Identifying News Shocks with Forecast Data[*]

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Abstract

Recent studies attempt to quantify the empirical importance of news shocks (i.e., anticipated future shocks) in business cycle fluctuations. This paper identifies news shocks in a dynamic stochastic general equilibrium model estimated with not only actual data but also forecast data. The estimation results show new empirical evidence that anticipated future technology shocks are the most important driving force of U.S. business cycles. The use of the forecast data makes the anticipated shocks play a much more important role in fitting model-implied expectations to this data, since such shocks have persistent effects on the expectations and thereby help to replicate the observed persistence of the forecasts.

Keywords: Business cycle fluctuation, News shock, Anticipated future technology shock, Forecast data, Bayesian estimation

JEL Classification: E30, E32

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1 Introduction

What is the source of business cycle fluctuations? The conventional wisdom in the literature is that technology shocks are the main driving force of cyclical movements in economic activity (e.g., King and Rebelo, 1999). Moreover, since the seminal work by Beaudry and Portier (2004), there has been a surge of interest in the business cycle implications of news shocks (i.e., anticipated future shocks) about technology.[1]

To quantify the empirical importance of news shocks, Fujiwara, Hirose, and Shintani (2011), Khan and Tsoukalas (2010), and Schmitt-Grohe and Uribe (2010) investigate estimated dynamic stochastic general equilibrium (DSGE) models.[2] In particular, Schmitt-Grohe and Uribe analyze the business cycle implications of news shocks not only about technology but also about demand.[3] These studies identify news shocks on the basis of the feature that observed variables in their models respond differently to news shocks and to associated unanticipated shocks. All of the three empirical studies, however, reach the conclusion that news shocks about technology are not a major source of business cycle fluctuations.

This paper identifies news shocks in a DSGE model estimated with not only actual data but also forecast data. The motivation of this approach is twofold. First, forecast data conveys information about the future state of the economy expected by forecasters, and therefore it helps to pin down the evolution of anticipated future shocks.[4] Second, the identification of news shocks in the previous studies is dubious in that the number of shocks is far more than that of observables due to the addition of news shocks to their models. Thus, adding forecast data increases the number of observables and thereby ameliorates the over-identification issue.

In the model estimation, this paper employs forecast data of output growth, inflation, and

[1] See also Christiano et al. (2010), Fujiwara (2010), Jaimovich and Rebelo (2009), and Lorenzoni (2009) for theoretical studies on news shocks.

[2] Beaudry and Portier (2006) and Barsky and Sims (2011) estimate a structural vector autoregression model to examine the effect of news shocks about technology on U.S. business cycle fluctuations.

[3] Milani and Treadwell (2011) examine the effects of news shocks about monetary policy, as well as about technology and demand, on output.

[4] To identify anticipated future monetary policy shocks, Hirose and Kurozumi (2011) use U.S. Treasury bond yields data, which contains information on the future path of the federal funds rate expected by market participants. With the estimated news shocks about monetary policy, they examine the changes in the Fed's communication strategy during the 1990s as well as the business cycle implications of such news shocks.

the interest rate in the Survey of Professional Forecasters (SPF).[5] Moreover, for informational consistency with the forecast data, the paper uses real-time data of output growth and inflation in the Real-Time Data Set for Macroeconomists provided by the Federal Reserve Bank of Philadelphia.[6] The model is a small-scale DSGE model with sticky prices and a Taylor (1993) type monetary policy rule, and thus it enables intuitive, clear-cut identification of anticipated and unanticipated components of shocks to technology, demand, and monetary policy using the actual and forecast data of output growth, inflation, and the interest rate. The Bayesian estimation of the model demonstrates that the forecast data is quite informative in identifying news shocks as well as other parameters of the model. The credible intervals of estimated parameters are all concentrated around their posterior mean when the SPF data is included in the set of observables, whereas the intervals are dispersed with no use of the forecast data.

The estimation results provide new empirical evidence on business cycle fluctuations in the U.S. The variance decompositions indicate that anticipated future technology shocks are the most important driving force of output fluctuations. This finding is in stark contrast with the empirical result of the previous studies that news shocks about technology are not a major source of U.S. business cycles. It is also shown that when the SPF data is not used in the model estimation, the business cycle implications of news shocks are altered; unanticipated technology shocks play the most important role in explaining output fluctuations, in line with the result of Schmitt-Grohe and Uribe (2010). This difference between the estimation results with and without the forecast data arises from the fact that the forecast data exhibits high persistence, even compared with the actual data. The use of the forecast data thus makes anticipated shocks play a much more important role in fitting model-implied expectations to this data, since the anticipated shocks have persistent effects on the expectations and thereby help to replicate the observed persistence of the forecasts.[7]

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[5] Del Negro and Eusepi (2011) and Milani (2011) use the SPF data in estimating DSGE models. Leduc and Sill (2010) use forecast data in the SPF and the Livingston Survey in estimating vector autoregression models.

[6] We also estimated the model using revised data of output growth and inflation and confirmed that the main results obtained with the real-time data did not alter.

[7] The use of the forecast data also yields lower estimates of model parameters that determine the persistence of the economy, such as habit persistence in spending and price indexation to past inflation. This result is similar to that of Milani (2007), who estimates a DSGE model without news shocks in the absence of forecast data and indicates that the estimates of such parameters are lower under adaptive learning than under rational expectations.

The remainder of this paper proceeds as follows. Section 2 presents an example that explains the identifiability of news shocks when expectation variables are observable. Section 3 describes a DSGE model with news shocks. Section 4 accounts for the data and econometric methods for estimating this model. Section 5 shows empirical results. Section 6 conducts robustness analysis. Finally, Section 7 concludes.

2 Identification of News Shocks

Before proceeding to the analysis of news shocks in a DSGE model estimated with actual and forecast data, this section presents an example that shows the identifiability of news shocks when expectation variables are observable.

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

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

where $\theta > 1$ is a constant, E_t is the expectation operator conditional on information available in period t, and ε_t is an exogenous shock that consists of both anticipated and unanticipated 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 an anticipated shock that is expected in period $t-1$ to materialize in period t. It is assumed that $\nu_{0,t}$ and $\nu_{1,t}$ are mutually and serially uncorrelated and have mean zero and standard deviation σ_i, $i = 0, 1$. These two equations can be written as the system

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

In this system, the set of state variables is $(\nu_{1,t-1}, \nu_{0,t}, \nu_{1,t})$, and thus the undetermined coefficient method gives the determinate rational expectations solution[8]

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

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

Therefore, y_t is driven by both anticipated and unanticipated shocks. These shocks have a different effect on the evolution of y_t. The unanticipated shock $\nu_{0,t}$ has a temporary effect in period t, while the anticipated 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 the parameter θ by a full-information likelihood-based econometric procedure. This seeks to bring the evolution of the model-implied variable y_t given by (1) as close to its corresponding data as possible. When y_t is the only one observed variable, the standard deviations σ_0, σ_1 of the two disturbances $\nu_{0,t}, \nu_{1,t}$ would be hard to identify, and only a joint distribution of the standard deviations as well as the parameter θ is obtained at best. Moreover, the marginal probability density for each of these three would be dispersed.

