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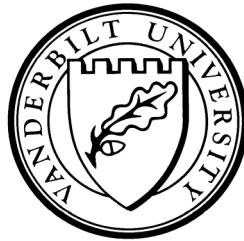
by

Ippei Fujiwara, Yasuo Hirose, and Mototsugu Shintani

DEPARTMENT OF ECONOMICS
VANDERBILT UNIVERSITY
NASHVILLE, TN 37235

www.vanderbilt.edu/econ

Can News Be a Major Source of Aggregate Fluctuations?
A Bayesian DSGE Approach[*]

Ippei Fujiwara[†]   Yasuo Hirose[‡]   Mototsugu Shintani[§]

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Abstract

We examine whether the news shocks, as explored in Beaudry and Portier (2004), can be a major source of aggregate fluctuations. For this purpose, we extend a standard dynamic stochastic general equilibrium model of Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2003, 2007) by allowing news shocks on the total factor productivity, and estimate the model using Bayesian methods. Estimation results on the U.S. and Japanese economies suggest that (1) news shocks play a relatively more important role in the U.S. than in Japan; (2) a news shock with a longer forecast horizon has larger effects on nominal variables; and (3) the overall effect of the total factor productivity on hours worked becomes ambiguous in the presence of news shocks.

JEL Classification:	E30; E40; E50
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[†]Financial Markets Department, Bank of Japan. E-mail: `ippei.fujiwara@boj.or.jp`
[‡]Monetary Affairs Department, Bank of Japan. E-mail: `yasuo.hirose@boj.or.jp`
[§]Department of Economics, Vanderbilt University. E-mail: `mototsugu.shintani@vanderbilt.edu`

1 Introduction

Macroeconomists have long realized that changes in expectations about the future can be a major source of economic fluctuations. This tradition can be traced back to Pigou (1926), who emphasized the possibility that capital accumulation, caused by optimistic expectations of future demand increase, may result in recessions when the expectations are not met.[1] This idea of expectation-driven cycles, sometimes referred to as "Pigou cycles," has recently been reformulated in the framework of modern equilibrium business cycle models.[2] Theoretical works that successfully yielded procyclical labor, investment, and consumption in the presence of news shocks include Beaudry and Portier (2004), Beaudry, Collard, and Portier (2006), Denhaan and Kaltenbrunner (2007), Fujiwara (2007), Kobayashi, Nakajima, and Inaba (2007), Christiano, Ilut, Motto, and Rostagno (2008) and Jaimovich and Rebelo (2009). In contrast to growing interest in the theoretical analysis, the empirical evidence on the importance of news shocks in business cycles is quite limited. Some exceptions are Beaudry and Portier (2006) for the United States and Beaudry and Portier (2005) for Japan. They identified the news shocks by estimating a structural vector autoregression (VAR) model with an assumption that the news shock has an impact on both the stock price and total factor productivity (TFP) in the long run but not on the latter in the short run.

In this paper, we empirically examine the role of news shocks in explaining business cycles through an estimated dynamic stochastic general equilibrium (DSGE) model. In particular, we introduce both anticipated and unanticipated components in the TFP and evaluate the relative contribution of the two components to aggregate fluctuations by estimating a standard New Keynesian DSGE model based on the U.S. and Japanese data. Although our analysis is similar to Beaudry and Portier (2005, 2006) in spirit, it has several advantages over their VAR approach. First, we directly estimate a fully specified DSGE model, and thus interpretation of our results, such as variance decompositions and impulse responses, is straightforward.[3] Second, since our

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[1] Pigou (1926) states that "while recognizing that the varying expectations of business men may themselves be in part a psychological reflex of good and bad harvests - while not, indeed, for the present inquiring how these varying expectations themselves come about - we conclude definitely that they, and not anything else, constitute the immediate cause and direct causes or antecedents of industrial fluctuations."

[2] For example, the term of "Pigou cycles" has been used by Beaudry and Portier (2004).

[3] Recent works by Schmitt-Grohé and Uribe (2008), Khan and Tsoukalas (2009) and

model allows the presence of multiple news shocks with different forecast horizons, the role of horizons in news shocks can be systematically examined.

As pointed out by Barro and King (1984), generating the expectation-driven cycles in equilibrium models has been a difficult task, since "with a simple one-capital-good technology, no combination of income effects and shifts to the perceived profitability of investment will yield positive comovements of output, employment, investment, and consumption (p. 818)." Only recently have the Pigou cycles been successfully described by balancing the tension between the wealth effect and the substitution effect stemming from the expectation of changes in future productivity.[4] The pioneering work by Beaudry and Portier (2004) has shown that the introduction of the multi-sectoral adjustment cost intensifies the complementarity between consumption and investment, which leads to the comovement of consumption, labor, and investment. Later, Christiano, Ilut, Motto, and Rostagno (2008) pointed out that the Pigou cycles could also be produced in the *de facto* standard macroeconomic model of Christiano, Eichenbaum and Evans (2005) (hereafter CEE), namely, a DSGE model that incorporates the investment growth adjustment cost, habit formation in consumption, sticky prices and wages, and the inflation-targeting monetary policy.

To examine the role of news shocks, we follow Smets and Wouters (2003, 2007) and estimate a CEE-type DSGE model using the Bayesian procedure. We choose to focus on the CEE-type model in our analysis for various reasons. First, this model is one of the most commonly used sticky price models among practitioners because it can account for many important characteristics of macroeconomic data, such as the inflation inertia and output persistence.[5] Second, the model contains all essential features, according to Christiano, Ilut, Motto, and Rostagno (2008), in producing Pigou cycles. Third, Smets and Wouters (2003, 2007) have already established that the CEE-type model estimated by Bayesian methods fits well with the U.S. and Euro data, and that the out-of-sample forecasting performance of the estimated model is comparable to that of

Milani and Treadwell (2009) also employed a Bayesian DSGE method similar to ours.

[4]With a positive news shock in TFP, for example, the wealth effect reduces labor and investment, while the substitution effect reduces consumption. A Dynare toolkit created by Fujiwara and Kang (2006) can be used to compute the impulse responses to news shocks under many different scenarios.

[5]In fact, many models developed by central banks can be viewed as variations of CEE. For example, see Laxton and Pesenti (2003), Erceg, Guerrieri, and Gust (2006), Adolfson, Laseen, Linde, and Villani (2007), and Sugo and Ueda (2008).

a standard Bayesian VAR model.

Our estimation results from U.S. quarterly data show that, while the anticipated and unanticipated shocks in the TFP together can account for only 20 to 30 percent of the aggregate fluctuations at most, the contribution of the news shocks in TFP is often larger than that of the unanticipated TFP shocks. When the forecast horizon of the news shock becomes longer, the effects of the news shocks on nominal variables become larger. Furthermore, the overall effect of the TFP innovations on hours worked, which has been one of the key issues in the recent business cycle literature, becomes ambiguous when both news and contemporaneous shocks occur simultaneously. In contrast to the U.S. case, estimates from Japanese quarterly data show that the unanticipated TFP shocks are the dominant driver of aggregate output fluctuation, and the contributions of the anticipated shocks in TFP are much smaller than those of the unanticipated shocks.

The remainder of this paper is structured as follows. In Section 2, the concepts of news shocks are first introduced, followed by the description of the log-linearized model. In Section 3, the estimation strategy is explained. Estimation results using U.S. data are demonstrated in Section 4. In Section 5, discussions, including a comparison with Japanese results, are provided. Concluding remarks are made in Section 6. The details of the theoretical model are provided in an appendix.

