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Abstract

The empirical importance of news shocks—anticipated future shocks—in business cycle fluctuations has been explored by using only actual data when estimating models augmented with news shocks. This paper additionally exploits forecast data to identify news shocks in a canonical dynamic stochastic general equilibrium model. The estimated model shows new empirical evidence that technology news shocks are a major source of fluctuations in U.S. output growth. Exploiting the forecast data not only generates more precise estimates of news shocks and other parameters in the model, but also increases the contribution of technology news shocks to the fluctuations.

JEL Classification: E30, E32

Keywords: Business Cycle Fluctuation, Technology Shock, Technology News Shock, Forecast Data, Bayesian Estimation

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1 Introduction

What is the source of business cycle fluctuations? In the literature there has been the widely accepted view that technology shocks are the main driver of cyclical movements in economic activity.[1] Moreover, since the seminal work by Beaudry and Portier (2004), there has been a surge of interest in business cycle implications of technology news shocks, that is, anticipated future technology shocks.[2] A considerable amount of research has explored the empirical importance of news shocks in business cycle fluctuations by embedding a variety of news shocks in dynamic stochastic general equilibrium (DSGE) models.[3] While Fujiwara, Hirose, and Shintani (2011) introduce only technology news shocks in the model of Smets and Wouters (2007), Khan and Tsoukalas (2012) use its extended model with both technology and non-technology news shocks. In contrast to these models with nominal rigidity, Schmitt-Grohé and Uribe (2012) employ a real business cycle model augmented with technology and non-technology news shocks. Notwithstanding the use of the distinct models, the three previous studies employ only actual data in estimating their models and adopt the common strategy for identifying news shocks that is based on the feature that observed variables in the models respond differently to news shocks and to related unanticipated shocks.[4] Although Schmitt-Grohé and Uribe (2012) emphasize the empirical importance of non-technology news shocks, all of the three studies obtain the same empirical result that technology news shocks

[1] For a literature review, see, e.g., King and Rebelo (1999). Prescott (1986) claims that "technology shocks account for more than half the fluctuations in the postwar period, with a best point estimate near 75 percent."

[2] See also Christiano et al. (2010), Fujiwara (2010), Jaimovich and Rebelo (2009), and Lorenzoni (2009) for theoretical studies on news shocks in dynamic stochastic general equilibrium models. Beaudry and Portier (2014) review the literature on news driven business cycles.

[3] Beaudry and Portier (2006) and Barsky and Sims (2011) estimate structural vector autoregressions (VARs) to examine the effect of technology news shocks on U.S. business cycle fluctuations. Yet several studies, such as Fernández-Villaverde et al. (2007), Leeper, Walker, and Yang (2013), and Blanchard, L'Huillier, and Lorenzoni (2013), point to identification issues—non-invertibility and non-fundamentalness problems—that can arise when estimating structural VARs in the presence of news or information shocks. Thus our paper focuses on DSGE models with news shocks.

[4] Milani and Treadwell (2012) estimate a canonical DSGE model incorporated with technology and non-technology news shocks and focus on the comparison of the effect on output between unanticipated and news shocks to monetary policy.

are not a major source of U.S. business cycle fluctuations.[5]

This paper exploits not only actual data but also forecast data to identify technology and non-technology news shocks in a canonical DSGE model with nominal rigidity. Specifically, the paper uses the forecast data on output growth, inflation, and the interest rate in the Survey of Professional Forecasters (SPF).[6] Because the data available at the time of forecasting are real-time data but not revised one, the Real-Time Data Set for Macroeconomists provided by the Federal Reserve Bank of Philadelphia is employed for the contemporaneously observed time series of output growth and inflation.[7] The motivation of our approach is twofold. First, forecast data conveys information about future states of the economy expected by forecasters. Therefore, the data should be informative for identifying anticipated future shocks, that is, news shocks.[8] Second, in previous studies there is an under-identification issue that the number of shocks is far more than the number of observables due to the addition of news shocks to their models. This issue could be ameliorated by adding forecast data so as to increase the number of observables related to news shocks. In particular, our identification strategy for news shocks sets the anticipation horizon of such shocks equal to the one available in their related forecast data. This strategy can help identify news shocks with different anticipation horizon more precisely.

The paper provides new empirical evidence on U.S. business cycle fluctuations. It shows that technology news shocks are a major source of fluctuations in U.S. output growth, in par-

[5]In contrast to the three studies, Born, Peter, and Pfeifer (2013) indicate that technology news shocks can be a major driver of fluctuations in U.S. output growth, by additionally incorporating distortionary taxes on capital and labor, policy rules for the tax rates, unanticipated and anticipated shocks to the rates, and the government budget constraint in a DSGE model with nominal rigidity.

[6]Forecast data in the SPF are employed by Del Negro and Eusepi (2011), Milani (2011, 2017), Ormeño and Molnár (2015), and Slobodyan and Wouters (2017) in estimating DSGE models. Leduc and Sill (2013) use forecast data in the SPF and the Livingston Survey when estimating a VAR.

[7]Real-time actual data as well as forecast data are used by Milani (2017), Milani and Rajbhandari (2012), Miyamoto and Nguyen (2018), and Slobodyan and Wouters (2017) when estimating DSGE models. We estimated our model using revised data on output growth and inflation and confirmed that the main results obtained in the estimation with the real-time actual data still hold in that with the revised one.

[8]To identify monetary policy news shocks, Hirose and Kurozumi (2016) use U.S. Treasury bond yield data, which contains information on the future path of the federal funds rate expected by market participants. Through the lens of the identified news shocks, the paper examines the changes in the Federal Reserve's communication strategy during the 1990s as well as business cycle implications of the shocks.

ticular, those with short forecast horizon play a key role.[9] This finding contrasts sharply with previous empirical studies on news shocks in DSGE models, which indicate that technology news shocks are not a major driver of U.S. business cycles. Our paper also demonstrates that when the forecast data is not exploited in the estimation, unanticipated technology shocks primarily drive fluctuations of output growth along with non-technology news shocks, in line with the result of Schmitt-Grohé and Uribe (2012). The differing results between the estimation with and without the forecast data arise from the facts that the model estimated with such data does a much better job in replicating the observed cross-correlations of actual output growth with the inflation forecasts than the one estimated without it and that technology news shocks play a key role in such replication. Indeed, when the data on the inflation forecasts are not exploited in the estimation, technology news shocks are no longer a major source of fluctuations in output growth.[10]

The paper also shows that exploiting the forecast data in the estimation generates more precise estimates of news shocks and other parameters in the model. Credible intervals of estimated parameters are all concentrated around their posterior mean when exploiting the forecast data; otherwise, the intervals are dispersed.[11]

In the literature there are two closely related studies, Milani and Rajbhandari (2012) and Miyamoto and Nguyen (2018), both of which estimate DSGE models with news shocks using forecast data as well as actual data. All the three studies, including ours, reach the same conclusion that exploiting forecast data in addition to actual data leads to more precise estimates of news shocks and other model parameters. Yet there are differences among them in what kind of news shocks are the most important for U.S. business cycles and to what extent news shocks generate aggregate fluctuations purely through changes in expectations, so-called "expectation driven business cycles." Milani and Rajbhandari (2012)

[9] Miyamoto and Nguyen (2018) also indicate the importance of news shocks with short anticipation horizon, which generate more expectational effects on business cycles than those with longer horizon.

[10] Miyamoto and Nguyen (2018) also demonstrate that including inflation expectations in the set of observables increases the contribution of news shocks to U.S. output fluctuations.

[11] By computing the measures of identification strength proposed by Iskrev (2010b), the present paper shows that adding the forecast data-related expectational variables to the set of observables strengthens the identification of almost all the estimated parameters in the model.

employ several forecast data in the SPF when estimating a model of Smets and Wouters (2007) augmented with news shocks. Their estimation result suggests that news shocks explain a sizable portion of U.S. aggregate fluctuations, in particular, news shocks about investment-specific technology and risk premium play the largest role. Miyamoto and Nguyen (2018) consider the decomposition of the total effects of news shocks into those associated with changes in expectations and with changes in fundamentals after news shocks materialize. They focus on the former component, which is referred to as the "expectational effects of news shocks," and find that such effects on U.S. output fluctuations are modest in a model that incorporates nominal rigidities into the model of Schmitt-Grohé and Uribe (2012).[12]

The remainder of the paper proceeds as follows. Section 2 presents an example that accounts for how news shocks can be identified when their related expectational variables are additionally observed. Section 3 describes a canonical DSGE model with technology and non-technology news shocks. Section 4 explains data and econometric methods for estimating the model. Section 5 shows results of empirical analysis. Section 6 conducts a robustness exercise on biases of forecast data. Section 7 concludes.

2 Illustrative Example

Before proceeding to the analysis of news shocks in a DSGE model estimated with actual and forecast data, this section presents an example to show that adding expectational variables to the set of observables is informative for identifying news shocks.

Consider a univariate linear rational expectations model that governs the behavior of an endogenous variable y_t

$$y_t = \frac{1}{\theta} E_t y_{t+1} + \varepsilon_t,$$

where $\theta > 1$ is a parameter, E_t is the expectation operator conditional on information

[12]To obtain news shocks' anticipation effects (before the shocks materialize) analyzed by Chahrour and Jurado (2018) and Sims (2016), we conducted one-quarter ahead forecast error variance decompositions. Such decompositions generally capture the effects of shocks upon impact, and thus applying the decompositions to news shocks enables us to measure their anticipation effects because any news shocks do not materialize upon impact. We then confirmed that technology news shocks are a major source of fluctuations in U.S. output growth even when focusing on the anticipation effects.

available in period t, and ε_t is an exogenous disturbance that consists of unanticipated and news (i.e., anticipated) components. Specifically, it is supposed that

$$\varepsilon_t = \nu_{0,t} + \nu_{1,t-1},$$

where $\nu_{0,t}$ denotes an unanticipated shock that is realized in period t and $\nu_{1,t-1}$ denotes a news shock that is anticipated in period $t-1$ to materialize in period t. The shocks $\nu_{0,t}$ and $\nu_{1,t}$ are assumed to be mutually and serially uncorrelated and have mean zero and standard deviation σ_n, $n = 0, 1$. The model can be written as the system

$$\begin{bmatrix} E_t y_{t+1} \\ \nu_{1,t} \end{bmatrix} = \begin{bmatrix} \theta & -\theta \\ 0 & 0 \end{bmatrix} \begin{bmatrix} y_t \\ \nu_{1,t-1} \end{bmatrix} + \begin{bmatrix} -\theta & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \nu_{0,t} \\ \nu_{1,t} \end{bmatrix},$$

which shows that the set of state variables is $\{\nu_{1,t-1}, \nu_{0,t}, \nu_{1,t}\}$. Thus, the undetermined coefficient method delivers the determinate rational expectations solution[13]

$$y_t = \nu_{1,t-1} + \nu_{0,t} + \frac{1}{\theta}\nu_{1,t}. \tag{1}$$

Hence, y_t is driven by both the unanticipated and news shocks. These shocks have distinct effects on the evolution of y_t. The unanticipated shock $\nu_{0,t}$ has a temporary effect in period t, while the news shock $\nu_{1,t}$ has a persistent effect in period $t+1$ as well as in period t.