The issue regarding the identification of anticipated and unanticipated shocks can be resolved when the expectation variable $E_t y_{t+1}$ is also observable. From (1), it follows that

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

and hence, given the observation of $E_t y_{t+1}$, the standard deviation σ_1 can be identified. Then, parameter θ and the standard deviation σ_0 can also be identified using (1). Moreover, the marginal probability densities for the standard deviations σ_0, σ_1 are isolated from each other. Therefore, the anticipated shock $\nu_{1,t}$ and the unanticipated shock $\nu_{0,t}$ can be fully pinned down.

For a general class of DSGE models, the identification issue about anticipated and unanticipated shocks may be more complicated than that in the example presented above. However, the ensuing empirical analysis demonstrates that the addition of forecast data to the set of observables helps to identify news shocks in a DSGE model.

3 The Model

This paper employs a small-scale DSGE model with sticky prices and a monetary policy rule. This model is chosen because it enables intuitive, clear-cut identification of anticipated and unanticipated components of shocks to technology, demand, and monetary policy as shown in Section 5. Consequently, the relative importance of each component in business cycle fluctuations can be successfully investigated.

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. For empirical validity, the model features external habit persistence in consumption preferences, price indexation to recent past inflation and steady-state inflation, and a stochastic trend in output, i.e., 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 is the steady-state gross rate of technological change and z_t^a is a shock to the rate of this change, called a technology shock.

The log-linearized equilibrium conditions are summarized as follows.[9]

$$\begin{aligned}
\hat{y}_t =& \frac{\gamma}{\gamma+b} E_t \hat{y}_{t+1} + \frac{b}{\gamma+b} \hat{y}_{t-1} - \frac{\gamma-b}{\gamma+b} \left(\hat{r}_t - E_t \hat{\pi}_{t+1}\right) \\
&- \frac{1}{\gamma+b} \left(b z_t^a - \gamma E_t z_{t+1}^a\right) + \frac{\gamma-b}{\gamma+b} \left(z_t^d - E_t z_{t+1}^d\right), \qquad (3)\\
\hat{\pi}_t =& \frac{\beta}{1+\iota\beta} E_t \hat{\pi}_{t+1} + \frac{\iota}{1+\iota\beta} \hat{\pi}_{t-1} \\
&+ \frac{(1-\xi)(1-\xi\beta)}{\xi(1+\iota\beta)} \left[\left(\eta + \frac{\gamma}{\gamma-b}\right) \hat{y}_t - \frac{b}{\gamma-b} \hat{y}_{t-1} + \frac{b}{\gamma-b} z_t^a\right], \qquad (4)\\
\hat{r}_t =& \phi_r \hat{r}_{t-1} + (1-\phi_r)\left(\phi_\pi \hat{\pi}_t + \phi_y \hat{y}_t\right) + z_t^m. \qquad (5)
\end{aligned}$$

Equation (3) is the spending Euler equation, where $\hat{y}_t$ denotes output expressed in terms of log-deviations from its stochastic trend, $\hat{r}_t$ and $\hat{\pi}_t$ are the interest rate and inflation in terms of log-deviations from their steady-state values, z_t^d is a shock to households' period utility, called a demand shock, and $b \in [0,1]$ is the degree of habit persistence. Equation (4) is the so-called New Keynesian Phillips curve, where $\beta \in (0,1)$ is the subjective discount factor determined by the steady-state relationship $\beta = \gamma\pi/r$, $\iota \in [0,1]$ is the weight of price indexation to recent past inflation π_{t-1} relative to steady-state inflation π, $\xi \in (0,1)$ is the so-called Calvo (1983) parameter that measures 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 $\phi_r \in [0,1)$ is the degree of interest rate smoothing, ϕ_π, ϕ_y represent the degrees of interest rate policy responses to inflation and output, and z_t^m is a monetary policy shock.

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

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

[9] See Appendix for the full description of the model.

where $\rho_x \in [0, 1)$ is an autoregressive coefficient and ε_t^x is a disturbance that consists not only of an unanticipated component but also of anticipated components up to five periods ahead

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

where each component $\nu_{n,t-n}^x$, $n = 0, 1, \ldots, 5$ is a normally distributed innovation with mean zero and standard deviation σ_{xn}. The length of the anticipation horizon is determined on the basis of the horizon for the quarterly forecasts of output growth, inflation, and the interest rate in the SPF, where the maximum horizon is five quarters. As explained in the preceding section, matching the number of forecast data and that of anticipated components helps to identify the standard deviations of each shock component.

4 Econometric Methodology

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, this set includes quarterly forecasts for these three rates up to five quarters ahead $\{100\Delta \log E_t^* Y_{t+n}, 100 \log E_t^* \pi_{t+n}, 100 \log E_t^* r_{t+n}\}_{n=1}^5$, where E_t^* denotes expectations formed by forecasters, to identify each shock's unanticipated component and anticipated components up to five quarters ahead. The data on the rates of output growth, inflation, and interest are respectively the per capita real GDP growth rate, the inflation rate of the GDP implicit price deflator, and the interest rate on three-month Treasury bills. This paper employs the forecasts for these three rates in the SPF. Moreover, taking account of the fact that this survey's timing is geared to the release of the Bureau of Economic Analysis' advance report on the national income and product accounts, the present paper uses 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.

The observation equations that relate the data to the model-implied variables are given by

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

where $\bar{\gamma} = 100(\gamma - 1)$, $\bar{\pi} = 100(\pi - 1)$, and $\bar{r} = 100(\gamma\pi/\beta - 1)$ are the steady-state rates of output growth, inflation, and interest. In the baseline estimation, the forecast data are related to the model-implied variables under rational expectations. A deviation from this assumption is examined in the robustness analysis presented later.

The sample period is from 1983:1Q to 2008:4Q. The beginning of the sample is determined to exclude the possibility of equilibrium indeterminacy based on the results of Clarida, Galí, and Gertler (2000) and Lubik and Schorfheide (2004). The end of the sample follows from the fact that the estimation strategy is not able to take into account the non-linearity in monetary policy rules due to the zero lower bound on the nominal interest rate, which has been binding since 2009:1Q.

The prior distributions of parameters to be estimated are shown in Table 1. The priors of structural parameters, monetary policy parameters, and shock persistence parameters are chosen based on those in Smets and Wouters (2007). As for the steady-state rates of output growth, inflation, and interest $\bar{\gamma}$, $\bar{\pi}$, $\bar{r}$, the priors are centered at the sample mean. Moreover, the priors of the standard deviations of unanticipated technology and demand shocks σ_{a0}, σ_{d0} are distributed around 2.0, whereas that of unanticipated monetary policy shock σ_{m0} are centered at 0.5. Regarding the standard deviations of anticipated components of each shock, equal weights on the unanticipated component and on the sum of anticipated components are set in the priors; that is, each σ_{xn}, $x \in \{a, d, m\}$, $n = 0, 1, \ldots, 5$ is distributed around $5^{-1/2} \times \sigma_{x0}$ so that $\sum_{n=1}^{5} \sigma_{xn}^2 = \sigma_{x0}^2$.

