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Understanding the Effects of Unanticipated Future Monetary Policy Shocks*

경제주체들에게 관측되지 않은 미래 통화정책 충격의 효과 분석

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This paper studies the effects of future monetary policy shocks unanticipated by private agents using an estimated new Keynesian dynamic stochastic general equilibrium model framework. Analysis of U.S. data from 1967 Q1 to 2008 Q1 shows that the information structure on monetary policy substantially improves the model's fit to data compared to the conventional contemporaneous-shocks-only counterpart. To examine the role of agents' foresight about future monetary policy shocks, a counterfactual analysis on agents' information flows is conducted. If, throughout the sample period, agents had possessed perfect foresight about future monetary policy shocks, the business cycle fluctuations would have been milder as the volatility of key macroeconomic variables drops markedly. In addition, we find that the model-implied uncertainty about future monetary policy contains significant explanatory power for disagreement—cross-sectional dispersion of forecasts—in the Survey of Professional Forecasters.

Key words: New Keynesian Model, Information Flows, News Shocks, Imperfect Information, Bayesian Estimation

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Ⅰ. Introduction

The effects of "news" in monetary actions appear in the empirical macro literature (Milani and Treadwell, 2012). Coincident with news about fiscal actions existing work typically posits that monetary policy shocks—the non-systematic component of policy distinguished from its systematic responses to inflation and output fluctuations—which will be realized in the future are well anticipated by private agents.

Given the nature of institutional structure of policy decisions, it is remarkable that degrees of foresight about future monetary actions are intrinsically different from news about changes in taxes or government spending. In the context of fiscal policy, there is a plethora of literature documenting how agents would learn today about shocks that will hit far into the future, as well as well-established evidence of this happening (Poterba, 1988; Ramey and Shapiro, 1998; Yang, 2005; Mertens and Ravn, 2010; Ramey, 2011; Leeper et al., 2013). However, it may be different in the monetary policy context. As both Blinder et al. (2001) and Goodfriend (2010) point out, the Federal Reserve's communicating more openly with the public in terms of interest rate policy is a relatively recent phenomenon that has occurred since the mid-1990s. This finding suggests that any ability of the public to anticipate future monetary policy shocks may have to be a lot more limited than that in the existing literature.

The main objective of this paper is to examine the role of an alternative assumption about how information about future monetary policy shocks flows to private agents. In particular, I study the empirical implications of future monetary policy shocks unanticipated by agents, using an estimated new Keynesian dynamic stochastic general equilibrium (NK-DSGE) model framework. Before detailing the main information structure of this article, I introduce two benchmark specifications for ease of explanation. Both information structures assume agents' perfect observation on exogenous shocks, but the only difference between them is the presence of anticipated components of monetary policy shocks. In the first benchmark structure, there is only a contemporaneous innovation in monetary policy, and any changes in the innovation are directly observed by agents. In reference to Milani and Treadwell (2012), the second benchmark specification posits that they receive news about future monetary policy shocks which take the i.i.d. form as examined in Schmitt-Grohe and Uribe (2012).

In contrast to the information flows as above, the main information specification of this paper employs agents' incapability of accessing future shocks on monetary policy. In this specification, agents know that the underlying monetary policy rule obeys the i.i.d. specification as in the second benchmark. In addition, they possess perfect information about current exogenous shocks, including the current component of monetary policy shocks. Agents, however, have no foresight on the future components of monetary policy shocks. Consequently, the difference between the second benchmark and main information structures is attributable entirely to the anticipation of future monetary policy shocks.

These information structures are inserted into an otherwise standard NK-DSGE model. Together with monetary policy at various horizons, two more shocks drive economic fluctuations in the NK-DSGE model. They are shocks to technology and household preference, both of which are modeled as first-order autoregressive processes. The models are estimated on quarterly U.S. data ranged from 1967:Q1 to 2008:Q1. The estimation results are then compared across the information structures based on the following criteria:

Overall model fit, impulse responses, and spectrums of model-implied data.[1] The only difference across the three models is their information structures, thus, any variations in these quantities should correspond to an assessment of the information specifications.

The first contribution of this paper is to illuminate the role of the information structure endowed with the unanticipated future monetary policy shocks. Three main findings are obtained regarding this issue. First, this information structure turns out to be the best favored specification by the U.S. time series data. It significantly improves the model's fit to the data compared to the conventional contemporaneous-shocks-only counterpart. On the other hand, there is almost no gain of embedding monetary policy news shocks in enhancing model fit. Note that this finding is robust to various measures of model fit, including the posterior marginal density as in Geweke (1999), deviance information criterion as in Spiegelhalter et al. (2002), and Bayesian predictive information criterion as in Ando (2007).

Second, incorporating future components of monetary policy disturbances unobservable to agents improves the model's performance by producing more data-consistent short-run fluctuations in interest rate dynamics. I find that embedding the information structure generates additional high frequency variations in the nominal interest rate, which fosters the statistical relationships between the model-generated interest rate series and actual data.

Third, the information structure induces a more persistent equilibrium even though it relies less on the persistence generated by internal propagation mechanisms, such as habit formation in consumption. The underlying

1) The choice of model-implied spectrums as a part of model comparison is guided by Walker and Leeper (2011), who argue that alternative information structures, such as news or noise, alter the persistence of a model's equilibrium.

mechanism of this phenomenon is in line with Granger (1966), who argues that the “typical spectral shape” of macroeconomic time series allocates most of the spectral power to low frequencies. The less persistent equilibrium interest-rate process caused by augmenting unanticipated future monetary policy shocks is corrected through higher estimates for the shock autocorrelation parameters. Consequently, the equilibrium dynamics induced by non- policy shocks becomes relatively more persistent than the other information structures assuming agents' complete information.

Having established these empirical properties, the second contribution of the article is to explore the quantitative importance of agents' foresight about future monetary policy shocks to the business cycle. Based on the estimates from the model with the unanticipated future monetary policy shocks, I conduct a counterfactual analysis on agents' information flows for future monetary policy shocks in which they are assumed to be perfectly anticipated by agents. This analysis makes two key points. First, the fluctuations in output and inflation as well as nominal interest rate would have been milder if agents had possessed perfect foresight about future monetary pol- icy shocks. More importantly, the gap between the actual and counterfactual series is much more pronounced in the sample prior to the 1990s, indicating that agents' observability of future monetary policy shocks matters more for the macroeconomic performance of this period than the later sample. Note that this finding is consistent with the historical evidence on changes in the Federal Reserve's communication strategy toward greater transparency since the early to mid-1990s, as in Blinder et al. (2001), Blinder et al. (2008), and Goodfriend (2010).

Second, uncertainty about future monetary policy emerged from the model has significant explanatory power for disagreement—cross-sectional dispersion of forecasts—in the Survey of Professional Forecasters (SPF). In particular, the model-implied output series driven by the policy uncertainty tracks the trend component of the corresponding SPF disagreement series quite closely. This finding provides a supportive view of Dovern et al. (2012), who insist that a crucial factor affecting variations in the cross-sectional dispersion of forecasts is uncertainty about monetary policy.

This paper is closely related to the literature seeking the role of either “news” or “noise” in NK-DSGE models. Milani and Treadwell (2012) illustrate the effects of anticipated (news) and unanticipated monetary policy shocks. A primary difference of this paper from Milani and Treadwell (2012) is to explore the implications of future monetary policy shocks unanticipated by agents. From a different perspective, Collard et al. (2009) and Levine et al. (2012) argue that the agents’ imperfect information assumption improves the models’ fit relative to the models that possess complete information. A common feature of both studies is to exploit agents’ imperfect knowledge of the occurrence of exogenous shocks in the current period by positing that the number of fundamental shocks exceeds the number of observable variables measured with errors.[2] Then this setup creates confusion in agents so that imperfect information models benefit from the anonymity of the types of current shock. Unlike these works, the main source of imperfect information that this paper utilizes is private agents’ inability to observe future shocks on monetary policy, while they have perfect knowledge of the occurrence of exogenous shocks in the current period.

2) In this context, agents’ misperception between permanent and transitory shocks is employed extensively for specifying total factor productivity shocks in the business cycle literature. For example, see Boz et al. (2011) and Blanchard et al. (2012).

Ⅱ. The Model

This section presents the baseline model. The model is a standard new Keynesian model featuring both nominal price rigidities à la Calvo (1983) and Yun (1996) and real rigidity in the form of internal habit formation in consumption.

1. Households

A representative household chooses sequences $\{c_t, n_t, b_t\}_{t=0}^{\infty}$ to maximize expected lifetime utility, given by,

$$E_0 \sum_{t=0}^{\infty} \beta^t u_t \left\{ \frac{(c_t - \vartheta c_{t-1})^{1-\sigma}}{1-\sigma} - \chi \frac{n_t^{1+\eta}}{1+\eta} \right\}, \tag{1}$$

where β is the subjective discount factor, $1/\sigma$ is the intertemporal elasticity of substitution, $1/\eta$ is the Frisch elasticity of labor supply, c_t is consumption of the final good, ϑc_{t-1} is an internal habit stock where $\vartheta \in [0,1)$, and n_t is labor hours. u_t is a preference shock that follows

$$u_t = \bar{u}(u_{t-1}/\bar{u})^{\rho_u} \exp(\varepsilon_{u,t}),$$

where $\bar{u}$ is the mean, $0 \leq \rho_u < 1$, and $\varepsilon_{u,t} \sim N(0, \sigma_u^2)$.

The representative household's choices are constrained by

$$c_t + b_t = w_t n_t + r_{t-1} b_{t-1}/\pi_t + \tau_t,$$

where $\pi_t = p_t/p_{t-1}$ is the gross inflation rate, w_t is the real wage, τ_t is a lump-sum tax, b_t is a one-period real bond, and r_t is the gross nominal interest rate. The representative household's optimality conditions imply

$$\Lambda_t = u_t(c_t - \vartheta c_{t-1})^{-\sigma} - \beta\vartheta E_t\left[u_{t+1}(c_{t+1} - \vartheta c_t)^{-\sigma}\right],$$
$$\Lambda_t = \left(\chi u_t n_t^{\eta}\right)/w_t,$$
$$\Lambda_t = \beta r_t E_t\left(\Lambda_{t+1}/\pi_{t+1}\right),$$

where Λ_t denotes the Lagrange multiplier on the budget constraint.