Now consider the estimation of the standard deviations σ_0, σ_1 and parameter θ using a full-information likelihood-based econometric procedure. This procedure seeks a combination of $\{\sigma_0, \sigma_1, \theta\}$ that matches the evolution of observed variables in the model as closely to their corresponding data as possible. When only the current variable y_t is observable, the standard deviations σ_0, σ_1 of the two disturbances $\nu_{0,t}, \nu_{1,t}$ as well as parameter θ cannot be identified using (1).

The issue on the identification of the unanticipated and news shocks can be resolved when the expectational variable $E_t y_{t+1}$ is observable as well. From (1) we have

$$E_t y_{t+1} = \nu_{1,t}. \tag{2}$$

[13]Note that $\theta > 1$ is a sufficient condition for determinacy of equilibrium in the system, since there is the only one non-predetermined variable y_t and the eigenvalues of the coefficient matrix are θ and 0.

Thus, given the observation of $E_t y_{t+1}$, the standard deviation σ_1 can be identified. Then, given σ_1, parameter θ and the standard deviation σ_0 can also be identified using (1). Therefore, the unanticipated shock $\nu_{0,t}$ and the news shock $\nu_{1,t}$ can be pinned down independently.

For a general class of DSGE models, the identification issue about unanticipated and news shocks may be more complicated than in the example presented above.[14] However, the subsequent empirical analysis demonstrates that the addition of forecast data to the set of observables in estimation leads to more precise estimates of news shocks in a DSGE model.

3 The Model

This section presents a canonical DSGE model with technology and non-technology news shocks for our estimation.[15]

In the model economy, there are households, perfectly competitive final-good firms, monopolistically competitive intermediate-good firms that face price stickiness, and a monetary authority. In light of observed persistence of output and inflation, the model features (external) habit formation in households' consumption preferences and intermediate-good firms' price indexation to past inflation. The model also incorporates a stochastic trend in output by assuming that the technology level A_t follows the non-stationary stochastic process

$$\log A_t = \log \gamma + \log A_{t-1} + z_t^a,$$

where γ represents the steady-state (gross) rate of technological change—which turns out to coincide with the steady-state (gross) rate of output growth—and z_t^a denotes a (non-

[14] The example is simple enough to see the basic idea of our approach for identifying news shocks. In the subsequent empirical analysis, however, each exogenous disturbance is assumed to follow a more complicated stochastic process. Specifically, it is governed by a first-order autoregressive process incorporated with news shocks up to five quarters ahead. The example is thus extended to the case of the shock ε_t with such a stochastic process in the online appendix. In the extended example, we also confirmed that adding expectational variables to the set of observables is informative for identifying news shocks.

[15] The full description of the DSGE model is shown in the online appendix. While recent empirical studies on DSGE models use medium scale models of the sort proposed by Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007), our paper exploits the relatively small scale model. We choose the model because, compared with our model, a medium scale model of that sort contains more shocks and then our approach for identifying news shocks requires more forecast data in estimating the medium scale model. In the SPF, however, forecast data that help identify the additional news shocks are not necessarily available, which would induce an under-identification issue.

stationary) technology shock.

The log-linearized equilibrium conditions are summarized as the three equations

$$\hat{y}_t = (1-\omega_y)(\hat{y}_{t-1} - z_t^a) + \omega_y\big(E_t\hat{y}_{t+1} + E_t z_{t+1}^a\big) - \tau\big(\hat{r}_t - E_t\hat{\pi}_{t+1} - z_t^d + E_t z_{t+1}^d\big), \tag{3}$$

$$\hat{\pi}_t = \omega_b\hat{\pi}_{t-1} + \omega_f E_t\hat{\pi}_{t+1} + \kappa\left[(1+\eta)\hat{y}_t + \frac{b}{\gamma-b}(\hat{y}_t - \hat{y}_{t-1} + z_t^a)\right], \tag{4}$$

$$\hat{r}_t = \phi_r\hat{r}_{t-1} + (1-\phi_r)(\phi_\pi\hat{\pi}_t + \phi_y\hat{y}_t) + z_t^m. \tag{5}$$

Equation (3) is the spending Euler equation, where $\hat{y}_t$, $\hat{\pi}_t$, and $\hat{r}_t$ are log-deviations of detrended output $y_t = Y_t/A_t$, the (gross) inflation rate π_t, and the (gross) interest rate r_t from their respective steady-state values y, π, and r; z_t^d denotes a preference shock; ω_y and τ are the composite coefficients given by $\omega_y \equiv \gamma/(\gamma+b)$ and $\tau \equiv (\gamma-b)/(\gamma+b)$; and $b \in [0,1]$ represents the degree of habit persistence. Equation (4) is the so-called New Keynesian Phillips curve, where ω_b, ω_f, and κ are the composite coefficients given by $\omega_b \equiv \iota/(1+\iota\beta)$, $\omega_f \equiv \beta/(1+\iota\beta)$, and $\kappa \equiv (1-\xi)(1-\xi\beta)/[\xi\,(1+\iota\beta)]$; $\beta \in (0,1)$ is the subjective discount factor; $\iota \in [0,1]$ is the weight of price indexation to the past inflation rate π_{t-1} relative to the steady-state inflation rate π; $\xi \in (0,1)$ is the so-called Calvo (1983) parameter that represents the degree of price stickiness; and $\eta \geq 0$ is the inverse of the elasticity of labor supply. Equation (5) is a Taylor (1993) type monetary policy rule, where $\phi_r \in [0,1)$ represents the degree of interest rate smoothing, ϕ_π and ϕ_y are the degrees of monetary policy responses to inflation and (detrended) output, and z_t^m denotes a monetary policy shock.

The shocks z_t^x, $x \in \{a,d,m\}$ are all governed by first-order autoregressive processes

$$z_t^x = \rho_x z_{t-1}^x + \varepsilon_t^x,$$

where $\rho_x \in [0,1)$ is the shock persistence parameter and ε_t^x is a disturbance that consists not only of an unanticipated component but also of news components. Specifically, for the quarterly model, the disturbance is of the form

$$\varepsilon_t^x = \nu_{0,t}^x + \sum_{n=1}^{5} \nu_{n,t-n}^x,$$

where each component $\nu^x_{n,t-n}$, $n = 0, 1, \ldots, 5$ is a normally distributed innovation with mean zero and standard deviation σ_{xn}. That is, the disturbance ε^x_t contains news components up to five quarters ahead. The maximum anticipation horizon of five quarters is determined on the basis of the maximum horizon for the quarterly forecasts of output growth, inflation, and the interest rate in the SPF, which are used in our estimation as explained in the next section. As shown in the ensuing empirical analysis, setting the anticipation horizon of each disturbance's news components equal to the one available in the related forecast data of the SPF helps identify the standard deviations of each component of the disturbance as well as other parameters in the model.

4 Econometric Methodology

This section explains data and econometric methods for estimating the model presented in the preceding section.

4.1 Data used in model estimation

The model is estimated with Bayesian methods using quarterly U.S. time series. The set of observables contains the output growth rate $100\Delta \log Y_t$, the inflation rate $100 \log \pi_t$, and the interest rate $100 \log r_t$. In addition, the set includes forecasts for these three rates up to five quarters ahead $\{100E^*_t \Delta \log Y_{t+n}, 100E^*_t \log \pi_{t+n}, 100E^*_t \log r_{t+n}\}^5_{n=1}$, where E^*_t denotes expectations formed by forecasters. The data on the rates of output growth, inflation, and nominal interest are respectively the growth rate of real GDP per capita,[16] the inflation rate of the GDP implicit price deflator, and the interest rate on three-month Treasury bills. The data on forecasts for the three rates are those in the SPF. Moreover, taking into consideration that forecasters use real-time data, but not revised one, at the time of forming their expectations, we use the contemporaneously realized rates of output growth and inflation in the Real-Time Data Set for Macroeconomists provided by the Federal Reserve Bank of Philadelphia.

In the baseline estimation, it is assumed that forecasters' expectations are consistent

[16]Note that the forecast and real-time actual data on output growth are based on real GNP before 1992.

with rational expectations.[17] Thus, the observation equations that relate the data to model variables are given by

$$\begin{bmatrix} 100\Delta\log Y_t \\ 100\log\pi_t \\ 100\log r_t \\ 100E_t^*\Delta\log Y_{t+1} \\ \vdots \\ 100E_t^*\Delta\log Y_{t+5} \\ 100E_t^*\log\pi_{t+1} \\ \vdots \\ 100E_t^*\log\pi_{t+5} \\ 100E_t^*\log r_{t+1} \\ \vdots \\ 100E_t^*\log r_{t+5} \end{bmatrix} = \begin{bmatrix} \bar\gamma \\ \bar\pi \\ \bar r \\ \bar\gamma \\ \vdots \\ \bar\gamma \\ \bar\pi \\ \vdots \\ \bar\pi \\ \bar r \\ \vdots \\ \bar r \end{bmatrix} + \begin{bmatrix} \hat y_t - \hat y_{t-1} + z_t^a \\ \hat\pi_t \\ \hat r_t \\ E_t\hat y_{t+1} - \hat y_t + E_t z_{t+1}^a \\ \vdots \\ E_t\hat y_{t+5} - E_t\hat y_{t+4} + E_t z_{t+5}^a \\ E_t\hat\pi_{t+1} \\ \vdots \\ E_t\hat\pi_{t+5} \\ E_t\hat r_{t+1} \\ \vdots \\ E_t\hat r_{t+5} \end{bmatrix},$$

where $\bar\gamma = 100(\gamma - 1)$, $\bar\pi = 100(\pi - 1)$, and $\bar r = 100(r - 1)$.

The sample period is from 1984:Q1 through 2008:Q4. The start of the sample period is determined so as to exclude the period of possible indeterminacy of equilibrium on the basis of the results of Clarida, Galí, and Gertler (2000) and Lubik and Schorfheide (2004). The end of the sample period follows from the fact that our estimation strategy is not able to deal with the non-linearity of the monetary policy rule arising from the zero lower bound on the nominal interest rate.

4.2 Priors for model parameters

The prior distributions for model parameters to be estimated are shown in Table 1. The priors for structural parameters, monetary policy parameters, and shock persistence parameters are chosen on the basis of Smets and Wouters (2007). As for the steady-state rates of output growth, inflation, and nominal interest, $\bar\gamma$, $\bar\pi$, $\bar r$, the prior mean is set equal to the sample mean. The subjective discount factor β is determined so as to satisfy the steady-state condition $1 = \beta r/(\gamma\pi) = \beta(1 + \bar r/100)/[(1 + \bar\gamma/100)(1 + \bar\pi/100)]$. The prior mean of the standard deviations of the unanticipated technology and preference shocks σ_{a0}, σ_{d0} are set at 2, while that of the unanticipated monetary policy shock σ_{m0} is chosen at 0.25. Regarding the

[17]Relaxing this assumption is considered in the robustness exercise presented later.

standard deviations of news components of each shock, this paper follows Fujiwara, Hirose, and Shintani (2011) to set equal weights on the unanticipated component and on the sum of news components in the priors, and thus, in terms of prior mean, each σ_{xn}, $x \in \{a, d, m\}$, $n = 1, 2, \ldots, 5$ is set at $5^{-1/2} \times \sigma_{x0}$ (so that $\sum_{n=1}^{5} \sigma_{xn}^2 = \sigma_{x0}^2$).[18]

In the Bayesian estimation, the Kalman filter is used to evaluate the likelihood function for the system of log-linearized equilibrium conditions of the model, and the Metropolis-Hastings algorithm is applied to generate draws from the posterior distribution of model parameters.[19] These draws yield inference on model parameters, variance decompositions, and impulse responses.

