estimation.

VIII.2.2. *The best-fit model.* Tables 5 and 6 report variance decompositions in forecast errors of output, investment, hours, the real wage, and inflation under the two shock regimes at different forecasting horizons for our best-fit model. Consistent with our estimation results discussed in Section VII, capital depreciation shocks, neutral technology shocks, and wage markup shocks play an important role in accounting for business cycle fluctuations under each of the two regimes. Taken together, these three shocks account for about $70-90\%$ of the fluctuations in output, investment, hours, and inflation under each regime for the forecast horizons beyond eight quarters.

The wage markup shock acts as a wedge between the intratemporal marginal rate of substitution (MRS) and the marginal product of labor, which, as argued by Chari, Kehoe, and McGrattan (2007), plays an important role in generating the business cycle.

The neutral technology shock is also important in accounting for the fluctuations in output and the real wage under both regimes, consistent with the finding in Arias, Hansen, and Ohanian (2006). Monetary policy shock accounts for a sizable fraction of inflation fluctuations under the first regime but otherwise it is unimportant. The price markup shock contributes to about $15-30\%$ of the real wage fluctuations under both regimes. It also plays an important role for inflation fluctuations under the second regime. The remaining three shocks, including the government spending shock, the preference shock, and the biased technology shock are not important in explaining the business-cycle fluctuations.

The depreciation shock, on the other hand, acts as a wedge in the intertemporal capital accumulation decision. Since we use observations on the biased technological changes in our estimation, estimated biased technology shocks are much smaller in size than those when these observations are not used. Like the biased technology shock emphasized in Justiniano, Primiceri, and Tambalotti (2008), the depreciation shock fills the gap by capturing the intertemporal wedge, which is important in generating the business cycle. Unlike the biased technology shock, however, it generates the comovements of consumption and output, as discussed in the pervious section.

Greenwood, Hercowitz, and Krusell (1997) draw a mapping between the growth rate of investment-specific technological changes and the economic depreciation rate. Since the economic depreciation rate rises when the equipment price relative to the consumption price is expected to decline in the future, which leads to faster economic depreciation than physical depreciation, (unexpected) shocks to investment-specific technological changes play a less important role. Unlike economic depreciation, positive shocks to the depreciation of physical capital represent contractions in all real economic activities; these shocks are found important in our estimated model.

VIII.3. **Parameter uncertainty.** Figure 6 plots the posterior distribution of some key parameters. The distribution of the inflation target concentrate tightly around the estimate of 2%, while there is considerable uncertainty around the wage indexation parameter. The posterior distribution of the price-stickiness parameter implies that the price rigidity is much smaller than what is obtained in the previous literature. The wage rigidity is even less important, with little probability above 0.5. The posterior distribution of the investment technology trend puts a significant amount of probability around 4%, consistent with the data on the relative price of investment. The posterior distribution of the response coefficient to inflation in the Taylor indicate that there is practically no probability for indeterminate equilibria for our DSGE model.

There are two reasons why we obtain estimates that imply shorter durations of price and wage contracts than those obtained in the literature such as Altig, Christiano, Eichenbaum, and Linde (2004) and Smets and Wouters (2007). First, our estimates suggest that the price markup is very small, implying that the demand curve for differentiated goods is very flat. Thus, a small increase in the relative price can lead to large declines in relative output demand. Even if firms can re-optimize their pricing decisions very frequently, they choose not to adjust their relative prices too much. In this sense, the small average markup and thus the large demand elasticity become a source of strategic complementarity in firms' pricing decisions. Second, unlike Altig, Christiano, Eichenbaum, and Linde (2004) who use a minimum-distance estimator that matches the model's impulse responses to those in the data, we use full-information maximum likelihood estimation. This difference is important because Altig, Christiano, Eichenbaum, and Linde (2004) find that, while a neutral technology shock leads to rapid adjustment in prices, a monetary policy shock leads to small and gradual price adjustments. Under their estimation approach, matching the impulse responses following the monetary policy shock is important so that price adjustments need to be small and gradual. Our estimation approach differs from theirs and we find that the most important shocks are neutral technology shocks, capital depreciation shocks, and wage markup shocks, all of which lead to rapid adjustments in prices. Consequently, our estimated durations of nominal contracts are shorter than those in the literature.

IX. Conclusion

We have studied a variety of fairly large DSGE models within a unified framework to reexamine the sources of the Great Moderation observed in the post-WWII U.S. economy. Our econometric estimation suggests that heteroscedastic shock disturbances are important and different types of shock variances tend to change regime simultaneously rather than independently. Three shocks stand out as the most important sources of macroeconomic volatilities: the wage markup shock that serves as an intratemporal labor supply wedge, the neutral technology shock that acts as an efficiency wedge, and the depreciation shock that acts like an intertemporal wedge. Our best-fit model does not provide evidence of systematic changes in the inflation target, nor does it support strong nominal rigidities in prices and nominal wages. These findings are robust across a large set of models.

Appendix A. Detailed Data Description

All data are either taken directly from the Haver Analytics Database or constructed by Patrick Higgins at the Federal Reserve Bank of Atlanta. The construction methods developed or used by Patrick Higgins, available on request, will be briefly described below.

The model estimation is based on eight U.S. aggregate variables: real per capita GDP (Y_t^{Data}), real per capita consumption (C_t^{Data}), real per capita investment (I_t^{Data}) in capital goods, real wage (w_t^{Data}), the quarterly GDP-deflator inflation rate (π_t^{Data}), per capita hours (L_t^{Data}), the federal funds rate ($\text{FFR}_t^{\text{Data}}$), and the inverse of the relative price of investment (Q_t^{Data}).