2. Firms

The production sector consists of monopolistically competitive intermediate goods producing firms who produce a continuum of differentiated inputs and a representative final goods producing firm. Each firm $i \in [0,1]$ in the intermediate goods sector produces a differentiated good, $y_t(i)$, with identical technologies given by $y_t(i) = n_t(i)$, where $n_t(i)$ is the level of employment used by firm i. Each intermediate firm chooses its labor supply to minimize its operating costs, $w_t n_t(i)$, subject to its production function.

Using a Dixit and Stiglitz (1977) aggregator, the representative final goods producer purchases $y_t(i)$ units from each intermediate firm to produce the final good, $y_t \equiv \left[\int_0^1 y_t(i)^{(\theta_p - 1)/\theta_p} di\right]^{\theta_p/(\theta_p - 1)}$, where $\theta_p > 1$ is the price elasticity of

demand for good i. Maximizing profits for a given level of output yields the demand function for intermediate inputs, $y_t(i) = \left(p_t(i)/p_t\right)^{-\theta_p} y_t$, where $p_t \equiv \left[\int_0^1 p_t(i)^{1-\theta_p} di\right]^{1/(1-\theta_p)}$ is the price of the final good. Following Calvo (1983), a fraction of intermediate firms, ω cannot update their prices each period. Firms that are unable to optimally reset their price partially index their price to past inflation according to $p_t(i) = p_{t-1}(i)\pi_{t-1}^{\lambda}\overline{\pi}^{1-\lambda}$, where $\lambda \in [0,1]$ is the degree of indexation and $\overline{\pi}$ is steady state inflation. Thus, firms that are able to reset their price at t choose their optimal price, p_t^*, to maximize the expected discounted present value of real profits, $E_t \sum_{k=t}^{\infty} w^{k-t} q_{t,k} d_k(i)$, where $q_{t,k} \equiv 1$ and $q_{t,k} \equiv \prod_{j=t+1}^{k} q_{j-1,j}$ is the discount factor between periods t and $k > t$. The optimality

condition is given by

$$\frac{p_t^*}{p_t} = \frac{\theta_p}{\theta_p - 1} \frac{E_t \sum_{s=t}^{\infty} (\beta\omega)^{s-t} \Lambda_s \left[p_s / (\widetilde{\pi_{t,s}} p_t)\right]^{\theta_p} w_s y_s}{E_t \sum_{s=t}^{\infty} (\beta\omega)^{s-t} \Lambda_s \left[p_s / (\widetilde{\pi_{t,s}} p_t)\right]^{\theta_p - 1} w_s y_s} \equiv \frac{\theta_p}{\theta_p - 1} \frac{x_{1,t}}{x_{2,t}}, \tag{2}$$

where $\widetilde{\pi_{t,t}} = 1$ and $\widetilde{\pi_{t,s}} = \prod_{j=t}^{s-1} \pi_j^{\lambda} \overline{\pi}^{1-\lambda}$ for $s > t$. Written recursively $x_{1,t}$ and $x_{2,t}$ are given by

$$x_{1,t} = \Lambda_t w_t y_t + \beta\omega \overline{\pi}^{(\lambda-1)\theta_p} E_t \left[\pi_{t+1}^{\theta_p} \pi_t^{-\lambda\theta_p} x_{1,t+1}\right],$$

$$x_{2,t} = \Lambda_t y_t + \beta\omega \overline{\pi}^{(1-\lambda)(1-\theta_p)} E_t \left[\pi_{t+1}^{\theta_p - 1} \pi_t^{\lambda(1-\theta_p)} x_{2,t+1}\right].$$

The optimal firm pricing equation, (2), and the aggregate price index imply

$$\omega \overline{\pi}^{(1-\lambda)(1-\theta_p)} \pi_t^{\theta_p - 1} \pi_{t-1}^{\lambda(1-\theta_p)} = 1 - (1-\omega)(\mu^p x_{1,t}/x_{2,t})^{1-\theta_p},$$

where $\mu_p = \theta_p / (\theta_p - 1)$ is the markup of price over marginal cost when prices are flexible.

Aggregate output is given by $\Psi_t y_t = n_t$, where $\Psi_t \equiv \int_0^1 (p_t(i)/p_t)^{-\theta_p} di$

measures price dispersion, which, written recursively, is given by

$$\Psi_t = (1-\omega)(\mu^p x_{1,t}/x_{2,t})^{-\theta_p} + \omega \overline{\pi}^{(\lambda-1)\theta_p} \pi_t^{\theta_p} \pi_{t-1}^{-\lambda\theta_p} \Psi_{t-1}.$$

3. Monetary Policy

Before describing the main information structure on monetary policy rules of this article, which is named as the partial-foresight information structure, I introduce two benchmark specifications for ease of explanation. In the first benchmark specification, the monetary authority sets policy according to

$$r_t = r_{t-1}^{\rho_r} \left[\overline{r} (\pi_t / \overline{\pi})^{\phi_\pi} (y_t / y_{t-1})^{\phi_y} \right]^{1-\rho_r} \exp(\varepsilon_{r,t}), \tag{3}$$

where ϕ_π and ϕ_y measure the policy responses to inflation and output growth, and $\varepsilon_{r,t} \sim N(0, \sigma_r^2)$. This monetary policy rule is the conventional one that appears throughout the modern macroeconomics literature. In this specification, agents have no foresight about future realizations of the monetary policy shocks. I denote this "No-Foresight."

The second benchmark specification simplifies the news process in Schmitt-Grohe and Uribe (2012) and is given by

$$r_t = r_{t-1}^{\rho_r} \left[\overline{r} (\pi_t / \overline{\pi})^{\phi_\pi} (y_t / y_{t-1})^{\phi_y} \right]^{1-\rho_r} \exp(\varepsilon_{r,t}^{0} + \varepsilon_{r,t}^{k_1} + \varepsilon_{r,t}^{k_2} + \varepsilon_{r,t}^{k_3} + \ldots), \tag{4}$$

where $\varepsilon_{r,t}^{k_j}$ denotes the k_j-period anticipated changes in the log deviation of the nominal interest rate from its steady state and $\varepsilon_{r,t}^{k_j} \sim N(0, (\sigma_r^{k_j})^2)$. These shocks are assumed to be independent across time and anticipation horizon, i.e., $E\left(\varepsilon_{r,t-j}^{j} \varepsilon_{r,t-k}^{k}\right) = 0$ for any $k \neq j$ and $E\left(\varepsilon_{r,t}^{j} \varepsilon_{r,t}^{k}\right) = 0$ for any $k \neq j$. The information set of the agent consists of current and past realizations of the exogenous shocks $\varepsilon_{r,t}^{j}$. By observing $\varepsilon_{r,t}^{2}$, for example, agents know precisely how this shock will impinge upon r_{t+2} and agents will respond as soon as the shock is observed. I refer to this information structure as "Complete-Foresight."

The main information structure on monetary policy is similar to Complete-Foresight except for agents' incapability of anticipating future monetary policy shocks. In this specification, agents know that the underlying monetary policy rule obeys the same specification as in Complete-Foresight, given by equation (4). They observe contemporaneous realizations of the exogenous shocks, including the current component of monetary policy shocks ($\varepsilon_{r,t}^{0}$), but not the future components of monetary policy shocks ($\varepsilon_{r,t}^{k_j}$ for all $k_j > 0$). This information structure on monetary policy shocks is denoted as "Partial-Foresight."

In sum, the difference between Complete- and Partial-Foresight is attributable entirely to the anticipation of future monetary policy shocks. Under the Complete-Foresight specification, agents have foresight over discretionary monetary policy changes in the future, whereas Partial-Foresight assumes that they are unaware of realizations of future monetary policy shocks. Both specifications, however, would coincide regarding the agents' ability to perfectly specify the current components of exogenous shocks.

4. Equilibrium

In equilibrium, good market clearing imposes $c_t = y_t$. Under the No-Foresight specification, the log-linear equilibrium system is given by

$$\widehat{\Lambda}_t = \frac{\sigma}{(1-\vartheta)(1-\beta\vartheta)}\left[\beta\vartheta E_t(\widehat{c_{t+1}}) - (1+\beta\vartheta^2)\widehat{c}_t + \vartheta\widehat{c_{t-1}}\right] - \frac{1}{1-\beta\vartheta}\left[\beta\vartheta E_t(\widehat{u_{t+1}}) - \widehat{u}_t\right] \quad (5)$$

$$\widehat{\Lambda}_t = \eta\widehat{n}_t - \widehat{w}_t + \widehat{u}_t \quad (6)$$

$$\widehat{\Lambda}_t = E_t\widehat{\Lambda_{t+1}} + (\widehat{r}_t - E_t\widehat{\pi_{t+1}}) \quad (7)$$

$$\widehat{x_{1,t}} = (1-\beta\omega)(\widehat{w_t} + \widehat{y_t} + \widehat{\Lambda_t}) + \beta\omega E_t\left\{\widehat{x_{1,t+1}} + \theta_p \widehat{\pi_{t+1}} - \lambda\theta_p \widehat{\pi_t}\right\} \tag{8}$$

$$\widehat{x_{2,t}} = (1-\beta\omega)(\widehat{y_t} + \widehat{\Lambda_t}) + \beta\omega E_t\left\{\widehat{x_{2,t+1}} + (\theta_p - 1)\widehat{\pi_{t+1}} - \lambda(1-\theta_p)\widehat{\pi_t}\right\} \tag{9}$$

$$\omega\left(\widehat{\pi_t} - \lambda\widehat{\pi_{t-1}}\right) = (1-\omega)\left(\widehat{x_{1,t}} - \widehat{x_{2,t}}\right) \tag{10}$$

$$\widehat{r_t} = \rho_r \widehat{r_{t-1}} + (1-\rho_r)\left[\phi_\pi \widehat{\pi_t} + \phi_y(\widehat{y_t} - \widehat{y_{t-1}})\right] + \varepsilon_{r,t} \tag{11}$$

$$\widehat{y_t} = \widehat{z_t} + \widehat{n_t} \tag{12}$$

$$\widehat{u_t} = \rho_u \widehat{u_{t-1}} + \varepsilon_{u,t}, \tag{13}$$

where $\widehat{z_t}$ represents the technology shock process, which is common across firms and follows

$$\widehat{z_t} = \rho_z \widehat{z_{t-1}} + \varepsilon_{z,t}, \tag{14}$$

$0 \le \rho_z < 1$, and $\varepsilon_{z,t} \sim N(0, \sigma_z^2)$.