5 Results of Empirical Analysis

This section presents results of empirical analysis. A novelty of the analysis is that the forecast data is additionally exploited to identify the news shocks in the DSGE model presented above. Thus, the model is estimated with and without the forecast data to compare estimation results with each other.

5.1 Posterior estimates of model parameters

The posterior estimates of model parameters are shown in Table 2. The second and third columns of the table present each parameter's posterior mean and 90 percent credible interval in the baseline estimation, that is, the estimation with the forecast data, while the fourth and fifth columns show those in the estimation without it. Note that in the latter estimation,

[18]Schmitt-Grohé and Uribe (2012) argue that the use of inverse gamma distributions for priors of the standard deviations of shock innovations does not allow for a positive density at zero. Thus, following them, we also estimated the model by replacing the inverse gamma distributions with the gamma distributions for the priors of the standard deviations of all the shock innovations in the model, and confirmed that the main results obtained in the baseline estimation (with the inverse gamma distributions) still hold in the estimation with the gamma distributions, as reported in the online appendix.

[19]In each estimation, 200,000 draws are generated and the first 100,000 draws are discarded. The scale factor for the jumping distribution in the Metropolis-Hastings algorithm is adjusted so that the acceptance rate is approximately 24 percent. The Brooks and Gelman (1998) measure is used to check the convergence of the posterior distribution of model parameters. For each estimated parameter of the model, the prior and posterior distributions and MCMC convergence diagnostics in the baseline estimation are presented in the online appendix.

revised data on output growth and inflation are used instead of the real-time data, as in previous empirical studies on DSGE models with news shocks, and that there is no crucial difference between the results of the estimation with the real-time data and with the revised data (as well as the forecast data).[20]

In Table 2, four notable differences are detected between the estimation with and without the forecast data. First of all, the standard deviations of all the components of the technology shock, σ_{an}, $n = 0, 1, \ldots, 5$, have larger posterior mean in the baseline estimation than in the estimation with no forecast data. Remarkable differences are found in the one- and four-quarter ahead news components' standard deviations σ_{a1}, σ_{a4}, whose 90 percent credible intervals do not overlap between the estimation with and without the forecast data. Regarding the preference shock, the posterior mean of the standard deviation σ_{d0} of the unanticipated component is over twice larger in the baseline estimation, whereas that of each news component—the one-quarter ahead one σ_{d1} in particular—is substantially smaller. As for the monetary policy shock, the posterior mean of the standard deviations of all the components except the one-quarter ahead news one σ_{m1} is smaller in the baseline estimation.

Second, for most of the parameters that determine the degree of persistence in the model, the posterior estimates are significantly lower in the baseline estimation than in the estimation with no forecast data.[21] The posterior mean estimates of the habit persistence parameter b, the price indexation parameter ι, the price stickiness parameter ξ, and the technology and monetary policy shocks' persistence parameters ρ_a, ρ_m are substantially smaller in the baseline estimation, and their 90 percent credible intervals do not overlap between the estimation with and without the forecast data.[22] As noted in Section 2, news shocks have a persistent effect, and thus the larger standard deviations of the technology shock's news components in the baseline estimation make up for the lower values of the parameters that determine the

[20]The result of the estimation with the revised data is reported in the online appendix.

[21]A similar result is obtained by Fuhrer (2017), who incorporates forecasters' expectations in a dynamic macro model.

[22]On the other hand, the posterior estimates of the interest rate smoothing parameter ϕ_r and the preference shock's persistence parameter ρ_d are higher in the baseline estimation, and their 90 percent credible intervals do not overlap between the estimation with and without the forecast data.

degree of persistence in the model.[23]

Third, the posterior mean estimates of the steady-state rates of output growth, inflation, and nominal interest, $\bar{\gamma}$, $\bar{\pi}$, $\bar{r}$, differ between the estimation with and without the forecast data. In particular, the 90 percent credible interval of the steady-state interest rate does not overlap between them. These differences suggest the possibility that the forecasts are biased to a certain degree. This possibility is examined in the robustness exercise presented later.

Last but not least, the 90 percent credible intervals of all the estimated parameters are concentrated around their posterior mean in the baseline estimation, whereas the intervals are dispersed in the estimation with no forecast data. Thus, exploiting the forecast data in the estimation enables us to obtain much more precise estimates of not only the news shocks but also the other parameters in the model. To analyze this more formally, we compute the identification strength of each parameter in the estimation with and without the forecast data in the set of observables, following Iskrev (2010b). In his approach, let ϑ_i denote the i-th element of a set of estimated parameters ϑ, and then the identification strength of each parameter $\vartheta_i \in \vartheta$ is measured as

$$s_i = \sqrt{\frac{\vartheta_i^2}{\left(\mathcal{I}_T(\vartheta)^{-1}\right)_{(i,i)}}},$$

where $\mathcal{I}_T(\vartheta)$ is the Fisher information matrix given a sample size T. Figure 1 plots the pair of the identification strength for each parameter in the estimation with and without the forecast data on a log scale using the asymptotic information matrix, evaluated at the posterior mean estimates of model parameters. Because the vertical and horizontal axes correspond respectively to the identification strength in the estimation with and without the forecast data, the point for the parameter in question above the 45-degree line represents an improvement in the identification of the parameter in the estimation with the forecast data. The figure shows that, for almost all the estimated parameters, the strength measures are substantially larger in the estimation with the forecast data, indicating that adding the forecast data to the set of observables is very informative for identifying the parameters in

[23] A similar result is obtained by Milani (2017), who analyzes sentiment shocks in a DSGE model with adaptive learning that is estimated using real-time actual data and forecast data.

the model.[24]

Before proceeding to the paper's main question of which shock is a major source of fluctuations in U.S. output growth, we note that fitting the model to the forecast data as well as the actual data brings about not only the aforementioned benefit of substantially improving the identification of model parameters but also a cost of deteriorating the estimated model's ability to replicate the second moments of the actual data. The variances of the output growth rate $\Delta \log Y_t$, the inflation rate $\log \pi_t$, and the interest rate $\log r_t$ implied by the model estimated without the forecast data, evaluated at the posterior mean of parameters, are 0.83, 0.41, and 0.29, while those of the corresponding (revised) actual data used in the estimation are 0.38, 0.07, and 0.30, respectively. On the other hand, their counterparts implied by the model estimated with the forecast data are 1.51, 1.19, and 0.38, whereas those of the (real-time) actual data used in the estimation are 0.23, 0.09, and 0.30, respectively.

5.2 What is the source of fluctuations in U.S. output growth?

With the estimates of model parameters presented above, we now examine the main question of which shock is a major source of fluctuations of U.S. output growth in the model.

Table 3 reports the relative contribution of all the shock innovations to the variances of the output growth rate $\Delta \log Y_t$, the inflation rate $\log \pi_t$, and the interest rate $\log r_t$, obtained by spectrum decomposition at the business cycle frequency of 6–32 quarters.[25] Before presenting the variance decompositions based on the posterior estimates, the second to fourth columns of the table display the decompositions evaluated at the prior mean of model parameters (shown in Table 1). The prior suggests that the unanticipated technology shock $\nu^a_{0,t}$ accounts for more than half of fluctuations in output growth, while each of the technology news shocks $\nu^a_{n,t-n}$, $n = 1, 2, ..., 5$ explains less than 10 percent of the fluctuations.

The fifth to seventh columns of Table 3 show the variance decompositions evaluated at

[24] We also conducted the (local) identification analysis proposed by Iskrev (2010a) and found that all the estimated parameters are identified in both the estimation with and without the forecast data.

[25] Forecast error variance decompositions at the horizon of 4, 8, and 16 quarters as well as the infinite horizon are reported in the online appendix. These decompositions are not qualitatively different from the spectrum decompositions presented here.

the posterior mean of model parameters in the baseline estimation (presented in the second column of Table 2). As can be seen in the fifth column (of Table 3), it is evident that the technology news shocks $\nu^a_{n,t-n}$, $n = 1, 2, ..., 5$ are a major source of fluctuations in output growth when the forecast data is exploited in the estimation.[26] The shocks explain almost half of the fluctuations. In particular, the one-quarter ahead technology news shock $\nu^a_{1,t-1}$ plays a crucial role in accounting for the fluctuations. This finding is novel in the literature, since previous studies, such as Fujiwara, Hirose, and Shintani (2011), Khan and Tsoukalas (2012), and Schmitt-Grohé and Uribe (2012), have shown that technology news shocks are not a major driver of U.S. business cycles although they play a non-negligible role. The unanticipated technology shock $\nu^a_{0,t}$ is also important for fluctuations of output growth, in line with the results of many existing studies on business cycles. Regarding inflation variability, its primary source is the unanticipated preference shock $\nu^d_{0,t}$. This shock is also the primary source of interest rate volatility, since the estimated monetary policy response to inflation is much larger than the one to output.

It is worth noting that each news shock involves two distinct effects, anticipation effects (before the shock materializes) and realization ones (after it materializes), as pointed out by Chahrour and Jurado (2018) and Sims (2016). The variance decompositions presented above inherently measure the total effects of these two. To obtain the anticipation effects, we conduct one-quarter ahead forecast error variance decompositions.[27] Table 4 reports the decompositions evaluated at the posterior mean of model parameters in the baseline estimation. Though the relative contribution of the technology news shocks $\nu^a_{n,t-n}$, $n = 1, 2, ..., 5$ to fluctuations of output growth in terms of the anticipation effects is slightly less than that in terms of the total effects reported in the fifth column of Table 3, the shocks are a major source of fluctuations in U.S. output growth even when focusing on the anticipation effects.

[26]This finding is also obtained when the real-time data on output growth and inflation are replaced with the revised one in the estimation, as reported in the online appendix.

[27]One-quarter ahead forecast error variance decompositions generally capture the effects of shocks upon impact, and thus applying the decompositions to news shocks enables us to measure their anticipation effects because any news shocks do not materialize upon impact.

When the forecast data is not exploited in the estimation as in previous empirical studies on DSGE models with news shocks, the importance of technology news shocks is diminished. The eighth to tenth columns of Table 3 report the variance decompositions in the estimation with no forecast data (evaluated at the posterior mean of model parameters presented in the fourth column of Table 2). As shown in the eighth column, the primary source of fluctuations in output growth here is the unanticipated technology shock $\nu_{0,t}^{a}$. Besides, instead of the technology news shocks, the preference news shocks—the one-quarter ahead one $\nu_{1,t-1}^{d}$ in particular—make substantial contribution to the fluctuations. These results—the unanticipated technology shock and the non-technology news shocks mainly drive fluctuations of output growth—are consistent with the result of Schmitt-Grohé and Uribe (2012). The preference news shocks are also the primary drivers of inflation variability and interest rate volatility.

5.3 Features of shocks driving fluctuations of U.S. output growth

What causes the differing primary sources of fluctuations of output growth between the estimation with and without the forecast data? To address this question, we begin by analyzing impulse responses to the three shocks that are major drivers of the fluctuations in either the baseline estimation or the estimation with no forecast data: the unanticipated technology shock $\nu_{0,t}^{a}$, the one-quarter ahead technology news shock $\nu_{1,t-1}^{a}$, and the one-quarter ahead preference news shock $\nu_{1,t-1}^{d}$.