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.[10] These draws yield inference on the parameters, impulse response functions, and variance decompositions.

5 Empirical Results

This section presents the results of empirical analysis. A novelty in the analysis is that the forecast data is used in the estimation of the stylized DSGE model with news shocks. Thus, the model is estimated with and without the forecast data, and then these estimation results are compared. In the estimation without the forecast data, revised data of output growth and inflation are used instead of the real-time data, as in the previous empirical studies on DSGE models with news shocks.

5.1 Parameter Estimates

The posterior estimates of parameters are reported in Table 2. The second and third columns present the posterior mean and the 90 percent credible posterior intervals of parameters in the estimation with the forecast data (i.e., baseline estimation), while the fourth and fifth columns show those in the estimation with no forecast data. Notable differences between the estimation with and without the forecast data are found in most of the parameters. First, the parameters that determine the persistence of the model economy, such as the habit persistence parameter b, the price indexation parameter ι, and the autoregressive parameters of technology and monetary policy shocks ρ_a, ρ_m, are smaller in the baseline estimation than those in the estimation with no forecast data. This result is similar to that of Milani (2007), who estimates a DSGE model without news shocks in the absence of forecast data and indicates that the

[10] In each estimation, 200,000 draws were generated and the first half of these draws was discarded. The scale factor for the jumping distribution in the Metropolis-Hastings algorithm was adjusted so that the acceptance rate of approximately 25 percent would be obtained. The Brooks and Gelman (1998) measure was used to check the convergence of parameters.

estimates of parameters regarding habit persistence in spending and price indexation to past inflation are lower under adaptive learning than under rational expectations. Second, the estimate of the Calvo parameter ξ, which measures the degree of price stickiness, is smaller in the baseline estimation. Third, the estimated steady-state rates of output growth, inflation, and interest $\bar{\gamma}$, $\bar{\pi}$, $\bar{r}$, differ between the estimation with and without the forecast data, suggesting the possibility of a bias in the forecasts. This possibility is examined in the robustness analysis presented later.

The primary interest of this paper lies in the estimated standard deviations of anticipated and unanticipated components of each shock. Regarding technology shocks, the posterior mean of the standard deviation of each component is larger in the baseline estimation than that in the estimation with no forecast data. Remarkable increases are found in the standard deviations of one- and four-quarter-ahead anticipated components σ_{a1}, σ_{a4}. As for demand shocks, the estimate of the standard deviation of the unanticipated component is almost twice larger, whereas those of the anticipated components are substantially smaller. In particular, the posterior mean of the standard deviation of one-quarter-ahead anticipated disturbance σ_{d1} is less than half of that in the estimation with no forecast data. The estimated standard deviations of anticipated and unanticipated components of monetary policy shocks, except that of one-quarter-ahead anticipated component, are smaller in the baseline estimation.

It is worth emphasizing that the 90 percent credible posterior intervals for all the estimated parameters are concentrated around their posterior mean in the baseline estimation whereas those are dispersed in the estimation with no forecast data. This finding shows that the forecast data is quite informative in identifying not only anticipated shocks but also the other parameters of the model.

The baseline estimation uses the real-time data of output growth and inflation for informational consistency between the actual and forecast data, whereas the estimation with no forecast data uses the corresponding revised data as in the previous studies. Thus, the use of the real-time data may amount to the difference between the two estimation results. To investigate this possibility, the last two columns in Table 2 show the posterior estimates of parameters in the estimation with the revised data as well as the forecast data. These estimates are similar to those in the baseline estimation (which uses the real-time data and forecast data) presented in the second and third columns of the same table. Therefore, the difference between the baseline estimation and the estimation without the forecast data is attributable to the use of the forecast data but not to that of the real-time data.

5.2 Impulse Responses

In Section 2, the identifiability of news shocks has been explained in a simple univariate setting. In general, the identification issue about news shocks may be more complicated for multivariate DSGE models. However, the identifiability of the anticipated and unanticipated components of shocks to technology, demand, and monetary policy in the present model can be verified by computing impulse response functions; if each shock generates different comovement of the observables, the parameters associated with the shock can be identified.

Figure 1 illustrates the impulse responses to the unanticipated component and three-quarter-ahead anticipated component of technology and demand shocks, evaluated at the posterior mean estimates of parameters. The demand-and-supply relationships in the sticky price DSGE model lead to the following fairly straightforward interpretation of the responses.

The two upper panels plot the impulse responses of the actual rates and three-quarter-ahead forecast rates of output growth and inflation to a one-standard-deviation technology shock added in period one. The upper-left panel shows the case of an unanticipated technology shock. This shock has an expansionary effect not only on the actual rate of output growth but also on the forecast rate of future output growth owing to habit persistence in spending. Actual inflation declines because the unanticipated technology shock reduces contemporaneous real marginal cost, while the forecast of future inflation changes little due to the very low degree of price indexation to past inflation.

The upper-right panel presents the case of an anticipated technology shock that is expected in period one to materialize in period four. In period one, when future technological progress is anticipated, the forecast of the future output growth rate increases whereas that of future inflation decreases. As a consequence, real wage growth expectations are heightened and hence the actual output growth rate rises. Because the technological progress has not yet materialized in period one, the demand-driven growth of actual output raises actual inflation.

Next turn to the two lower panels, which illustrate the impulse responses to a one-standard-deviation demand shock added in period one. The case of an unanticipated demand shock is depicted in the lower-left panel. This contemporaneously demand-stimulating shock raises both the actual rates of output growth and inflation. Because such a shock gives rise to no expansion of the production frontier, the forecast of future output growth declines on the rebound. However, the future inflation forecast increases due to the very high persistence of demand shocks.

The lower-right panel shows the case of an anticipated demand shock that is expected in period one to materialize in period four. In reaction to the anticipated increase in future demand, both the forecasts of future output growth and future inflation increases. Then, households substitute current with future spending due to its smoothing, and hence the actual output growth rate declines immediately after the shock was added. Consequently, actual inflation also decreases.

The impulse responses examined above demonstrate that each component of technology and demand shocks generates distinct comovement among actual and forecast variables of output growth and inflation. Since these variables are all fitted to their corresponding data in the model estimation, it follows that available information is fully utilized to identify each shock. If the model were estimated only with the actual data, it would be hard to identify each shock because both an anticipated technology shock and an unanticipated demand shock lead to the contemporaneous positive comovement between actual output and actual inflation.

The identifiability of the anticipated and unanticipated components of monetary policy shocks is straightforward. They are well identified from the Taylor-type monetary policy rule and the actual and forecast data of the interest rate.