To simplify the system, subtract (8) from (9) to obtain

$$\widehat{x_{1,t}} - \widehat{x_{2,t}} = (1-\beta\omega)\widehat{w_t} + \beta\omega\left(E_t\widehat{x_{1,t+1}} - E_t\widehat{x_{2,t+1}} + E_t\widehat{\pi_{t+1}} - \lambda\widehat{\pi_t}\right).$$

Then use (10), which implies

$$\widehat{x_{1,t}} - \widehat{x_{2,t}} = \frac{\omega}{1-\omega}\left(\widehat{\pi_t} - E_t\widehat{\pi_{t+1}}\right),$$

to substitute for $\widehat{x_1} - \widehat{x_2}$ and simplify to obtain

$$\widehat{\pi_t} = \frac{(1-\beta\omega)(1-\omega)}{\omega(1+\beta\lambda)}\widehat{w_t} + \frac{\beta}{1+\beta\lambda}E_t\widehat{\pi_{t+1}} + \frac{\lambda}{1+\beta\lambda}\widehat{\pi_{t-1}}. \tag{15}$$

The equilibrium system is given by (11) through (14), a New Keynesian Phillips curve (derived by combining (5), (6), and (15)), and the IS equation (obtained jointly from (5) and (7), together with $y_t = c_t$). Finally, the equilibrium system for the Complete- and Partial-Foresight specifications can be derived by altering the equation (11).

The baseline specifications in this paper assume no price indexation (i.e., $\lambda = 0$). Backward indexation is often added to a NK-DSGE model to generate inertia in inflation dynamics observed in the data. Hence, having no indexation is a reasonable benchmark for the main purpose of this work, which examines how alternative specifications of information flow affect the persistence of model-generated processes. The sensitivity analysis in the later sections considers alternative specifications including the models with estimated price indexation as well as the models with perfect price indexation (i.e., $\lambda = 1$) as in Christiano et al. (2005) and Collard et al. (2009).

Ⅲ. Inference

The model parameters $\Theta = \left\{\sigma, \eta, \vartheta, \phi_\pi, \phi_y, \rho_r, \rho_z, \rho_u, \left[\sigma_r^k\right]_{k \geq 0}, \sigma_z, \sigma_u, \omega, \overline{\pi}, \overline{r}\right\}$ are estimated using Bayesian inference methods to construct the parameters' posterior distribution, which integrates the likelihood function with prior information (see An and Schorfheide (2007) for a survey). I use U.S. quarterly data on the output, inflation, and nominal interest rate from 1967:Q1 to 2008:Q1 as observable variables. I detrend the logarithm of each time series with its own linear trend as in Collard et al. (2009), except for the nominal interest rate, which is detrended by the trend in inflation.

1. Identification of Various Information Structures

As a first step for the estimation procedure, the log-linearized system (5)-(15) is solved by Sims's (2002) gensys algorithm. In particular, the No-Foresight specification assumes that agents' information set at date t consists of the model endogenous variables as well as structural innovations dated t and earlier, including the shocks, $\{\varepsilon_{z,t}, \varepsilon_{u,t}, \varepsilon_{r,t}\}$. The agents' information set associated with Complete-Foresight is an extension of the No-Foresight specification so that it contains variables dated t and earlier, including the shocks, $\{\varepsilon_{z,t}, \varepsilon_{u,t}, \varepsilon^0_{r,t}, \varepsilon^1_{r,t}, \varepsilon^2_{r,t}, \cdots\}$. Given the monetary policy rule in (4), this implies that at t the agent has (perfect) knowledge of monetary policy shocks which will be realized in the future.

For the Partial-Foresight specification, I use the partial information version of gensys algorithm by Chris Sims. As mentioned in the previous section, the primary difference between Complete-Foresight and Partial-Foresight is agents' capability of anticipating future monetary policy shocks, whereas both information structures posit that they have perfect knowledge about contemporaneous shocks. In order to be consistent with the Partial-Foresight setup, the usage of the partial information version of gensys algorithm is to take out the anticipated component of monetary policy shocks, $\{\varepsilon^1_{r,t}, \varepsilon^2_{r,t}, \cdots\}$, from the agents' information set. Now, the agents only observe the model endogenous variables dated t and earlier, and contemporaneous structural shocks. Therefore, although the agents are aware that monetary policy follows the rule in (4), they have no foresight about future monetary policy disturbances under the Partial-Foresight specification.[3)]

3) By construction, solving the model associated with the monetary policy rule in (3), instead of (4), by using the partial information version of gensys algorithm yields the identical solution to that using its complete information counterpart.

2. Bayesian Inference Procedure

Having obtained the model solution, I then use the Sims optimization routine csminwel to maximize the log posterior function, which combines the priors and the likelihood of the data. For this step, I check whether multiple modes exist by initiating the search for the posterior mode from 50 initial values. For all the estimated specifications, more than half of the searches converge to the same likelihood values. Finally, the random walk Metropolis-Hastings (MH) algorithm simulates 1,000,000 draws, with the first 400,000 used as a burn-in period and every 20th thinned, leaving a sample size of 30,000.

Columns 2 to 3 in Table 2 list the prior distributions for all estimated parameters. The prior specifications in this work are mainly taken from Collard et al. (2009), which is similar to Smets and Wouters (2007). The prior distribution of risk aversion, σ, is a Gamma with mean 1.5 and standard deviation 0.375, whereas that of the inverse of the Frisch elasticity of labor, η, follows a Gamma with mean 2 and standard deviation 0.75. The mean and standard deviation values of these priors are drawn from Smets and Wouters (2007). The prior for the consumption habit formation, ϑ, and the average probability of price non-resetting, ω, are drawn from Collard et al. (2009)so that they follow Beta distribution of mean 0.5 and the 95% confidence interval covers from 0.096 to 0.903. Prior distributions for the rest of the parameters are coherent with Collard et al. (2009). The nominal interest rate reactions to inflation, ϕ_π, and output growth, ϕ_y, are assumed to be positive, with a normal distribution centered at 1.5 and 0.125, respectively.

For the shock AR(1) parameters, I assume that they follow a beta distribution with a mean of 0.5 and standard deviation of 0.25 so that the 95%

percentile interval is ranged from 0.1 to 0.9. An inverse gamma distribution with a mean of 0.38 and standard deviation of 0.18 is given to the shock standard deviation parameters, except for the monetary policy shock. I assume inverse Gamma distribution with mean 0.1 and standard deviation 2 for the standard deviation of current monetary policy shocks as in Milani and Treadwell (2012). I further assume that the priors on the future components of monetary policy shocks have mean 0.05 and standard deviation 1, which are 50% of the values used for the current component of monetary policy shocks. This selection reflects the prior view that the forward-looking components (whether or not they are anticipated by agents) of discretionary changes in monetary policy are less significant than their contemporaneous component in determining the nominal interest rate today. As discussed in Blinder et al. (2001), the Federal Reserve's communicating more openly with the public is a relatively recent phenomenon. Given that a large fraction of the data used for estimation is associated with a period when the Federal Reserve was not transparent, the asymmetric priors between current and future components of monetary policy shocks seem to be a reasonable strategy in controlling for the relative importance of monetary policy shocks of different horizons.

Ⅳ. Estimation Results

1. Optimal Horizon for Future Monetary Policy Shocks

The Complete- and Partial-Foresight information structures entail a selection of future monetary policy shock horizons. In this paper, I choose the optimal horizon based on various goodness-of-fit statistics, the strategy employed by Fujiwara et al. (2011) and Milani and Treadwell (2012).[4] To do so, I use three measures of model fit: (1) the average log marginal density; (2) the deviance information criterion (DIC) as in Spiegelhalter et al. (2002); and (3) the Bayesian predictive information criterion (BPIC) as in Ando (2007). The average log marginal density, calculated by using the Geweke's (1999) modified harmonic mean estimator, is a conventional measure of model fit for the class of linearized DSGE models. However, the log marginal densities may tend to prefer models with extra free parameters to be estimated. Compared to the No-Foresight specification, Complete- and Partial-Foresight both have additional parameters, the future component of monetary policy shocks. In order to explore this issue, the latter two measures are considered which penalize over-fitted models with more free parameters.

In doing so, I set the maximum anticipation horizon to be 4 quarters, a lot lower than the values employed in the literature on news about technology shocks (Schmitt-Grohé and Uribe, 2012; Fujiwara et al., 2011). Compared to technology shocks, however, any ability of private agents to anticipate future monetary policy shocks should be small and limited to a few quarters ahead. As illustrated above, this is particularly because the sample span used for estimating the model largely overlaps with a period when the Federal Reserve's guidance on future monetary policy actions was opaque (Blinder et al., 2001; Blinder et al., 2008).

Table 1 reports the negative of average log marginal densities for models with various horizons of future monetary policy shocks, together with the two alternative measures of model fit.[5] By any criterion, there is a gain in terms of model fit when incorporating the future components of monetary policy

4) Unlike this work, however, both Fujiwara et al. (2011) and Milani and Treadwell (2012) only consider the average log marginal density in evaluating model fit.
5) Models with smaller measure should be preferred to models with larger one.

shocks unanticipated by agents. The data prefers the model with Partial-Foresight to the No-Foresight specification. In contrast, augmenting anticipated monetary policy shocks cannot enhance the model's ability to fit the data better, which contrasts with the finding by Milani and Treadwell (2012).[6] The average log marginal data densities become larger under the Complete-Foresight specification, relatively to No-Foresight. A similar finding is observed for the DIC and BPIC measures, with an exception of the combination of horizon $k=0,2$.