Figure 2 illustrates the impulse responses of the current and one-quarter ahead expected future rates of (quarterly) output growth and inflation, $100\Delta\log Y_t$, $100\log\pi_t$, $100E_t\Delta\log Y_{t+1}$, $100E_t\log\pi_{t+1}$, to the three shocks $\nu_{0,t}^{a}$, $\nu_{1,t-1}^{a}$, $\nu_{1,t-1}^{d}$, evaluated at the posterior mean of model parameters in each estimation. In each panel of the figure, a one-standard-deviation shock is added in period one. The left panels present the impulse responses in the baseline estimation, while the right panels show those in the estimation with no forecast data. As shown in the figure, qualitative properties of the impulse responses are the same between the estimation with and without the forecast data, and thus the rest of this subsection explains the dynamic properties of the responses solely in the baseline estimation.

The top left panel plots the impulse responses to the unanticipated technology shock $\nu_{0,t}^a$. This shock has two features. First, the shock generates strong persistence of the current and expected future rates of output growth. Second, it gives rise to strongly negative comovements between output growth and inflation in terms of both the current and expected future rates for the first two or three quarters and thereafter weakly positive ones.

The middle left panel illustrates the impulse responses to the one-quarter ahead technology news shock $\nu_{1,t-1}^a$. This technology shock is anticipated in period one to materialize in period two. The shock has three features. First, it generates strong persistence of the current and expected future rates of output growth, as is similar to the unanticipated technology shock. Second, the current rates of output growth and inflation comove until the news shock materializes, and thereafter the shock yields a negative comovement between them for the subsequent three quarters and a weakly positive one afterwards. Third, the shock brings about a negative comovement between current output growth and expected future inflation for the first three quarters and a weakly positive one thereafter. Notice that the technology news shock has more impact on expected future inflation than the unanticipated technology shock, as can be seen from the comparison of the top and middle left panels.

One may wonder whether the one-quarter ahead technology news shock $\nu_{1,t-1}^a$ is actually different from the unanticipated technology shock $\nu_{0,t}^a$ in an unconditional sense. To investigate this, we simulate the model only with either $\nu_{0,t}^a$ or $\nu_{1,t-1}^a$, each of which has unit variance, given the other model parameters fixed at the posterior mean in the baseline estimation, and calculate the unconditional variances and correlations with respect to the current and one-quarter ahead expected future rates of output growth and inflation, $\Delta \log Y_t$, $\log \pi_t$, $\Delta \log E_t Y_{t+1}$, and $\log E_t \pi_{t+1}$, as shown in Table 5. While the variances of $\Delta \log Y_t$ and $\Delta \log E_t Y_{t+1}$ and their correlation are almost the same between the cases of $\nu_{0,t}^a$ and $\nu_{1,t-1}^a$, the variances of $\log \pi_t$ and $\log E_t \pi_{t+1}$ and the correlations of $\log \pi_t$ with $\Delta \log Y_t$, $\Delta \log E_t Y_{t+1}$, and $\log E_t \pi_{t+1}$ generated by $\nu_{1,t-1}^a$ are approximately half of those generated by $\nu_{0,t}^a$. Moreover, the correlations between $\Delta \log Y_t$ and $\log E_t \pi_{t+1}$ and between $\Delta \log E_t Y_{t+1}$

and $\log E_t\pi_{t+1}$ are nearly doubled in the case of $\nu^a_{1,t-1}$. Thus, these two shocks can generate the distinct comovement patterns among the contemporaneous and expectational variables.

The bottom left panel in Figure 2 presents the impulse responses to the one-quarter ahead preference news shock $\nu^d_{1,t-1}$. This preference shock is anticipated in period one to materialize in period two. The shock generates negative comovements of current output growth with current and expected future inflation until the shock materializes, and thereafter it yields positive ones.

5.4 Why are technology news shocks a major driver of fluctuations of U.S. output growth in the presence of forecast data?

In light of the aforementioned features of the three shocks, we now address the question of why the technology news shocks are a major driver of fluctuations of output growth in the baseline estimation. To this end, we compare the time-series properties of the actual and forecast data with those implied by the models estimated with and without the forecast data, by calculating the autocorrelations of output growth and its cross-correlations with the other observed variables.

Each panel in Figure 3 plots the correlograms of output growth with each observed variable in the data and the corresponding series implied by the model estimated with the forecast data and the one without it. The number shown in the legend for the model estimated with or without the forecast data is the root mean square errors (RMSE) in each cross-correlation over the lead and lag range from $i = -5$ to $i = 5$ relative to the corresponding data.[28] Crucial differences in the RMSE between the model estimated with the forecast data and the one without it are detected in the cross-correlations between current output growth $\Delta \log Y_t$ and expected future inflation $\log E^*_{t+i}\pi_{t+i+n}$, $n = 1, 2, 3, 4$. The model estimated with the forecast data does a much better job of replicating the observed

[28]In calculating the RMSE in the autocorrelation of output growth and its cross-correlations with inflation and the interest rate, the real-time data on output growth and inflation are used for the model estimated with the forecast data, while the revised data on them are used for the model estimated without it, conforming to the data used in each estimation. On the other hand, in computing the RMSE in the cross-correlations of output growth with all the forecasts, the real-time data on output growth are employed for both the model estimated with the forecast data and the one without it.

cross-correlations between actual output growth and the inflation forecasts than the model estimated without it.

When the forecast data is not used in the estimation, the observed variables are output growth, inflation, and the interest rate. The model is then estimated so that the evolution of these three variables would be as close to the corresponding revised actual data as possible. Thus, the estimated model should be able to well replicate the observed persistence of output growth and the observed cross-correlations between output growth and inflation, in particular, the slightly negative cross-correlations between current output growth and past inflation and the almost zero cross-correlations between current output growth and future inflation. The impulse responses presented above show that the unanticipated technology shock generates not only persistent dynamics of output growth but also a strongly negative comovement between output growth and lagged inflation and a weakly positive one between output growth and leading inflation, while the preference news shocks give rise to a positive comovement between output growth and lagged inflation after the news shocks materialize. Thus, a combination of these shocks can well replicate the observed tendency of the autocorrelations of output growth and its cross-correlations with inflation. Therefore, in the absence of the forecast data in the estimation, the unanticipated technology shock can be a primary driver of fluctuations in output growth along with the preference news shocks.

The model estimated without the forecast data, however, tends to yield positive cross-correlations between current output growth and the lags of expected future inflation (the first- and second-order lags in particular), which are at odds with the data. The impulse responses shown above indicate that these positive correlations are mainly due to the preference news shocks. When the forecast data is exploited as well, the model is estimated so that the time-series properties of the expected future rates of output growth, inflation, and nominal interest up to five quarters ahead as well as their current rates would be matched as closely to those of the corresponding forecast and real-time actual data as possible. According to the impulse responses, the technology news shocks have more impact on expected future inflation than the unanticipated technology shock, thus generating stronger negative comovements between current output growth and the lags of expected future inflation. On the other hand, the technology news shocks bring about a positive comovement between the current rates of output growth and inflation to some extent, whereas the unanticipated technology shock generates a strongly negative comovement between them. Thus, some combination of the unanticipated and news shocks to technology can generate a slightly negative correlation between them. Therefore, in the model estimated with the forecast data, the increased role of the technology news shocks (rather than the preference news shocks) helps replicate the observed cross-correlations of actual output growth with both actual inflation and the inflation forecasts along with the unanticipated technology shock.

5.5 Importance of inflation forecast data

Before closing this section, it is worth stressing that the data on the inflation forecasts are of crucial importance for the main result that the technology news shocks are a major driver of fluctuations in output growth.

When the data on the inflation forecasts are not exploited in the estimation, the posterior estimates of almost all the parameters that determine the degree of persistence in the model, i.e., b, ι, ξ, ϕ_r, ρ_a, ρ_m, are significantly larger than their counterparts in the baseline estimation, as reported in the last two columns of Table 2.[29] More importantly, compared with the baseline estimation, the standard deviations of all the components of the preference shock, σ_{dn}, $n = 0, 1, ..., 5$, are substantially larger, whereas that of the one-quarter ahead technology news shock σ_{a1} is significantly smaller. Consequently, the technology news shocks no longer make major contribution to fluctuations of output growth, as shown in the third to last column of Table 3. In the absence of the inflation forecast data, the combination of the unanticipated preference shock $\nu^d_{0,t}$, the preference news shocks $\nu^d_{n,t-n}$, $n = 1, 2, ..., 5$, and the unanticipated technology shock $\nu^a_{0,t}$ are the main drivers of fluctuations in output growth. In this case, the model is estimated without matching the evolution of model-implied expected

[29]The only exception is the preference shock's persistence ρ_d, whose posterior estimate is lower than in the baseline estimation. As for the other parameters, the posterior estimate of the monetary policy response to output ϕ_y is larger than in the baseline estimation, while that of the steady-state inflation rate $\bar{\pi}$ is smaller.

future inflation closely to the inflation forecast data, and thus the estimated model does not necessarily replicate the observed cross-correlations between actual output growth and the inflation forecasts. Therefore, in such a model, the technology news shocks cannot be a major source of fluctuations in output growth.

6 Robustness Exercise on Biases of Forecast Data

In the baseline estimation, it is assumed that forecasters' expectations are completely consistent with rational expectations. Yet their expectations are likely to deviate from rational expectations. Indeed, as mentioned in Section 5.1, the estimated steady-state rates of output growth, inflation, and nominal interest, $\bar{\gamma}$, $\bar{\pi}$, $\bar{r}$, differ between the estimation with and without the forecast data, suggesting the possibility of biases in the forecasts.

To assess the robustness of the baseline estimation results with respect to possible biases of the forecasts relative to rational expectations, the observation equations are generalized as follows.