2 The Model

2.1 News Shocks in Productivity

As in Beaudry and Portier (2004), we consider the case where agents can observe signals that contain information on future technological innovations. Other than allowing for such an information structure, both our production function and innovation process are fairly standard. In what follows, all the variables are expressed in terms of log deviation from the steady-state values. Let y_t, k_t^s, l_t, and z_t be the output, the current capital services in production, the hours worked, and the TFP around the deterministic linear trend, respectively. Our (log-linearized)

aggregate production function is given by

$$y_t = \phi_p \left[\alpha k_t^s + (1 - \alpha) l_t + z_t \right]$$

where ϕ_p denotes one plus the share of the fixed costs in production and α represents the capital share. The detrended TFP z_t is assumed to follow an AR (1) process:

$$z_t = \rho_z z_{t-1} + \varepsilon_t^z, \quad \varepsilon_t^z \sim \text{i.i.d. } N(0, \sigma_z^2)$$

where ε_t^z is a technological innovation in productivity. To introduce the information structure, it is convenient to rewrite ε_t^z as a summation of the unanticipated component, $\nu_{0,t}$, and the anticipated component, ν_t^*. At the beginning of period t, $\nu_{0,t}$ is not known but ν_t^* is known to agents. To allow for the variation in the timing of the arrival of the news, we further decompose the latter component ν_t^* into a summation of news shocks, or $\sum_{h=1}^{H} \nu_{h,t-h}$, where $\nu_{h,t-h}$ is news of the h-period-ahead technological innovation learned at period $t - h$, where $0 < h \leq H$. For identification, we assume

$$\nu_{h,t} \sim \text{i.i.d. } N(0, \sigma_{zh}^2), \quad \text{for } h = 0, 1, ..., H.$$

This assumption implies zero correlation between the news and contemporaneous shocks as well as zero cross-correlation among news shocks of different horizons. The variance of ε_t^z can be simply computed as $\sigma_z^2 = \sum_{h=0}^{H} \sigma_{zh}^2$. As an example, let us consider the case when the agents can obtain news about future technology up to four periods ahead ($H = 4$). The technology process can then be written as

$$
\begin{aligned}
z_t &= \rho_z z_{t-1} + \nu_{0,t} + \nu_t^* \\
&= \rho_z z_{t-1} + \nu_{0,t} + \nu_{1,t-1} + \nu_{2,t-2} + \nu_{3,t-3} + \nu_{4,t-4}.
\end{aligned}
$$

In this case, at the period t, agents form rational expectations on the future productivity z_{t+h}, $h > 0$, using the information set $\{z_t, \nu_{1,t}, ..., \nu_{4,t}, \nu_{1,t-1}, ..., \nu_{4,t-1}, ...\}$. To understand this information updating structure, it is convenient to rewrite the above equation in the canonical form

as

$$
\begin{pmatrix} z_t \\ \nu_{1,t} \\ \nu_{2,t} \\ \nu_{2,t-1} \\ \nu_{3,t} \\ \nu_{3,t-1} \\ \nu_{3,t-2} \\ \nu_{4,t} \\ \nu_{4,t-1} \\ \nu_{4,t-2} \\ \nu_{4,t-3} \end{pmatrix}
=
\begin{pmatrix}
\rho_z & 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{pmatrix}
\begin{pmatrix} z_{t-1} \\ \nu_{1,t-1} \\ \nu_{2,t-1} \\ \nu_{2,t-2} \\ \nu_{3,t-1} \\ \nu_{3,t-2} \\ \nu_{3,t-3} \\ \nu_{4,t-1} \\ \nu_{4,t-2} \\ \nu_{4,t-3} \\ \nu_{4,t-4} \end{pmatrix}
+
\begin{pmatrix} \nu_{0,t} \\ \nu_{1,t} \\ \nu_{2,t} \\ 0 \\ \nu_{3,t} \\ 0 \\ 0 \\ \nu_{4,t} \\ 0 \\ 0 \\ 0 \end{pmatrix}
\tag{1}
$$

or $\mathbf{s}_t = A\mathbf{s}_{t-1} + \boldsymbol{\varepsilon}_t$, where $\mathbf{s}_t = (z_t, \nu_{1,t}, \nu_{2,t}, \nu_{2,t-1}, ..., \nu_{4,t-3})'$ and $\boldsymbol{\varepsilon}_t = (\nu_{0,t}, \nu_{1,t}, \nu_{2,t}, 0, \nu_{3,t}, ..., 0)'$. Note that $\mathrm{E}_t z_{t+h}$, the h-period-ahead forecast of z_t at period t, can be easily obtained as an element in $\mathrm{E}_t \mathbf{s}_{t+h}$ using $\mathbf{s}_{t+h} = A^h \mathbf{s}_{t+h-1} + ... + \boldsymbol{\varepsilon}_{t+h}$. For example, the news $\nu_{4,t}$, the 4-period-ahead technological progress learned at period t, will have no effect on z_t, $\mathrm{E}_t z_{t+1}$, $\mathrm{E}_t z_{t+2}$, and $\mathrm{E}_t z_{t+3}$. However, $\nu_{4,t}$ will have an impact on $\mathrm{E}_t z_{t+4}$ (and $\mathrm{E}_t z_{t+h}$ for $h > 4$), since the first element of $\mathrm{E}_t \mathbf{s}_{t+4}$ is given by

$$
\begin{aligned}
\mathrm{E}_t z_{t+4} &= \rho_z^4 z_{t-1} + \rho_z^3 \left(\nu_{1,t} + \nu_{2,t-1} + \nu_{3,t-2} + \nu_{4,t-3} \right) \\
&\quad + \rho_z^2 \left(\nu_{2,t} + \nu_{3,t-1} + \nu_{4,t-2} \right) + \rho_z \left(\nu_{3,t} + \nu_{4,t-1} \right) + \nu_{4,t}.
\end{aligned}
$$

In the empirical section, we search for the news horizon H based on the data.

2.2   Other Shocks in the Linearized System

The remaining part of the model is a slightly simplified version of the CEE-type model used in Smets and Wouters (2003, 2007). Here we only show the log-linearized system of equations (see the appendix for the full model). Let c_t, i_t, r_t^k, and k_t be the consumption, the investment, the rental rate of capital, and the physical capital. The current capital services in production k_t^s are defined as

$$
k_t^s = k_{t-1} + u_t
$$

where u_t is the capacity utilization rate, which is given by

$$
u_t = \frac{1 - \psi}{\psi} r_t^k
$$

where ψ is a positive function of the elasticity of capacity utilization adjustment cost function normalized to be between zero to unity. The aggregate resource constraint is

$$y_t = \frac{c}{y} c_t + \frac{i}{y} i_t + \frac{r^k k}{y} u_t + g_t$$

where g_t is the government expenditure shock. The variables without time subscript are steady state values. The consumption Euler equation is expressed as

$$
\begin{aligned}
c_t &= \frac{\lambda}{\gamma \left(1 + \frac{\lambda}{\gamma}\right)} c_{t-1} + \left[1 - \frac{\lambda}{\gamma \left(1 + \frac{\lambda}{\gamma}\right)}\right] \mathrm{E}_t c_{t+1} \\
&\quad + \frac{(\sigma_c - 1)\left(\frac{wl}{C}\right)}{\sigma_c \left(1 + \frac{\lambda}{\gamma}\right)} (l_t - \mathrm{E}_t l_{t+1}) \\
&\quad - \frac{1 - \frac{\lambda}{\gamma}}{\sigma_c \left(1 + \frac{\lambda}{\gamma}\right)} (r_t - \mathrm{E}_t \pi_{t+1})
\end{aligned}
$$