Regarding the best-fitting combination, the log marginal density criterion is in favor of the model with the combination of horizon $k=0,1,2,3,4$, whereas the DIC and BPIC both prefer that with $k=0,1,2,3$. In order to be free from the overfitting issue discussed above, I rely on the DIC and BPIC measures in judging the best-fitting combination of future monetary policy shock horizons under the Partial-Foresight specification. Accordingly, I set the horizons to 0, 1, 2, and 3 for the empirical results of the Partial-Foresight information structure. In addition, I present the results of Complete-Foresight with the same combination of horizons for comparison.

6) A prominent explanation for the discrepancy between the results herein and that of Milani and Treadwell (2012) is the choice of the anticipation horizon. Their best-fitting model is augmented with the anticipation horizons of 4, 8, and 12 quarters, whereas the maximum anticipation horizon in this work is restricted to 4 quarters.

〈Table 1〉 Log Marginal Data Densities, Deviance Information Criterion(DIC), and Bayesian Predictive Information Criterion (BPIC) of the Models with Various Information Structures

Log Marginal Data Densities	Complete Foresight	Partial Foresight
$k=0$ (No Foresight)	170.96	
$k=0,1$	171.71	166.01
$k=0,2$	172.15	166.08
$k=0,3$	172.21	166.13
$k=0,4$	171.73	166.10
$k=0,1,2$	172.77	164.07
$k=0,1,2,3$	173.66	162.60
$k=0,1,2,3,4$	174.49	162.03*
DIC	Complete Foresight	Partial Foresight
$k=0$ (No Foresight)	239.95	
$k=0,1$	240.11	237.21
$k=0,2$	239.53	237.07
$k=0,3$	242.29	236.88
$k=0,4$	241.57	238.12
$k=0,1,2$	242.40	236.95
$k=0,1,2,3$	243.99	235.88*
$k=0,1,2,3,4$	244.78	238.64
BPIC	Complete Foresight	Partial Foresight
$k=0$ (No Foresight)	245.54	
$k=0,1$	244.62	243.77
$k=0,2$	244.15	243.62
$k=0,3$	248.65	243.28
$k=0,4$	247.60	245.53
$k=0,1,2$	247.84	243.95
$k=0,1,2,3$	249.69	242.07*
$k=0,1,2,3,4$	249.91	246.66

Notes: 1) The log margina ldata densities use Geweke's modified harmonic mean estimator.
2) An asterisk (*) denotes the best-fitting combination of horizons under each goodness-of-fit measure.

2. Posterior Estimates

The last three columns of Table 2 provide the mean, and 95th percentile intervals from the posterior distributions.[7] Overall, the data seems to be informative in identifying the parameters of the models as the comparison of the prior to posterior densities reveals. Throughout this section, I focus on comparing the results of the models with No- and Partial-Foresight since the estimates of the Complete-Foresight are almost identical to that of No-Foresight as their 95th percentile intervals largely overlap.

The estimates of the risk aversion parameter become higher under Partial-Foresight with the mean of 1.86, compared to the No-Foresight model. On the contrary, the estimates of the inverse of the Frisch elasticity of labor supply parameter, η, are not sensitive to the information structures. For both parameters, the posterior estimates are slightly larger than the values estimated in Smets and Wouters (2007).

The model in this paper embeds with real rigidity given as the form of internal consumption habit. It turns out that there are trade-offs between the information structures and consumption habit formation. The parameter estimates tend to be smaller under the Partial-Foresight specification than the other information structures considered. Interestingly, this result is a reminiscent of the finding proposed by Walker and Leeper (2011), who argue that alternative information structures, such as news or noise, alter the persistency of a model's equilibrium. As Del Negro et al. (2007) illustrate, consumption habit is an important propagation mechanism that generates model endogenous persistency consistent with the data. The gap between the habit parameter estimates of the No- and Partial-Foresight specifications suggests that the information flow assuming agents' partial foresight on

7) Although not reported herein, the companion estimation appendix includes details of the distribution of the posterior estimates.

monetary policy shocks alters the spectral properties of the equilibrium.

〈Table 2〉 Prior and Posterior Distributions of Each Estimated Parameter

Parameter	Prior		Posterior		
	Dist.	Mean (Std)	No-Foresight	Complete-Foresight	Partial-Foresight
σ	G	1.5 (0.38)	1.59	1.64	1.86
(Risk Aversion)		[0.86, 2.32]	[1.10, 2.21]	[1.13, 2.27]	[1.32, 2.50]
η	G	2.0 (0.75)	2.59	2.61	2.65
(Inverse Frisch Elasticity)		[0.81, 3.72]	[1.34, 4.28]	[1.32, 4.37]	[1.35, 4.45]
ϑ	B	0.5 (0.25)	0.38	0.39	0.31
(Cons. Habit)		[0.10, 0.90]	[0.24, 0.56]	[0.25, 0.57]	[0.17, 0.44]
ϕ_π	N	1.5 (0.25)	1.53	1.54	1.49
(MP Rule Inflation)		[1.09, 1.91]	[1.20, 1.89]	[1.21, 1.90]	[1.17, 1.86]
ϕ_y	G	0.13 (0.1)	0.86	0.82	0.60
(MP Rule Output Growth)		[0.01, 0.39]	[0.56, 1.21]	[0.53, 1.16]	[0.29, 0.93]
ρ_r	B	0.5 (0.25)	0.87	0.88	0.91
(MP Rule AR(1))		[0.10, 0.90]	[0.84, 0.90]	[0.85, 0.91]	[0.88, 0.93]
ρ_z	B	0.5 (0.25)	0.94	0.94	0.95
(Technology AR(1))		[0.10, 0.90]	[0.89, 0.98]	[0.89, 0.98]	[0.90, 0.98]
ρ_u	B	0.5 (0.25)	0.85	0.85	0.86
(Preference AR(1))		[0.10, 0.90]	[0.73, 0.92]	[0.74, 0.92]	[0.79, 0.92]
σ_r^0	IG	0.1 (2.00)	0.15	0.14	0.05
(Current MP Std.)		[0.02, 0.40]	[0.13, 0.17]	[0.12, 0.17]	[0.02, 0.10]
σ_r^1	IG	0.05 (1.00)		0.02	0.08
(1-qrt ahead MP Std.)		[0.01, 0.21]		[0.01, 0.04]	[0.01, 0.15]
σ_r^2	IG	0.05 (1.00)		0.02	0.07
(2-qrt ahead MP Std.)		[0.01, 0.21]		[0.01, 0.04]	[0.01, 0.15]

Note: This table reports the mean and associated [2.5%, 97.5%] percentile intervals(in brackets).

〈Table 2〉 Prior and Posterior Distributions of Each Estimated Parameter (continued)

Parameter	Prior		Posterior		
	Dist.	Mean (Std)	No-Foresight	Complete-Foresight	Partial-Foresight
σ_r^3	IG	0.05 (1.00)		0.02	0.08
(3-qrt ahead MP Std.)		[0.01, 0.21]		[0.01, 0.04]	[0.01, 0.15]
σ_z	IG	0.38 (0.18)	3.91	3.89	3.59
(Technology Std.)		[0.20, 0.83]	[2.30, 6.93]	[2.26, 6.95]	[2.16, 6.33]
σ_u	IG	0.38 (0.18)	2.00	2.08	1.38
(Preference Std.)		[0.20, 0.83]	[1.38, 2.95]	[1.43, 3.04]	[0.92, 2.07]
ω	B	0.5 (0.25)	0.93	0.93	0.93
(Calvo Param.)		[0.10, 0.90]	[0.89, 0.96]	[0.89, 0.96]	[0.89, 0.96]
$\overline{\pi}$	G	0.62 (0.1)	0.87	0.87	0.86
(SS Inflation)		[0.44, 0.83]	[0.63, 1.14]	[0.63, 1.14]	[0.62, 1.11]
$\overline{r}$	G	0.25 (0.1)	0.81	0.81	0.74
(SS Real Interest Rate)		[0.09, 0.48]	[0.51, 1.09]	[0.53, 1.09]	[0.45, 1.02]

Note: This table reports the mean and associated [2.5%, 97.5%] percentile intervals(in brackets).

The posterior estimates for the Calvo parameter are much larger than the range typically reported in existing literature. The mean values are around 0.93 for all specifications, and these values are substantially higher than the estimates in Smets and Wouters (2007), which have a mean of 0.66. The estimates of the Calvo parameters are, however, relatively close to the value of 0.90 which Milani and Treadwell (2012) obtain using a similar sample period.

Turning to the parameters appeared in the monetary policy rule, the inflation responsiveness parameter, ϕ_π, remains unaltered by various information structures. In contrast, its responsiveness to output growth, ϕ_y, and the autoregressive parameter, ρ_r, are quite sensitive across the information flows. The parameter on the reaction of the Taylor rule to output growth is estimated to be lower under Partial-Foresight with the range of 0.29 to 0.93, whereas its 95th percentile interval is from 0.56 to 1.21 under No-Foresight. Regarding the interest rate smoothing parameter, the Partial-Foresight specification makes the monetary policy rule more persistent as its posterior mean increases from 0.87 to 0.91.

The estimated autoregressive parameters of the exogenous shocks tend to be slightly higher when the model is associated with the Partial-Foresight structure. Although the mean estimates are similar across the information structures, this tendency is particularly pronounced for the preference shock AR(1) parameter, ρ_u. Under Partial-Foresight, its 95% interval becomes a lot tighter with a significantly higher estimate for the lower 2.5th percentile. As will be discussed formally below, the relatively higher estimates of the shock AR(1) and interest rate smoothing parameters under Partial-Foresight play a crucial in explaining the model endogenous persistence produced by the information structure.