5.3 Variance Decompositions

In the presence of the anticipated and unanticipated components of each shock, this subsection analyzes the sources of business cycle fluctuations using the variance decompositions. Table 3 shows the forecast error variance decompositions of the actual rates of output growth, inflation, and interest at an infinite horizon evaluated at the posterior mean estimates of parameters in the baseline estimation and in the estimation with no forecast data. In this table, the contribution of each anticipated shock is the sum of the contribution of the anticipated components from one to five quarters ahead.

The top rows of Table 3 present the variance decompositions in the baseline estimation.[11]

[11] The variance decompositions in the estimation with the revised data as well as the forecast data are almost the same as those in the baseline estimation, since the posterior estimates of parameters are very similar as shown in Table 2.

It is shown that anticipated technology shocks are the most important driving force of output fluctuations in the U.S. This finding is novel in the literature, since previous studies, such as Fujiwara, Hirose, and Shintani (2011), Khan and Tsoukalas (2010), and Schmitt-Grohe and Uribe (2010), have shown that news shocks about technology are not a major source of U.S. business cycle fluctuations although they play a non-negligible role in explaining the fluctuations. Unanticipated technology shocks are also important in the output fluctuations, in line with the results of many previous business cycle studies. The inflation variability is mainly explained by unanticipated demand shocks. This finding reflects the observed tendency of positive contemporaneous correlation between output growth and inflation. The variance decomposition of the interest rate is similar to that of inflation, since the estimated monetary policy rule shows that the Fed reacts to inflation much more aggressively than to output.

When the forecast data is not used in the model estimation as in the previous empirical studies on DSGE models with news shocks, the business cycle implications of news shocks are altered. The bottom rows of Table 3 present the variance decompositions in the estimation with no forecast data. It is shown that unanticipated technology shocks play the most important role in explaining fluctuations in output growth, in line with the result of Schmitt-Grohe and Uribe (2010). Moreover, anticipated demand shocks have a substantial contribution to the output fluctuations.

What makes the difference in the business cycle implications of news shocks between the estimation with and without the forecast data? To answer this question, the time-series property of the forecast data is investigated. Specifically, the persistence of each data is measured by estimating a univariate first-order autoregressive coefficient. Table 4 summarizes the estimated persistence of the forecast and actual data for output growth and inflation. The persistence of inflation forecasts for all the forecast horizons is much higher than that of actual inflation. Moreover, the one- to four-quarter-ahead forecasts of output growth exhibit higher persistence than real-time actual output growth. Taking account of the fact that the anticipated shocks have persistent effects on the expectations as shown in Figure 1, the use of the forecast data in the model estimation makes anticipated shocks play a much more important role in order to fit model-implied expectations to the observed persistence of the forecasts. Therefore, the contribution of anticipated future technology shocks to output fluctuations is much larger in the baseline estimation than in the estimation without the forecast data.

6 Robustness Analysis

In the baseline estimation, the forecast data in the SPF are related to the model-implied variables under rational expectations. However, the forecasts could be biased or randomly deviate from rational expectations. As indicated in the previous section, the estimated steady-state rates of output growth, inflation, and interest differ between the estimation with and without the forecast data, which suggests the possibility of a bias in the forecasts. Moreover, the real-time data of output growth and inflation could also be biased or have measurement errors.

To examine the robustness of the baseline results with respect to such possible discrepancy between observed and model-implied variables, the observation equations are generalized as follows.

$$\begin{bmatrix} 100\Delta\log Y_t \\ 100\log \pi_t \\ 100\log r_t \\ 100\Delta\log E_t^* Y_{t+1} \\ \vdots \\ 100\Delta\log E_t^* Y_{t+5} \\ 100\log E_t^*\pi_{t+1} \\ \vdots \\ 100\log E_t^*\pi_{t+5} \\ 100\log E_t^* r_{t+1} \\ \vdots \\ 100\log E_t^* r_{t+5} \end{bmatrix} = \begin{bmatrix} \bar{\gamma}+\bar{b}_{Y0} \\ \bar{\pi}+\bar{b}_{\pi 0} \\ \bar{r}+\bar{b}_{r0} \\ \bar{\gamma}+\bar{b}_{Y1} \\ \vdots \\ \bar{\gamma}+\bar{b}_{Y5} \\ \bar{\pi}+\bar{b}_{\pi 1} \\ \vdots \\ \bar{\pi}+\bar{b}_{\pi 5} \\ \bar{r}+\bar{b}_{r1} \\ \vdots \\ \bar{r}+\bar{b}_{r5} \end{bmatrix} + \begin{bmatrix} \hat{y}_t - \hat{y}_{t-1} + z_t^a + \zeta_t^{Y0} \\ \hat{\pi}_t + \zeta_t^{\pi 0} \\ \hat{r}_t + \zeta_t^{r0} \\ E_t\hat{y}_{t+1} - \hat{y}_t + E_t z_{t+1}^a + \zeta_t^{Y1} \\ \vdots \\ E_t\hat{y}_{t+5} - E_t\hat{y}_{t+4} + E_t z_{t+5}^a + \zeta_t^{Y5} \\ E_t\hat{\pi}_{t+1} + \zeta_t^{\pi 1} \\ \vdots \\ E_t\hat{\pi}_{t+5} + \zeta_t^{\pi 5} \\ E_t\hat{r}_{t+1} + \zeta_t^{r1} \\ \vdots \\ E_t\hat{r}_{t+5} + \zeta_t^{r5} \end{bmatrix},$$

where $\bar{b}_{Xn}$ and $\zeta_t^{Xn} \sim N(0, \sigma_{Xn}^2)$, $X \in \{Y, \pi, r\}$, $n = 0, 1, \ldots, 5$ represent, respectively, a bias and a measurement or forecast error in each observable. The prior distribution of $\bar{b}_{Xn}$ is set to be the normal distribution with mean zero and standard deviation 0.25, and that of σ_{Xn} is the inverse gamma distribution with mean 0.25 (i.e., annually one percent) and standard deviation 2. The other priors are the same as in the baseline estimation.

Table 5 reports the posterior mean and the 90 percent credible posterior interval for each parameter in the estimation with the generalized observation equations. The habit persistence parameter b, the price indexation parameter ι, and the autoregressive parameter of technology shock ρ_a are large compared with those in the baseline estimation presented in Table 2. This is because noisy movements in the observables are partly captured by the measurement or forecast errors. Consequently, the movements of model-implied variables are smooth. This should be characterized by the larger estimates of the parameters that determine the persistence of the model economy (i.e., b, ι, ρ_a). Relatively large increases are found in the standard deviations of one- and four-quarter-ahead anticipated technology shocks σ_{a1}, σ_{a4}, whereas the standard deviations of the other shocks are in line with the baseline estimates. The estimates of biases in the real-time and forecast data $\bar{b}_{Xn}$ and the standard deviations of the measurement or forecast errors σ_{Xn} explicate the properties of the forecasts in the SPF. According to the estimates of $\bar{b}_{Xn}$, no large biases are found although the inflation forecasts may have a slightly positive bias. As for σ_{Xn}, the estimates of σ_{Y0} and $\sigma_{\pi 0}$ imply that the measurement errors in the real-time data of output growth and inflation are non-negligible. By contrast, the standard deviations of the forecast errors are very small except the error in the one-quarter-ahead forecast of output growth, which has a relatively large standard deviation.