$$\begin{bmatrix} 100\Delta\log Y_t \\ 100\log\pi_t \\ 100\log r_t \\ 100\Delta\log E_t^* Y_{t+1} \\ \vdots \\ 100\Delta\log E_t^* Y_{t+5} \\ 100\log E_t^*\pi_{t+1} \\ \vdots \\ 100\log E_t^*\pi_{t+5} \\ 100\log E_t^* r_{t+1} \\ \vdots \\ 100\log E_t^* r_{t+5} \end{bmatrix} = \begin{bmatrix} \bar{\gamma} \\ \bar{\pi} \\ \bar{r} \\ \bar{\gamma}+\bar{b}_{Y1} \\ \vdots \\ \bar{\gamma}+\bar{b}_{Y5} \\ \bar{\pi}+\bar{b}_{\pi 1} \\ \vdots \\ \bar{\pi}+\bar{b}_{\pi 5} \\ \bar{r}+\bar{b}_{r1} \\ \vdots \\ \bar{r}+\bar{b}_{r5} \end{bmatrix} + \begin{bmatrix} \hat{y}_t - \hat{y}_{t-1} + z_t^a \\ \hat{\pi}_t \\ \hat{r}_t \\ E_t\hat{y}_{t+1} - \hat{y}_t + E_t z_{t+1}^a + \zeta_t^{Y1} \\ \vdots \\ E_t\hat{y}_{t+5} - E_t\hat{y}_{t+4} + E_t z_{t+5}^a + \zeta_t^{Y5} \\ E_t\hat{\pi}_{t+1} + \zeta_t^{\pi 1} \\ \vdots \\ E_t\hat{\pi}_{t+5} + \zeta_t^{\pi 5} \\ E_t\hat{r}_{t+1} + \zeta_t^{r1} \\ \vdots \\ E_t\hat{r}_{t+5} + \zeta_t^{r5} \end{bmatrix},$$

where $\bar{b}_{Xn}$ and ζ_t^{Xn}, $X \in \{Y, \pi, r\}$, $n = 1, 2, \ldots, 5$ respectively denote the constant and time-varying components of biases of the n-quarter ahead forecasts for output growth, inflation, and the interest rate relative to the corresponding rational expectations. The time-varying components ζ_t^{Xn} are all governed by first-order autoregressive processes with the persistence parameter $\rho_{Xn} \in [0, 1)$ and the innovation $\nu_{Xn} \sim N(0, \sigma_{Xn}^2)$. The autoregressive processes are employed because the adjustment of forecasters' expectations is generally considered to be more sluggish than that of rational expectations. In estimating the model with the generalized observation equations, $\bar{b}_{rn}$ are determined so as to satisfy the steady-state condition $1 = \beta[1 + (\bar{r} + \bar{b}_{rn})/100]/\{[1 + (\bar{\gamma} + \bar{b}_{Yn})/100][1 + (\bar{\pi} + \bar{b}_{\pi n})/100]\}$. Then, for each $X \in \{Y, \pi\}$ and each $n = 1, 2, \ldots, 5$, we set the prior of the constant component $\bar{b}_{Xn}$ to be the normal distribution with mean zero and standard deviation 0.25, that of the time-varying component's persistence parameter ρ_{Xn} to be the beta distribution with mean 0.5 and standard deviation 0.1, and that of its innovation's standard deviation σ_{Xn} to be the inverse gamma distribution with mean 0.25 (i.e., one percent in annualized terms) and standard deviation 2. The other priors are the same as in the baseline estimation.

Table 6 reports each parameter's posterior mean and 90 percent credible interval in the estimation. In this table, two remarkable features are detected. First, the estimates of the constant components $\bar{b}_{Xn}$ and the time-varying components' standard deviations σ_{Xn} suggest no large biases of the forecasts, whereas those of the persistence parameters ρ_{Xn} show a considerable degree of the persistence in the time-varying components ζ_t^{Xn}. Thus, some fraction of the persistence in the forecasts is captured by the time-varying components of the biases. This gives rise to the second feature. The estimates of the standard deviations σ_{a3}, σ_{a4}, σ_{a5} of the three- to five-quarter ahead technology news shocks are smaller than their counterparts in the baseline estimation. As noted above, news shocks have a persistent effect. Then, the persistent time-varying components of the biases reduce the size of the technology news shocks.[30]

The second column of Table 7 reports the variance decomposition of the output growth rate $\Delta \log Y_t$ in the estimation with the generalized observation equations. While both the unanticipated and news shocks to technology account for most of the fluctuations of output growth in line with the result of the baseline estimation, the relative contribution of the technology news shocks is slightly smaller than that of the unanticipated technology shock.

[30]Besides, the posterior estimate of the price stickiness parameter ξ is higher than in the baseline estimation. As for the other parameters (except those related to the biases of the forecasts), the posterior estimates are similar to their counterparts in the baseline estimation in that the 90 percent credible intervals overlap between the baseline estimation and the estimation with the generalized observation equations.

This is because the standard deviations of the three- to five-quarter ahead technology news shocks are smaller in the estimation with the generalized observation equations. Nevertheless, as is the case with the baseline estimation, the one-quarter ahead technology news shock plays a key role in explaining the fluctuations; its relative contribution to them is 37 percent. Therefore, the main results obtained in the baseline estimation still hold even when the possibility of forecast biases is taken into consideration. One point to be emphasized here is that the log marginal likelihood is 1303 in the estimation with the generalized observation equations, while it is 1595 in the baseline estimation. The log Bayes factor in favor of the latter relative to the former estimation is 292. According to Jeffreys (1961), this value—which exceeds $\log 100$ ($= 4.61$)—constitutes "decisive evidence" in favor of the baseline estimation relative to the estimation with the generalized observation equations.

7 Concluding Remarks

This paper has exploited not only actual data but also forecast data to identify technology and non-technology news shocks in a canonical DSGE model. According to the estimation results, technology news shocks are a major source of fluctuations in U.S. output growth. This finding is novel in the literature because previous studies with DSGE models have concluded that technology news shocks are not a major driver of U.S. business cycles although they play a non-negligible role. Moreover, it has been shown that exploiting the forecast data and setting the anticipation horizon of the news shocks equal to the one available in their related forecast data generates much more precise estimates of the news shocks and other parameters in the model.

One of the limitations in the present analysis is that forecasters' expectations behind the forecast data are assumed to be consistent with rational expectations in the baseline estimation. The robustness exercise has demonstrated that the main results obtained in the baseline estimation survive to a considerable extent even when exogenous biases of the forecasts relative to rational expectations are allowed. Yet the replacement of rational expectations with learning in the model along the lines of Milani (2007, 2011, 2017), Slobodyan and Wouters (2012a, b, 2017), and Ormeño and Molnár (2015) might yield a differing estimation result. Moreover, there has been a growing literature on DSGE models with subjective expectations or beliefs, as reviewed by, for example, Coibion, Gorodnichenko, and Kamdar (2018). It is of great interest to formalize forecasters' expectations in our model along the lines of the literature. Extending our analysis to these dimensions is left for future research.

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Table 1: Prior distributions for parameters in the model

Parameter		Distribution	Mean	Std. dev.
η	Inverse of elasticity of labor supply	Gamma	2.000	0.200
b	Habit persistence	Beta	0.700	0.150
ι	Price indexation	Beta	0.500	0.100
ξ	Price stickiness	Beta	0.500	0.100
ϕ_r	Interest rate smoothing	Beta	0.750	0.100
ϕ_π	Monetary policy response to inflation	Gamma	1.500	0.200
ϕ_y	Monetary policy response to output	Gamma	0.125	0.050
$\bar{\gamma}$	Steady-state output growth rate (quarterly)	Gamma	0.470	0.100
$\bar{\pi}$	Steady-state inflation rate (quarterly)	Gamma	0.640	0.100
$\bar{r}$	Steady-state interest rate (quarterly)	Gamma	1.230	0.100
ρ_a	Persistence of technology shock	Beta	0.500	0.100
ρ_d	Persistence of preference shock	Beta	0.500	0.100
ρ_m	Persistence of monetary policy shock	Beta	0.500	0.100
σ_{a0}	Std. dev. of unanticipated technology shock	Inv. Gamma	2.000	∞
σ_{a1}	Std. dev. of 1-quarter ahead technology news shock	Inv. Gamma	0.894	∞
σ_{a2}	Std. dev. of 2-quarter ahead technology news shock	Inv. Gamma	0.894	∞
σ_{a3}	Std. dev. of 3-quarter ahead technology news shock	Inv. Gamma	0.894	∞
σ_{a4}	Std. dev. of 4-quarter ahead technology news shock	Inv. Gamma	0.894	∞
σ_{a5}	Std. dev. of 5-quarter ahead technology news shock	Inv. Gamma	0.894	∞
σ_{d0}	Std. dev. of unanticipated preference shock	Inv. Gamma	2.000	∞
σ_{d1}	Std. dev. of 1-quarter ahead preference news shock	Inv. Gamma	0.894	∞
σ_{d2}	Std. dev. of 2-quarter ahead preference news shock	Inv. Gamma	0.894	∞
σ_{d3}	Std. dev. of 3-quarter ahead preference news shock	Inv. Gamma	0.894	∞
σ_{d4}	Std. dev. of 4-quarter ahead preference news shock	Inv. Gamma	0.894	∞
σ_{d5}	Std. dev. of 5-quarter ahead preference news shock	Inv. Gamma	0.894	∞
σ_{m0}	Std. dev. of unanticipated monetary policy shock	Inv. Gamma	0.250	∞
σ_{m1}	Std. dev. of 1-quarter ahead monetary policy news shock	Inv. Gamma	0.112	∞
σ_{m2}	Std. dev. of 2-quarter ahead monetary policy news shock	Inv. Gamma	0.112	∞
σ_{m3}	Std. dev. of 3-quarter ahead monetary policy news shock	Inv. Gamma	0.112	∞
σ_{m4}	Std. dev. of 4-quarter ahead monetary policy news shock	Inv. Gamma	0.112	∞
σ_{m5}	Std. dev. of 5-quarter ahead monetary policy news shock	Inv. Gamma	0.112	∞

Table 2: Posterior estimates of parameters in the model

	Baseline		No forecast data		No inflation forecast data	
Parameter	Mean	90% interval	Mean	90% interval	Mean	90% interval
η	2.097	[1.795, 2.376]	2.039	[1.691, 2.363]	2.093	[1.765, 2.440]
b	0.729	[0.699, 0.758]	0.843	[0.792, 0.892]	0.941	[0.925, 0.958]
ι	0.058	[0.047, 0.071]	0.234	[0.135, 0.326]	0.127	[0.072, 0.181]
ξ	0.769	[0.750, 0.789]	0.865	[0.837, 0.896]	0.913	[0.899, 0.927]
ϕ_r	0.912	[0.902, 0.923]	0.836	[0.795, 0.881]	0.955	[0.945, 0.966]
ϕ_π	1.630	[1.445, 1.804]	1.577	[1.255, 1.881]	1.566	[1.280, 1.892]
ϕ_y	0.016	[0.006, 0.025]	0.094	[0.034, 0.153]	0.081	[0.031, 0.127]
$\bar{\gamma}$	0.386	[0.340, 0.430]	0.455	[0.316, 0.603]	0.343	[0.251, 0.432]
$\bar{\pi}$	0.760	[0.708, 0.810]	0.639	[0.511, 0.769]	0.516	[0.393, 0.633]
$\bar{r}$	1.565	[1.458, 1.665]	1.192	[1.061, 1.328]	1.495	[1.405, 1.584]
ρ_a	0.059	[0.047, 0.072]	0.351	[0.221, 0.484]	0.301	[0.190, 0.404]
ρ_d	0.938	[0.927, 0.952]	0.734	[0.620, 0.849]	0.847	[0.815, 0.880]
ρ_m	0.436	[0.397, 0.476]	0.667	[0.556, 0.774]	0.601	[0.531, 0.670]
σ_{a0}	1.388	[1.153, 1.615]	0.917	[0.494, 1.331]	1.669	[1.249, 2.055]
σ_{a1}	1.408	[1.147, 1.663]	0.414	[0.220, 0.613]	0.482	[0.219, 0.732]
σ_{a2}	0.714	[0.581, 0.845]	0.437	[0.213, 0.660]	0.470	[0.226, 0.728]
σ_{a3}	0.740	[0.599, 0.883]	0.432	[0.218, 0.631]	0.440	[0.222, 0.656]
σ_{a4}	0.873	[0.712, 1.028]	0.468	[0.221, 0.705]	0.469	[0.220, 0.714]
σ_{a5}	0.679	[0.565, 0.796]	0.496	[0.227, 0.761]	0.575	[0.251, 0.905]
σ_{d0}	2.660	[2.273, 3.017]	1.257	[0.513, 2.041]	7.422	[5.624, 9.196]
σ_{d1}	1.303	[1.078, 1.522]	3.154	[1.974, 4.401]	6.272	[4.469, 7.957]
σ_{d2}	0.438	[0.370, 0.509]	0.854	[0.210, 1.687]	2.146	[1.549, 2.710]
σ_{d3}	0.404	[0.341, 0.463]	0.735	[0.221, 1.348]	1.815	[1.354, 2.302]
σ_{d4}	0.368	[0.315, 0.421]	0.656	[0.220, 1.136]	1.556	[1.134, 1.942]
σ_{d5}	0.373	[0.324, 0.422]	0.811	[0.201, 1.502]	1.631	[1.157, 2.061]
σ_{m0}	0.050	[0.044, 0.056]	0.067	[0.049, 0.083]	0.047	[0.041, 0.053]
σ_{m1}	0.075	[0.066, 0.083]	0.045	[0.028, 0.062]	0.076	[0.068, 0.085]
σ_{m2}	0.026	[0.023, 0.029]	0.039	[0.025, 0.052]	0.032	[0.027, 0.036]
σ_{m3}	0.019	[0.016, 0.021]	0.038	[0.024, 0.050]	0.019	[0.017, 0.021]
σ_{m4}	0.022	[0.019, 0.024]	0.043	[0.027, 0.059]	0.020	[0.017, 0.022]
σ_{m5}	0.021	[0.018, 0.023]	0.040	[0.025, 0.054]	0.019	[0.016, 0.021]

Note: This table shows each parameter's posterior mean and 90 percent credible interval in the baseline estimation, the estimation with no forecast data, and that with no inflation forecast data.