Regarding the shock standard deviation parameters, the Partial-Foresight specification alters the relative magnitude of the two demand shocks—preference and monetary policy shocks. In order to illustrate this aspect, I compare the estimates under Partial-Foresight to their complete information counterpart. The Complete-Foresight model's mean standard deviation estimates of the current monetary policy shock are as much as seven times that of the future shocks. This finding illustrates that the unanticipated component is the most important in characterizing the monetary policy behavior under the assumption of agents' perfect foresight. This pattern is in contrast to the results in Milani and Treadwell (2012), which state that the anticipated component of monetary policy shocks is given more weight than the unanticipated component.

In contrast, the posterior distributions of the monetary policy standard deviation parameters for Partial-Foresight display a substantially different pattern. In terms of the mean and 95th percentile intervals, the standard deviation is lowest for the current shock. This finding implies that the data puts more weight on the future monetary policy shocks than the current one, when agents fully characterize the underlying structure of monetary shock processes but have no foresight about them. As the future components of monetary policy shocks become more volatile, the standard deviation of a preference shock declines substantially under Partial-Foresight. In terms of the mean estimates, the standard deviations of a preference shock are 1.38 and 2.00 under the Partial- and No-Foresight, respectively. This finding indicates that there is a trade-off between the two demand shocks, influenced by the relative magnitude of the current and future monetary policy shocks.

Finally, the steady state real interest rate, $\bar{r}$, is estimated to be lower under Partial-Foresight. Its 95th percentile interval is from 0.45 to 1.02, which implies the discount factor, calculated by $\beta = 1/(1+\bar{r}/100)$, ranges from 0.9899 to 0.9955. The estimates under No-Foresight have the 95th percentile interval of [0.53,1.09] that corresponds to the interval for the discount factor from 0.9892 to 0.9947. It turns out that the steady state inflation, $\bar{\pi}$, is not affected by the information flows as its 95th percentile intervals remain invariant across the models.

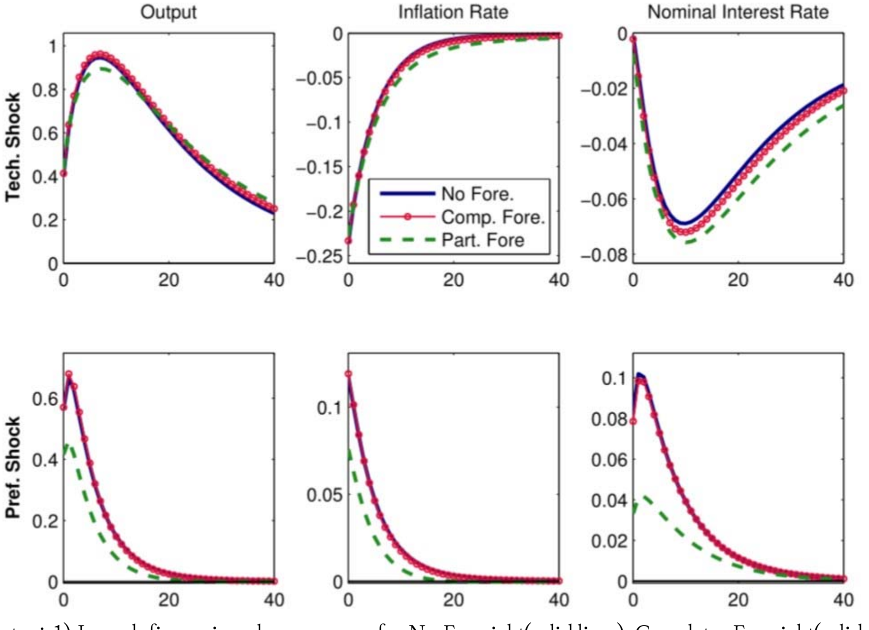
V. The Role of Information Flows

This section draws on empirical implications of the information structures. In particular, I demonstrate how the information flows affect a model's equilibrium dynamics by focusing on the following quantitative results—the impulse response functions and properties of model-implied data.

1. Impulse Response Functions

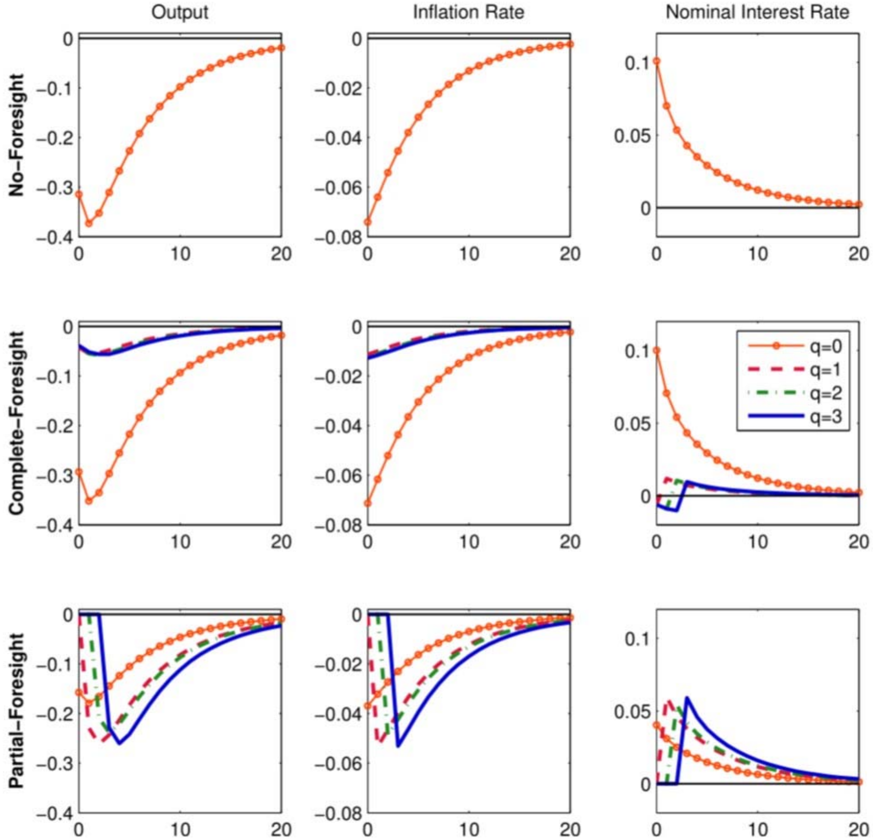
Figure 1 displays the estimated mean impulse responses of some key variables to technology and preference shocks across the various information flows. The overall features of the impulse responses to a technology shock are almost unaltered by the information structures. Output surges, and nominal interest rate as well as inflation rate fall in response to a positive technology shock. This pattern in the responses are consistent with those obtained in the existing DSGE literature (e.g., Smets and Wouters (2007)).

〈Figure 1〉 Mean Impulse Responses to Technology(Top Panel) and Preference(Bottom Panel) Shocks Across the Models with Various Information Structures



Notes: 1) In each figure, impulse responses for No-Foresight(solid lines), Complete- Foresight(solid lines with circles), and Partial-Foresight(dashed lines) specifications are reported.
2) The x-axis measures quarters.

〈Figure 2〉 Mean Impulse Responses to Monetary Policy Shocks of Various Horizons (q) across the Models with Various Information Structures



Note: The x-axis measures quarters.

Similarly, the effects of a preference shock are invariant across the information specifications. A minor difference emerges from the Partial-Foresight specification, in that the magnitude of impulse responses is consistently smaller than the other structures. This finding attributes to the decline in the preference shock standard deviation under Partial-Foresight.

Figure 2 reports the estimated mean impulse responses of output, inflation, and interest rate to monetary policy shocks with various horizons. The effects of current monetary policy shocks display quite similar patterns across the three specifications, with mild level-differences under Partial-Foresight originated from the smaller shock volatility estimates. Regarding the consequences of future monetary policy shocks, however, the results vary substantially across the information structures. If the shock is perfectly observable, inflation plummets when agents receive news about future monetary policy shocks and then, given the the AR(1) structure on the shock, it would gradually rise over time. The same pattern is observed in the output impulse responses. Consequently, nominal interest rate responds negatively to a future monetary policy tightening throughout the anticipation horizon with a sharp increase in the period immediately before the interest rate hike. Note that the response pattern of nominal interest rate in response to anticipated monetary policy shocks is due to the expectational effects of foresight. Driven by the intertemporal consumption smoothing motive, contractionary monetary policy shocks in the future produce declines in current consumption which is, in turn, mapped into lower inflation in the current period. The nominal interest rate, governed by the monetary policy rule as in (11), responds negatively to a future monetary policy shock throughout the anticipation horizon.

If the future shock components are unobservable, by contrast, agents recognize no changes in those variables until a monetary policy shock is realized. This makes the impulse responses stay at zero for the time being. The agents react to the changes in interest rate only when they perceive a monetary policy shock, which precludes fluctuations in the impulse responses caused by the expectational effects of foresight. Future monetary policy shocks result in similar response patterns to a current policy disturbance once the shock is materialized.

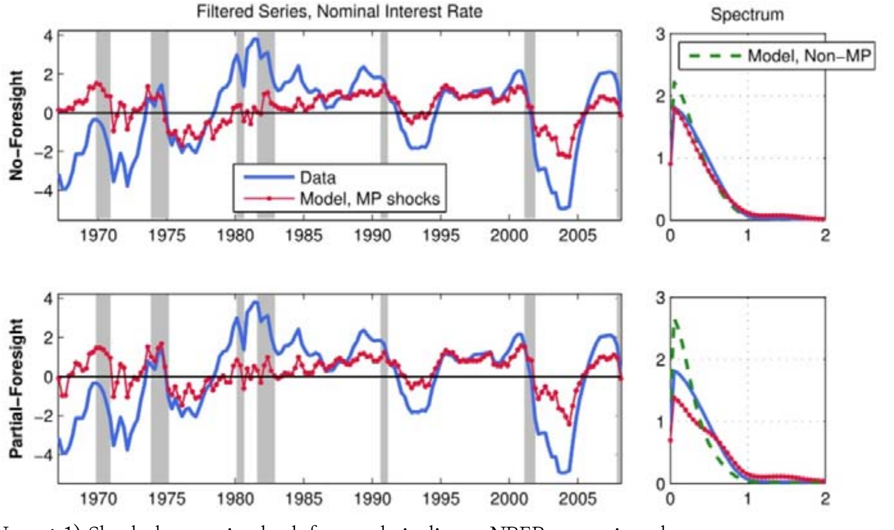
2. Information Flows and The Effects of Monetary Policy Shocks

In order to explore how the alternative information structure affects interest rate dynamics, the left panels of Figure 3 display the demeaned filtered and actual series of annualized nominal interest rate. The filtered series are obtained by feeding the model only the estimated monetary policy shocks in which the difference in information structure occurs. To facilitate comparison, I repeat this exercise for the two information structures—No-Foresight and Partial-Foresight. A common feature of these two panels is that monetary policy shocks mainly account for the short-run fluctuations in the interest rate, which can be attributed to the i.i.d. nature of the monetary policy disturbances.

