Online Appendix to "Identifying News Shocks with Forecast Data"

Yasuo Hirose* Takushi Kurozumi†

This appendix is organized as follows. Section A presents another example to show that adding expectational variables to the set of observables is informative for identifying news shocks. Section B provides the full description of the model of the paper. Section C shows the estimation results that are mentioned but not reported in the paper.

A Another Illustrative Example

This section provides another example to demonstrate that adding expectational variables to the set of observables is informative for identifying news shocks.

The example in Section 2 of the paper is simple enough to see the basic idea of our approach for identifying news shocks. In the empirical analysis presented in the subsequent sections of the paper, 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. To analyze the role of observed expectational variables in the identification of news shocks with longer forecast horizon, the model presented in Section 2 is extended to

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

$$\varepsilon_t = \rho\varepsilon_{t-1} + \nu_{0,t} + \nu_{1,t-1} + \nu_{2,t-2} + \nu_{3,t-3} + \nu_{4,t-4} + \nu_{5,t-5}, \tag{A.2}$$

*Keio University, 2-15-45 Mita, Minato-ku, Tokyo, 108-8345, Japan, yhirose@econ.keio.ac.jp.

†Bank of Japan, 2-1-1 Nihonbashi-Hongokucho, Chuo-ku, Tokyo, 103-8660, Japan, takushi.kurozumi@boj.or.jp.

‡Supplement DOI: https://doi.org/10.24149/gwp366supp

where ρ is the persistence parameter and $\nu_{n,t-n}$, $n = 1, 2, \ldots, 5$ are news shocks that are anticipated in period $t - n$ to materialize in period t. All the shocks $\nu_{n,t-n}$, $n = 0, 1, \ldots, 5$ are assumed to be mutually and serially uncorrelated and be normally distributed with mean zero and standard deviation σ_n. Because it is no longer easy to show analytically how these shocks can be identified, we conduct Monte Carlo experiments.

The experiments proceed as follows. First, artificial time series of the current and expectational variables, $\{y_t, E_t y_{t+1}, E_t y_{t+2}, ..., E_t y_{t+5}\}_{t=0}^T$, are generated using the rational expectations solution to the model that consists of (A.1) and (A.2), given the parameter values: $\theta = 2$, $\rho = 0.5$, and $\sigma_n = 1$, $n = 0, 1, \ldots, 5$. The sample size is set equal to $T = 200$ observations, which correspond to quarterly observations for 50 years.[1] Second, the model is estimated using the series of all the variables, $\{y_t, E_t y_{t+1}, E_t y_{t+2}, ..., E_t y_{t+5}\}_{t=0}^T$ and using only the series of the current variable, $\{y_t\}_{t=0}^T$. In the estimation, Bayesian methods are employed. The prior distributions for θ and ρ are set to be the normal distributions with, respectively, mean 2 and 0.5 and standard deviation 1 and 0.25, while those for σ_n, $n = 0, 1, \ldots, 5$ are chosen to be the inverse gamma distributions with mean 1 and standard deviation 0.5. Posterior modes are then obtained using a numerical optimization routine. These steps are replicated for 500 times, and posterior modes and standard deviations at the modes are averaged over the replications.

Table A.1 reports the results of the Monte Carlo experiments. The second column of the table presents the true values of parameters in the extended model, and the third column displays the averages of the posterior modes when the expectational variables $E_t y_{t+n}$, $n = 1, 2, \ldots, 5$ are included in the set of observables in addition to the current variable y_t. These two columns are almost the same, and the fourth column shows that the averages of the standard deviations at the posterior modes are very small. By contrast, the last two columns indicate that, in the absence of the expectational variables in the set of observables, the averages of the posterior modes are biased and that those of the standard deviations at the modes are substantially larger. These results suggest that adding expectational variables to

[1]The simulation is carried out for 250 periods and the first 50 observations are discarded.

the set of observables is considerably helpful in identifying news shocks.

B Full Description of the Model

This section provides the full description of the model presented in Section 3 of the paper.

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

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

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, $b \in [0,1]$ represents the degree of (external) habit persistence in consumption preferences, $\eta > 0$ is the inverse of the elasticity of labor supply, C_t is aggregate consumption of final goods, z_t^d is a preference shock, P_t is the price of final goods, W_t is the real wage, r_t is the (gross) interest rate, 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

$$\Lambda_t = \frac{\exp(z_t^d)}{C_t - bC_{t-1}}, \tag{A.3}$$

$$W_t = \frac{l_t^{\eta} \exp(z_t^d)}{\Lambda_t}, \tag{A.4}$$

$$1 = E_t \beta \frac{\Lambda_{t+1}}{\Lambda_t} \frac{r_t}{\pi_{t+1}}, \tag{A.5}$$

where Λ_t is the marginal utility of consumption, l_t is aggregate labor (supply), and $\pi_t = P_t/P_{t-1}$ denotes the (gross) inflation rate.

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 the 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 given by

$$Y_{f,t} = Y_t \left(\frac{P_{f,t}}{P_t} \right)^{-(1+\lambda^p)/\lambda^p}.$$

Then, the CES production technology 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 $l_{f,t}$, 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 the log of A_t follows the non-stationary stochastic process

$$\log A_t = \log \gamma + \log A_{t-1} + z_t^a, \tag{A.6}$$

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

$$mc_t = \frac{W_t}{A_t}. \tag{A.7}$$

In the face of the final-good firm's demand curve 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 firms reoptimizes prices, while the remaining fraction ξ indexes prices to a weighted average of the past inflation rate π_{t-1} and the steady-state inflation rate π. Then, firms that reoptimize prices in the current period maximize related expected profit

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

subject to the final-good firm's demand curve

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

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

$$E_t \sum_{j=0}^{\infty} \left\{ \begin{array}{l} (\beta\xi)^j \dfrac{\Lambda_{t+j}}{\Lambda_t} Y_{t+j} \left[\dfrac{P_t^o}{P_t} \displaystyle\prod_{k=1}^{j} \left(\dfrac{\pi_{t+k-1}}{\pi} \right)^{\iota} \dfrac{\pi}{\pi_{t+k}} \right]^{-(1+\lambda^p)/\lambda^p} \\ \times \left[\dfrac{P_t^o}{P_t} \displaystyle\prod_{k=1}^{j} \left(\dfrac{\pi_{t+k-1}}{\pi} \right)^{\iota} \dfrac{\pi}{\pi_{t+k}} - (1+\lambda^p)\, mc_{t+j} \right] \end{array} \right\} = 0. \tag{A.8}$$

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

$$1 = (1-\xi) \left(\frac{P_t^o}{P_t} \right)^{-\frac{1}{\lambda^p}} + \xi \left[\left(\frac{\pi_{t-1}}{\pi} \right)^{\iota} \frac{\pi}{\pi_t} \right]^{-\frac{1}{\lambda^p}}. \tag{A.9}$$

The final-good market clearing condition is

$$Y_t = C_t, \tag{A.10}$$

while the labor market clearing condition leads to

$$l_t = \int_0^1 l_{f,t} df = \int_0^1 \frac{Y_{f,t}}{A_t} df = \frac{1}{A_t} \int_0^1 Y_t \left(\frac{P_{f,t}}{P_t} \right)^{-\frac{1+\lambda^p}{\lambda^p}} df = \frac{Y_t d_t}{A_t}, \tag{A.11}$$

where $d_t = \int_0^1 (P_{f,t}/P_t)^{-(1+\lambda^p)/\lambda^p} df$ represents relative price distortion. The staggered price-setting then yields

$$d_t = (1-\xi) \left(\frac{P_t^o}{P_t} \right)^{-\frac{1+\lambda^p}{\lambda^p}} + \xi \left[\left(\frac{\pi_{t-1}}{\pi} \right)^{\iota} \frac{\pi}{\pi_t} \right]^{-\frac{1+\lambda^p}{\lambda^p}} d_{t-1}. \tag{A.12}$$

Note that the relative price distortion is of second order and its steady-state value is unity.

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

$$\log r_t = \phi_r \log r_{t-1} + (1 - \phi_r)\left(\log r + \phi_\pi \log \frac{\pi_t}{\pi} + \phi_y \log \frac{Y_t/A_t}{y}\right) + z_t^m, \tag{A.13}$$

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 monetary policy responses to inflation and (detrended) output.

The equilibrium conditions are given by (A.3)–(A.13). These conditions are rewritten in terms of 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 (5)–(7) of the paper.

C Estimation Results that Are Mentioned But Not Reported in the Paper

This section presents the estimation results that are mentioned but not reported in the paper.

C.1 Baseline estimation

This subsection provides supplementary materials regarding the baseline estimation.