Table 3: Variance decompositions of output growth, inflation, and the interest rate

	Prior			Baseline			No forecast data			No inflation forecast data		
Shock	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$
$\nu^a_{0,t}$	57.5	0.5	0.9	34.8	4.1	4.5	33.7	2.8	7.2	16.5	3.7	6.7
$\nu^a_{1,t-1}$	8.5	2.9	2.5	30.7	2.1	2.1	6.0	0.4	0.9	1.3	0.3	0.5
$\nu^a_{2,t-2}$	7.2	10.0	9.2	5.8	1.1	0.7	5.4	0.6	0.9	1.1	0.2	0.4
$\nu^a_{3,t-3}$	7.4	17.4	17.4	4.2	3.9	2.7	4.0	1.7	1.9	0.8	0.2	0.3
$\nu^a_{4,t-4}$	8.4	21.4	23.9	4.1	11.2	9.1	3.5	4.3	4.6	0.8	0.3	0.4
$\nu^a_{5,t-5}$	9.3	21.6	27.6	2.1	10.0	9.5	2.9	7.8	8.9	1.0	0.8	0.8
$\nu^d_{0,t}$	0.8	5.0	5.3	8.0	31.6	48.4	5.0	4.8	6.2	36.1	30.2	20.3
$\nu^d_{1,t-1}$	0.1	1.0	1.0	1.9	6.1	10.1	23.8	34.9	40.7	22.9	23.9	14.9
$\nu^d_{2,t-2}$	0.1	1.0	1.0	0.6	0.6	1.1	2.0	2.5	2.9	2.7	2.8	1.7
$\nu^d_{3,t-3}$	0.1	1.1	1.1	0.8	0.7	1.0	1.9	1.7	2.0	2.2	1.9	1.2
$\nu^d_{4,t-4}$	0.1	1.3	1.2	0.7	0.8	1.1	1.8	1.2	1.4	1.8	1.3	0.8
$\nu^d_{5,t-5}$	0.1	1.5	1.3	0.7	1.0	1.4	3.0	1.8	2.1	2.1	1.2	0.8
$\nu^m_{0,t}$	0.4	7.1	0.3	1.6	6.1	1.2	3.3	9.7	3.8	2.4	6.7	13.8
$\nu^m_{1,t-1}$	0.1	1.7	0.4	3.4	15.3	0.8	1.4	5.3	0.6	6.4	19.0	27.6
$\nu^m_{2,t-2}$	0.0	1.8	1.0	0.3	2.0	0.7	0.9	4.4	0.9	1.1	3.4	4.1
$\nu^m_{3,t-3}$	0.0	1.7	1.6	0.1	1.0	0.9	0.7	4.5	2.3	0.4	1.3	1.6
$\nu^m_{4,t-4}$	0.0	1.5	2.1	0.1	1.4	2.1	0.6	6.2	5.7	0.3	1.4	2.0
$\nu^m_{5,t-5}$	0.0	1.3	2.3	0.1	1.2	2.6	0.4	5.4	7.1	0.3	1.3	2.2

Note: This table shows the variance decompositions of the output growth rate $\Delta \log Y_t$, the inflation rate $\log \pi_t$, and the interest rate $\log r_t$ at the business cycle frequency of 6–32 quarters, evaluated at the prior mean and posterior mean of model parameters in the baseline estimation, the estimation with no forecast data, and that with no inflation forecast data.

Table 4: One-quarter ahead forecast error variance decompositions of output growth, inflation, and the interest rate

Shock	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$
$\nu^a_{0,t}$	33.4	7.0	7.7
$\nu^a_{1,t-1}$	25.4	0.2	0.2
$\nu^a_{2,t-2}$	5.0	1.6	1.7
$\nu^a_{3,t-3}$	4.2	4.2	4.3
$\nu^a_{4,t-4}$	4.7	8.7	8.9
$\nu^a_{5,t-5}$	2.4	6.5	6.6
$\nu^d_{0,t}$	12.0	39.7	40.2
$\nu^d_{1,t-1}$	4.7	1.7	1.6
$\nu^d_{2,t-2}$	0.4	0.0	0.0
$\nu^d_{3,t-3}$	0.3	0.1	0.1
$\nu^d_{4,t-4}$	0.2	0.1	0.1
$\nu^d_{5,t-5}$	0.1	0.2	0.2
$\nu^m_{0,t}$	2.2	7.3	5.4
$\nu^m_{1,t-1}$	4.1	17.1	17.3
$\nu^m_{2,t-2}$	0.4	2.1	2.1
$\nu^m_{3,t-3}$	0.2	1.0	1.0
$\nu^m_{4,t-4}$	0.2	1.4	1.4
$\nu^m_{5,t-5}$	0.2	1.2	1.2

Note: This table shows the one-quarter ahead forecast error variance decompositions of the output growth rate $\Delta \log Y_t$, the inflation rate $\log \pi_t$, and the interest rate $\log r_t$, evaluated at the posterior mean of model parameters in the baseline estimation.

Table 5: Unconditional variances and correlations generated by unanticipated technology shock or one-quarter ahead technology news shock

(a) Unanticipated technology shock $\nu^a_{0,t}$

	$\Delta \log Y_t$	$\log \pi_t$	$\Delta \log E_t Y_{t+1}$	$\log E_t \pi_{t+1}$
Variances:	0.249	0.024	0.128	0.007
Correlations:				
$\Delta \log Y_t$	1.000	-0.763	0.997	-0.381
$\log \pi_t$		1.000	-0.809	0.885
$\Delta \log E_t Y_{t+1}$			1.000	-0.450
$\log E_t \pi_{t+1}$				1.000

(b) One-quarter ahead technology news shock $\nu^a_{1,t-1}$

	$\Delta \log Y_t$	$\log \pi_t$	$\Delta \log E_t Y_{t+1}$	$\log E_t \pi_{t+1}$
Variances:	0.215	0.014	0.126	0.014
Correlations:				
$\Delta \log Y_t$	1.000	-0.482	0.997	-0.736
$\log \pi_t$		1.000	-0.475	0.328
$\Delta \log E_t Y_{t+1}$			1.000	-0.790
$\log E_t \pi_{t+1}$				1.000

Note: This table shows the unconditional variances and correlations of the output growth rate $\Delta \log Y_t$, the inflation rate $\log \pi_t$, the one-quarter ahead expected future output growth rate $\Delta \log E_t Y_{t+1}$, and the one-quarter ahead expected future inflation rate $\log E_t \pi_{t+1}$, generated by either the unanticipated technology shock $\nu^a_{0,t}$ or the one-quarter ahead technology news shock $\nu^a_{1,t-1}$, each of which has unit variance, given the other model parameters fixed at the posterior mean in the baseline estimation.

Table 6: Posterior estimates of model parameters in the estimation with the generalized observation equations

Parameter	Mean	90% interval	Parameter	Mean	90% interval
η	2.130	[2.039, 2.215]	$\bar{b}_{\pi 1}$	0.052	$[0.036, 0.069]$
b	0.775	[0.751, 0.799]	$\bar{b}_{\pi 2}$	0.028	$[0.007, 0.050]$
ι	0.067	[0.047, 0.084]	$\bar{b}_{\pi 3}$	0.031	$[0.009, 0.054]$
ξ	0.832	[0.820, 0.845]	$\bar{b}_{\pi 4}$	0.029	$[0.007, 0.054]$
ϕ_r	0.894	[0.882, 0.904]	$\bar{b}_{\pi 5}$	0.042	$[0.013, 0.072]$
ϕ_π	1.946	[1.796, 2.088]	ρ_{Y1}	0.448	[0.421, 0.467]
ϕ_y	0.038	[0.021, 0.055]	ρ_{Y2}	0.439	[0.386, 0.508]
$\bar{\gamma}$	0.368	[0.341, 0.394]	ρ_{Y3}	0.406	[0.336, 0.460]
$\bar{\pi}$	0.760	[0.716, 0.802]	ρ_{Y4}	0.540	[0.506, 0.574]
$\bar{r}$	1.397	[1.327, 1.472]	ρ_{Y5}	0.402	[0.369, 0.429]
ρ_a	0.088	[0.057, 0.120]	$\rho_{\pi 1}$	0.453	[0.424, 0.490]
ρ_d	0.939	[0.924, 0.953]	$\rho_{\pi 2}$	0.417	[0.398, 0.438]
ρ_m	0.438	[0.412, 0.464]	$\rho_{\pi 3}$	0.373	[0.310, 0.431]
σ_{a0}	1.728	[1.457, 1.994]	$\rho_{\pi 4}$	0.387	[0.342, 0.428]
σ_{a1}	1.654	[1.345, 1.964]	$\rho_{\pi 5}$	0.666	[0.616, 0.722]
σ_{a2}	0.572	[0.385, 0.764]	ρ_{r1}	0.409	[0.379, 0.438]
σ_{a3}	0.348	[0.244, 0.447]	ρ_{r2}	0.483	[0.454, 0.516]
σ_{a4}	0.333	[0.233, 0.431]	ρ_{r3}	0.540	[0.483, 0.597]
σ_{a5}	0.366	[0.278, 0.451]	ρ_{r4}	0.536	[0.510, 0.569]
σ_{d0}	2.723	[2.240, 3.163]	ρ_{r5}	0.517	[0.462, 0.562]
σ_{d1}	1.493	[1.238, 1.728]	σ_{Y1}	0.073	[0.050, 0.095]
σ_{d2}	0.479	[0.381, 0.574]	σ_{Y2}	0.055	[0.042, 0.067]
σ_{d3}	0.413	[0.327, 0.496]	σ_{Y3}	0.052	[0.040, 0.063]
σ_{d4}	0.257	[0.188, 0.323]	σ_{Y4}	0.056	[0.043, 0.069]
σ_{d5}	0.276	[0.208, 0.340]	σ_{Y5}	0.098	[0.081, 0.114]
σ_{m0}	0.062	[0.053, 0.071]	$\sigma_{\pi 1}$	0.079	[0.064, 0.094]
σ_{m1}	0.065	[0.055, 0.075]	$\sigma_{\pi 2}$	0.048	[0.039, 0.057]
σ_{m2}	0.023	[0.018, 0.028]	$\sigma_{\pi 3}$	0.045	[0.037, 0.053]
σ_{m3}	0.021	[0.017, 0.025]	$\sigma_{\pi 4}$	0.051	[0.043, 0.059]
σ_{m4}	0.020	[0.016, 0.024]	$\sigma_{\pi 5}$	0.051	[0.042, 0.060]
σ_{m5}	0.019	[0.015, 0.022]	σ_{r1}	0.032	[0.029, 0.034]
$\bar{b}_{Y1}$	-0.044	$[-0.065, -0.025]$	σ_{r2}	0.031	[0.029, 0.034]
$\bar{b}_{Y2}$	-0.001	$[-0.020, 0.019]$	σ_{r3}	0.031	[0.029, 0.033]
$\bar{b}_{Y3}$	0.016	$[0.000, 0.035]$	σ_{r4}	0.031	[0.029, 0.033]
$\bar{b}_{Y4}$	0.036	$[0.019, 0.055]$	σ_{r5}	0.033	[0.029, 0.037]
$\bar{b}_{Y5}$	0.038	$[0.017, 0.059]$	—	—	—