These series are derived from the original data in the Haver Analytics Database (with the relevant data codes provided) or from the constructed data.

- $Y_t^{\text{Data}} = \frac{\text{GDPH}}{\text{POP25-64}}$.
- $C_t^{\text{Data}} = \frac{(\text{CN@USECON} + \text{CS@USECON})*100/\text{JGDP}}{\text{POP25-64}}$.

- $I_t^{\text{Data}} = \frac{(\text{CD@USECON} + \text{F@USECON})*100/\text{JGDP}}{\text{POP25-64}}$.
- $w_t^{\text{Data}} = \frac{\text{LXNFC@USECON}/100}{\text{JGDP}}$.
- $\pi_t^{\text{Data}} = \frac{\text{JGDP}_t}{\text{JGDP}_{t-1}}$.
- $L_t^{\text{Data}} = \frac{\text{LXNFH@USECON}}{\text{POP25-64}}$.
- $\text{FFR}_t^{\text{Data}} = \frac{\text{FFED@USECON}}{400}$.
- $Q_t^{\text{Data}} = \frac{\text{JGDP}}{\text{TornPriceInv4707CV}}$.

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

POP25-64: civilian noninstitutional population with ages 25-64 by eliminating breaks in population from 10-year censuses and post 2000 American Community Surveys using "error of closure" method. This fairly simple method was used by the Census Bureau to get a smooth population monthly population series. This smooth series reduces the unusual influence of drastic demographic changes.

GDPH: real gross domestic product (2000 dollars). Source: BEA.

CN@USECON: nominal personal consumption expenditures: nondurable goods. Source: BEA

CS@USECON: nominal consumption expenditures: services. Source: BEA.

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

F@USECON: nominal private fixed investment. Source: BEA.

JGDP: gross domestic product: chain price index (2000=100). Source: BEA.

LXNFC@USECON: nonfarm business sector: compensation per hour (1992=100). Source: BLS.

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

FFED@USECON: annualized federal funds effective rate. Source: FRB.

TornPriceInv4707CV: investment deflator. The Tornquist procedure is used to construct this deflator as a weighted aggregate index from the four quality-adjusted price indexes: private nonresidential structures investment, private residential investment, private nonresidential equipment & software investment, and personal consumption expenditures on durable goods. Each price index is a weighted one from a number of individual price series within this categories. For each individual price series from 1947 to 1983, we use Gordon (1990)'s quality-adjusted price index. Following Cummins and Violante (2002), we estimate an econometric model of Gordon's price series as a function of a time trend and a few NIPA indicators (including the current and lagged values of the corresponding NIPA price series); the estimated coefficients are then used to extrapolate the quality-adjusted price index for each individual price series for the sample from 1984 to 2007. These constructed price series are annual. Denton (1971)'s method is used to interpolate these annual series on a quarterly frequency. The Tornquist procedure is then used to construct each quality-adjusted price index from the appropriate interpolated quarterly price series.

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Table 1. Schwarz Criterion for the Set of DSGE Models

Model	Baseline	Restricted
DSGE-con	5859.71	5811.14
DSGE-2v	5963.03	5920.01
DSGE-2c	5853.13	5805.27
DSGE-2cv	5960.71	5907.00
DSGE-2c2v	5958.78	5913.85
DSGE-2v2v	5958.18	5912.22
DSGE-3v	5950.73	5926.91

Note: Column 1 lists the models studied: the DSGE model with all parameters that are constant across time (DSGE-con), the DSGE model with two regimes in shock variances (DSGE-2v), the DSGE model with two regimes in the inflation target only (DSGE-2c), the DSGE model with two common regimes for both shock variances and the inflation target (DSGE-2cv), and the DSGE model with two independent Markov processes, one controlling two regimes in shock variances and the other controlling two regimes in the inflation target (DSGE-2c2v), the DSGE model with two independent Markov processes, one controlling two regimes in variances of two technology shocks and the other controlling two regimes in variances of all the other shocks (DSGE-2v2v), and the DSGE model with three regimes in shock variances (DSGE-3v). Column 2 reports the posterior densities at the posterior mode, adjusted by Schwarz criterion. Column 3 displays the posterior densities evaluated at the posterior modes for models with the persistence parameters in both the price and wage markup processes set to zero.

Table 2. Comprehensive Measures of Model Fits

Model	Marginal Data Density
DSGE-con	5741.24
DSGE-2v	5832.38
DSGE-2c	5739.32
DSGE-2cv	5832.60
DSGE-2c2v	5830.84
DSGE-2v2v	5826.95
DSGE-3v	5813.91