where r_t denotes the nominal interest rate, w_t is the nominal wage, and π_t represents the inflation rate, while λ is the parameter on the external habit, γ is the steady-state growth rate, and σ_c represents the inverse of the intertemporal elasticity of substitution. The investment Euler equation is given by

$$i_t = \frac{1}{1 + \beta\gamma^{1-\sigma_c}} i_{t-1} + \left(1 - \frac{1}{1 + \beta\gamma^{1-\sigma_c}}\right) \mathrm{E}_t i_{t+1} + \frac{1}{(1 + \beta\gamma^{1-\sigma_c})\gamma^2 \varphi} q_t + v_t$$

where q_t is the real value of existing capital and v_t is the investment-specific technology process, while β denotes the subjective discount factor and φ represents the steady-state elasticity of the investment adjustment cost function. The capital Euler equations is now expressed as

$$
\begin{aligned}
q_t &= \beta\gamma^{-\sigma_c}(1 - \delta)\mathrm{E}_t q_{t+1} + \left[1 - \beta\gamma^{-\sigma_c}(1 - \delta)\right]\mathrm{E}_t r_{t+1}^k \\
&\quad - (r_t - \mathrm{E}_t \pi_{t+1}) + f_t
\end{aligned}
$$

where f_t is the external finance premium shock and δ is the capital depreciation rate. The capital accumulation is given by

$$k_t = \frac{1 - \delta}{\gamma} k_{t-1} + \left(1 - \frac{1 - \delta}{\gamma}\right) i_t + \left(1 - \frac{1 - \delta}{\gamma}\right)\left(1 + \beta\gamma^{1-\sigma_c}\right)\gamma^2 \varphi v_t.$$

The definition of the price markup μ_t^p is

$$\mu_t^p = \alpha\left(k_t^s - l_t\right) + z_t - w_t.$$

The new Keynesian Phillips curve is given by

$$\pi_t = \frac{\iota_p}{1 + \beta\gamma^{1-\sigma_c}\iota_p}\pi_{t-1} + \frac{\beta\gamma^{1-\sigma_c}}{1 + \beta\gamma^{1-\sigma_c}\iota_p}\mathrm{E}_t\pi_{t+1} - \frac{\left(1 - \beta\gamma^{1-\sigma_c}\xi_p\right)\left(1 - \xi_p\right)}{\left(1 + \beta\gamma^{1-\sigma_c}\iota_p\right)\xi_p\left[\left(\phi_p - 1\right)\epsilon_p + 1\right]}\mu_t^p + a_t$$

where a_t is the cost-push shock, while ι_p denotes the degree of indexation to past inflation, ξ_p is the degree of price stickiness, and ϵ_p is the curvature of the Kimball (1995) goods market aggregator. The rental rate of capital can be computed from

$$r_t^k = -\left(k_t^s - l_t\right) + w_t.$$

The definition of the wage markup μ_t^w is given by

$$\mu_t^w = w_t - \left[\sigma_l l_t + \frac{1}{1 - \frac{\lambda}{\gamma}}\left(c_t - \frac{\lambda}{\gamma}c_{t-1}\right)\right]$$

where σ_l denotes the elasticity of labor supply to the real wage. The wage Phillips curve is given by:

$$
\begin{aligned}
w_t = \ & \frac{1}{1 + \beta\gamma^{1-\sigma_c}}w_{t-1} + \left(1 - \frac{1}{1 + \beta\gamma^{1-\sigma_c}}\right)\left(\mathrm{E}_t w_{t+1} + \mathrm{E}_t\pi_{t+1}\right) \\
& -\frac{1 + \beta\gamma^{1-\sigma_c}\iota_w}{1 + \beta\gamma^{1-\sigma_c}}\pi_t + \frac{\iota_w}{1 + \beta\gamma^{1-\sigma_c}}\pi_{t-1} \\
& -\frac{\left(1 - \beta\gamma^{1-\sigma_c}\xi_w\right)\left(1 - \xi_w\right)}{\left(1 + \beta\gamma^{1-\sigma_c}\right)\xi_w\left[\left(\phi_w - 1\right)\epsilon_w + 1\right]}\mu_t^w + b_t
\end{aligned}
$$

where b_t is the wage markup disturbance, while ι_w denotes the degree of indexation to past wage inflation, ξ_w is the degree of nominal wage stickiness, and ϵ_w is the curvature of the Kimball (1995) labor market aggregator. Finally, we use the Taylor (1993)-type monetary policy rule as

$$r_t = \rho r_{t-1} + \left(1 - \rho\right)\left(r_\pi \pi_t + r_y \Delta y_t\right) + m_t$$

where m_t is the monetary policy shock, while ρ, r_π and r_y are positive policy parameters. There are six exogenous disturbances in addition to the TFP shock in the system. These six additional

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driving forces are assumed to follow the following AR (1) processes:

$$f_t = \rho_f f_{t-1} + \varepsilon_t^f, \quad \varepsilon_t^f \sim \text{i.i.d. } N(0, \sigma_f^2),$$

$$g_t = \rho_g g_{t-1} + \varepsilon_t^g, \quad \varepsilon_t^g \sim \text{i.i.d. } N(0, \sigma_g^2),$$

$$v_t = \rho_v v_{t-1} + \varepsilon_t^v, \quad \varepsilon_t^v \sim \text{i.i.d. } N(0, \sigma_v^2),$$

$$m_t = \rho_m m_{t-1} + \varepsilon_t^m, \quad \varepsilon_t^m \sim \text{i.i.d. } N(0, \sigma_m^2),$$

$$a_t = \rho_a a_{t-1} + \varepsilon_t^a, \quad \varepsilon_t^a \sim \text{i.i.d. } N(0, \sigma_a^2), \text{ and}$$

$$b_t = \rho_b b_{t-1} + \varepsilon_t^b, \quad \varepsilon_t^b \sim \text{i.i.d. } N(0, \sigma_b^2).$$

Note that unlike the TFP shocks, each innovation term is given as a single component, implying that all the shocks are unanticipated.[6]

3 Estimation Strategy

We use Bayesian techniques to estimate the model parameters and to evaluate the importance of the news shocks. Bayesian estimation strategies help to estimate DSGE models with cross-equation restrictions, coping well with misspecification and identification problems, and provide a coherent model evaluation procedure.