Figures A.1 and A.2 graph the prior and posterior distributions for each estimated parameter of the model in the baseline estimation. In each panel of the figures, the grey and black solid lines respectively represent the prior and posterior distributions, while the green dashed line indicates the posterior mode. Moreover, for each of the model parameters, Figures A.3–A.8 show the MCMC univariate convergence diagnostics and demonstrate that each measure tends to be stable toward the end of each chain.

The forecast error variance decompositions at the horizon of 4, 8, and 16 quarters as well as the infinite horizon are reported in Tables A.2–A.5. These decompositions are not qualitatively different from the spectrum decompositions at the business cycle frequency of 6–32 quarters displayed in Table 3 of the paper.

C.2 Estimation with gamma distributions for priors of standard deviations of shock innovations

This subsection reports the results of the estimation in which gamma distributions are employed for the priors of the standard deviations of all the shock innovations instead of the inverse gamma distributions used in the baseline estimation, following Schmitt-Grohé and Uribe (2012), as mentioned in footnote 18 in Section 4.2 of the paper. Specifically, as presented in the second to fourth columns of Table A.6, the prior mean of each shock innovation's standard deviation is the same as in the baseline estimation but its prior standard deviation is set at the value of its prior mean. Then, each parameter's posterior mean and 90 percent credible interval are reported in the fifth and sixth columns of the table. They are very close to their counterparts in the baseline estimation shown in the last two columns of the table. As a consequence, the variance decompositions are also very close. The second to fourth columns of Table A.7 report the relative contribution of each shock innovation to the variances of the output growth rate $\Delta \log Y_t$, the inflation rate $\log \pi_t$, and the interest rate $\log r_t$ at the business cycle frequency of 6–32 quarters, evaluated at the posterior mean of model parameters in the estimation with the gamma distributions. The results are very close to their counterparts in the fifth to seventh columns, that is, in the baseline estimation. Therefore, the main results obtained in the baseline estimation still hold in the estimation with the gamma distributions.

C.3 Estimation with revised actual data and forecast data

This subsection presents the results of the estimation with the revised actual data as well as the forecast data mentioned in Section 5.1 of the paper. The second and third columns of Table A.8 report each parameter's posterior mean and 90 percent credible interval in the estimation, while the fourth and fifth columns show those in the baseline estimation (i.e., the estimation with the real-time actual data and the forecast data). As noted in the paper, the posterior mean of each parameter is similar and its credible interval overlaps between the estimation with the revised actual data and the baseline estimation.

Regarding the source of fluctuations in U.S. output growth, the third to last column of Table A.7 reports the variance decomposition of the output growth rate $\Delta \log Y_t$ in the estimation with the revised actual data (and the forecast data). In line with the baseline estimation, the technology news shocks $\nu^a_{n,t-n}$, $n = 1, 2, ..., 5$ are a major source of fluctuations of U.S. output growth; they explain nearly half of the fluctuations (42 percent). In particular, the one-quarter ahead one $\nu^a_{1,t-1}$ plays a crucial role in accounting for the fluctuations (28 percent).

References

[1] Calvo, Guillermo A. (1983) "Staggered Prices in a Utility-Maximizing Framework." *Journal of Monetary Economics*, 12(3), 383–398. https://doi.org/10.1016/0304-932(83)90060-0

[2] Jeffreys, Harold. (1961) *The Theory of Probability*. Oxford, UK: Oxford University Press.

[3] Schmitt-Grohé, Stephanie, and Martín Uribe. (2012) "What's News in Business Cycles." *Econometrica*, 80(6), 2733–2764. https://doi.org/10.3982/ecta8050

[4] Taylor, John B. (1993) "Discretion Versus Policy Rules in Practice." *Carnegie-Rochester Conference Series on Public Policy*, 39(1), 195–214. https://doi.org/10.1016/0167-2231(93)90009-l

Table A.1: Posterior Estimates of Parameters in the Monte Carlo Experiments

Parameter	True value	With $E_t y_{t+n}$		Without $E_t y_{t+n}$	
		Mode	Std.	Mode	Std.
θ	2.000	2.005	0.167	1.308	0.375
ρ	0.500	0.498	0.033	0.383	0.171
σ_0	1.000	0.988	0.056	0.908	0.281
σ_1	1.000	0.993	0.049	0.935	0.249
σ_2	1.000	0.994	0.049	0.800	0.253
σ_3	1.000	0.990	0.049	0.745	0.235
σ_4	1.000	0.989	0.049	0.728	0.227
σ_5	1.000	0.992	0.054	0.723	0.224

Notes: This table shows each parameter's averages of posterior modes and standard deviations at the modes in the Monte Carlo experiments. The third and fourth columns of the table report the posterior estimates in the case where the expectational variables $E_t y_{t+n}$, $n = 1, 2, \ldots, 5$ are included in the set of observables in addition to the current variable y_t. The fifth and sixth columns display those in the case where the expectational variables are not included.

Table A.2: Forecast error variance decompositions at the horizon of 4 quarters

	Prior			Baseline			No forecast data			No inflation forecast data		
Shock	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$
$\nu^a_{0,t}$	74.8	0.9	0.8	34.9	4.1	4.8	35.1	2.6	8.3	23.4	2.8	7.1
$\nu^a_{1,t-1}$	9.6	6.1	3.0	30.2	2.5	1.7	6.2	0.3	0.5	1.8	0.2	0.3
$\nu^a_{2,t-2}$	5.9	13.6	10.5	5.9	1.6	0.4	5.7	0.5	0.3	1.6	0.1	0.1
$\nu^a_{3,t-3}$	2.7	16.5	18.9	4.4	3.6	2.3	4.3	1.2	1.5	1.2	0.1	0.0
$\nu^a_{4,t-4}$	0.7	16.7	24.6	4.0	6.5	8.1	3.9	2.8	4.3	1.2	0.1	0.1
$\nu^a_{5,t-5}$	0.5	16.3	23.7	1.7	5.4	7.7	3.3	5.4	7.5	1.6	0.2	0.2
$\nu^d_{0,t}$	2.6	7.4	6.8	7.1	38.4	56.3	3.9	5.3	7.4	32.5	29.3	23.4
$\nu^d_{1,t-1}$	0.7	1.2	1.3	5.5	6.5	8.5	28.1	35.8	41.4	22.3	22.3	15.3
$\nu^d_{2,t-2}$	0.7	1.3	0.9	0.9	0.5	0.4	2.3	2.4	2.2	2.4	2.5	1.5
$\nu^d_{3,t-3}$	0.6	1.2	0.4	0.7	0.3	0.1	1.6	1.3	0.9	1.2	1.5	0.8
$\nu^d_{4,t-4}$	0.1	0.2	0.1	0.2	0.1	0.1	0.2	0.5	0.3	0.2	0.8	0.4
$\nu^d_{5,t-5}$	0.0	0.1	0.1	0.1	0.2	0.2	0.3	0.4	0.2	0.2	0.6	0.3
$\nu^m_{0,t}$	0.9	9.1	0.4	1.3	7.0	1.3	2.3	11.6	5.1	2.3	8.0	20.6
$\nu^m_{1,t-1}$	0.1	2.1	0.6	2.6	17.2	1.9	1.0	6.3	0.7	6.1	22.7	25.6
$\nu^m_{2,t-2}$	0.1	2.2	1.4	0.3	2.2	0.9	0.6	5.1	1.4	1.0	4.1	1.7
$\nu^m_{3,t-3}$	0.1	2.0	2.1	0.1	1.1	1.0	0.4	5.2	3.5	0.4	1.6	0.5
$\nu^m_{4,t-4}$	0.1	1.7	2.5	0.1	1.6	2.3	0.4	7.2	8.0	0.3	1.7	1.1
$\nu^m_{5,t-5}$	0.0	1.4	2.0	0.1	1.4	2.0	0.3	6.2	6.7	0.3	1.6	1.0

Note: This table shows the forecast error variance decompositions of the output growth rate $\Delta \log Y_t$, the inflation rate $\log \pi_t$, and the interest rate $\log r_t$ at the forecast horizon of 4 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 A.3: Forecast error variance decompositions at the horizon of 8 quarters