Nevertheless, embedding unobservable future components of monetary policy shocks has an important implication for the equilibrium interest rate dynamics. The right panels of Figure 3 show the spectrums of the filtered and actual series. I additionally report the spectrums of the filtered series obtained by feeding the model only the non-monetary policy shocks. Compared to the No-Foresight specification, introducing the additional i.i.d. shocks in monetary policy rules makes the equilibrium interest-rate process less persistent, with higher frequencies—those further away from the origin in the figure—are given relatively more importance. Meanwhile, the equilibrium dynamics induced by non-monetary shocks becomes relatively more persistent than that of the No-Foresight specification. This finding is consistent with Granger (1966) who argues that the “typical spectral shape” of macroeconomic time series allocates most of the spectral power to low frequencies. The Partial-Foresight information structure pushes spectral power of the interest rate into higher frequencies, which the estimation is in need of propagation mechanisms to correct this pattern. In this regard, the higher estimates for the shock AR(1) parameters reported in Section 4.2 may play a key role in generating a more persistent equilibrium dynamics of the interest rate via the non-monetary policy shocks.

Given that how monetary policy shocks are modeled is crucial for the higher frequency components of the interest-rate fluctuations, a natural concern is whether the Partial-Foresight specification is more consistent with the data. In order to illustrate this issue, Table 3 reports two statistics regarding the relationship between the nominal interest rate data and model-implied series generated only by the estimated monetary policy shocks—correlation

〈Figure 3〉 [Left panels] Actual Nominal Interest Rate Data(Solid Lines) and the Mean of Model-implied Series Simulated by Feeding Only the Estimated Monetary Policy Shocks(Solid Lines with Circles). [Right panels] Spectrums of Actual Nominal Interest Rate Data(Solid Lines), and the Mean Spectrums of Model-implied Series Simulated by Feeding Only the Estimated Monetary Policy Shocks(Solid Lines with Circles) and Non-monetary Policy Shocks(Dashed Lines).



Notes: 1) Shaded areas in the left panels indicate NBER recession dates.
2) In the right panels, the x-axis measures frequencies between 0 and 2 out of the entire domain $[0,2\pi]$.

〈Table 3〉 Correlation Coefficients and R^2 between the Actual Nominal Interest Rate Data and Model-implied Series Simulated by Feeding Only the Estimated Monetary Policy Shocks

	No Foresight	Partial Foresight
Correlation Coefficient	0.62	0.67
	[0.51, 0.71]	[0.54, 0.80]
R^2	0.38	0.46
	[0.26, 0.51]	[0.29, 0.64]

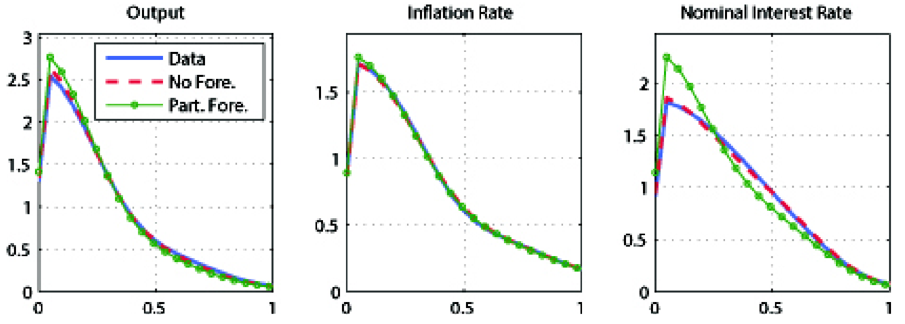
Note: This table reports the mean and associated [2.5%, 97.5%] percentile interval(in brackets) estimates.

coefficients and R^2 from the regression of the data on the model-implied series. It turns out that both measures rise when the Partial-Foresight specification is considered. This result suggests that incorporating future components of monetary policy disturbances unobservable to agents can improve the model's performance by producing more data-consistent higher frequency variations bared in interest rate dynamics.

3. Spectrums of Information Flows

Having delineated the effects of individual shocks, I now examine the aggregate effects of the whole model shocks on the equilibrium dynamics. This section explores the model's ability to generate the persistence observed in the actual time series. To this end, I compare the spectrums of model-implied output, inflation, and interest rate to that of the actual data. The model-implied series are obtained by feeding sequences of all the model shocks into the model's equilibrium system.

Figure 4 makes a comparison between the spectrums of the actual time series and the mean estimates of model-implied spectrums under the No- and Partial-Foresight information structures. The Partial-Foresight specification, 〈Figure 4〉 Actual Data Spectrums(Solid Lines), and the Mean Spectrums of Model-implied Series under No-Foresight(Dashed Lines) and Partial-Foresight(Solid Lines with Circles)



Note: The x-axis measures frequencies between 0 and 1 out of the entire domain [0, 2π].

as it turns out, tilts the spectrum of all variables so that lower frequencies are given relatively more weight. This tendency is more pronounced for output and nominal interest rate than inflation. Based on the posterior estimates in Section 4.2, it is worthwhile to mention that Partial-Foresight induces a more persistent equilibrium even though it relies less on the persistence generated by internal propagation mechanisms, such as habit formation in consumption. A part of the factors explaining this, as illustrated in the previous section, may be the higher estimates for the shock AR(1) parameters, which make the propagation mechanism of exogenous shocks more persistent. Given the enhanced data fit by the Partial-Foresight specification, this finding also reconfirms the argument in Collard et al. (2009), in that the model's capability of generating inertia in endogenous variables can play a crucial role in determining the data fit for small-scale new Keynesian DSGE models.

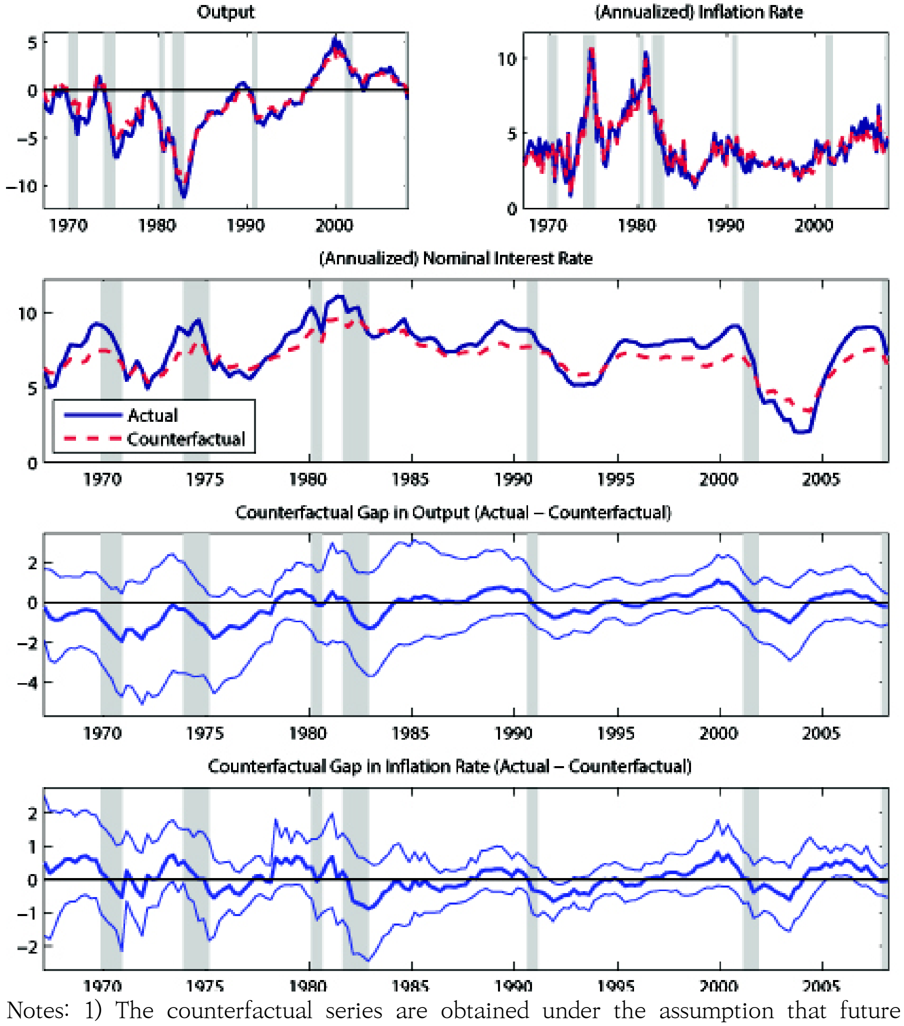
Ⅵ. Counterfactual Analysis

1. Observability of Future Monetary Policy Shocks and Business Cycles

The equilibrium dynamics induced by unobservable future monetary policy shocks can have quite distinct business-cycle implications from the case in which those shocks are perfectly anticipated by private agents. In order to explore this issue, I conduct a counterfactual experiment on agents' information flows for future monetary policy shocks. Using the best-fitting model (Partial-Foresight) as a benchmark, the counterfactual scenario considered in this section asks how the business cycle fluctuations would have been altered if the future components of monetary policy shocks were in agents' information sets. To make the results consistent with this scenario, the counterfactual exercise is constructed by re-solving the Partial-Foresight model, but assuming that agents have perfect foresight about future changes in monetary policy shocks.