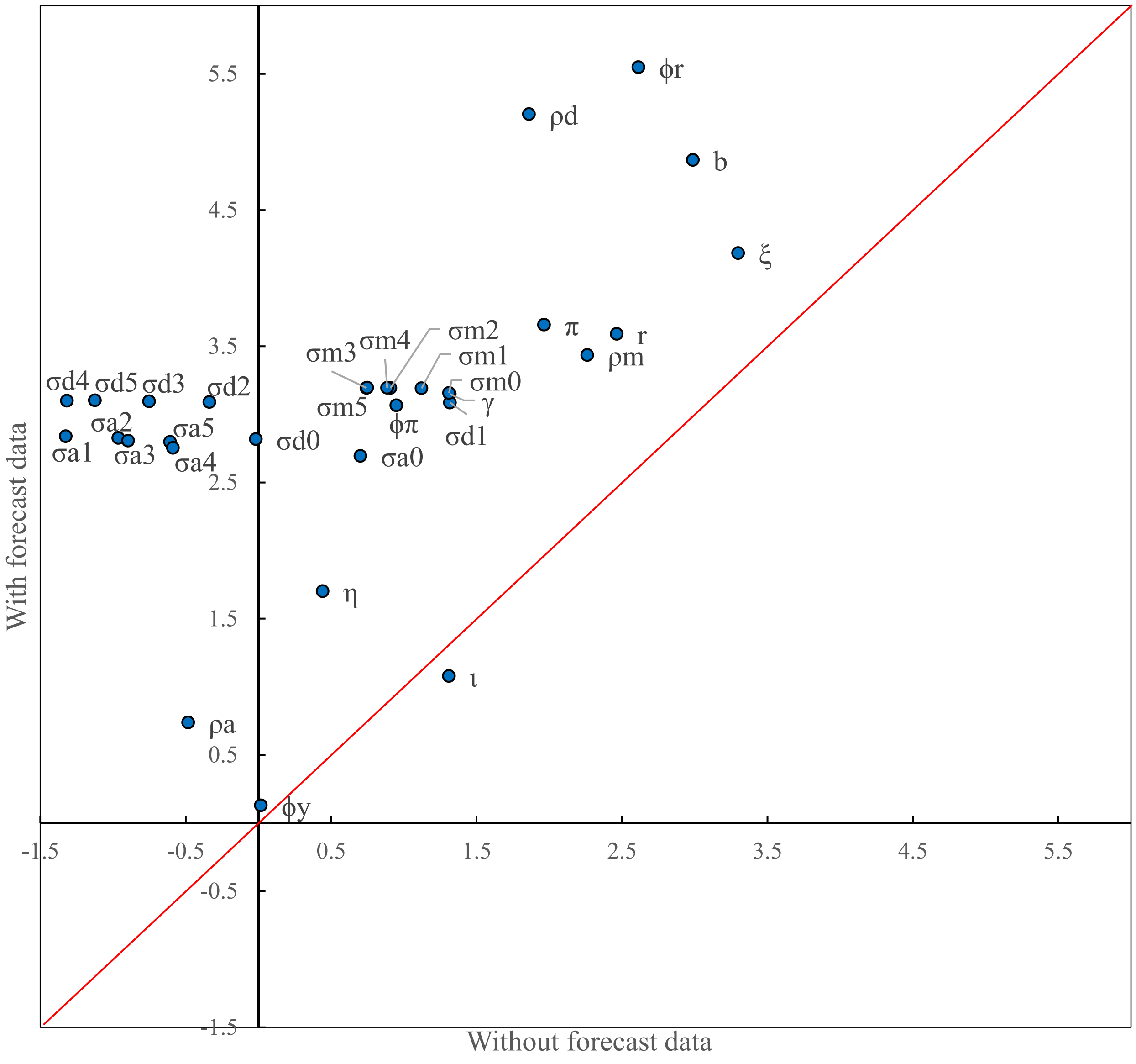
Notes: This table shows each parameter's posterior mean and 90 percent credible interval in the estimation with the generalized observation equations.

Table 7: Variance decompositions in the estimation with the generalized observation equations

Shock	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$
$\nu^a_{0,t}$	45.1	11.2	12.9
$\nu^a_{1,t-1}$	36.5	5.8	6.4
$\nu^a_{2,t-2}$	3.5	0.9	0.6
$\nu^a_{3,t-3}$	0.9	1.0	0.6
$\nu^a_{4,t-4}$	0.6	2.0	1.4
$\nu^a_{5,t-5}$	0.5	3.8	3.1
$\nu^d_{0,t}$	5.1	38.1	48.6
$\nu^d_{1,t-1}$	2.2	9.1	12.1
$\nu^d_{2,t-2}$	0.7	0.8	1.1
$\nu^d_{3,t-3}$	0.8	0.8	1.0
$\nu^d_{4,t-4}$	0.4	0.5	0.5
$\nu^d_{5,t-5}$	0.4	0.8	0.8
$\nu^m_{0,t}$	1.4	9.0	4.7
$\nu^m_{1,t-1}$	1.5	11.3	2.0
$\nu^m_{2,t-2}$	0.2	1.5	0.4
$\nu^m_{3,t-3}$	0.1	1.3	0.8
$\nu^m_{4,t-4}$	0.1	1.2	1.3
$\nu^m_{5,t-5}$	0.0	1.0	1.6

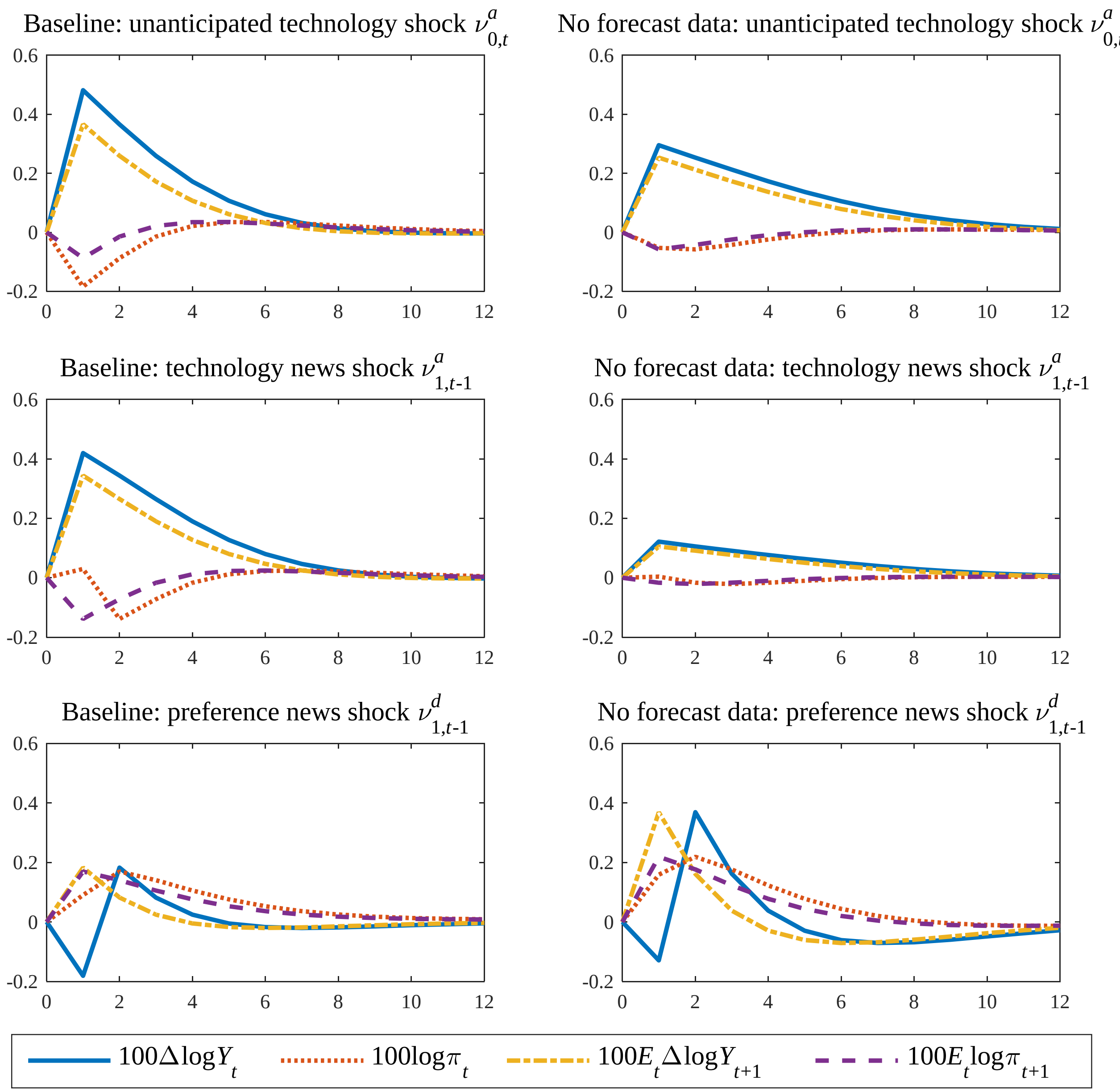
Note: This table shows the variance decompositions of the output growth rate $\Delta \log Y_t$, the inflation rate $\log \pi_t$, and the interest rate $\log r_t$ at the business cycle frequency of 6–32 quarters, evaluated at the posterior mean of model parameters in the estimation with the generalized observation equations.