	Prior			Baseline			No forecast data			No inflation forecast data		
Shock	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$
$\nu^a_{0,t}$	56.4	0.8	1.0	32.0	3.9	2.7	33.6	2.2	8.1	29.6	2.2	8.8
$\nu^a_{1,t-1}$	8.2	5.4	2.7	28.4	2.3	1.3	6.2	0.3	0.9	2.3	0.2	0.5
$\nu^a_{2,t-2}$	7.5	12.3	9.2	5.9	1.5	0.3	6.0	0.5	0.5	2.0	0.1	0.3
$\nu^a_{3,t-3}$	7.8	16.4	16.5	5.2	3.7	1.2	5.0	1.3	0.9	1.6	0.1	0.1
$\nu^a_{4,t-4}$	7.8	17.6	22.7	6.0	8.5	4.0	4.9	2.9	2.5	1.7	0.2	0.1
$\nu^a_{5,t-5}$	7.1	17.5	27.6	3.0	7.0	4.5	4.4	5.2	5.7	2.2	0.4	0.1
$\nu^d_{0,t}$	1.9	6.6	5.9	7.2	35.6	65.3	3.7	4.5	7.6	26.3	25.7	29.2
$\nu^d_{1,t-1}$	0.5	1.1	1.1	5.0	6.6	13.1	24.7	31.6	49.7	18.7	20.3	20.8
$\nu^d_{2,t-2}$	0.5	1.2	1.1	0.8	0.7	1.1	2.0	2.3	3.5	2.3	2.5	2.3
$\nu^d_{3,t-3}$	0.5	1.3	1.1	0.7	0.7	0.7	1.6	1.7	2.2	1.7	1.7	1.5
$\nu^d_{4,t-4}$	0.5	1.3	1.1	0.6	0.6	0.4	1.4	1.2	1.4	1.3	1.2	0.9
$\nu^d_{5,t-5}$	0.5	1.3	1.1	0.6	0.7	0.3	2.2	1.8	1.5	1.4	1.3	0.8
$\nu^m_{0,t}$	0.7	7.9	0.3	1.4	6.3	0.6	2.1	11.3	2.8	2.0	8.8	11.1
$\nu^m_{1,t-1}$	0.1	1.9	0.5	2.7	15.8	0.9	0.9	6.3	0.5	5.2	25.1	19.4
$\nu^m_{2,t-2}$	0.1	1.9	1.2	0.3	2.1	0.4	0.5	5.3	0.7	0.9	4.6	2.2
$\nu^m_{3,t-3}$	0.0	1.9	1.8	0.1	1.1	0.5	0.4	5.7	1.7	0.3	1.8	0.6
$\nu^m_{4,t-4}$	0.0	1.9	2.3	0.1	1.5	1.1	0.4	8.3	4.3	0.3	2.0	0.6
$\nu^m_{5,t-5}$	0.0	1.8	2.7	0.1	1.4	1.4	0.3	7.6	5.7	0.3	1.8	0.6

Note: This table shows the forecast error variance decompositions of the output growth rate $\Delta \log Y_t$, the inflation rate $\log \pi_t$, and the interest rate $\log r_t$ at the forecast horizon of 8 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 A.4: Forecast error variance decompositions at the horizon of 16 quarters

	Prior			Baseline			No forecast data			No inflation forecast data		
Shock	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$
$\nu^a_{0,t}$	55.2	0.8	1.0	31.6	3.9	1.8	32.3	2.2	7.5	31.0	2.6	9.6
$\nu^a_{1,t-1}$	8.1	5.4	2.7	28.1	2.3	0.9	6.0	0.3	0.9	2.5	0.2	0.7
$\nu^a_{2,t-2}$	7.4	12.3	9.1	5.9	1.5	0.2	5.9	0.5	0.6	2.2	0.1	0.5
$\nu^a_{3,t-3}$	7.7	16.3	16.4	5.2	3.7	0.8	5.1	1.3	0.9	1.8	0.1	0.3
$\nu^a_{4,t-4}$	8.1	17.6	22.7	6.2	8.5	2.7	5.2	2.9	2.4	2.0	0.2	0.3
$\nu^a_{5,t-5}$	8.3	17.5	27.7	3.4	7.0	3.0	5.2	5.3	5.1	2.7	0.4	0.3
$\nu^d_{0,t}$	1.9	6.6	5.9	7.2	35.5	67.4	3.7	4.4	7.3	25.7	24.6	34.1
$\nu^d_{1,t-1}$	0.5	1.1	1.1	5.0	6.7	15.3	24.6	31.1	50.3	17.8	19.4	25.7
$\nu^d_{2,t-2}$	0.5	1.2	1.1	0.8	0.7	1.6	2.0	2.3	3.8	2.1	2.4	3.1
$\nu^d_{3,t-3}$	0.5	1.3	1.1	0.7	0.7	1.3	1.6	1.6	2.8	1.5	1.7	2.2
$\nu^d_{4,t-4}$	0.5	1.3	1.2	0.6	0.7	1.0	1.4	1.2	2.1	1.1	1.2	1.6
$\nu^d_{5,t-5}$	0.5	1.3	1.2	0.6	0.8	1.0	2.2	1.9	3.1	1.3	1.3	1.6
$\nu^m_{0,t}$	0.7	7.9	0.3	1.4	6.3	0.4	2.2	11.2	2.4	1.8	9.1	6.2
$\nu^m_{1,t-1}$	0.1	1.9	0.5	2.7	15.7	0.6	0.9	6.3	0.4	4.8	26.1	11.4
$\nu^m_{2,t-2}$	0.1	1.9	1.2	0.3	2.1	0.3	0.6	5.3	0.6	0.8	4.8	1.4
$\nu^m_{3,t-3}$	0.0	1.9	1.8	0.1	1.1	0.3	0.4	5.7	1.5	0.3	1.9	0.4
$\nu^m_{4,t-4}$	0.0	1.9	2.3	0.1	1.5	0.7	0.5	8.5	3.6	0.3	2.1	0.4
$\nu^m_{5,t-5}$	0.0	1.8	2.7	0.1	1.4	0.9	0.3	8.0	4.8	0.2	2.0	0.4

Note: This table shows the forecast error variance decompositions of the output growth rate $\Delta \log Y_t$, the inflation rate $\log \pi_t$, and the interest rate $\log r_t$ at the forecast horizon of 16 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 A.5: Forecast error variance decompositions at the infinite horizon

	Prior			Baseline			No forecast data			No inflation forecast data		
Shock	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$
$\nu^a_{0,t}$	55.2	0.8	1.0	31.6	3.9	1.5	32.3	2.2	7.5	30.2	3.0	9.3
$\nu^a_{1,t-1}$	8.1	5.4	2.7	28.1	2.3	0.7	6.0	0.3	0.9	2.4	0.2	0.7
$\nu^a_{2,t-2}$	7.4	12.3	9.1	5.9	1.5	0.2	5.9	0.5	0.6	2.2	0.2	0.5
$\nu^a_{3,t-3}$	7.7	16.3	16.4	5.2	3.6	0.6	5.1	1.3	0.9	1.8	0.2	0.4
$\nu^a_{4,t-4}$	8.1	17.6	22.7	6.2	8.5	2.2	5.2	2.9	2.4	2.0	0.2	0.3
$\nu^a_{5,t-5}$	8.3	17.5	27.7	3.4	7.0	2.5	5.2	5.3	5.1	2.8	0.4	0.4
$\nu^d_{0,t}$	1.9	6.6	5.9	7.2	35.6	67.9	3.7	4.4	7.3	25.8	25.1	34.9
$\nu^d_{1,t-1}$	0.5	1.1	1.1	5.0	6.7	15.9	24.6	31.1	50.2	17.9	19.8	26.7
$\nu^d_{2,t-2}$	0.5	1.2	1.1	0.8	0.7	1.7	2.0	2.3	3.8	2.1	2.4	3.3
$\nu^d_{3,t-3}$	0.5	1.3	1.1	0.7	0.7	1.5	1.6	1.6	2.8	1.5	1.7	2.4
$\nu^d_{4,t-4}$	0.5	1.3	1.2	0.6	0.7	1.2	1.4	1.2	2.1	1.2	1.2	1.8
$\nu^d_{5,t-5}$	0.5	1.3	1.2	0.6	0.8	1.3	2.2	1.9	3.2	1.3	1.3	2.0
$\nu^m_{0,t}$	0.7	7.9	0.3	1.4	6.3	0.3	2.2	11.1	2.4	1.9	8.8	5.3
$\nu^m_{1,t-1}$	0.1	1.9	0.5	2.7	15.7	0.5	0.9	6.3	0.4	5.2	25.2	9.8
$\nu^m_{2,t-2}$	0.1	1.9	1.2	0.3	2.0	0.2	0.6	5.3	0.6	0.9	4.6	1.2
$\nu^m_{3,t-3}$	0.0	1.9	1.8	0.1	1.1	0.3	0.4	5.7	1.5	0.3	1.8	0.4
$\nu^m_{4,t-4}$	0.0	1.9	2.3	0.1	1.5	0.6	0.5	8.5	3.6	0.3	2.0	0.4
$\nu^m_{5,t-5}$	0.0	1.8	2.7	0.1	1.4	0.8	0.3	8.0	4.8	0.3	1.9	0.4