TABLE 3. Prior Distribution and Posterior Mode of Structural Parameters

	Prior			Posterior		
Parameter	Distribution	Low	High	DSGE-con	DSGE-2v	DSGE-con-lp
b	Beta	0.05	0.948	0.876	0.907	0.579
η	Gamma	0.2	10.0	2.235	2.888	1.689
$100\,(\beta^{-1}-1)$	Beta	0.2	4.0	0.109	0.175	0.336
α_1	Beta	0.15	0.35	0.153	0.163	0.122
α_2	Beta	0.35	0.75	0.837	0.835	0.528
$100(\lambda_q-1)$	Gamma	0.1	1.5	0.999	1.000	0.559
$100(\lambda_*-1)$	Gamma	0.1	1.5	0.179	0.237	0.372
σ_u	Gamma	0.5	3.0	2.266	2.263	1.417
S''	Gamma	0.5	5.0	1.525	2.000	2.031
4δ	Beta	0.05	0.2	0.107	0.134	0.164
μ_p-1	Gamma	0.01	0.50	0.002	0.000	0.065
μ_w-1	Gamma	0.01	0.50	0.069	0.060	0.096
ξ_p	Beta	0.1	0.75	0.545	0.412	0.592
γ_p	Beta	0.05	0.95	0.118	0.178	0.204
ξ_w	Beta	0.1	0.75	0.185	0.213	0.345
γ_w	Beta	0.05	0.95	1.000	1.000	0.263
ρ_r	Beta	0.05	0.948	0.730	0.816	0.801
ϕ_π	Gamma	0.5	5.0	1.185	1.655	2.081
ϕ_y	Gamma	0.05	3.0	0.005	0.043	0.474
$400\log\pi^*(1)$	Gamma	1.0	8.0	1.981	2.283	3.219
$400\log\pi^*(2)$	Gamma	1.0	8.0	1.981	2.283	3.219

Note: "Low" and "High" denote the bounds of the 5%-95% probability interval for the prior distributions. "DSGE-con" denotes the model with no regime switching. "DSGE-2v" denotes the model with two regimes in shock variances. "DSGE-con-lp" denotes the model with no regime switching and with a lower posterior peak.

Table 4. Prior Distribution and Posterior Mode of Shock Parameters

	Prior			Posterior		
Parameter	Distribution	Low	High	DSGE-con	DSGE-2v	DSGE-con-lp
ρ_p	Beta	0.05	0.948	0.999	0.949	0.778
ϕ_p	Beta	0.05	0.948	0.675	0.698	0.483
ρ_w	Beta	0.05	0.948	0.999	0.999	0.840
ϕ_w	Beta	0.05	0.948	0.645	0.749	0.513
ρ_{gz}	Gamma	0.2	3.0	1.446	0.894	0.664
ρ_a	Beta	0.05	0.948	0.061	0.107	0.881
ρ_q	Beta	0.05	0.95	0.993	0.994	1.000
ρ_z	Beta	0.05	0.95	0.997	0.992	0.999
ρ_d	Beta	0.05	0.948	0.899	0.934	0.823
$\sigma_r(1)$	Inverse Gamma	0.0005	1.0	0.002	0.004	0.002
$\sigma_r(2)$	Inverse Gamma	0.0005	1.0	0.002	0.001	0.002
$\sigma_p(1)$	Inverse Gamma	0.0005	1.0	0.024	0.039	0.060
$\sigma_p(2)$	Inverse Gamma	0.0005	1.0	0.024	0.028	0.060
$\sigma_w(1)$	Inverse Gamma	0.0005	1.0	0.105	0.255	0.118
$\sigma_w(2)$	Inverse Gamma	0.0005	1.0	0.105	0.144	0.118
$\sigma_g(1)$	Inverse Gamma	0.0005	1.0	0.026	0.041	0.025
$\sigma_g(2)$	Inverse Gamma	0.0005	1.0	0.026	0.021	0.025
$\sigma_z(1)$	Inverse Gamma	0.0005	1.0	0.007	0.010	0.012
$\sigma_z(2)$	Inverse Gamma	0.0005	1.0	0.007	0.006	0.012
$\sigma_a(1)$	Inverse Gamma	0.0005	1.0	0.027	0.043	0.018
$\sigma_a(2)$	Inverse Gamma	0.0005	1.0	0.027	0.037	0.018
$\sigma_q(1)$	Inverse Gamma	0.0005	1.0	0.004	0.007	0.004
$\sigma_q(2)$	Inverse Gamma	0.0005	1.0	0.004	0.002	0.004
$\sigma_d(1)$	Inverse Gamma	0.0005	1.0	0.138	0.193	0.287
$\sigma_d(2)$	Inverse Gamma	0.0005	1.0	0.138	0.099	0.287
q_{11}	Dirichlet			*	0.807	*
q_{22}	Dirichlet			*	0.940	*

Table 5. Forecast Error Variance Decomposition: Regime I

Horizon	MP	PM	WM	GS	Ntech	Pref	Btech	Dep
				Output				
4Q	5.1443	4.1486	21.7621	12.8076	21.7050	1.4694	0.2106	32.7525
8Q	2.6618	4.1472	36.6626	6.3157	23.4311	0.5821	0.3289	25.8707
16Q	1.2227	2.9278	49.3857	3.4905	25.7249	0.2658	0.3942	16.5885
20Q	0.9756	2.5166	52.4044	2.9881	26.1211	0.2121	0.4119	14.3702
				Investment				
4Q	8.2082	5.7979	14.4682	0.7438	4.7909	0.5182	1.5667	63.9061
8Q	4.6292	6.2905	22.8817	1.1375	7.1533	0.7034	2.2140	54.9904
16Q	3.2021	5.9545	30.5410	1.2310	10.2411	0.6839	3.6330	44.5134
20Q	3.0318	5.7789	32.0371	1.1764	11.1034	0.6478	4.2787	41.9460
				Hours				
4Q	6.2409	4.6560	33.5268	18.7046	3.9659	2.0046	0.0815	30.8198
8Q	3.4031	4.8188	58.8519	10.9127	1.8040	0.9368	0.1388	19.1339
16Q	1.7212	3.0812	76.6957	6.8522	0.9926	0.4698	0.1114	10.0761
20Q	1.3929	2.5430	79.8568	6.0511	0.8162	0.3841	0.0938	8.8619
				Real wage				
4Q	6.2726	14.9794	24.5772	0.2213	34.1127	1.1717	0.2982	18.3668
8Q	5.6839	19.8200	12.8581	0.1161	31.7275	0.5643	0.2978	28.9321
16Q	3.3235	20.6873	6.9996	0.1603	36.8344	0.3290	0.3967	31.2691
20Q	2.8272	19.7771	5.9603	0.1726	39.2705	0.2857	0.4580	31.2486
				Inflation				
4Q	17.1586	11.2160	34.3253	1.1835	0.1755	1.1923	0.5994	34.1493
8Q	17.1334	9.3782	36.9222	1.1124	0.1509	1.0689	0.7772	33.4568
16Q	14.3407	7.9953	40.9412	0.9402	0.1589	0.9094	0.7557	33.9585
20Q	12.8011	7.2902	42.2714	0.8484	0.2053	0.8251	0.6802	35.0783