In solving a rational expectations system, we follow the approach of Sims (2002).[7] In his approach, the log-linearized system can be written in the following canonical form:

$$\Gamma_0(\theta) \mathbf{s}_t = \Gamma_1(\theta) \mathbf{s}_{t-1} + \Psi_0(\theta) \boldsymbol{\varepsilon}_t + \Pi_0(\theta) \boldsymbol{\eta}_t \tag{2}$$

where Γ_0, Γ_1, Ψ_0, and Π_0 are the conformable matrices of coefficients that depend on the structural parameters θ, $\mathbf{s}_t$ is a stacked vector of endogenous variables including expectations at t, and $\boldsymbol{\varepsilon}_t$ is a vector of fundamental shocks. $\boldsymbol{\eta}_t$ is a vector of endogenous forecast errors, defined as

$$\boldsymbol{\eta}_t = \widehat{\mathbf{s}}_t - \mathrm{E}_{t-1} \widehat{\mathbf{s}}_t$$

where $\widehat{\mathbf{s}}_t$ is a subvector of $\mathbf{s}_t$ that contains expectational variables. In the present model, $\widehat{\mathbf{s}}_t$ consists of i_t, r_t^k, q_t, c_t, l_t, π_t, and w_t. Note that the canonical representation of news shocks in (1) has been incorporated into the form (2). The solution is then given by[8]

$$\mathbf{s}_t = \Gamma\left(\theta\right)\mathbf{s}_{t-1} + \Psi\left(\theta\right)\varepsilon_t. \tag{3}$$

Let Y^T be a set of observable data. Since the rational expectations solution (3) and a set of measurement equations that relates data to the model variables $\mathbf{s}_t$ provide a state-space representation, the likelihood function $L(\theta|Y^T)$ can be evaluated using the Kalman filter. The Bayesian approach places a prior distribution $p\left(\theta\right)$ on parameters and updates the prior through the likelihood function. Bayes' Theorem provides the posterior distribution of θ:

$$p\left(\theta|Y^T\right) = \frac{L\left(\theta|Y^T\right)p\left(\theta\right)}{\int L\left(\theta|Y^T\right)p\left(\theta\right)d\theta}.$$

Markov Chain Monte Carlo methods are used to generate the draws from the posterior distribution. Based on the posterior draws, we can make an inference on the parameters.[9] Details of its computational implementation are shown in Schorfheide (2000). The marginal data density, which assesses the overall fit of the model, is given by[10]

$$p\left(Y^T\right) = \int L(\theta|Y^T)p(\theta)d\theta. \tag{4}$$

4 Main Results

We follow Smets and Wouters (2007) and use the data set consists of seven U.S. quarterly series: the log difference of real GDP; real consumption; real investment; and the real wage; the log of hours worked; the log difference of the GDP deflator; and the federal funds rate.[11] Since the model contains $H + 7$ exogenous shocks, it is exactly identified if there is no news shock ($H = 0$) and is over-identified in the presence of new shocks ($H > 0$). The model is estimated over the sample period from 1983:1 to 2004:4.[12]

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[8]We consider only the parameter space that leads to equilibrium determinacy.

[9]For our subsequent analysis, 300,000 draws are generated with a random-walk Metropolis Algorithm, and the first 30,000 draws are discarded.

[10]The marginal data densities are approximated using the harmonic mean estimator proposed by Geweke (1999).

[11]For a detailed description of the data, see Smets and Wouters (2007).

[12]The beginning of the sample is determined to exclude the possibility of equilibrium indeterminacy, based on the finding in Clarida, Galí, and Gertler (2000) and Lubik and Schorfheide (2004).

Prior distributions for the structural parameters are summarized in the first block of columns in Table 1. Most of the priors are similar to those in Smets and Wouters (2007) except for the news shocks that are not included in their analysis. Here, the standard deviations of news shocks, σ_{z1}, σ_{z2}, ..., σ_{zH}, are distributed around $H^{-1/2} \times \sigma_{z0}$, so that $\sum_{h=1}^{H} \sigma_{zh}^2$, the variance of the total anticipated component ν_t^* in productivity, is equal to σ_{z0}^2, the variance of unanticipated component $\nu_{0,t}$.[13]

In this paper, we search for the news horizon H using the following procedure. First, we set the maximum possible value of H at 12 quarters. Then, we estimate the model for each $H \in \{0, 1, 2, ..., 12\}$ and select H that provides the maximum marginal data density (4). As a result of this specification search, we select $H = 5$ to be the optimal horizon.

The second block of columns in Table 1 reports the posterior distributions of the parameters under our baseline specification with news shocks. Basically, the posterior estimates are in line with those reported in Smets and Wouters (2007) including a highly persistence estimate of TFP shocks. The only exception is that our estimated degrees of wage and price stickiness are slightly lower than those in Smets and Wouters (2007). This difference may come from the introduction of the news shocks, or our AR (1) specification for all shocks instead of the ARMA specification used by Smets and Wouters (2007) for some shocks. Regarding the news shocks, the posterior distributions of their standard deviations are almost the same, irrespective of the news horizon. The similarity in variance of each news shock, however, does not imply that the role of the news shock for a different horizon is nearly equivalent, which is discussed later in this section.

Let us now use our estimated model and examine the importance of news shocks in the U.S. aggregate fluctuations in terms of the variance decomposition. To this end, we first classify shocks in the model into three subgroups: (i) an unanticipated (contemporaneous) TFP shock, $\nu_{0,t}$; (ii) news shocks in TFP, $\nu_{1,t}$, $\nu_{2,t}$, $\nu_{3,t}$, $\nu_{4,t}$,and $\nu_{5,t}$; and (iii) other six non-TFP shocks, ε_t^f, ε_t^g, ε_t^v, ε_t^m, ε_t^a and ε_t^b. We then decompose the variance of each variable used in the estimation into components explained by three groups of shocks. In particular, we com-

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[13]We use an equal weight on unexpected and expected TFP components in the prior distribution since there are no previous results of estimated DSGE models with news shocks available. The main results of the analysis, however, remain unchanged even if we set the prior weight on the unexpected shock as twice as large as the one on the news shock, or set the latter weight as twice as large as the former one.

pute the forecast error variance decomposition evaluated at the infinite horizon by solving the dynamic Lyapunov-equation. The estimated relative contributions of each group of shocks to consumption, investment, output, hours worked, inflation, the real wage, and the interest rate are reported in Table 2.

An interesting finding here is that, on the whole, the contributions of the anticipated (news) components of the productivity shock to fluctuations of seven aggregate variables are somewhat comparable to those of the standard unanticipated (contemporaneous) technology shock. This finding is the first empirical evidence of the possibility of coexistence of these two types of shocks, under the fully specified DSGE modeling framework. The relative contribution of news shocks is generally higher for nominal variables (inflation, wage and interest rate) than for real variables (consumption, investment, output and hours). The presence of news shocks is also supported when we compare the variance decompositions with those based on the model under the assumption of no news shock, namely the case of $H = 0$, obtained in the previous specification search procedure. Since there are only an unanticipated TFP shock and non-TFP shocks when there is no news shock, the variance decomposition of each variable into two corresponding components is also reported in Table 2 along with the result of the baseline specification. For all seven variables, the contribution of the (unanticipated) TFP shocks is smaller when news shocks are excluded from the model. In addition, for all variables, the estimated contribution of the group of news shocks in the baseline model is larger than that of the (unanticipated) TFP shocks when news shocks are excluded. As a result, the total contribution of TFP related shocks, $\varepsilon_t^z = \sum_{h=0}^{H} \nu_{h,t-h}$, in the baseline specification is much larger in the presence of news shocks, than in the case of no news shocks.

The effect of the news shocks on the productivity in our estimated model can be also understood from the impulse responses in Figure 1. The figure depicts the impulse responses of seven aggregate series to one-standard-deviation unanticipated TFP shocks and news shocks on TFP at horizons 1, 3 and 5. In the present model with the habit persistence in consumption, adjustment cost in investment and nominal rigidities, hours worked decrease for a positive unanticipated productivity shock, while consumption and investment increase. Thus, in the

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absence of news shocks, our model cannot generate observed procyclical labor. On the other hand, the impulse responses to the news shocks in Figure 1 imply that a news shock can generate the comovement among consumption, investment, and hours worked. For this reason, to match the observed procyclical labor, news shocks need to make some contribution in aggregate fluctuations.