Note: This table shows the forecast error variance decompositions of the output growth rate $\Delta \log Y_t$, the inflation rate $\log \pi_t$, and the interest rate $\log r_t$ at the infinite forecast horizon, 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 A.6: Prior distributions and posterior estimates of model parameters in the estimation with gamma distributions for priors of the standard deviations of shock innovations

	Prior			Posterior		Posterior (Baseline)	
Parameter	Distribution	Mean	Std.	Mean	90% interval	Mean	90% interval
η	Gamma	2.000	0.200	2.114	[1.792, 2.446]	2.097	[1.795, 2.376]
b	Beta	0.700	0.150	0.735	[0.705, 0.764]	0.729	[0.699, 0.758]
ι	Beta	0.500	0.100	0.057	[0.047, 0.069]	0.058	[0.047, 0.071]
ξ	Beta	0.500	0.100	0.777	[0.757, 0.797]	0.769	[0.750, 0.789]
ϕ_r	Beta	0.750	0.100	0.915	[0.905, 0.925]	0.912	[0.902, 0.923]
ϕ_π	Gamma	1.500	0.200	1.560	[1.387, 1.725]	1.630	[1.445, 1.804]
ϕ_y	Gamma	0.125	0.050	0.014	[0.005, 0.023]	0.016	[0.006, 0.025]
$\bar{\gamma}$	Gamma	0.470	0.100	0.385	[0.338, 0.430]	0.386	[0.340, 0.430]
$\bar{\pi}$	Gamma	0.640	0.100	0.755	[0.699, 0.804]	0.760	[0.708, 0.810]
$\bar{r}$	Gamma	1.230	0.100	1.570	[1.473, 1.675]	1.565	[1.458, 1.665]
ρ_a	Beta	0.500	0.100	0.058	[0.047, 0.071]	0.059	[0.047, 0.072]
ρ_d	Beta	0.500	0.100	0.937	[0.925, 0.950]	0.938	[0.927, 0.952]
ρ_m	Beta	0.500	0.100	0.438	[0.400, 0.478]	0.436	[0.397, 0.476]
σ_{a0}	Gamma	2.000	2.000	1.468	[1.214, 1.725]	1.388	[1.153, 1.615]
σ_{a1}	Gamma	0.894	0.894	1.510	[1.211, 1.801]	1.408	[1.147, 1.663]
σ_{a2}	Gamma	0.894	0.894	0.761	[0.616, 0.904]	0.714	[0.581, 0.845]
σ_{a3}	Gamma	0.894	0.894	0.794	[0.629, 0.950]	0.740	[0.599, 0.883]
σ_{a4}	Gamma	0.894	0.894	0.933	[0.761, 1.112]	0.873	[0.712, 1.028]
σ_{a5}	Gamma	0.894	0.894	0.720	[0.592, 0.846]	0.679	[0.565, 0.796]
σ_{d0}	Gamma	2.000	2.000	2.728	[2.335, 3.100]	2.660	[2.273, 3.017]
σ_{d1}	Gamma	0.894	0.894	1.343	[1.120, 1.575]	1.303	[1.078, 1.522]
σ_{d2}	Gamma	0.894	0.894	0.447	[0.376, 0.519]	0.438	[0.370, 0.509]
σ_{d3}	Gamma	0.894	0.894	0.408	[0.343, 0.467]	0.404	[0.341, 0.463]
σ_{d4}	Gamma	0.894	0.894	0.371	[0.318, 0.427]	0.368	[0.315, 0.421]
σ_{d5}	Gamma	0.894	0.894	0.375	[0.324, 0.426]	0.373	[0.324, 0.422]
σ_{m0}	Gamma	0.250	0.250	0.045	[0.040, 0.050]	0.050	[0.044, 0.056]
σ_{m1}	Gamma	0.112	0.112	0.076	[0.067, 0.084]	0.075	[0.066, 0.083]
σ_{m2}	Gamma	0.112	0.112	0.025	[0.022, 0.028]	0.026	[0.023, 0.029]
σ_{m3}	Gamma	0.112	0.112	0.016	[0.014, 0.018]	0.019	[0.016, 0.021]
σ_{m4}	Gamma	0.112	0.112	0.020	[0.018, 0.022]	0.022	[0.019, 0.024]
σ_{m5}	Gamma	0.112	0.112	0.019	[0.016, 0.021]	0.021	[0.018, 0.023]

Notes: This table shows each parameter's prior distribution and its posterior mean and 90 percent credible interval in the estimation with gamma distributions for priors of the standard deviations of all the shock innovations as well as the baseline estimation. To compute the posterior distribution, 200,000 draws were generated using the Metropolis-Hastings algorithm, and the first half of the draws was discarded.

Table A.7: Variance decompositions in the estimation with gamma distributions for priors of the standard deviations of shock innovations and in the estimation with the revised actual data and the forecast data

	Gamma distribution			Baseline			Revised actual data		
Shock	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$	$\Delta \log Y_t$	$\log \pi_t$	$\log r_t$
$\nu^a_{0,t}$	33.9	4.2	4.6	34.8	4.1	4.5	41.7	5.2	5.7
$\nu^a_{1,t-1}$	30.9	2.3	2.3	30.7	2.1	2.1	27.5	1.9	2.0
$\nu^a_{2,t-2}$	5.9	1.0	0.6	5.8	1.1	0.7	5.4	1.1	0.7
$\nu^a_{3,t-3}$	4.4	3.7	2.5	4.2	3.9	2.7	3.8	4.0	2.8
$\nu^a_{4,t-4}$	4.1	10.7	8.4	4.1	11.2	9.1	3.6	11.3	9.4
$\nu^a_{5,t-5}$	2.0	9.6	8.9	2.1	10.0	9.5	1.8	10.1	9.8
$\nu^d_{0,t}$	8.8	33.4	50.5	8.0	31.6	48.4	7.0	30.2	47.2
$\nu^d_{1,t-1}$	1.9	6.6	10.8	1.9	6.1	10.1	1.5	5.6	9.4
$\nu^d_{2,t-2}$	0.5	0.6	1.1	0.6	0.6	1.1	0.5	0.6	1.0
$\nu^d_{3,t-3}$	0.7	0.6	1.0	0.8	0.7	1.0	0.6	0.6	1.0
$\nu^d_{4,t-4}$	0.6	0.6	0.9	0.7	0.8	1.1	0.6	0.7	1.0
$\nu^d_{5,t-5}$	0.6	0.8	1.2	0.7	1.0	1.4	0.6	0.9	1.4
$\nu^m_{0,t}$	1.4	5.1	1.1	1.6	6.1	1.2	1.4	6.2	1.3
$\nu^m_{1,t-1}$	3.7	16.0	0.9	3.4	15.3	0.8	3.2	16.0	0.9
$\nu^m_{2,t-2}$	0.3	1.8	0.6	0.3	2.0	0.7	0.3	2.0	0.7
$\nu^m_{3,t-3}$	0.1	0.8	0.7	0.1	1.0	0.9	0.1	1.0	0.9
$\nu^m_{4,t-4}$	0.1	1.2	1.8	0.1	1.4	2.1	0.1	1.4	2.2
$\nu^m_{5,t-5}$	0.1	1.0	2.2	0.1	1.2	2.6	0.1	1.2	2.8