Note that the 90 percent credible posterior interval of each parameter widens compared with that in the baseline estimation. The dispersed estimates here are ascribed to the increase in the number of shocks. This finding suggests that matching the number of data and that of shocks is a key factor for the identification of model parameters, as argued in Section 2.

Table 6 demonstrates the variance decompositions of the actual rates of output growth, inflation, and interest in the estimation with the generalized observation equations. Although the contribution of the measurement or forecast errors is not able to be ignored, the baseline result that anticipated future technology shocks are the most important driving force of U.S. output fluctuations, presented in Table 3, still holds in the estimation here. It is also shown that the volatilities of inflation and the interest rate are mainly explained by the unanticipated demand shock, as is the case with the baseline estimation. Therefore, the main results obtained in the baseline estimation are robust with respect to the deviation from the rational expectations assumption.

7 Concluding Remarks

This paper identifies news shocks about technology, demand, and monetary policy in a DSGE model with actual and forecast data of output growth, inflation, and the interest rate. It has been shown that the use of the forecast data in the model estimation pins down the evolution of news shocks more efficiently. The estimation results have demonstrated that anticipated future technology shocks are the primary source of U.S. business cycle fluctuations. This finding is novel in the literature because the previous studies have shown that news shocks about technology are not a major source of the business cycles although they play a non-negligible role.

One of the limitations in this analysis may be that the forecast data are related to the model-implied variables under rational expectations. The robustness analysis has demonstrated that the baseline results survive even when discrepancy between the observed and model-implied variables is allowed. Yet the introduction of learning in the model along the lines of Milani (2011) and Mitra, Evans, and Honkapohja (2011) might yield a differing estimation result. This would be a fruitful extension of the present analysis.

Appendix

This appendix presents the full description of the model. In the model economy, there are a continuum of households, a representative final-good firm, a continuum of intermediate-good firms, and a monetary authority.

Each household $h \in [0,1]$ consumes final goods $C_{h,t}$, supplies labor $l_{h,t}$, and purchases one-period riskless bonds $B_{h,t}$ so as to maximize the utility function

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\log \left(C_{h,t} - bC_{t-1} \right) - \frac{l_{h,t}^{1+\eta}}{1+\eta} \right] \exp(z_t^d)$$

subject to the budget constraint

$$P_t C_{h,t} + B_{h,t} = P_t W_t l_{h,t} + r_{t-1} B_{h,t-1} + T_{h,t},$$

where E_t is the expectation operator conditional on information available in period t, $\beta \in (0,1)$ is the subjective discount factor, $b \in [0,1]$ is the degree of external habit persistence in consumption preferences, $\eta > 0$ is the inverse of the elasticity of labor supply, z_t^d represents a demand shock, P_t is the price of final goods, W_t is the real wage, and $T_{h,t}$ is the sum of a lump-sum public transfer and profits received from firms. The first-order conditions for optimal decisions on consumption, labor supply, and bond-holding are identical among households and therefore become

$$\Lambda_t = \frac{\exp(z_t^d)}{C_t - bC_{t-1}}, \tag{6}$$

$$W_t = \frac{l_t^{\eta} \exp(z_t^d)}{\Lambda_t}, \tag{7}$$

$$1 = E_t \beta \frac{\Lambda_{t+1}}{\Lambda_t} \frac{r_t}{\pi_{t+1}}, \tag{8}$$

where Λ_t is the marginal utility of consumption and $\pi_t = P_t / P_{t-1}$ denotes gross inflation.

The representative final-good firm produces output Y_t under perfect competition by choosing a combination of intermediate inputs $\{Y_{f,t}\}$ so as to maximize profit $P_t Y_t - \int_0^1 P_{f,t} Y_{f,t} df$ subject to a CES production technology $Y_t = \left(\int_0^1 Y_{f,t}^{1/(1+\lambda^p)} df \right)^{1+\lambda^p}$, where $P_{f,t}$ is the price of intermediate good f and $\lambda^p \geq 0$ denotes the intermediate-good price markup. The first-order condition for profit maximization yields the final-good firm's demand for intermediate good f, $Y_{f,t} = Y_t \left(P_{f,t} / P_t \right)^{-(1+\lambda^p)/\lambda^p}$, while perfect competition in the final-good market leads to $P_t = \left(\int_0^1 P_{f,t}^{-1/\lambda^p} df \right)^{-\lambda^p}$.

Each intermediate-good firm f produces one kind of differentiated goods $Y_{f,t}$ under monopolistic competition by choosing a cost-minimizing labor input l_t given the real wage W_t subject to the production function

$$Y_{f,t} = A_t l_{f,t},$$

where A_t represents the technology level and follows the non-stationary stochastic process:

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

where γ denotes the steady-state gross rate of technological change and z_t^a represents a technology shock. The first-order condition for cost minimization shows that real marginal cost is identical among intermediate-good firms and is given by

$$mc_t = \frac{W_t}{A_t}. \tag{9}$$

In the face of the final-good firm's demand and the marginal cost, intermediate-good firms set prices of their products on a staggered basis à la Calvo (1983). In each period, a fraction $1 - \xi \in (0, 1)$ of intermediate-good firms reoptimizes prices while the remaining fraction ξ indexes prices to a weighted average of past inflation π_{t-1} and steady-state inflation π. Then, firms that reoptimize prices in the current period maximize expected profit

$$E_t \sum_{j=0}^{\infty} \xi^j \frac{\beta^j \Lambda_{t+j}}{\Lambda_t} \left[\frac{P_{f,t}}{P_{t+j}} \prod_{k=1}^{j} \left(\pi_{t+k-1}^{\iota} \pi^{1-\iota} \right) - mc_{t+j} \right] Y_{f,t+j}$$

subject to the final-good firm's demand

$$Y_{f,t+j} = Y_{t+j} \left[\frac{P_{f,t}}{P_{t+j}} \prod_{k=1}^{j} \left(\pi_{t+k-1}^{\iota} \pi^{1-\iota} \right) \right]^{-\frac{1+\lambda^p}{\lambda^p}},$$

where $\iota \in (0, 1)$ denotes the weight of price indexation to past inflation relative to steady-state inflation. The first-order condition for the reoptimized price P_t^o is given by

$$E_t \sum_{j=0}^{\infty} \left\{ \begin{array}{l} (\beta\xi)^j \dfrac{\Lambda_{t+j}}{\Lambda_t} Y_{t+j} \left[\dfrac{P_t^o}{P_t} \displaystyle\prod_{k=1}^{j} \left(\dfrac{\pi_{t+k-1}}{\pi} \right)^{\iota} \dfrac{\pi}{\pi_{t+k}} \right]^{-\frac{1+\lambda^p}{\lambda^p}} \\ \times \left[\dfrac{P_t^o}{P_t} \displaystyle\prod_{k=1}^{j} \left(\dfrac{\pi_{t+k-1}}{\pi} \right)^{\iota} \dfrac{\pi}{\pi_{t+k}} - (1 + \lambda^p)\, mc_{t+j} \right] \end{array} \right\} = 0. \tag{10}$$