Another interesting observation from Figure 1 involves the asymmetric responses of nominal variables to the news shocks with different forecast horizons. When the forecast horizon of the news shock becomes longer, the effects of the news shock become larger on nominal than on real variables. This outcome also reflects the discussions above. The hours worked, and therefore the marginal cost, increase up until the expectation actually materializes. At the same time, for the longer forecast horizon, the present discounted value of the reduction in the marginal cost becomes smaller. Consequently, the changes in expectation at the longer horizon have more impact on nominal variables.[14]

The first column of Table 3 reports the relative contribution of news shock at each horizon to the variances of output and inflation. The relative contributions of news shocks do not seem to decrease with the horizon for the output. In contrast, they significantly increase with the horizon for the inflation, a nominal variable. So far, in the studies on the news shocks, such as Beaudry and Portier (2004), Jaimovich and Rebelo (2009), Denhaan and Kaltenbrunner (2007), Kobayashi, Nakajima, and Inaba (2007), Beaudry, Collard, and Portier (2006), and Christiano, Ilut, Motto, and Rostagno (2008), the theoretical responses to the news shocks are analyzed for some arbitrary forecast horizon. To the best of our knowledge, however, the sensitivity of responses to changes in the forecast horizon has never been systematically examined.

5 Discussions

5.1 Sensitivity Analysis

Multiple news shocks and a single news shock

In our analysis, we specify a model with multiple news shocks in the TFP. We can also

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[14]Yet this relationship is not monotonic. As the forecast horizon becomes longer, the wealth effects on current consumption and leisure become stronger. As a result, this effect can result in the further reduction of the marginal cost.

compare models with only a single news shock in the TFP to the baseline model with multiple news shocks as well as the no news case considered in the previous section. In Table 3, the contributions of the single news shock to the variances of output and inflation, along with the corresponding marginal likelihood, are provided. Each alternative specification includes only one from $\nu_{1,t}$, $\nu_{2,t}$, $\nu_{3,t}$, $\nu_{4,t}$ and $\nu_{5,t}$ in addition to an unanticipated shock $\nu_{0,t}$. We can point out several intriguing findings from Table 3. In each case, the contributions of the news shock are non-negligible but smaller in magnitude compared to the baseline estimate. Furthermore, none of additional cases with a single news shock dominate the baseline model in terms of the marginal data density. These results demonstrate the importance of including multiple news shocks to explain aggregate fluctuations.

Transitory news shocks and permanent news shocks

In our analysis, the TFP is assumed to be generated from a stationary AR(1) process around the (linear) deterministic trend following the specification employed in Smets and Wouters (2003, 2007). While our estimated AR coefficient suggests that the TFP shocks are highly persistent, our specification does not allow the TFP shock to have a permanent effect. In the literature of news shocks, the effects of an anticipated permanent change in the TFP are often discussed. In the bivariate VAR approach of Beaudry and Portier (2006), news shocks are identified under the assumption of a stochastic trend in the TFP. Also, in a recent study by Schmitt-Grohé and Uribe (2008), which is conducted independently of ours, both stationary and nonstationary shock components in the TFP are introduced in a flexible price DSGE model. Instead of estimating a model with a nonstationary TFP, let us here compare our results with other studies that incorporate permanent TFP shocks. According to Schmitt-Grohé and Uribe (2008), the VAR results of Beaudry and Portier (2006) imply that the contribution of (permanent) news shocks in the forecast error variance of output growth at a 30-quarter horizon varies from 55 to 75 percent, depending on the choice of the identification scheme. Based on a DSGE model estimated by Schmitt-Grohé and Uribe (2008), a permanent TFP news shock accounts for 31 percent of output growth fluctuation, while a permanent TFP unanticipated shock only accounts for 2 percent. On the other hand, contributions of stationary TFP news and unanticipated shocks

are 28 and 37 percent, respectively. In contrast, our stationary TFP news and unanticipated shocks, respectively, account for 12 and 9 percent of output fluctuation around the deterministic trend. While our estimates are somewhat smaller in magnitude than those in the other studies, the difference is mainly due to the presence of six additional non-TFP shocks in our CEE-type DSGE model. By construction, the bivariate VAR approach cannot identify more than two shocks. Also, TFP-related shocks altogether accounts for 98% of output growth variation in the analysis of Schmitt-Grohé and Uribe (2008) most likely because some of the important non-TFP shocks in our estimates are not included. In summary, it seems safe to say that the contribution of the news shocks in business cycles is non-negligible under both the stationary and nonstationary assumptions of the TFP.

5.2 Technology Shocks and Hours Worked Revisited

Let us now discuss the implication of our estimates for a controversial issue of the response of hours worked to a technology shock. In standard real business cycle models, hours should rise after a positive technology shock. However, Galí (1999) showed empirically that technology shocks identified from a structural VAR model have a negative effect on hours. He pointed out that the negative correlation between a technology shock and hours was consistent with a model with monopolistic competition and sticky prices. His view was later confirmed by Francis and Ramey (2005), who employed a structural VAR model using alternative identifying restrictions, and by Smets and Wouters (2007), who conducted a Bayesian estimation of a DSGE model with nominal price rigidities. In sharp contrast, Christiano, Eichenbaum, and Vigfusson (2003) provided the evidence of positive correlation between a technology shock and hours and claimed that the previous findings of a positive correlation might have been caused by misspecifications in the estimation. In particular, opposite results could be obtained by estimating a structural VAR model with identifying assumptions very similar to that of Galí (1999) and Francis and Ramey (2005), but allowing for the stationarity of hours worked.

Our estimates offer one possible solution to reconciling the two competing views regarding the sign of the correlation between the technology shock and hours. Recall that there are two components in the technology shock ε_t^z; one is the contemporaneous (unanticipated) component

$\nu_{0,t}$ and the other is the news component $\nu_t^* = \sum_{h=1}^{5} \nu_{h,t-h}$. As shown in Figure 1, each of the two components of the technology shock has an instantaneous effect on hours worked in the opposite direction. When all the technology disturbances are unanticipated, so that $\varepsilon_t^z = \nu_{0,t}$, the technology shock has an immediate and significant negative impact on the hours worked, thus our results strongly support the findings by Galí (1999), Francis and Ramey (2005), and Smets and Wouters (2007). In contrast, the same figure shows that the impact responses of hours worked to news shocks $\nu_{h,t}$, $h = 1, ..., 5$, are positive and significant. Because of this offsetting role of the news shocks, the overall effect of the broadly defined technology shock can become ambiguous. To confirm this conjecture, let us conduct a simple experiment by generating simultaneous positive shocks on both contemporaneous and news components. The weighted sum of each impulse response, weighted by σ_{zh} for $h = 0, 1, ..., 5$, is then interpreted as the total effect. The upper half of Figure 2 shows the responses of output, hours worked and productivity to such a composite shock. The lower half shows the response to the unanticipated shock $\nu_{0,t}$ using the model estimated under the assumption of no news shock. Note that the hour response is significantly negative in the latter case. In contrast, the immediate response of hours in the baseline is almost zero with its confidence band covering both positive and negative regions. This outcome suggests that the overall effect can be either positive or negative if we employ a broader, but somewhat atypical, definition of a "technology shock."