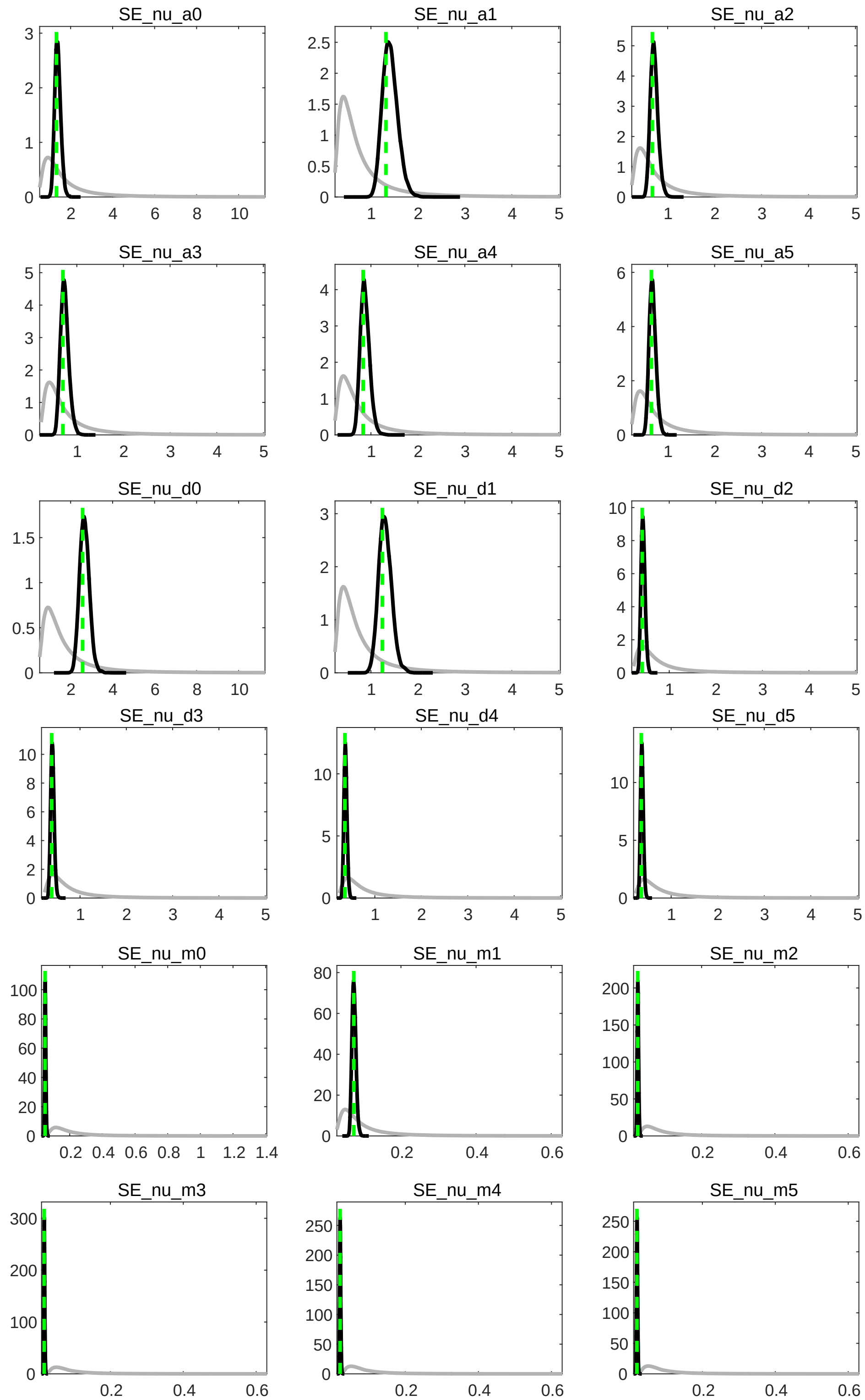
Note: This table shows the variance decompositions of the output growth rate $\Delta \log Y_t$, the inflation rate $\log \pi_t$, and the interest rate $\log r_t$ at the business cycle frequency of 6–32 quarters, evaluated at the posterior mean of model parameters in the estimation with gamma distributions for priors of the standard deviations of all the shock innovations, in the baseline estimation, and in the estimation with the revised actual data and the forecast data.

Table A.8: Posterior estimates of model parameters in the estimation with the revised actual data and the forecast data

	Revised actual data		Baseline	
Parameter	Mean	90% interval	Mean	90% interval
η	2.232	[1.904, 2.554]	2.097	[1.795, 2.376]
b	0.714	[0.685, 0.744]	0.729	[0.699, 0.758]
ι	0.057	[0.047, 0.068]	0.058	[0.047, 0.071]
ξ	0.777	[0.757, 0.797]	0.769	[0.750, 0.789]
ϕ_r	0.911	[0.900, 0.922]	0.912	[0.902, 0.923]
ϕ_π	1.584	[1.408, 1.760]	1.630	[1.445, 1.804]
ϕ_y	0.015	[0.005, 0.024]	0.016	[0.006, 0.025]
$\bar{\gamma}$	0.386	[0.341, 0.432]	0.386	[0.340, 0.430]
$\bar{\pi}$	0.761	[0.710, 0.812]	0.760	[0.708, 0.810]
$\bar{r}$	1.562	[1.461, 1.669]	1.565	[1.458, 1.665]
ρ_a	0.057	[0.047, 0.069]	0.059	[0.047, 0.072]
ρ_d	0.937	[0.925, 0.950]	0.938	[0.927, 0.952]
ρ_m	0.436	[0.396, 0.477]	0.436	[0.397, 0.476]
σ_{a0}	1.639	[1.377, 1.886]	1.388	[1.153, 1.615]
σ_{a1}	1.440	[1.155, 1.705]	1.408	[1.147, 1.663]
σ_{a2}	0.739	[0.606, 0.876]	0.714	[0.581, 0.845]
σ_{a3}	0.764	[0.610, 0.912]	0.740	[0.599, 0.883]
σ_{a4}	0.895	[0.731, 1.056]	0.873	[0.712, 1.028]
σ_{a5}	0.692	[0.571, 0.808]	0.679	[0.565, 0.796]
σ_{d0}	2.514	[2.151, 2.870]	2.660	[2.273, 3.017]
σ_{d1}	1.201	[0.994, 1.397]	1.303	[1.078, 1.522]
σ_{d2}	0.416	[0.351, 0.477]	0.438	[0.370, 0.509]
σ_{d3}	0.384	[0.330, 0.439]	0.404	[0.341, 0.463]
σ_{d4}	0.353	[0.305, 0.403]	0.368	[0.315, 0.421]
σ_{d5}	0.363	[0.316, 0.410]	0.373	[0.324, 0.422]
σ_{m0}	0.050	[0.044, 0.056]	0.050	[0.044, 0.056]
σ_{m1}	0.076	[0.067, 0.084]	0.075	[0.066, 0.083]
σ_{m2}	0.026	[0.023, 0.029]	0.026	[0.023, 0.029]
σ_{m3}	0.019	[0.016, 0.021]	0.019	[0.016, 0.021]
σ_{m4}	0.022	[0.019, 0.024]	0.022	[0.019, 0.024]
σ_{m5}	0.021	[0.018, 0.024]	0.021	[0.018, 0.023]

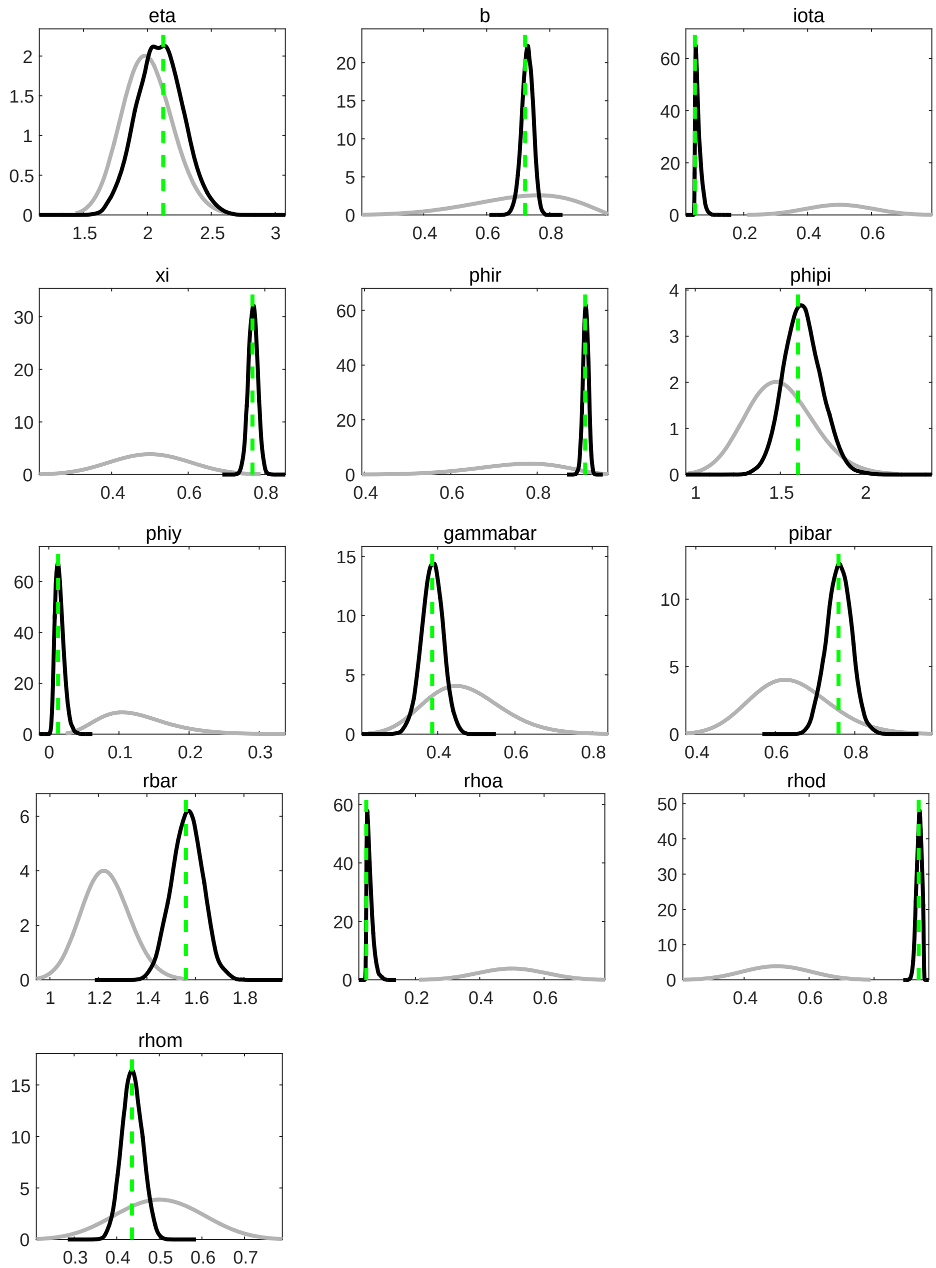
Notes: This table shows each parameter's posterior mean and 90 percent credible interval in the estimation with the revised actual data and the forecast data and in the baseline estimation. To compute the posterior distribution, 200,000 draws were generated using the Metropolis-Hastings algorithm, and the first half of the draws was discarded.