The first three panels of Figure 5 report the actual and counterfactual series for output, inflation, and interest rate. It is clear that these variables would have been less volatile if agents had been able to perfectly foresight future changes in monetary policy shocks. To highlight this aspect, Table 4 compares the volatilities of the actual and counterfactual series. One finding is that the reduction in volatility is most pronounced in the interest rate series, which can be attributed to the spectral property of the Partial-Foresight equilibrium illustrated in the previous section. Embedding unobservable future components of monetary policy shocks tilts the spectrum so that higher frequencies are given relatively more weight. And this effect is particularly

〈Figure 5〉 The First Three Panels Report the Mean Estimates of Actual(Solid Lines) and Counterfactual(Dashed Lines) Series. The Last Two Panels Report the Mean and Associated [2.5%, 97.5%] Percentile Intervals of the Gap between the Actual and Counterfactual Output and Inflation Rate Series



Notes: 1) The counterfactual series are obtained under the assumption that future monetary policy shocks are perfectly anticipated by agents.
2) Shaded areas indicate NBER recession dates.

〈Table 4〉 Standard Deviations of Actual and Counterfactual Series

	Actual	Counterfactual
Output	3.16	2.88
	[2.91, 3.72]	[2.00, 4.04]
Inflation Rate	1.78	1.71
	[1.74, 1.87]	[1.42, 2.06]
Nominal Interest Rate	1.84	1.24
	[1.80, 1.93]	[0.94, 1.65]

Notes: 1) This table reports the mean and associated [2.5%, 97.5%] percentile intervals (in brackets).
2) The counterfactual series are obtained under the assumption that future monetary policy shocks are perfectly anticipated by agents.

emphasized in the nominal interest rate dynamics. Hence, switching from the Partial- to Complete-Foresight assumption induces a more persistent equilibrium, which, in turn, suppresses high frequency fluctuations in interest rate.

The nature of the counterfactual experiment characterizes the source of the significantly diminished volatility of nominal interest rate. As Dovern et al. (2012) illustrate, volatility of the policy interest rate is often used as a proxy indicator for monetary policy uncertainty. In this regard, the relatively lower volatility of nominal interest rate indicates a reduction in policy uncertainty under the counterfactual scenario. Recall that in the model agents are aware of the presence of future components of monetary policy shocks. The only difference across the actual and counterfactual interest rate series is agents' capability of anticipating discretionary policy actions which will be realized in the future, so the reduced interest-rate volatility under the complete-foresight assumption can be ascribed to the resolution of future policy uncertainty.

The last two panels of Figure 5 detail the effects of the counterfactual scenario on output and inflation by showing the mean and associated 95%

error bands for the differences between their actual and counterfactual series. Overall, two notable features are commonly observed for both variables. First, the counterfactual gaps are strongly cyclical. The gap series expand over the boom phases and collapse during the economic downturns. This tendency implies that output and inflation increase (fall) less during expansions (recessions) under the counterfactual scenario, which reconfirms the aforementioned finding that the fluctuations in the key macroeconomic variables would have been milder if agents had possessed perfect foresight about future monetary policy shocks.

Second, there is evidence of a structural change in the width of the error bands, occurring in the late 1980s. Compared to the earlier sample period, the error bands become tighter since the 1990s. This finding suggests that agents' information structure about future monetary policy shocks matters more for the macroeconomic performance of the earlier sample period. One prominent explanation regarding the source of this phenomenon might be the change in the Federal Reserve's communication strategy. Blinder et al. (2001) demonstrate that the Fed has changed its communication strategy dramatically toward greater transparency since the early 1990s. As they argue, a more transparent communication stance contains the Fed's clearer guidance about the future path of interest rates. In a similar vein, Goodfriend (2010) find that, ever since the mid-1990s, the Fed has begun to communicate with financial markets more actively in terms of interest rate policy. The results emerged from the counterfactual exercise are consistent with the findings in the literature, in that assuming agents' perfect foresight about future monetary policy shocks alters the pre-break trajectory of the variables more profoundly. Also, the break point identified by the counterfactual analysis accords well with the historical evidence that these previous studies document.[8)]

2. Observability of Future Monetary Policy Shocks and Disagreement

This subsection seeks economic insights of the counterfactual gap series of output and inflation. To this end, I compare them to the corresponding disagreement series in the Survey of Professional Forecasters (SPF) collected by the Federal Reserve Bank of Philadelphia. The choice of the disagreement data for comparison is guided by Dovern et al. (2012), who argue that a crucial factor affecting variations in the cross-sectional dispersion of forecasts is uncertainty about monetary policy.

The first two panels of Figure 6 present the SPF disagreement series for real GDP and inflation rate, together with the corresponding counterfactual gap series.[9] At first glance, the two series exhibit substantially different degree of persistence. Compared to the model-implied series, high frequency variationsarerelativelymoreemphasizedin the SPF disagreement data. Focusing on the low-frequency movements of output, however, both series seem to display similar trends, which peak in the 1970s and decline afterward. To

8) There is an alternative framework which might be useful to interpret this finding—the state-dependent information rigidity framework as in Coibion and Gorodnichenko (2010). Theyarguethatthedegreeofagents' information rigidity is negatively related to the size of fundamental shocks perturbing the economy. Given that the post-break period largely overlaps with the Great Moderation, this framework could be useful in understanding the time-varying behavior of the error bands. The logic of the mechanism, however, reaches exactly the opposite of the empirical finding presented—the counterfactual gaps should be wider during the Great Moderation period. This is because the mechanism predicts a higher degree of information rigidity in the latter part of the sample period, which implies that the perfect foresight assumption should change the time paths of the variables more dramatically. The empirical results suggest that the mechanism discerned by the state-dependent information rigidity framework is not a crucial driving force of the counterfactual exercise performed herein.

9) In doing so, I take the absolute value of the counterfactual gap series to make them compatible to the construction of the SPF disagreement series, cross-sectional dispersions in GDP and inflation forecasts.

detail this aspect, the last two panels of Figure 6 make explicit comparisons between the model-implied series and low-frequency variations of the SPF disagreement data, approximated by four-quarter moving averages. A notable feature is that the model-implied output series tracks the low-frequency movements in the SPF disagreement series quite closely, with an exceptional period in the early 1980s. Nevertheless, this tendency is rather weaker for the inflation series.

Table 5 explores how the SPF disagreement series correlates with the model-implied counterfactual gap series by running a regression:

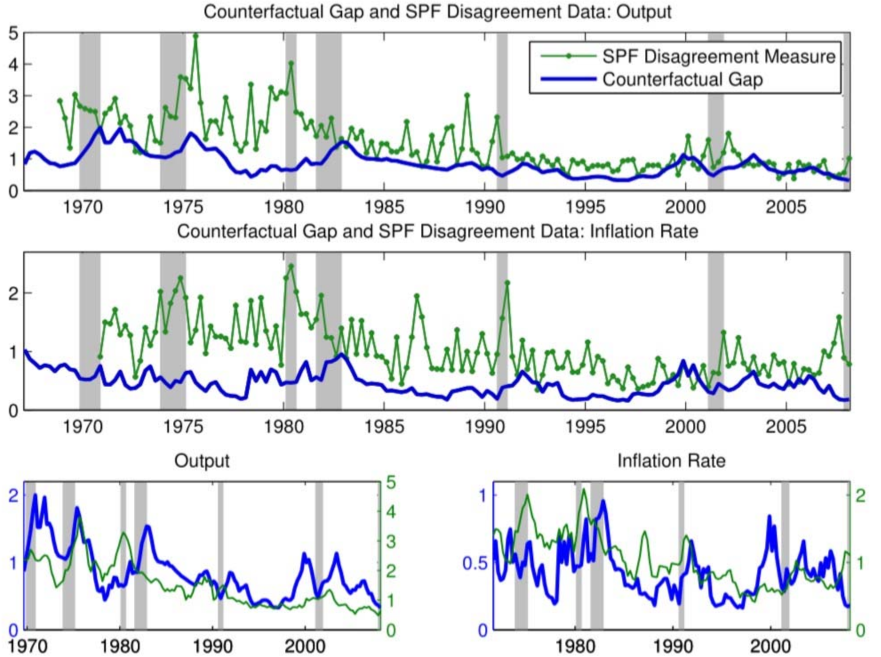
$$disagreement_t = \beta_0 + \beta_1 |counterfact.\, gap_t| + u_t \tag{16}$$

where $|counterfact.\, gap_t|$ denotes the mean estimates of the absolute value of the counterfactual gap series emerged from the model. For comparison, I additionally consider an alternative regression:

$$disagreement_t = \beta_0 + \beta_1 \Delta FFR_t^2 + u_t \tag{17}$$

where ΔFFR_t^2 denotes squared change in the federal funds rate, used as a proxy index for policy uncertainty in Dovern et al. (2012).

〈Figure 6〉 The First Two Panels Report Disagreement about Real GDP and Inflation in the Survey of Professional Forecasters(SPF) Dataset(Solid Lines with Circles) and the Mean Estimates of the Absolute Value of Counterfactual Gap Implied by the Model with Partial-Foresight(Solid Lines). The Last Two Panels Report the Moving Average of the SPF Disagreement Series(Thin Solid Lines with the Right Y-axis) and Mean Estimates of the Absolute Value of Counterfactual Gap Implied by the Model with Partial-Foresight(Thick Solid Lines with the Left Y-axis)



Notes: 1) The counterfactual series are obtained under the assumption that future monetary policy shocks are perfectly anticipated by agents.
2) Shaded areas indicate NBER recession dates.

〈Table 5〉 Regression Coefficients, GMM Corrected Standard Errors(in parenthesis, lag=4), and R^2 for Output and Inflation Rate

	β_0	β_1	R^2
	$disagreement_t = \beta_0 + \beta_1 \lvert counterfact.gap_t \rvert + u_t$		
Output	0.47	1.22	0.28
	(0.27)	(0.29)	
Inflation Rate	0.76	0.66	0.06
	(0.12)	(0.30)	
	$disagreement_t = \beta_0 + \beta_1 \Delta FFR_t^2 + u_t$		
Output	1.44	0.21	0.02
	(0.16)	(0.16)	
Inflation Rate	0.98	0.18	0.05
	(0.08)	(0.07)	

Note: “disagreement t ” denotes the SPF disagreement measures for output and inflation rate, while “$counterfact\,gap_t$ ” and “ΔFFR_t^2” denote the absolute value of the mean estimates of the counterfactual gap in output and inflation implied by the model with Partial-Foresight, and squared change in the federal funds rate, respectively.