Note: Columns $2-9$ correspond to the shocks: the monetary policy shock (MP), the price markup shock (PM), the wage markup shock (WM), the government spending shock (GS), the neutral technology shock (Ntech), the preference shock (Pref), the biased technology shock (Btech), and the depreciation shock (Dep).

TABLE 6. Forecast Error Variance Decomposition: Regime II

Horizon	MP	PM	WM	GS	Ntech	Pref	Btech	Dep
				Output				
4Q	1.4623	6.8572	22.2957	10.9572	27.1732	3.5101	0.0921	27.6522
8Q	0.7325	6.6368	36.3663	5.2312	28.4007	1.3462	0.1392	21.1470
16Q	0.3285	4.5746	47.8282	2.8228	30.4437	0.6002	0.1629	13.2390
20Q	0.2611	3.9167	50.5532	2.4070	30.7917	0.4770	0.1696	11.4238
				Investment				
4Q	2.6142	10.7376	16.6082	0.7130	6.7202	1.3870	0.7675	60.4524
8Q	1.3975	11.0425	24.8966	1.0335	9.5109	1.7845	1.0280	49.3065
16Q	0.9411	10.1760	32.3509	1.0888	13.2559	1.6891	1.6423	38.8559
20Q	0.8887	9.8499	33.8462	1.0379	14.3342	1.5957	1.9291	36.5185
				Hours				
4Q	1.8550	8.0476	35.9182	16.7333	5.1919	5.0074	0.0373	27.2093
8Q	0.9744	8.0232	60.7354	9.4043	2.2750	2.2543	0.0611	16.2724
16Q	0.4847	5.0454	77.8436	5.8075	1.2310	1.1118	0.0482	8.4277
20Q	0.3918	4.1596	80.9619	5.1229	1.0112	0.9081	0.0406	7.4039
				Real wage				
4Q	1.5771	21.9006	22.2722	0.1675	37.7754	2.4758	0.1153	13.7161
8Q	1.4263	28.9214	11.6296	0.0877	35.0659	1.1900	0.1150	21.5641
16Q	0.8150	29.4979	6.1863	0.1183	39.7808	0.6781	0.1496	22.7740
20Q	0.6917	28.1379	5.2561	0.1271	42.3184	0.5875	0.1724	22.7089
				Inflation				
4Q	5.3155	20.2044	38.3260	1.1035	0.2395	3.1041	0.2856	31.4214
8Q	5.3827	17.1324	41.8078	1.0518	0.2089	2.8220	0.3755	31.2189
16Q	4.4593	14.4569	45.8850	0.8799	0.2176	2.3764	0.3614	31.3634
20Q	3.9610	13.1172	47.1437	0.7901	0.2798	2.1456	0.3237	32.2388

Table 7. Forecast Error Variance Decomposition: the model with no regime switching and with lower posterior peak

Horizon	MP	PM	WM	GS	Ntech	Pref	Btech	Dep
				Output				
4Q	0.0007	0.0625	0.0000	0.0000	97.3630	1.6410	0.8873	0.0455
8Q	0.0003	0.0427	0.0000	0.0000	97.9274	0.7430	1.2537	0.0328
12Q	0.0002	0.0284	0.0000	0.0000	97.9745	0.5449	1.4282	0.0238
16Q	0.0001	0.0209	0.0000	0.0000	97.9928	0.4304	1.5376	0.0182
20Q	0.0001	0.0165	0.0000	0.0000	98.0053	0.3506	1.6130	0.0145
				Inflation				
4Q	0.0063	7.8444	0.0001	0.0001	0.1409	77.0744	14.5833	0.3504
8Q	0.0049	5.7245	0.0001	0.0002	0.4070	77.5122	15.5821	0.7691
12Q	0.0042	4.9742	0.0001	0.0002	2.0464	76.9793	14.9383	1.0573
16Q	0.0039	4.5371	0.0001	0.0003	4.4264	75.8520	14.0143	1.1659
20Q	0.0036	4.2595	0.0001	0.0003	6.9458	74.3397	13.2695	1.1816