Figure A.1: Prior and posterior distributions for model parameters in the baseline estimation



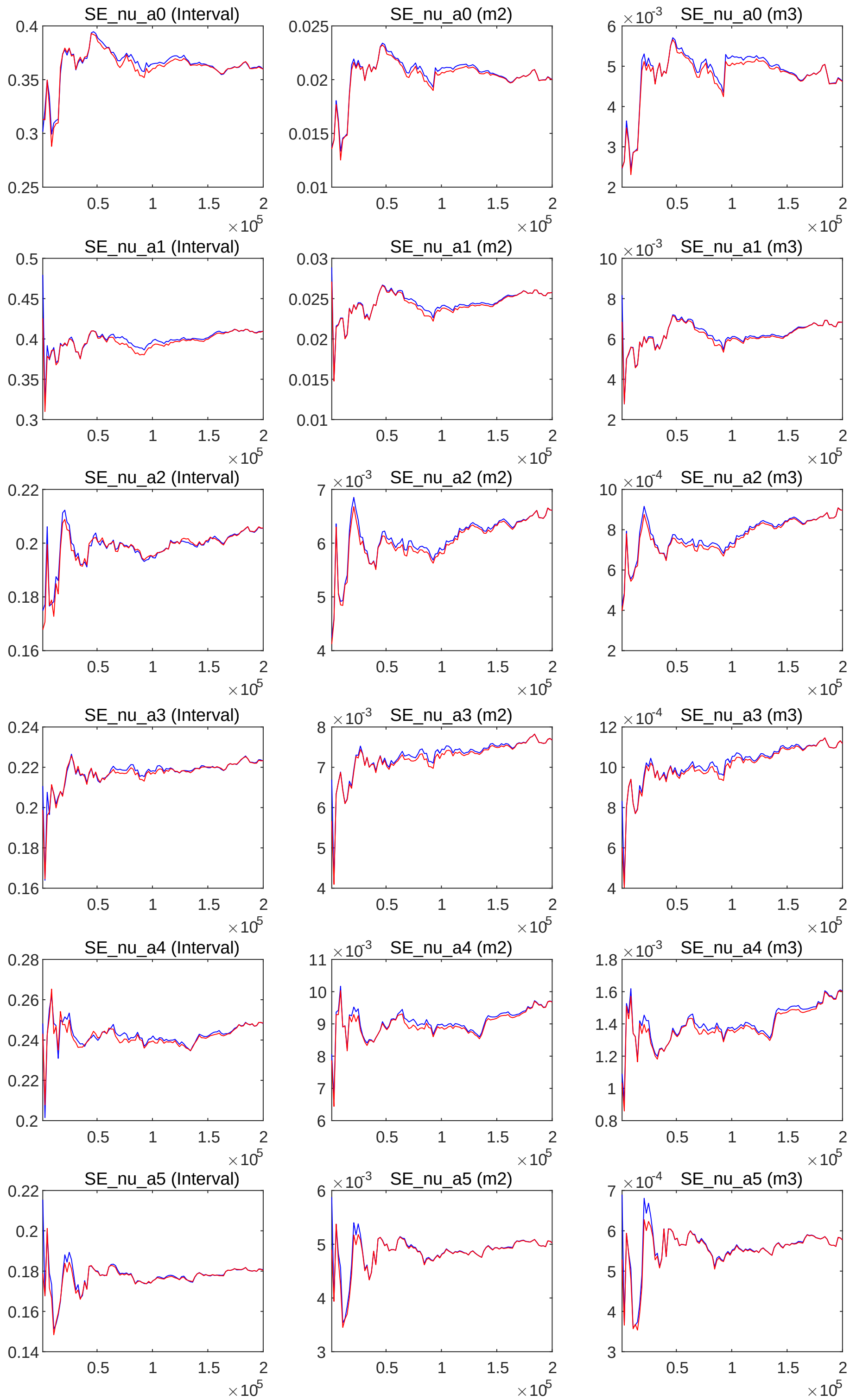
Notes: This figure graphs the prior and posterior distributions for each estimated parameter of the model in the baseline estimation. In each panel, the grey and black solid lines respectively represent the prior and posterior distributions, while the green dashed line indicates the posterior mode.

Figure A.2: Prior and posterior distributions for model parameters in the baseline estimation (cont.)



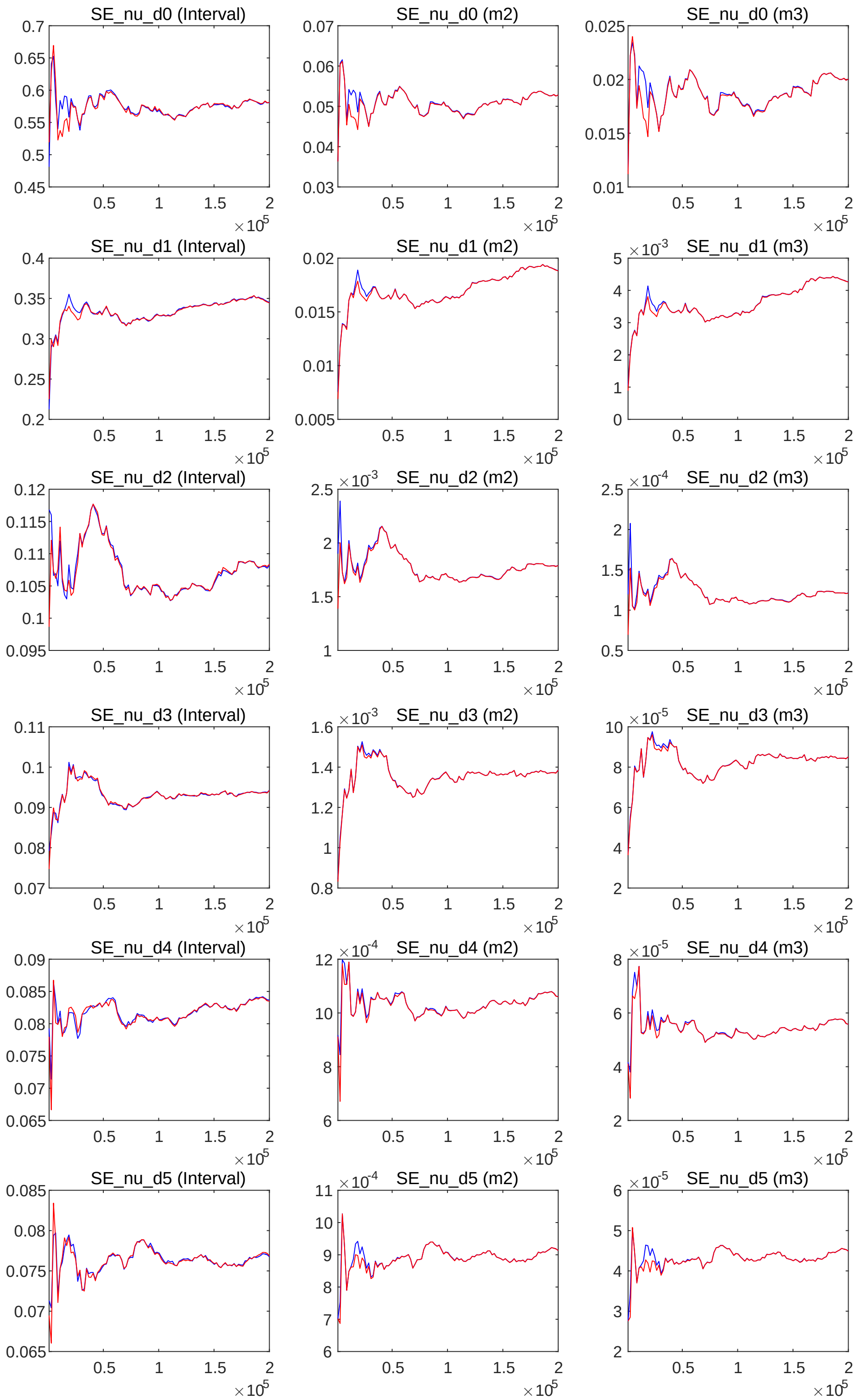
Notes: This figure graphs the prior and posterior distributions for each estimated parameter of the model in the baseline estimation. In each panel, the grey and black solid lines respectively represent the prior and posterior distributions, while the green dashed line indicates the posterior mode.