Finally, the same reasoning can be also used as a possible explanation of the well-known productivity-hours anomaly, namely, the empirical observation of near-zero (or negative) correlation between productivity and hours worked. By comparing the impulse responses of hours worked and productivity in Figure 2, the broadly defined "technology shock" generates a near-zero comovement between the two. The mechanism behind this result is identical to that of Galí (1999), who claimed that (unanticipated) TFP shocks generate a negative comovement between two variables rather than the positive one predicted in the standard real business cycle models. To offset this effect, however, positive comovement is generated from news shocks here, while Galí (1999) relied on non-technology shocks (such as monetary shocks). In the presence of the news component, the technology shock alone may account for the productivity-hours anomaly.

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5.3 An International Comparison: U.S. and Japan

In the discussion of Japan's lost decade in 1990s, Hayashi and Prescott (2002) pointed out the importance of news shocks by suggesting that "the unusual pickup in economic activities, particularly investment, was due to an anticipation of higher productivity growth that never materialized (p.228)."[15] In addition, the correlation between technology shocks and hours worked remains an unsettled question in Japan. For example, while Galí (2005) and Braun and Shioji (2004) showed the correlation to be positive, Watanabe (2006) claimed a near-zero correlation. In this subsection, we estimate the same CEE-type DSGE model with news shocks in TFP using Japanese data and compare the result with that of the U.S.

We follow Sugo and Ueda (2008) who estimated a similar CEE-type DSGE model for Japan, in the construction of the data. The GDP deflator and the federal funds rate used in the U.S. analysis are replaced by the CPI and the overnight call rate. We also allow deterministic trend breaks in 1991:2 and 2001:1. The model is estimated over the sample period from 1981:2 to 1998:4 for Japan.[16]

The main results from the estimation are summarized as follows. First, in contrast to the U.S. result, the fit of the model does not significantly improve by the addition of news shocks. When the same procedure is used to search for the news horizon, $H = 0$ is selected. Table 4 shows the marginal data densities of Japanese data for various specifications used in Table 3 for the U.S. Nevertheless, Tables 3 and 4 suggest that estimated contribution of each news shocks are comparable between two countries. In some cases of a single news shock, the magnitude is indeed higher in Japan than in the U.S.

Second, the contribution of news shocks relative to that of the unanticipated shock is very small in explaining the output fluctuation as shown in Table 4. This outcome is in contrast to the U.S. result where two types of shocks contribute almost equally to the variation in output. This difference is mainly due to the fact that an unanticipated TFP shock alone can account

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[15]Christiano and Fujiwara (2006) also argued that the news shock can be a potential candidate for the explanation of the bubble in Japan based on the calibrated model.

[16]The end of the sample period is determined in order not to include the period during which the zero nominal interest rate policy is adopted by the Bank of Japan. Our view is that the period with the zero bound on the nominal interest rate should be dealt with separately due to nonlinearity of the policy rules.

for about half the total output variance even if news shocks are excluded from the specification. This observation is consistent with the previous DSGE estimation result without incorporating news shocks. Sugo and Ueda (2008) report that the majority of the output fluctuation can be accounted for by the unanticipated TFP shocks in the Japanese economy, while Smets and Wouters (2007) show that the contribution of unanticipated TFP shocks to output fluctuation is between 15 to 30 percent in the U.S. economy.

Finally, we point out that, while evidence for Japan is not as strong as that for the U.S., our estimates with $H = 5$ suggest that a longer forecast horizon had larger effects on nominal variables, and that the overall effect of the TFP on hours worked became ambiguous. Again, these findings cannot be obtained from the bivariate VAR approach used by Beaudry and Portier (2005) to identify the news shock in Japanese economy.

6   Conclusion

In this paper, we have examined the role of news shocks in the aggregate fluctuations. Our Bayesian estimates of the canonical sticky price DSGE model suggested that news shocks have played a relatively more important role in the U.S. business cycles than Japanese business cycles. We also found that a news shock with a longer forecast horizon had larger effects on nominal variables, and that the overall effect of the TFP on hours worked became ambiguous in the presence of news shocks.

Possible future extensions of our approach include introducing news shocks to innovations other than TFP, and allowing for correlation between unanticipated shocks and news shocks. It may be possible to derive a different interpretation of wedges stemming from the TFP by allowing multiple forecast horizons in the news shocks introduced in our paper in the business cycle accounting approach of Chari, Kehoe, and McGrattan (2007). Furthermore, the standard CEE-type model may lack some important mechanisms such as the ones emphasized in the financial accelerator model of Bernanke, Gertler, and Gilchrist (1999). It is left for our future research to understand the contributions of news shocks in a model that incorporates the financial sector.

Appendix

This appendix summarizes a simplified model of Smets and Wouters (2003, 2007) that we estimate along with news shocks. Five agents in the model are: households; the final goods producer; the intermediate goods producers; the intermediate labor union; and the central bank. We first show the optimizing problem or the rule for each agent and then derive the equilibrium conditions.

A.1. Households

Household j chooses consumption $C_t(j)$, hours worked $L_t(j)$, bonds $B_t(j)$, investment $I_t(j)$, and capital utilization $u_t(j)$ to maximize the following welfare:

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{[C_t(j) - \lambda C_{t-1}]^{1-\sigma_c}}{1-\sigma_c} \exp\left[\frac{\sigma_c - 1}{1 + \sigma_l} L_t^{1+\sigma_l}(j)\right],$$

subject to the budget constraint:

$$
\begin{aligned}
C_t(j) + I_t(j) + \frac{B_t(j)}{R_t P_t} - T_t \quad \leq \quad & \frac{B_{t-1}(j)}{P_t} + \frac{W_t(j) L_t(j)}{P_t} + \frac{R_t^k u_t(j) K_{t-1}(j)}{P_t} \\
& - a\left[u_t(j); \psi\right] K_{t-1}(j) + \frac{D_t}{P_t},
\end{aligned}
$$

and the capital formation:

$$K_t(j) = (1-\delta) K_{t-1}(j) + \left\{1 - S\left[\frac{I_t(j)}{I_{t-1}(j)}; \varphi\right]\right\} I_t(j) \tag{A1}$$

where T_t is the lump-sum tax, P_t is the consumer price level, R_t^k is the cost of capital, Π_t is the dividend from firms, $a[x; \psi]$ is the cost function of changing the capacity utilization and $S[x; \varphi]$ is the cost function of changing the investment satisfying $S[\gamma; \varphi] = S'[\gamma; \varphi] = 0$ and $S'' > 0$.

A.2. Final Goods Producer

The final goods producer maximizes the profit

$$P_t Y_t - \int_0^1 P_t(i) Y_t(i) \, \mathrm{d}i$$

subject to the aggregating technology:

$$\int_0^1 G\left[\frac{Y_t(i)}{Y_t}; \epsilon_p\right] \mathrm{d}i = 1$$

where Y_t and $Y_t(i)$ are the final and intermediate goods, respectively, $P_t(i)$ is the intermediate goods price, and $G[x; \epsilon_p]$ is the Kimball (1995) aggregator.