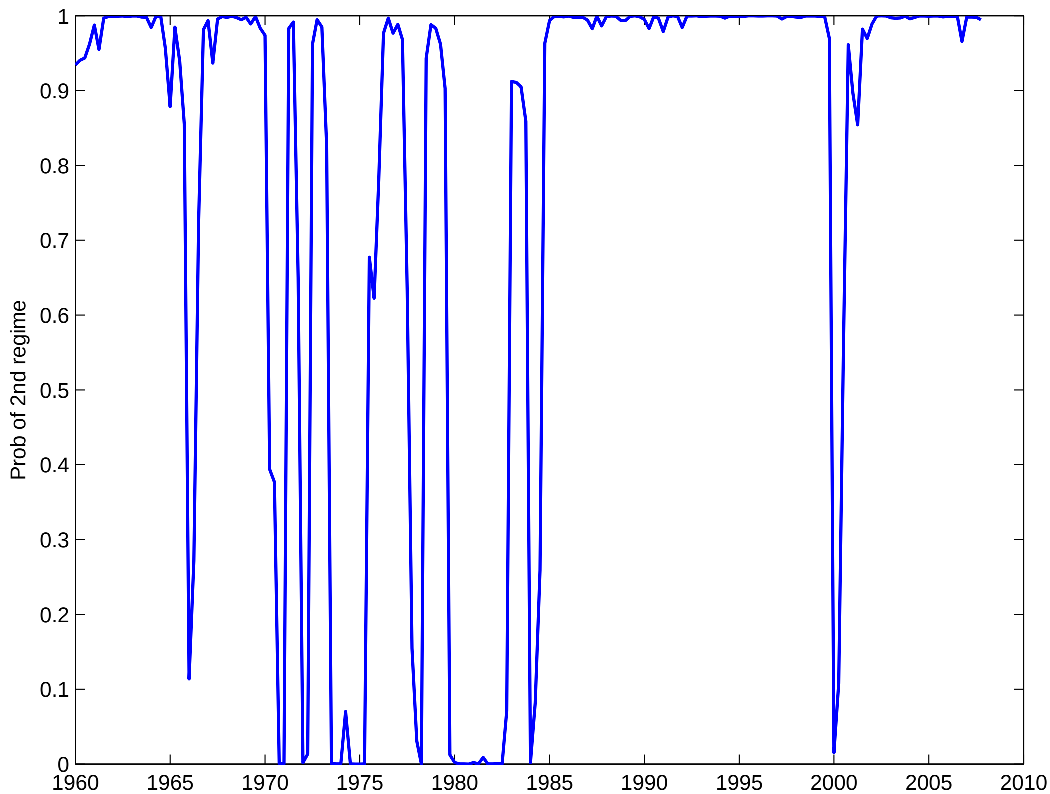

FIGURE 1. Posterior probabilities of the second regime for the baseline DSGE-2v.

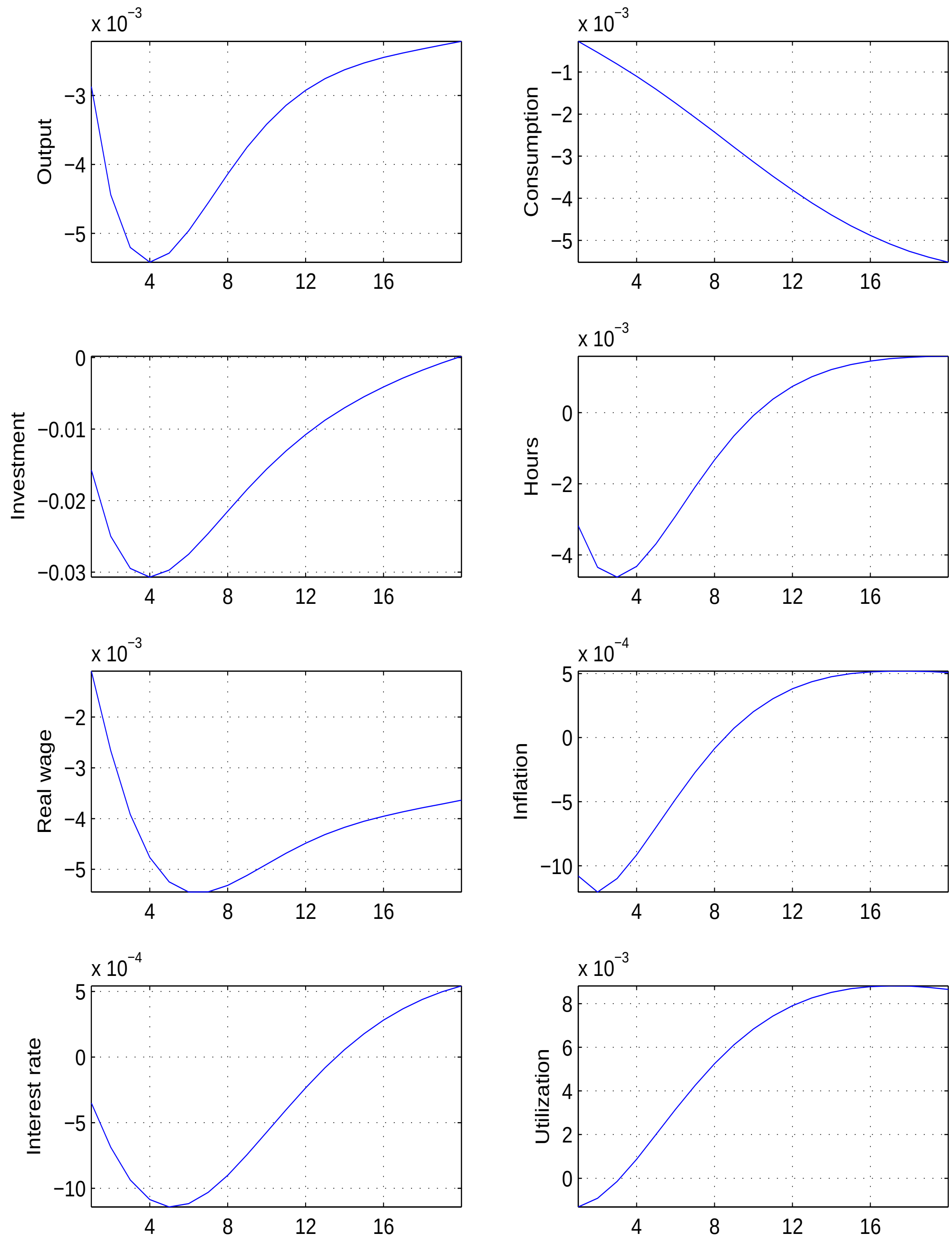

FIGURE 2. Impulse responses to a depreciation shock in the second regime.