Figure 1: Identification strength in the estimation with and without the forecast data



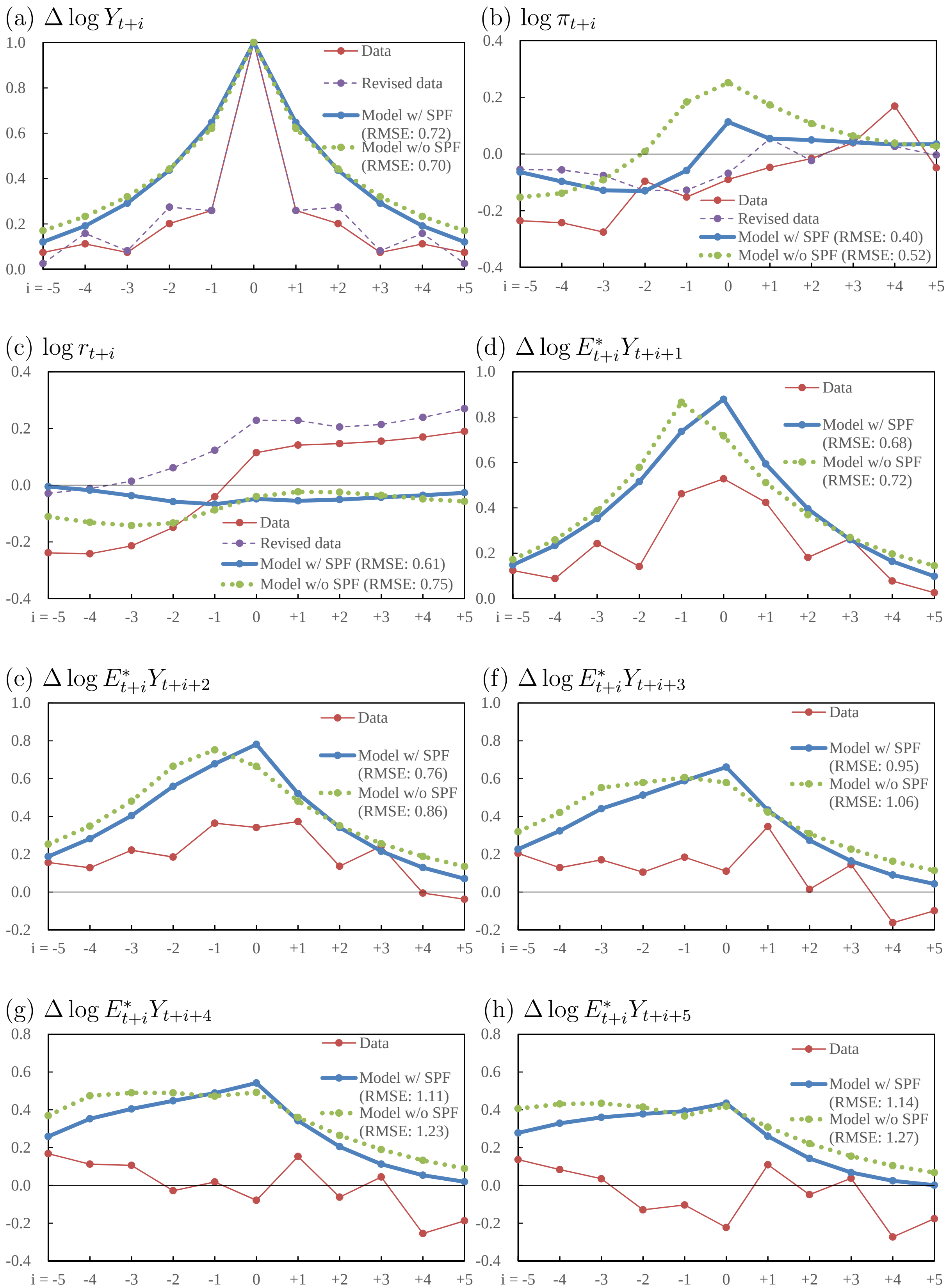
Note: This figure plots the pair of the identification strength for each parameter of the model in the estimation with and without the forecast data, evaluated at the posterior mean of parameters, on a log scale using the asymptotic information matrix following Iskrev (2010b).

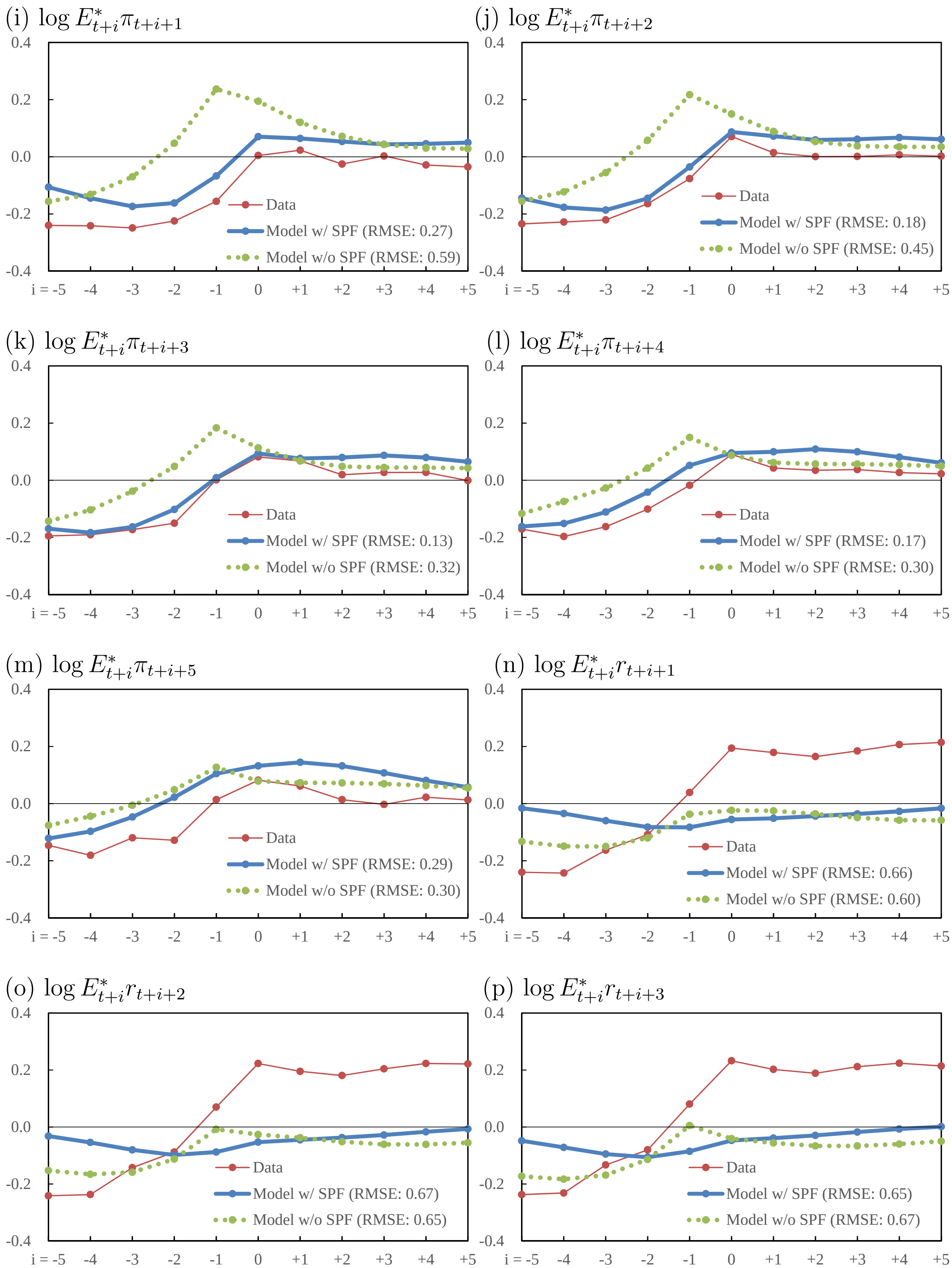
Figure 2: Impulse responses in the baseline estimation and the estimation with no forecast data



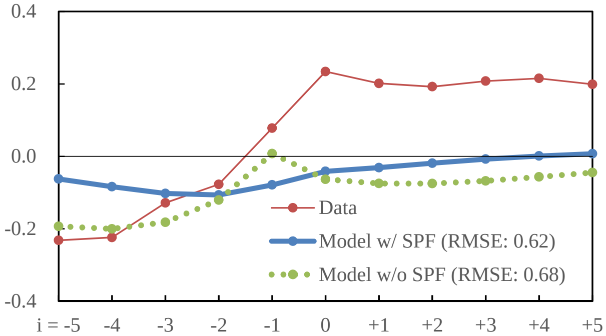
Notes: Each panel shows the impulse responses of the output growth rate $100\Delta\log Y_t$, the inflation rate $100\log\pi_t$, the one-quarter ahead expected future output growth rate $100E_t\Delta\log Y_{t+1}$, and the one-quarter ahead expected future inflation rate $100E_t\log\pi_{t+1}$ (in quarterly terms) to the shock in question, evaluated at the posterior mean of model parameters in the baseline estimation and the estimation with no forecast data. In period one, a one-standard-deviation shock innovation is added.

Figure 3: Correlograms of output growth with the observed variables

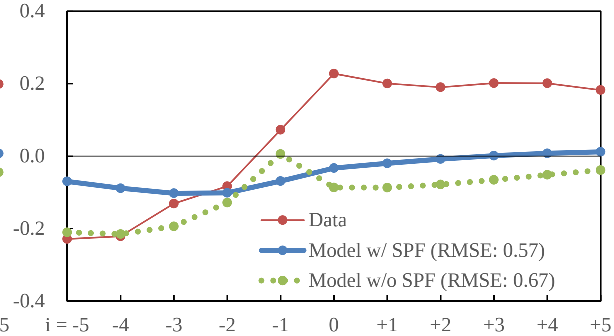



(i) $\log E^*_{t+i}\pi_{t+i+1}$
Data
Model w/ SPF (RMSE: 0.27)
Model w/o SPF (RMSE: 0.59)
(j) $\log E^*_{t+i}\pi_{t+i+2}$
Data
Model w/ SPF (RMSE: 0.18)
Model w/o SPF (RMSE: 0.45)
(k) $\log E^*_{t+i}\pi_{t+i+3}$
Data
Model w/ SPF (RMSE: 0.13)
Model w/o SPF (RMSE: 0.32)
(l) $\log E^*_{t+i}\pi_{t+i+4}$
Data
Model w/ SPF (RMSE: 0.17)
Model w/o SPF (RMSE: 0.30)
(m) $\log E^*_{t+i}\pi_{t+i+5}$
Data
Model w/ SPF (RMSE: 0.29)
Model w/o SPF (RMSE: 0.30)
(n) $\log E^*_{t+i}r_{t+i+1}$
Data
Model w/ SPF (RMSE: 0.66)
Model w/o SPF (RMSE: 0.60)
(o) $\log E^*_{t+i}r_{t+i+2}$
Data
Model w/ SPF (RMSE: 0.67)
Model w/o SPF (RMSE: 0.65)
(p) $\log E^*_{t+i}r_{t+i+3}$
Data
Model w/ SPF (RMSE: 0.65)
Model w/o SPF (RMSE: 0.67)
i = -5
-4
-3
-2
-1
0
+1
+2
+3
+4
+5

(q) $\log E^{*}_{t+i} r_{t+i+4}$



(r) $\log E^{*}_{t+i} r_{t+i+5}$



Notes: Each panel shows the correlograms of output growth ($\Delta \log Y_t$) with each observed variable in the data and the corresponding series implied by the model estimated with the forecast data and the one without it, evaluated at the posterior mean of parameters, for leads and lags ranging from $i = -5$ to $i = +5$. "RMSE" shown in the legend represents the root mean square errors in each cross-correlation over the range from $i = -5$ to $i = +5$ relative to the corresponding data.