A.3. Intermediate Goods Producers

The marginal cost $MC_t(i)$, which the intermediate goods producer i faces, is computed as the Lagrange multiplier from the following cost minimization problem:

$$\min_{W_t(i), L_t(i)} W_t(i) L_t(i) + R_t^k K_t(i),$$

subject to the production function

$$Y_t(i) = K_t^s(i)^\alpha \left[\gamma^t L_t(i)\right]^{1-\alpha} - \gamma^t \Phi, \tag{A2}$$

where Φ is a fixed cost of production, and the current capital services in production given by

$$K_t^s(i) = u_t(i) K_{t-1}(i). \tag{A3}$$

Using the marginal cost defined above, the intermediate goods firm i, with Calvo type frictions, chooses the newly set price $\tilde{P}_t(i)$ by maximizing the presented discounted value of profit:

$$E_t \sum_{\tau=0}^{\infty} \xi_p^\tau \beta^\tau m_{t,\tau} \left[\tilde{P}_t(i) \left(\prod_{n=1}^{\tau} \pi_{t+n-1}^{\iota_p} \pi_*^{1-\iota_p}\right) - MC_{t+n}\right] Y_{t+\tau}(i),$$

subject to the demand function:

$$Y_{t+\tau}(i) = G'^{-1} \left[\frac{\tilde{P}_t(i) \prod_{n=1}^{\tau} \pi_{t+n-1}^{\iota_p} \pi_*^{1-\iota_p}}{P_{t+\tau}} \int_0^1 G'\left(\frac{Y_{t+\tau}(i)}{Y_{t+\tau}}\right) \frac{Y_{t+\tau}(i)}{Y_{t+\tau}} di\right]$$

where $m_{t,\tau}$ is the stochastic discount factor that is defined as the intertemporal ratio of marginal utility out of consumption.

A.4. Intermediate Labor Union

The intermediate labor union first collects the homogenous labor supplied from households. It then differentiates labor services denoted by l and offers wages to firms. Under flexible wage setting, the desired wage W_t^h is determined by the household optimality conditions for labor supply which is same for all households. Here, the intermediate labor union faces Calvo-type frictions, and thus sets the wage $\tilde{W}_t(l)$ by maximinzing:

$$E_t \sum_{\tau=0}^{\infty} \xi_w^\tau \beta^\tau m_{t,\tau} \left[W_{t+\tau}(l) - W_{t+\tau}^h\right] L_{t+\tau}(l),$$

subject to the labor demand function:

$$L_{t+\tau}(l) = \left[\frac{W_{t+\tau}(l)}{W_{t+\tau}}\right]^{-\frac{1+\lambda_w}{\lambda_w}} L_{t+\tau},$$

and the trend in nominal wage growth:

$$W_{t+\tau}(l) = \tilde{W}_t(l) \left(\prod_{n=1}^{\tau} \pi_{t+n-1}^{\iota_w} \pi_*^{1-\iota_w}\right).$$

A.5. The Central Bank

The central bank sets the short-term nominal interest rate by following the simple instrument rule:

$$\frac{R_t}{R^*} = \left(\frac{R_{t-1}}{R^*}\right)^\rho \left[\left(\frac{\pi_t}{\pi^*}\right)^{r_\pi} \left(\frac{Y_t}{Y_{t-1}} \frac{Y_{t-1}^*}{Y_t^*}\right)^{r_y}\right]^{1-\rho} \tag{A4}$$

where Y_t^* is the natural output, which is defined as the output in the flexible price and wage equilibrium.

A.6. Equilibrium Conditions

We detrend the equilibrium conditions in level as follows:

$$k_t = \frac{K_t}{\gamma^t}, \ k_t^s = \frac{K_t^s}{\gamma^t}, w_t = \frac{W_t}{P_t\gamma^t}, \ r_t^k = \frac{R_t^k}{P_t}, \ c_t = \frac{K_t}{\gamma^t},$$

$$\pi_t = \frac{P_t}{P_{t-1}}, \ c_t = \frac{K_t}{\gamma^t}, \ i_t = \frac{I_t}{\gamma^t}, \ y_t = \frac{Y_t}{\gamma^t}, \ mc_t = \frac{MC_t}{P_t} = \frac{1}{\mu_t^p}.$$

We assume *ex post* symmetric equilibrium for the equilibrium conditions below. Equation (A1) can be transformed into

$$k_t = (1 - \delta)\frac{1}{\gamma}k_{t-1} + \left[1 - S\left(\frac{\gamma i_t}{i_{t-1}}\right)\right]i_t. \tag{A5}$$

Equation, (A2), (A3) and (A4) are also detrended as

$$y_t = (k_t^s)^\alpha L_t(i)^{1-\alpha} - \Phi, \tag{A6}$$

$$k_t^s = \frac{u_t}{\gamma}k_{t-1}, \tag{A7}$$

and

$$\frac{R_t}{R^*} = \left(\frac{R_{t-1}}{R^*}\right)^\rho \left[\left(\frac{\pi_t}{\pi^*}\right)^{r_\pi}\left(\frac{y_t}{y_{t-1}}\frac{y_{t-1}^*}{y_t^*}\right)^{r_y}\right]^{1-\rho}. \tag{A8}$$

The resource constraint in this economy is given by

$$y_t = c_t + i_t + \frac{a(u_t)}{\gamma}k_{t-1}. \tag{A9}$$

From household's first order necessary conditions, we can derive

$$\left(c_t - \frac{\lambda}{\gamma}c_{t-1}\right)^{-\sigma_c}\exp\left(\frac{\sigma_c - 1}{1 + \sigma_l}L_t^{1+\sigma_l}\right) = \beta\frac{R_t}{\pi_{t+1}}(\gamma c_{t+1} - \lambda c_t)^{-\sigma_c}\exp\left(\frac{\sigma_c - 1}{1 + \sigma_l}L_{t+1}^{1+\sigma_l}\right), \tag{A10}$$

$$r_t^k k_{t-1} = a'(u_t)k_{t-1}, \tag{A11}$$

$$q_t = \beta\frac{(\gamma c_{t+1} - \lambda c_t)^{-\sigma_c}\exp\left(\frac{\sigma_c-1}{1+\sigma_l}L_{t+1}^{1+\sigma_l}\right)}{\left(c_t - \frac{\lambda}{\gamma}c_{t-1}\right)^{-\sigma_c}\exp\left(\frac{\sigma_c-1}{1+\sigma_l}L_t^{1+\sigma_l}\right)}\left[r_{t+1}^k u_{t+1} - a(u_{t+1}) + q_{t+1}(1-\delta)\right], \tag{A12}$$

and

$$q_t = \frac{1 - \beta\frac{(\gamma c_{t+1}-\lambda c_t)^{-\sigma_c}\exp\left(\frac{\sigma_c-1}{1+\sigma_l}L_{t+1}^{1+\sigma_l}\right)}{\left(c_t-\frac{\lambda}{\gamma}c_{t-1}\right)^{-\sigma_c}\exp\left(\frac{\sigma_c-1}{1+\sigma_l}L_t^{1+\sigma_l}\right)}q_{t+1}S'\left(\frac{\gamma i_{t+1}}{i_t}\right)\left(\frac{\gamma i_{t+1}}{i_t}\right)^2}{1 - S\left(\frac{\gamma i_t}{i_{t-1}}\right) - S'\left(\frac{\gamma i_t}{i_{t-1}}\right)\frac{\gamma i_t}{i_{t-1}}} \tag{A13}$$

where q_t is the theoretical price of capital, which is the ratio of the Lagrange multiplier on the capital formation over that on the budget constraint.