Moreover, the final-good's price $P_t = \left(\int_0^1 P_{f,t}^{-1/\lambda^p} df \right)^{-\lambda^p}$ can be rewritten as

$$1 = (1 - \xi) \left(\frac{P_t^o}{P_t} \right)^{-\frac{1}{\lambda^p}} + \xi \left[\left(\frac{\pi_{t-1}}{\pi} \right)^{\iota} \frac{\pi}{\pi_t} \right]^{-\frac{1}{\lambda^p}}. \tag{11}$$

The final-good market clearing condition is

$$Y_t = C_t, \tag{12}$$

while the labor market clearing condition leads to

$$\frac{Y_t d_t}{A_t} = \int_0^1 l_{f,t} df = l_t, \tag{13}$$

where $d_t = \int_0^1 (P_{f,t}/P_t)^{-(1+\lambda^p)/\lambda^p} df$ represents price dispersion across intermediate-good firms. Note that this dispersion is of second order under the staggered price-setting and that its steady-state value is unity.

The monetary authority adjusts the interest rate following a Taylor (1993) type monetary policy rule

$$\log r_t = \phi_r \log r_{t-1} + (1-\phi_r)\left(\log r + \phi_\pi \log \frac{\pi_t}{\pi} + \phi_y \log \frac{Y_t}{Y}\right) + z_t^m, \tag{14}$$

where $\phi_r \in [0,1)$ is the degree of interest rate smoothing, r is the steady-state gross interest rate, and $\phi_\pi, \phi_y \geq 0$ are the degrees of interest rate policy responses to inflation and output.

The equilibrium conditions are (6)–(14). Because the log level of technology has a unit root with drift, the equilibrium conditions are rewritten in terms of stationary variables detrended by A_t: $y_t = Y_t/A_t$, $c_t = C_t/A_t$, $w_t = W_t/A_t$, and $\lambda_t = \Lambda_t A_t$. Log-linearizing the equilibrium conditions represented in terms of the detrended variables and rearranging the resulting equations yields (3)–(5).

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Table 1: Prior distributions of parameters

Parameter		Distribution	Mean	S.D.
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	Policy response to inflation	Gamma	1.500	0.200
ϕ_y	Policy response to output	Gamma	0.125	0.050
$\bar{\gamma}$	Steady-state output growth rate	Gamma	0.470	0.100
$\bar{\pi}$	Steady-state inflation rate	Gamma	0.640	0.100
$\bar{r}$	Steady-state interest rate	Gamma	1.230	0.100
ρ_a	Persistence of technology shock	Beta	0.500	0.100
ρ_d	Persistence of demand shock	Beta	0.500	0.100
ρ_m	Persistence of policy shock	Beta	0.500	0.100
σ_{a0}	S.D. of unanticipated technology shock	Inv. Gamma	2.000	2.000
σ_{a1}	S.D. of one-quarter-ahead anticipated technology shock	Inv. Gamma	0.894	2.000
σ_{a2}	S.D. of two-quarter-ahead anticipated technology shock	Inv. Gamma	0.894	2.000
σ_{a3}	S.D. of three-quarter-ahead anticipated technology shock	Inv. Gamma	0.894	2.000
σ_{a4}	S.D. of four-quarter-ahead anticipated technology shock	Inv. Gamma	0.894	2.000
σ_{a5}	S.D. of five-quarter-ahead anticipated technology shock	Inv. Gamma	0.894	2.000
σ_{d0}	S.D. of unanticipated demand shock	Inv. Gamma	2.000	2.000
σ_{d1}	S.D. of one-quarter-ahead anticipated demand shock	Inv. Gamma	0.894	2.000
σ_{d2}	S.D. of two-quarter-ahead anticipated demand shock	Inv. Gamma	0.894	2.000
σ_{d3}	S.D. of three-quarter-ahead anticipated demand shock	Inv. Gamma	0.894	2.000
σ_{d4}	S.D. of four-quarter-ahead anticipated demand shock	Inv. Gamma	0.894	2.000
σ_{d5}	S.D. of five-quarter-ahead anticipated demand shock	Inv. Gamma	0.894	2.000
σ_{m0}	S.D. of unanticipated policy shock	Inv. Gamma	0.250	2.000
σ_{m1}	S.D. of one-quarter-ahead anticipated policy shock	Inv. Gamma	0.112	2.000
σ_{m2}	S.D. of two-quarter-ahead anticipated policy shock	Inv. Gamma	0.112	2.000
σ_{m3}	S.D. of three-quarter-ahead anticipated policy shock	Inv. Gamma	0.112	2.000
σ_{m4}	S.D. of four-quarter-ahead anticipated policy shock	Inv. Gamma	0.112	2.000
σ_{m5}	S.D. of five-quarter-ahead anticipated policy shock	Inv. Gamma	0.112	2.000

Notes: The table shows the prior distributions of parameters. The priors are truncated at the boundary of the determinacy region.