Figure A.3: MCMC convergence diagnostics for model parameters in the baseline estimation



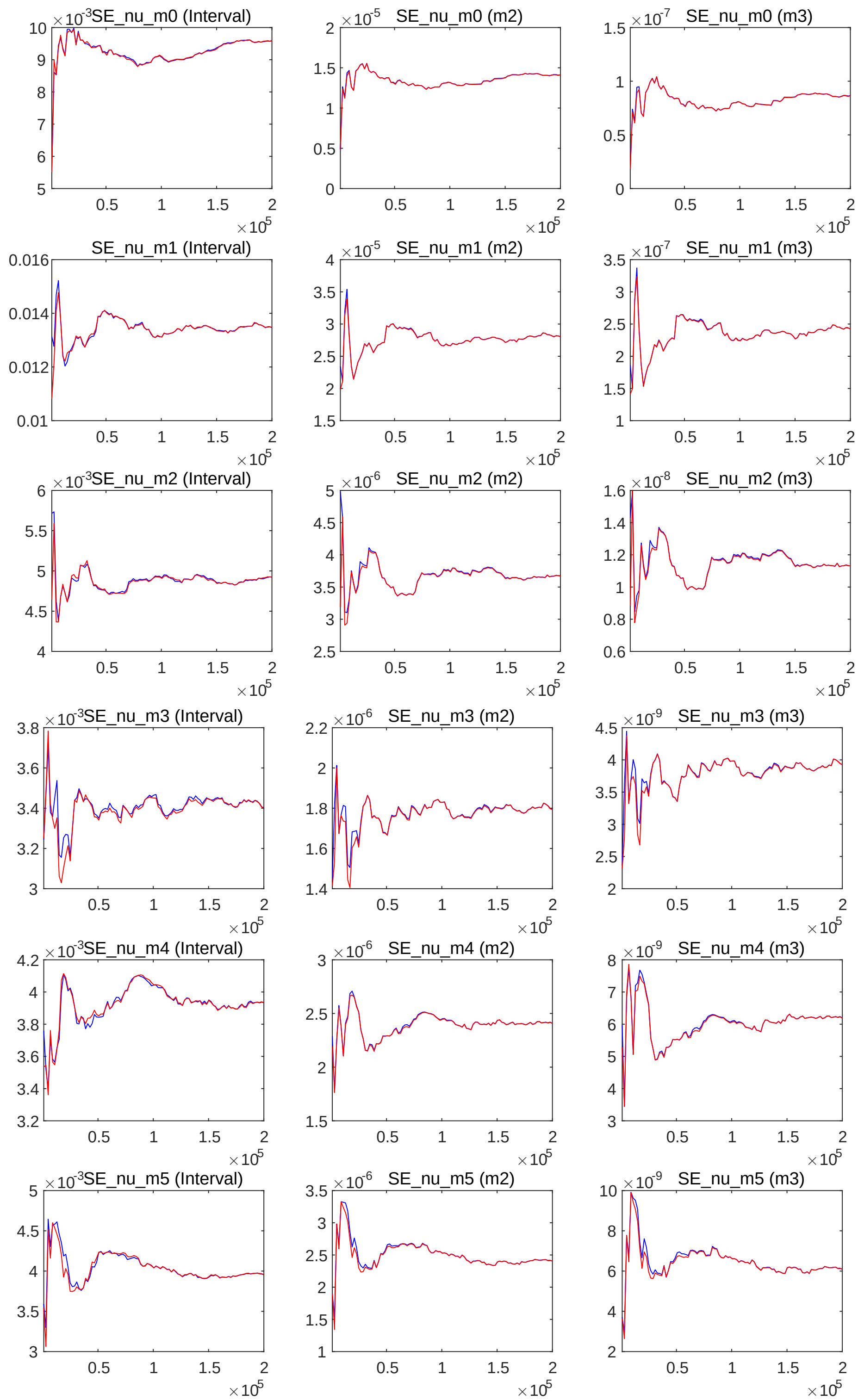
Notes: This figure shows the MCMC univariate diagnostics for each estimated parameter of the model in the baseline estimation. For each of the model parameters, there are three panels in which the red and blue lines represent the following three measures of the parameter draws within and between chains: "interval", being constructed from an 80 percent confidence interval around the parameter mean; "m2", being a measure of the variance; and "m3", based on third moments.

Figure A.4: MCMC convergence diagnostics for model parameters in the baseline estimation (cont.)



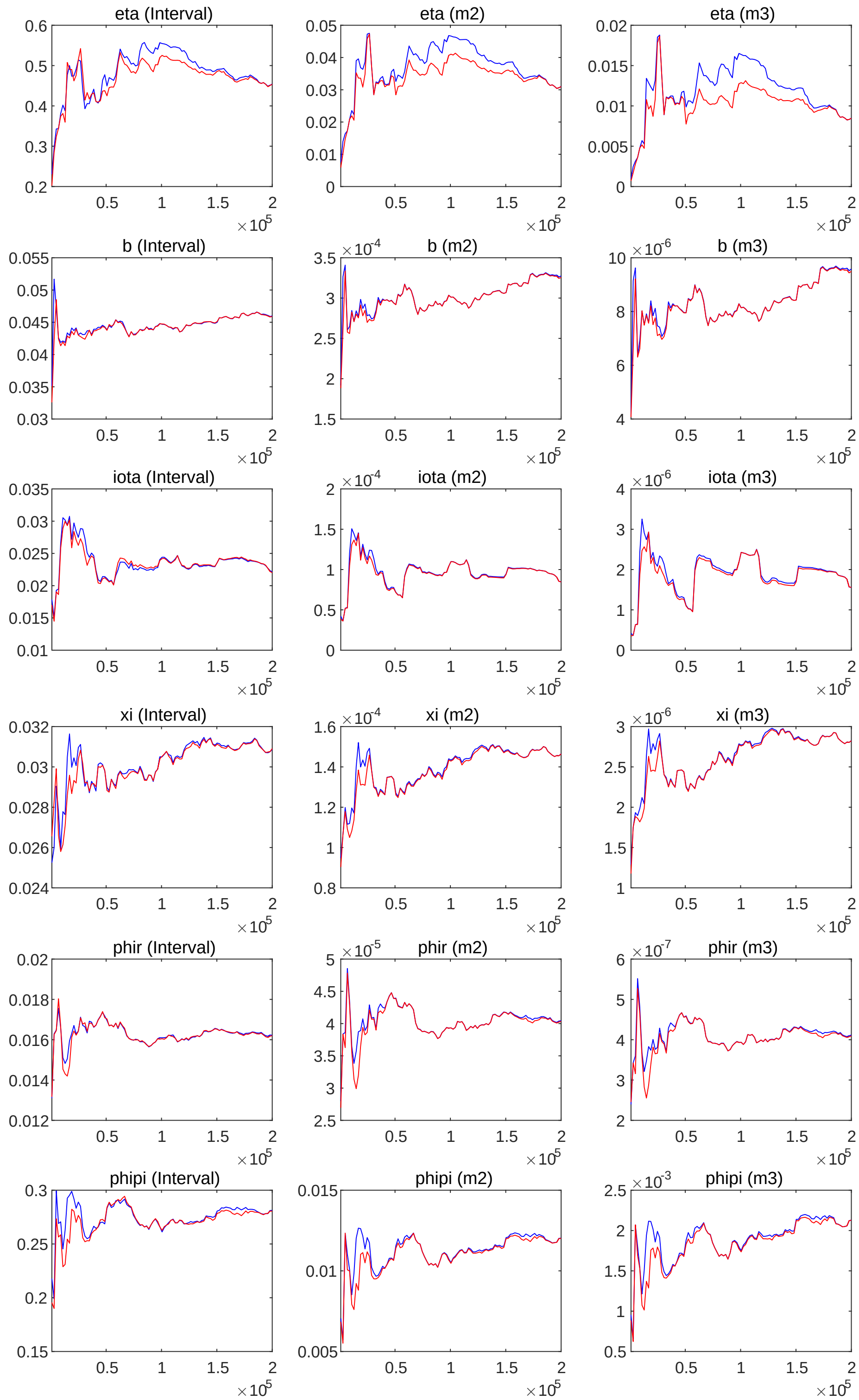
Notes: This figure shows the MCMC univariate diagnostics for each estimated parameter of the model in the baseline estimation. For each of the model parameters, there are three panels in which the red and blue lines represent the following three measures of the parameter draws within and between chains: "interval", being constructed from an 80 percent confidence interval around the parameter mean; "m2", being a measure of the variance; and "m3", based on third moments.