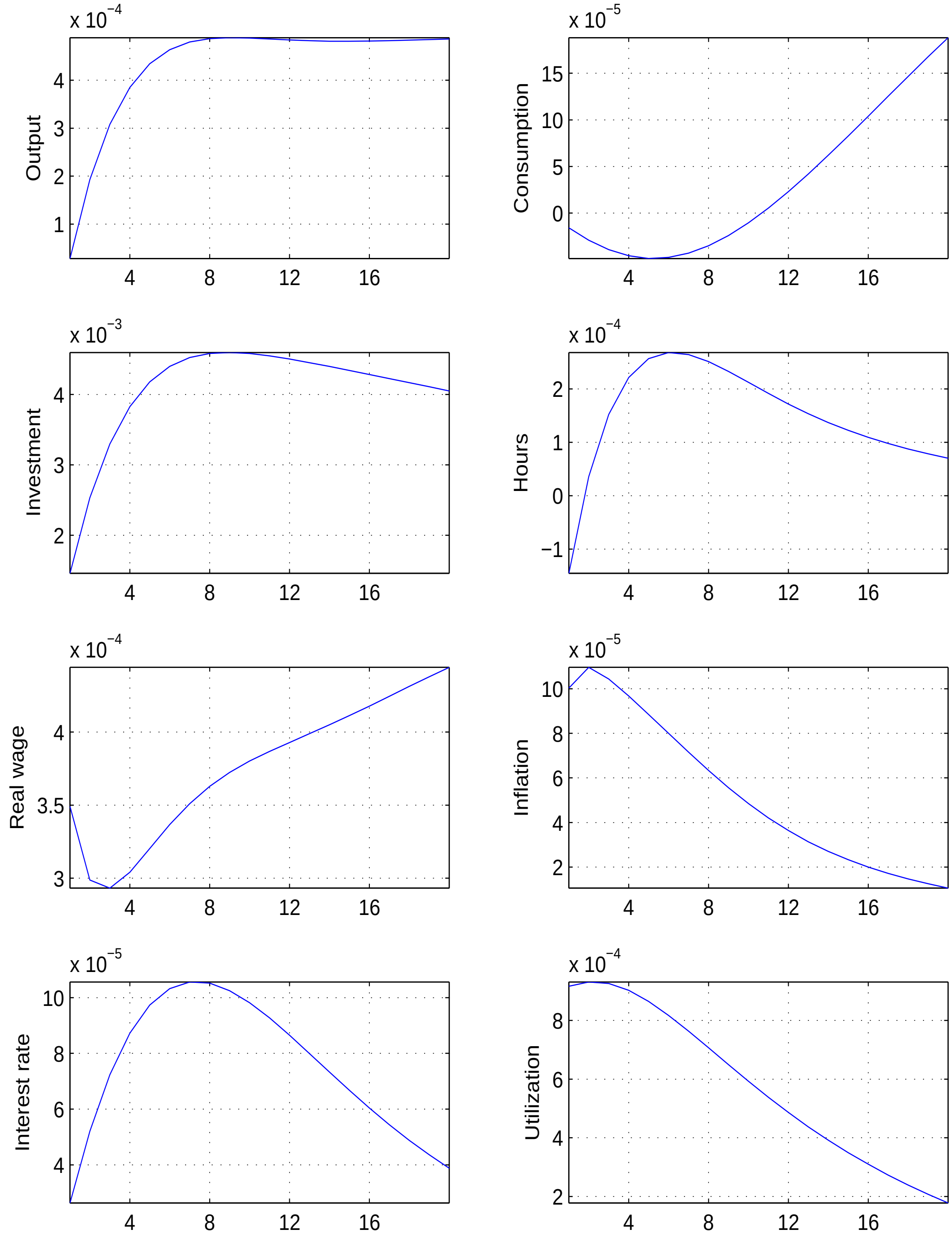

Figure 3. Impulse responses to an investment-specific technology shock in the second regime.