Table 2: Posterior distributions of parameters

Parameter	Baseline		No forecast data		Revised data	
	Mean	90% interval	Mean	90% interval	Mean	90% interval
η	2.158	[1.826, 2.491]	2.025	[1.698, 2.337]	2.212	[1.881, 2.541]
b	0.732	[0.703, 0.759]	0.854	[0.809, 0.900]	0.708	[0.679, 0.738]
ι	0.057	[0.047, 0.069]	0.219	[0.129, 0.312]	0.056	[0.047, 0.066]
ξ	0.771	[0.751, 0.790]	0.868	[0.839, 0.896]	0.767	[0.748, 0.787]
ϕ_r	0.915	[0.905, 0.925]	0.843	[0.800, 0.885]	0.918	[0.908, 0.928]
ϕ_π	1.671	[1.487, 1.844]	1.630	[1.312, 1.948]	1.660	[1.472, 1.849]
ϕ_y	0.016	[0.006, 0.026]	0.084	[0.032, 0.135]	0.017	[0.006, 0.027]
$\bar{\gamma}$	0.403	[0.358, 0.448]	0.460	[0.314, 0.603]	0.409	[0.364, 0.455]
$\bar{\pi}$	0.757	[0.705, 0.807]	0.645	[0.515, 0.775]	0.766	[0.712, 0.818]
$\bar{r}$	1.563	[1.458, 1.676]	1.213	[1.076, 1.352]	1.576	[1.459, 1.694]
ρ_a	0.058	[0.047, 0.071]	0.337	[0.209, 0.467]	0.112	[0.107, 0.119]
ρ_d	0.940	[0.930, 0.953]	0.747	[0.645, 0.859]	0.948	[0.934, 0.962]
ρ_m	0.415	[0.375, 0.456]	0.645	[0.533, 0.762]	0.421	[0.381, 0.460]
σ_{a0}	1.374	[1.142, 1.590]	1.079	[0.636, 1.508]	1.571	[1.323, 1.817]
σ_{a1}	1.380	[1.131, 1.614]	0.449	[0.229, 0.661]	1.383	[1.122, 1.647]
σ_{a2}	0.703	[0.575, 0.825]	0.475	[0.230, 0.713]	0.709	[0.578, 0.834]
σ_{a3}	0.754	[0.610, 0.889]	0.464	[0.234, 0.694]	0.738	[0.594, 0.878]
σ_{a4}	0.887	[0.732, 1.043]	0.491	[0.236, 0.752]	0.846	[0.694, 1.001]
σ_{a5}	0.676	[0.566, 0.783]	0.562	[0.248, 0.887]	0.635	[0.532, 0.744]
σ_{d0}	2.770	[2.386, 3.130]	1.489	[0.668, 2.307]	2.807	[2.338, 3.279]
σ_{d1}	1.319	[1.100, 1.530]	3.293	[2.050, 4.667]	1.160	[0.971, 1.348]
σ_{d2}	0.459	[0.388, 0.531]	0.783	[0.226, 1.391]	0.426	[0.359, 0.490]
σ_{d3}	0.405	[0.346, 0.464]	0.739	[0.239, 1.317]	0.382	[0.328, 0.434]
σ_{d4}	0.368	[0.316, 0.418]	0.658	[0.233, 1.148]	0.350	[0.300, 0.397]
σ_{d5}	0.404	[0.350, 0.454]	0.741	[0.232, 1.314]	0.384	[0.336, 0.430]
σ_{m0}	0.050	[0.044, 0.056]	0.067	[0.049, 0.083]	0.049	[0.043, 0.055]
σ_{m1}	0.078	[0.069, 0.087]	0.044	[0.028, 0.060]	0.078	[0.069, 0.086]
σ_{m2}	0.027	[0.023, 0.030]	0.039	[0.025, 0.052]	0.026	[0.023, 0.029]
σ_{m3}	0.019	[0.017, 0.021]	0.040	[0.026, 0.055]	0.018	[0.016, 0.020]
σ_{m4}	0.022	[0.020, 0.025]	0.042	[0.026, 0.056]	0.021	[0.019, 0.024]
σ_{m5}	0.022	[0.019, 0.025]	0.042	[0.026, 0.056]	0.021	[0.019, 0.024]

Notes: The table shows the posterior mean and the 90 percent credible posterior intervals of parameters. To compute the posterior distribution, 200,000 draws were generated using the Metropolis-Hastings algorithm, and the first half of these draws was discarded.

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

Baseline	Output growth	Inflation	Interest rate
Unanticipated technology shock	31.39	3.99	1.48
Anticipated technology shocks	48.54	22.94	6.02
Unanticipated demand shock	7.36	36.26	68.99
Anticipated demand shocks	8.02	9.44	20.89
Unanticipated policy shock	1.28	5.87	0.34
Anticipated policy shocks	3.39	21.50	2.29
No forecast data	Output growth	Inflation	Interest rate
Unanticipated technology shock	37.18	3.47	9.89
Anticipated technology shocks	27.49	11.00	9.54
Unanticipated demand shock	4.20	6.15	9.34
Anticipated demand shocks	27.10	39.17	59.70
Unanticipated policy shock	1.74	9.81	2.59
Anticipated policy shocks	2.27	30.43	8.94

Notes: The table shows the forecast error variance decompositions of the output growth rate, the inflation rate, and the interest rate at an infinite horizon evaluated at the posterior mean estimates of parameters.

Table 4: Persistence of actual and forecast data

	Forecast data					Actual data	
	1 quarter	2 quarter	3 quarter	4 quarter	5 quarter	Real-time	Revised
Output growth	0.66	0.53	0.40	0.36	0.28	0.35	0.41
Inflation	0.89	0.93	0.94	0.95	0.96	0.47	0.47

Notes: The table shows the persistence of actual and forecast data for the output growth rate and the inflation rate. The measure of persistence is the univariate AR(1) coefficient on each data.

Table 5: Posterior distribution of parameters in robustness analysis

Parameter	Mean	90% interval	Parameter	Mean	90% interval
η	2.044	[1.712, 2.360]	$\bar{b}_{Y3}$	0.004	[-0.122, 0.119]
b	0.893	[0.869, 0.915]	$\bar{b}_{Y4}$	0.018	[-0.100, 0.128]
ι	0.436	[0.285, 0.579]	$\bar{b}_{Y5}$	0.000	[-0.114, 0.111]
ξ	0.944	[0.937, 0.953]	$\bar{b}_{\pi 0}$	-0.052	[-0.175, 0.076]
ϕ_r	0.826	[0.784, 0.870]	$\bar{b}_{\pi 1}$	0.012	[-0.102, 0.134]
ϕ_π	1.851	[1.616, 2.101]	$\bar{b}_{\pi 2}$	0.032	[-0.076, 0.152]
ϕ_y	0.031	[0.012, 0.049]	$\bar{b}_{\pi 3}$	0.057	[-0.054, 0.170]
$\bar{\gamma}$	0.452	[0.312, 0.591]	$\bar{b}_{\pi 4}$	0.073	[-0.041, 0.180]
$\bar{\pi}$	0.671	[0.546, 0.792]	$\bar{b}_{\pi 5}$	0.082	[-0.026, 0.192]
$\bar{r}$	1.228	[1.073, 1.370]	$\bar{b}_{r0}$	-0.062	[-0.197, 0.085]
ρ_a	0.423	[0.304, 0.540]	$\bar{b}_{r1}$	-0.049	[-0.192, 0.087]
ρ_d	0.917	[0.883, 0.953]	$\bar{b}_{r2}$	-0.024	[-0.155, 0.113]
ρ_m	0.602	[0.506, 0.699]	$\bar{b}_{r3}$	0.006	[-0.117, 0.141]
σ_{a0}	0.964	[0.722, 1.203]	$\bar{b}_{r4}$	0.036	[-0.088, 0.162]
σ_{a1}	0.453	[0.232, 0.663]	$\bar{b}_{r5}$	0.068	[-0.054, 0.189]
σ_{a2}	0.390	[0.228, 0.550]	σ_{Y0}	0.408	[0.344, 0.478]
σ_{a3}	0.372	[0.227, 0.516]	σ_{Y1}	0.128	[0.095, 0.160]
σ_{a4}	0.436	[0.236, 0.666]	σ_{Y2}	0.062	[0.047, 0.075]
σ_{a5}	0.854	[0.533, 1.168]	σ_{Y3}	0.050	[0.040, 0.060]
σ_{d0}	2.616	[2.012, 3.198]	σ_{Y4}	0.050	[0.040, 0.060]
σ_{d1}	1.321	[0.423, 2.050]	σ_{Y5}	0.071	[0.057, 0.084]
σ_{d2}	0.544	[0.281, 0.802]	$\sigma_{\pi 0}$	0.208	[0.183, 0.230]
σ_{d3}	0.772	[0.572, 0.969]	$\sigma_{\pi 1}$	0.069	[0.059, 0.079]
σ_{d4}	0.439	[0.269, 0.603]	$\sigma_{\pi 2}$	0.048	[0.041, 0.055]
σ_{d5}	0.654	[0.483, 0.825]	$\sigma_{\pi 3}$	0.045	[0.038, 0.051]
σ_{m0}	0.050	[0.043, 0.058]	$\sigma_{\pi 4}$	0.051	[0.044, 0.058]
σ_{m1}	0.057	[0.043, 0.072]	$\sigma_{\pi 5}$	0.051	[0.043, 0.058]
σ_{m2}	0.023	[0.018, 0.028]	σ_{r0}	0.037	[0.031, 0.042]
σ_{m3}	0.021	[0.017, 0.026]	σ_{r1}	0.032	[0.030, 0.035]
σ_{m4}	0.022	[0.017, 0.026]	σ_{r2}	0.031	[0.030, 0.033]
σ_{m5}	0.021	[0.017, 0.025]	σ_{r3}	0.031	[0.030, 0.033]
$\bar{b}_{Y0}$	0.016	[-0.169, 0.197]	σ_{r4}	0.031	[0.030, 0.032]
$\bar{b}_{Y1}$	-0.064	[-0.219, 0.086]	σ_{r5}	0.033	[0.030, 0.036]
$\bar{b}_{Y2}$	-0.014	[-0.149, 0.115]			