The regression results for (16) show that the slope coefficients both for output and inflation are positive and significantly different from zero. Compared to the regression results for (17), employing the model-implied series substantially increases the explanatory power of the output regression, whereas its gain is likely to be limited for inflation rate. These findings suggest that the model-implied uncertainty about future monetary policy shocks can be a significant source of fluctuations in disagreement about output and inflation rate as they are positively related to one another. Meanwhile, the effect is particularly pronounced for output.

Ⅶ. Robustness

In order to examine the robustness of the main results and rankings presented above, this section illustrates the implications of considering alternative procedures for the empirical analyses.

1. Estimation of the Price Indexation Parameter

The baseline specifications restrict the price indexation parameter λ to be zero. Because of this restriction, one might wonder how the results change if the parameter is estimated from the data. In order to address this issue, I re-estimate extended baseline models with a different assumption. Now the indexation parameter can take any value between zero and one to maximize posterior likelihood. The prior for this parameter is chosen to be the same as the Calvo parameter, a beta distribution with a mean of 0.5 and a standard deviation of 0.25, which is fairly diffused and covers a reasonably large range of the parameter space.

Table 6 provides the mean and 95th percentiles of the posterior distribution for the price indexation parameters across various information structures. The estimated price indexation parameters are considerably low for all the information specifications (the means of 0.05 or below for all the specifications). All these estimates are relatively lower than the estimated mode of 0.21 reported in Smets and Wouters (2007) using the post-1983 sample. The estimates of this work, however, are relatively close to the valueof 0.08 obtained by Levin et al. (2006). Meanwhile, the other estimates remain quite similar to the baseline model parameters which are summarized in Table 2.

〈Table 6〉 The Prior and Posterior Distributions of the Price Indexation Parameter from the Models with Flexible Price Indexation(i.e., $\lambda \in [0,1]$)

Parameter	Prior		Posterior		
	Dist.	Mean (Std)	No Foresight	Complete Foresight	Partial Foresight
λ	B	0.5 (0.25)	0.04	0.05	0.05
(Price Index)		[0.10, 0.90]	[0.00, 0.13]	[0.00, 0.13]	[0.00, 0.14]

Note: This table reports the mean and associated [2.5%,97.5%] percentile intervals (inbrackets).

〈Table 7〉 Average Log Marginal Densities for the Baseline Models with No Price Indexation (i.e., $\lambda = 0$), Models in which the Price Indexation Parameter is Estimated (i.e., $\lambda \in [0,1]$), Models with Perfect Price Indexation (i.e., $\lambda = 1$), and Models for the Post-1983 Sample

	No Foresight	Complete Foresight	Partial Foresight
Baseline	170.96	173.66	162.60
Estimated price indexation	175.46	177.46	166.75
Perfect price indexation	205.11	206.64	193.23
Post-1983 sample	42.80	45.92	34.00

The second row of Table 7 presents the average log-marginal data densities for these alternative specifications. There is no change made in the ordering of model fit, compared to the baseline specification with no backward price indexation. Still, Partial-Foresight is the most preferred specification by the data.

2. Estimation with Perfect Indexation to Past Inflation

Many empirical DSGE researches advocate that price indexation to past inflation is a key model feature that improves a model's fit by capturing the sluggish response of inflation to exogenous shocks. Accordingly, Collard et al.

(2009) set the parameter to be one, followed by Christiano et al. (2005). To access the sensitivity in this dimension, I again re-estimate the baseline models under perfect price indexation, parameterized by $\lambda = 1$.

The third row of Table 7 reports the average log-marginal densities for the alternative models assuming perfect backward price indexation. Inspection of the table shows a decrease in the posterior log-likelihood for all models, compared to each model's no-price-indexation counterpart. This finding indicates that the complete indexation hampers data fit. Nonetheless, the ranking of the alternative models remains unchanged.

3. Estimation with Post-1983 Sample

Economists generally agree that there is a structural break in monetary policy, occurred in the mid-1980's (e.g., Clarida et al., 2000; Cogley and Sargent, 2005). Accordingly, I re-estimate the models using the post-1983 sample to examine if the main results of this paper are preserved when a more recent set of data is used for the estimation. The last row of Table 7 displays the average log-marginal densities for each information specification for the post-1983 sample. The rankings of model fit are not affected by the selection of this data period. The Partial-Foresight model performs better than the complete information models. The margins in model fit are quite similar to the baseline specifications that use data from 1967.

4. Estimation with Diffuse Priors

To show the sensitivity of the main empirical results to the priors, I re-estimate the baseline models under more uninformative, flatter priors. The priors mainly follow Collard et al. (2009) and are summarized in Table 8. Table

9 reports the average log-marginal data densities for the baseline models when the diffuse priors are employed.

Diffuse priors raise the posterior log-likelihood for all information specifications, but this does not alter the ranking of the alternative models' fit.[10] This finding suggests that the main results of this paper are not driven by a specific choice of the prior distributions.

VIII. Conclusion

In this paper, I formulate and estimate a small-scale new Keynesian DSGE model to examine the effects of alternative information flows in monetary policy. In particular, I focus on the empirical implications of embedding future components of monetary policy shocks unanticipated by private agents. I find that the information structure which assumes agents' inability to foresight future monetary policy shocks, in general, enhances the models' fit relative to that which is obtained from models under the "conventional" complete information assumption. The information structure induces a more persistent equilibrium of the NK-DSGE model with less reliance on internal propagation mechanisms, such as habit formation in consumption. In addition, it generates high frequency variations in interest-rate dynamics consistent with the data more than the other information specifications.

10) There are two parameters weakly identified, the steady-state inflation $\bar{\pi}$ and real interest rate $\bar{r}$, for all the information specifications. The parameter estimates under the diffuse priors are provided in the estimation appendix.

〈Table 8〉 Diffuse Prior Distributions

Parameter	Prior		
	Dist.	Mean (Std)	95% Interval
σ (Risk Aversion)	G	1.5 (0.75)	[0.41, 3.29]
η (Inverse Frisch Elasticity)	G	2.0 (1.5)	[0.20, 5.83]
ϑ (Cons. Habit)	U	[0, 1]	[0.025, 0.975]
ϕ_π (MP Rule Inflation)	N	1.5 (0.5)	[0.52, 2.47]
ϕ_y (MP Rule Output Growth)	G	0.13 (0.2)	[0.00, 0.71]
ρ_r (MP Rule AR(1))	U	[0, 1]	[0.025, 0.975]
ρ_z (Technology AR(1))	U	[0, 1]	[0.025, 0.975]
ρ_u (Preference AR(1))	U	[0, 1]	[0.025, 0.975]
σ_r^0 (Current MP Std.)	IG	0.1 (2.00)	[0.02, 0.40]
σ_r^1 (1-qrt ahead MP Std.)	IG	0.05 (1.00)	[0.01, 0.21]
σ_r^2 (2-qrt ahead MP Std.)	IG	0.05 (1.00)	[0.01, 0.21]
σ_r^3 (3-qrt ahead MP Std.)	IG	0.05 (1.00)	[0.01, 0.21]
σ_z (Technology Std.)	IG	0.37 (0.18)	[0.20, 0.83]
σ_u (Preference Std.)	IG	0.37 (0.18)	[0.20, 0.83]
ω (Calvo Param.)	U	[0, 1]	[0.025, 0.975]
$\bar{\pi}$ (SS Inflation)	U	[0, 4]	[0.10, 3.90]
$\bar{r}$ (SS Real Interest Rate)	U	[0, 4]	[0.10, 3.90]

〈Table 9〉 Average Log Marginal Densities for the Baseline Models and Models with Diffuse Prior Distributions

	No Foresight	Complete Foresight	Partial Foresight
Baseline	170.96	173.66	162.60
Diffuse Prior	156.87	160.05	151.79

Compared to the case in which agents cannot anticipate future monetary policy shocks, assuming their perfect foresight about the shocks could reduce the volatilities of key macroeconomic variables. Also, I show that uncertainty about future monetary policy can be a significant source of disagreement about output. These findings can be potentially linked to the literature emphasizing the role of the Fed's communication strategy in enhancing the effectiveness of monetary policy (Woodford, 2005; Blinder et al., 2008).

In sum, all these findings have implications that extend beyond the exercises performed here. More complicated models that are used to draw policy conclusions also employ frictions of various kinds—real, nominal, financial—to improvemodel fit. The main findings in this paper suggest that information structures on monetary policy shocks deserve careful scrutiny.

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요 약

본 연구는 민간 경제주체들에게 관측되지 않는 미래 통화정책 충격의 거시경제적 효과를 동태적확률균형모형을 추정하여 분석한다. 미국의 1967년 1분기부터 2008년 1분기까지의 데이터를 이용하여 분석한 결과 이와 같은 민간주체 정보집합의 가정은 모형의 데이터 적합도를 향상시켜주는 것으로 나타났다. 이러한 민간주체 정보집합이 가지는 거시경제적 함의를 분석하기 위하여 반사실적 실험을 실시한 결과 만약 민간 경제주체들이 미래의 통화정책 충격을 미리 관측할 수 있었다면 분석기간 동안 거시경제 변동성이 훨씬 감소했을 것이라는 결과를 얻었다. 마지막으로 이와 같은 미래 통화정책 충격의 관측 불가능성이 미국 전문가 설문조사(Survey of Professional Forecasters) 상의 미래 경제상황에 대한 불일치(Disagreement)를 설명하는 중요한 원인이 된다는 것을 보였다.

※ 국문 색인어 : 신케인지언 모형, 정보집합, 뉴스 충격, 불완전 정보, 베이지언 추정