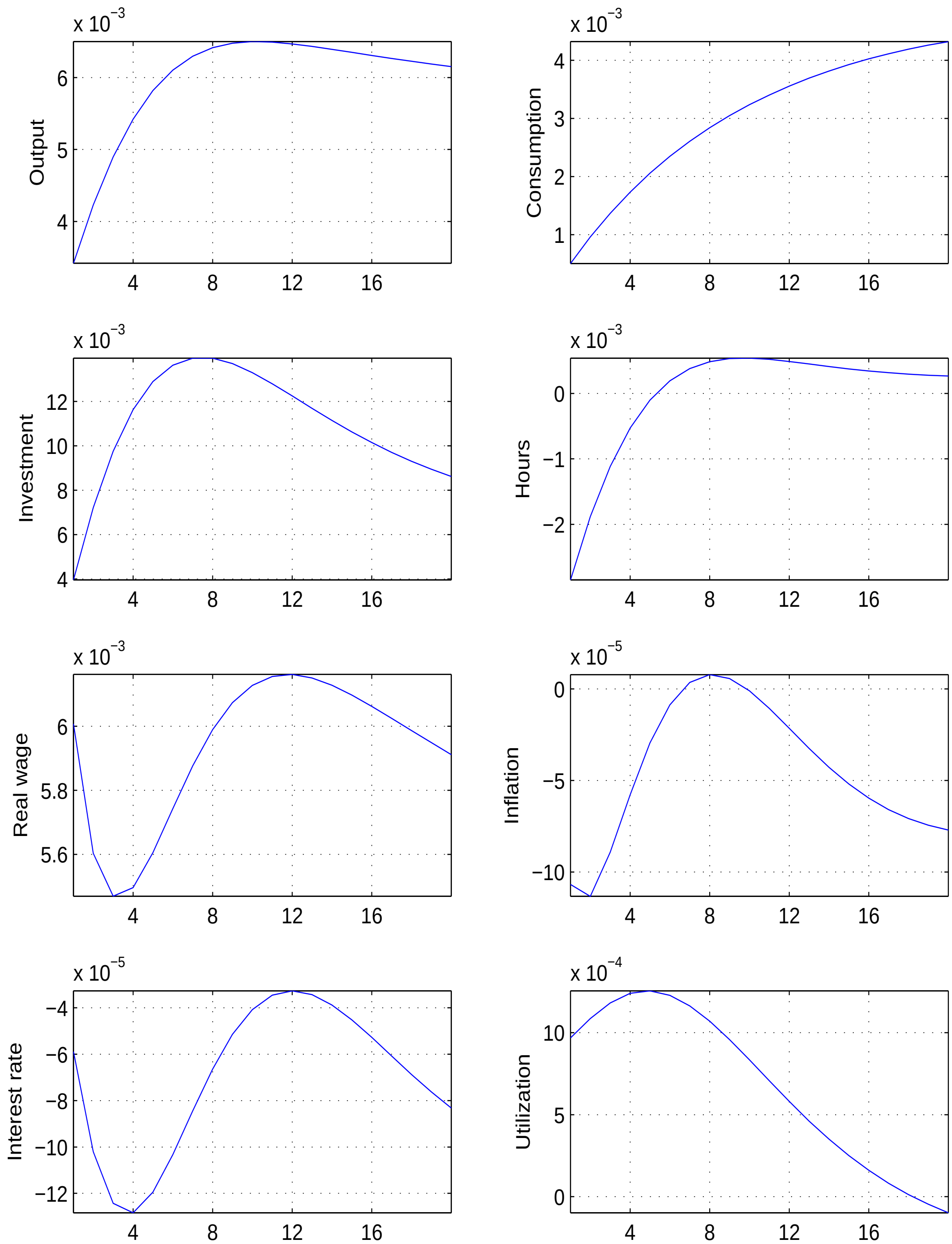

FIGURE 4. Impulse responses to a neutral technology shock in the second regime.