Notes: The table shows the posterior mean and the 90 percent credible posterior intervals of parameters. To compute the posterior distribution, 200,000 draws were generated using the Metropolis-Hastings algorithm, and the first half of these draws was discarded.

Table 6: Variance decompositions of output growth, inflation, and interest rate in robustness analysis

	Output growth	Inflation	Interest rate
Unanticipated technology shock	29.02	3.95	7.23
Anticipated technology shocks	36.43	5.07	5.02
Unanticipated demand shock	5.96	37.19	51.64
Anticipated demand shocks	5.67	17.82	24.37
Unanticipated policy shock	0.86	1.97	4.81
Anticipated policy shocks	1.80	6.52	6.51
Measurement or forecast errors	20.24	27.48	0.42

Notes: The table shows the forecast error variance decompositions of the output growth rate, the inflation rate, and the interest rate at an infinite horizon evaluated at the posterior mean estimates of parameters.

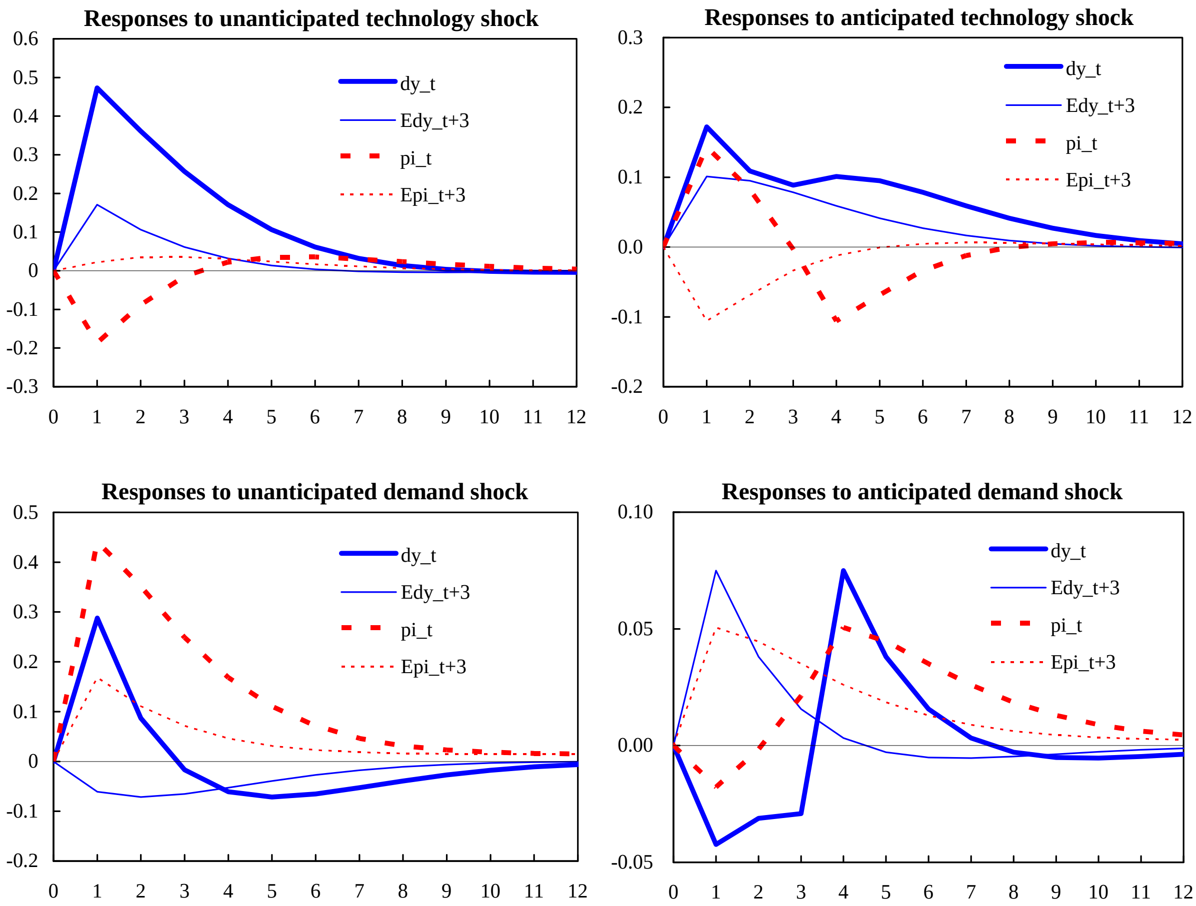

Figure 1: Impulse responses in the baseline estimation

Notes: Each panel shows the impulse responses of $100\Delta \log Y_t$ (dy_t), $100\Delta \log E_t^* Y_{t+3}$ (Edy_t+3), $100 \log \pi_t$ (pi_t), and $100 \log E_t^* \pi_{t+3}$ (Epi_t+3) to each one-standard-deviation shock in terms of percentage deviations from the steady-state rates, evaluated at the posterior mean estimates of parameters in the baseline estimation.