Figure A.5: MCMC convergence diagnostics for model parameters in the baseline estimation (cont.)



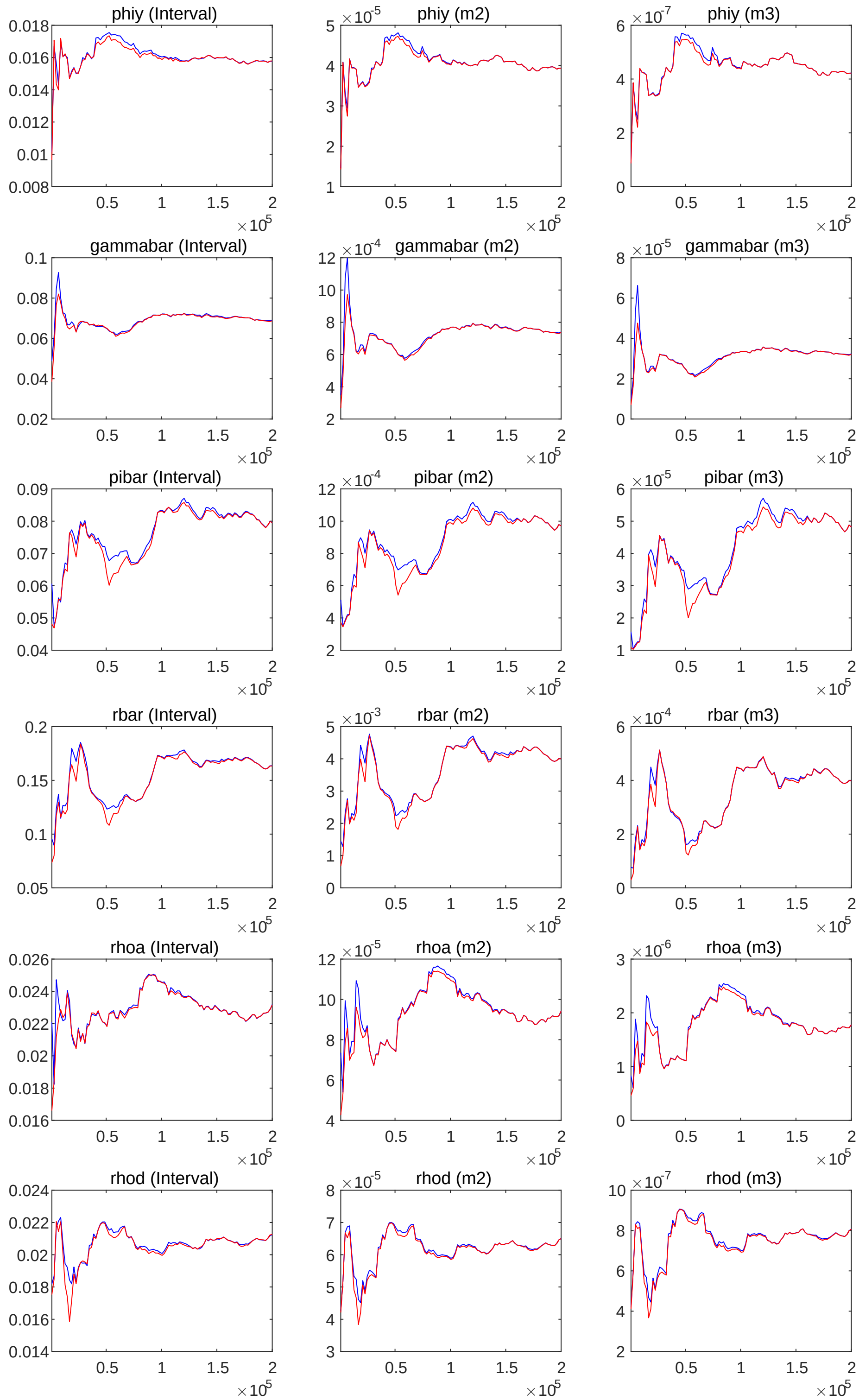
Notes: This figure shows the MCMC univariate diagnostics for each estimated parameter of the model in the baseline estimation. For each of the model parameters, there are three panels in which the red and blue lines represent the following three measures of the parameter draws within and between chains: "interval", being constructed from an 80 percent confidence interval around the parameter mean; "m2", being a measure of the variance; and "m3", based on third moments.

Figure A.6: MCMC convergence diagnostics for model parameters in the baseline estimation (cont.)



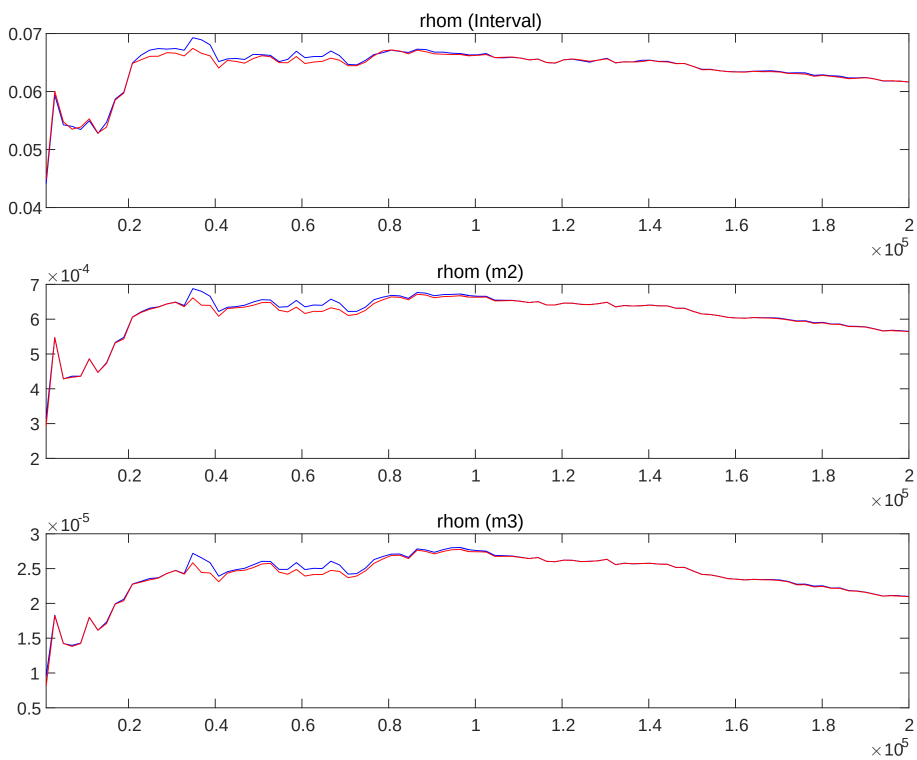
Notes: This figure shows the MCMC univariate diagnostics for each estimated parameter of the model in the baseline estimation. For each of the model parameters, there are three panels in which the red and blue lines represent the following three measures of the parameter draws within and between chains: "interval", being constructed from an 80 percent confidence interval around the parameter mean; "m2", being a measure of the variance; and "m3", based on third moments.

Figure A.7: MCMC convergence diagnostics for model parameters in the baseline estimation (cont.)



Notes: This figure shows the MCMC univariate diagnostics for each estimated parameter of the model in the baseline estimation. For each of the model parameters, there are three panels in which the red and blue lines represent the following three measures of the parameter draws within and between chains: “interval”, being constructed from an 80 percent confidence interval around the parameter mean; “m2”, being a measure of the variance; and “m3”, based on third moments.

Figure A.8: MCMC convergence diagnostics for model parameters in the baseline estimation (cont.)



Notes: This figure shows the MCMC univariate diagnostics for each estimated parameter of the model in the baseline estimation. For each of the model parameters, there are three panels in which the red and blue lines represent the following three measures of the parameter draws within and between chains: “interval”, being constructed from an 80 percent confidence interval around the parameter mean; “m2”, being a measure of the variance; and “m3”, based on third moments.