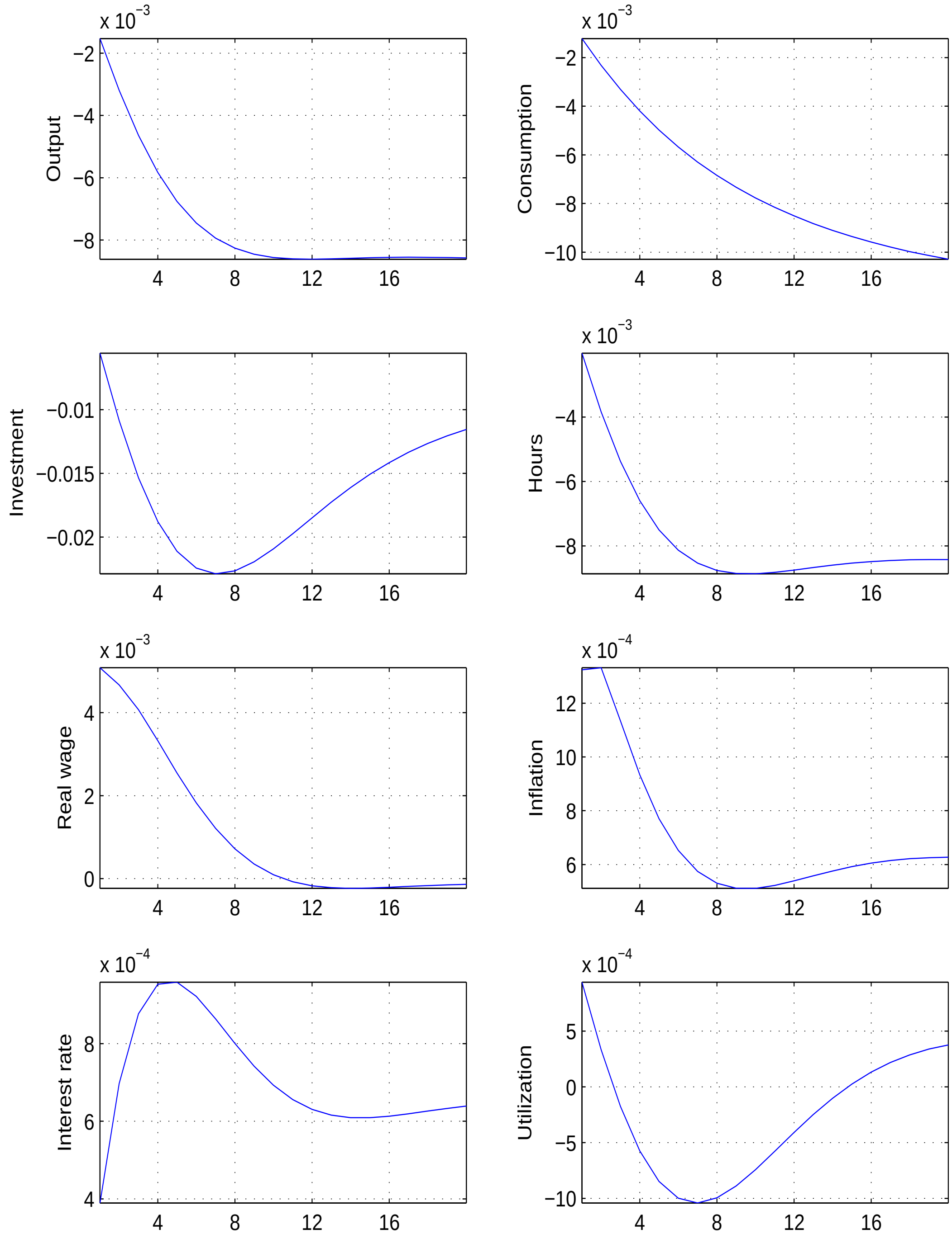

FIGURE 5. Impulse responses to a wage markup shock in the second regime.

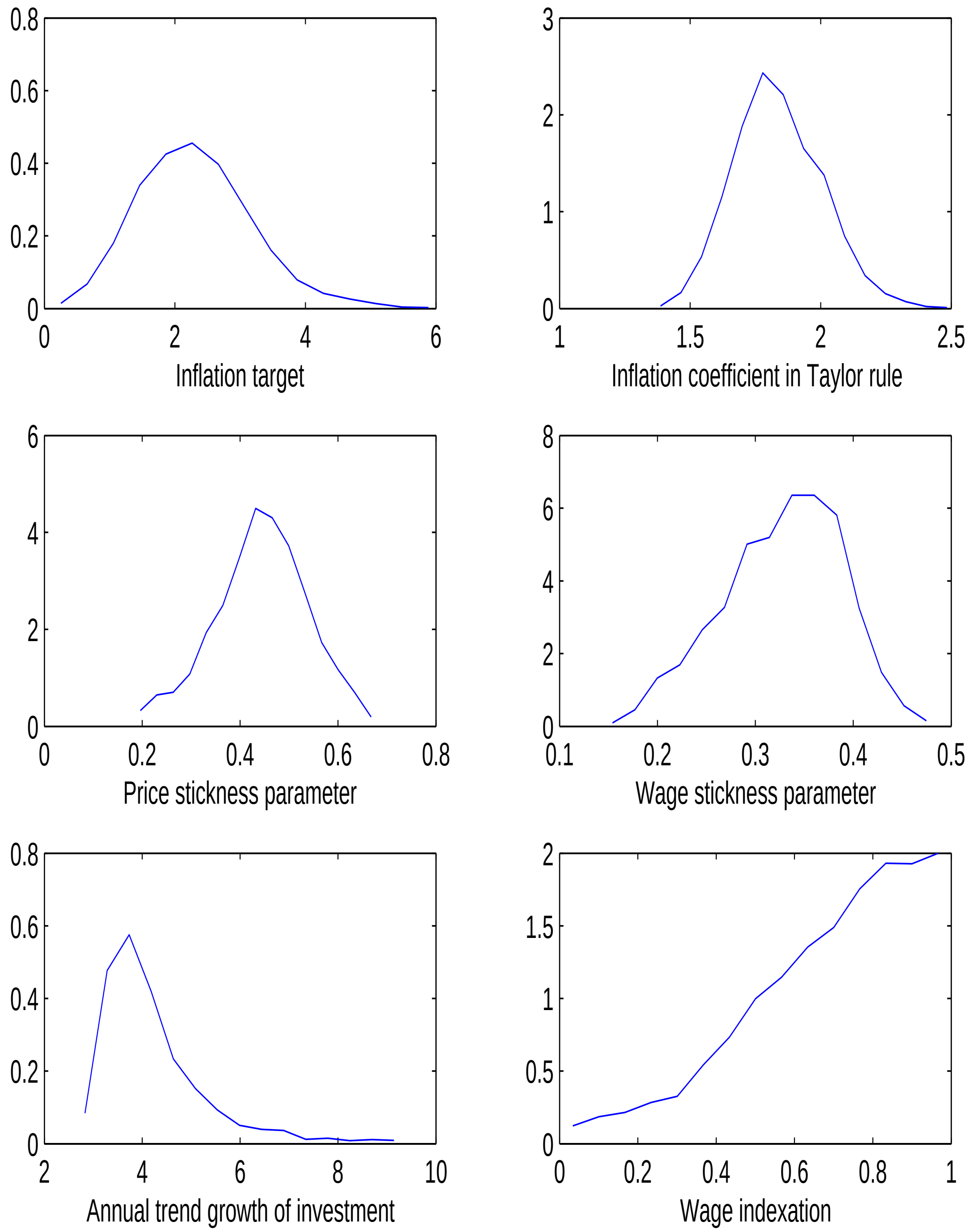

Figure 6. Marginal posterior distributions of some key parameters for the DSGE-2v model.

Federal Reserve Bank of San Francisco and Emory University, Federal Reserve Bank of Atlanta, Federal Reserve Bank of Atlanta and Emory University