From the cost minimization problem by intermediate goods producers, we can derive

$$k_t^s = \frac{\alpha}{1-\alpha}\frac{w_t}{r_t^k}L_t, \tag{A14}$$

and

$$mc_t = \frac{1}{\mu_t^p} = \left(\frac{r_t^k}{\alpha}\right)^\alpha\left[\frac{w_t}{(1-\alpha)}\right]^{1-\alpha} \tag{A15}$$

$$= \frac{w_t}{1-\alpha}\left(\frac{L_t}{k_t^s}\right)^\alpha.$$

Furthermore, from the optimal labor supply decision by households, we have

$$\left(c_t - \frac{\lambda}{\gamma}c_{t-1}\right) L_t^{\sigma_l}(j) = \frac{P_t\gamma^t w_t}{P_t\gamma^t w_t}\frac{W_t^h}{\gamma^t P_t} = \frac{w_t^h}{w_t}w_t = \frac{1}{\mu_t^w}w_t \tag{A16}$$

where we detrend the flexible desired wage using

$$w_t^h = \frac{W_t^h}{\gamma^t P_t}.$$

The rests are optimality conditions from staggered price and wage settings. From the optimal price setting problem, we have

$$\frac{1}{\lambda_p}\left[\tilde{p}_t - (1+\lambda_p)\,mc_t\right] y_t \tag{A17}$$

$$+ \mathrm{E}_t \sum_{\tau=0}^{\infty}\frac{\xi_p^\tau\beta^\tau\gamma^{\tau+\sigma_c}m_{t,\tau}}{\lambda_p}\left[\tilde{p}_t\frac{\prod_{n=1}^{\tau}\pi_{t+n-1}^{\iota_p}\pi_*^{1-\iota_p}}{\prod_{n=1}^{\tau}\pi_{t+n}} - (1+\lambda_p)\,mc_{t+\tau}\right] y_{t+\tau}$$

$$= \quad 0,$$

where we define

$$\tilde{p}_t = \frac{\tilde{P}_t}{P_t}.$$

Similarly, for the optimal wage setting, we can derive

$$\mathrm{E}_t \sum_{\tau=0}^{\infty}\frac{\xi_w^\tau\beta^\tau\gamma^{\tau+\sigma_c}m_{t,\tau}}{\lambda_w}\left[(1+\lambda_w)\,w_{t+\tau}^h - \frac{\prod_{n=1}^{\tau}\pi_{t+n-1}^{\iota_w}\pi_*^{1-\iota_w}}{\prod_{n=1}^{\tau}\pi_{t+n-1}}\tilde{w}_t\right] = 0 \tag{A18}$$

where we define

$$\tilde{w}_t = \frac{\tilde{W}_t}{\gamma^t P_t}.$$

By log-linearizing the equations (A5) to (A18) around the steady state, we can obtain the 14 linearized equilibrium conditions used in the main text. We can eliminate the newly set price and wage, namely $\tilde{p}_t$ and $\tilde{w}_t$ by log-linearization.

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Table 1: Prior and Posterior Distributions of the Parameters

Parameter	Range	Prior Distributions			Posterior Distributions	
		Density	Mean	90% Interval	Mean	90% Interval
φ	$\Re^+$	Normal	4.00	[1.58, 6.48]	4.82	[2.67, 6.97]
σ_c	$\Re^+$	Normal	1.50	[1.17, 1.83]	1.72	[1.50, 1.93]
λ	$[0, 1)$	Beta	0.70	[0.55, 0.87]	0.38	[0.30, 0.46]
ξ_w	$[0, 1)$	Beta	0.50	[0.33, 0.67]	0.26	[0.17, 0.35]
σ_l	$\Re^+$	Normal	2.00	[0.79, 3.26]	2.23	[1.28, 3.14]
ξ_p	$[0, 1)$	Beta	0.50	[0.33, 0.67]	0.40	[0.32, 0.48]
ι_w	$[0, 1)$	Beta	0.50	[0.25, 0.75]	0.51	[0.27, 0.75]
ι_p	$[0, 1)$	Beta	0.50	[0.25, 0.75]	0.18	[0.06, 0.29]
ψ	$[0, 1)$	Beta	0.50	[0.25, 0.75]	0.75	[0.60, 0.89]
ϕ_p	$\Re^+$	Normal	1.25	[1.05, 1.46]	1.53	[1.38, 1.68]
r_π	$\Re^+$	Normal	1.50	[1.12, 1.89]	2.10	[1.83, 2.37]
ρ	$[0, 1)$	Beta	0.75	[0.59, 0.91]	0.75	[0.69, 0.80]
r_y	$\Re^+$	Normal	0.12	[0.04, 0.21]	0.17	[0.09, 0.24]
π	$\Re^+$	Gamma	0.60	[0.43, 0.76]	0.61	[0.49, 0.74]
$100(\beta^{-1} - 1)$	$\Re^+$	Gamma	0.25	[0.09, 0.40]	0.17	[0.07, 0.27]
l	$\Re^+$	Normal	0.17	[0.01, 0.34]	0.17	[0.01, 0.33]
$100(\gamma - 1)$	$\Re^+$	Normal	0.55	[0.39, 0.71]	0.35	[0.29, 0.41]
α	$\Re^+$	Normal	0.30	[0.22, 0.38]	0.21	[0.17, 0.26]
ρ_z	$[0, 1)$	Beta	0.50	[0.25, 0.75]	0.98	[0.97, 0.99]
ρ_f	$[0, 1)$	Beta	0.50	[0.25, 0.75]	0.90	[0.85, 0.96]
ρ_g	$[0, 1)$	Beta	0.50	[0.25, 0.75]	0.96	[0.94, 0.98]
ρ_v	$[0, 1)$	Beta	0.50	[0.25, 0.75]	0.37	[0.15, 0.57]
ρ_m	$[0, 1)$	Beta	0.50	[0.25, 0.75]	0.36	[0.26, 0.46]
ρ_a	$[0, 1)$	Beta	0.50	[0.25, 0.75]	0.86	[0.78, 0.95]
ρ_b	$[0, 1)$	Beta	0.50	[0.25, 0.75]	0.96	[0.94, 0.98]
σ_{z0}	$\Re^+$	InvGamma	0.25	[0.11, 0.40]	0.34	[0.27, 0.40]
σ_{z1}	$\Re^+$	InvGamma	0.11	[0.05, 0.18]	0.14	[0.06, 0.21]
σ_{z2}	$\Re^+$	InvGamma	0.11	[0.05, 0.18]	0.13	[0.06, 0.19]
σ_{z3}	$\Re^+$	InvGamma	0.11	[0.05, 0.18]	0.11	[0.05, 0.17]
σ_{z4}	$\Re^+$	InvGamma	0.11	[0.05, 0.18]	0.12	[0.06, 0.18]
σ_{z5}	$\Re^+$	InvGamma	0.11	[0.05, 0.18]	0.16	[0.08, 0.23]
σ_f	$\Re^+$	InvGamma	0.25	[0.11, 0.40]	0.23	[0.13, 0.34]
σ_g	$\Re^+$	InvGamma	0.25	[0.11, 0.40]	0.44	[0.38, 0.49]
σ_v	$\Re^+$	InvGamma	0.25	[0.11, 0.40]	0.41	[0.28, 0.54]
σ_m	$\Re^+$	InvGamma	0.25	[0.11, 0.40]	0.16	[0.13, 0.18]
σ_a	$\Re^+$	InvGamma	0.25	[0.11, 0.40]	0.13	[0.10, 0.15]
σ_b	$\Re^+$	InvGamma	0.25	[0.11, 0.40]	0.47	[0.32, 0.62]

Table 2: Variance Decompositions

| Shock	Baseline	No News	Baseline	No News
	Consumption		Inflation	
Unanticipated technology	15.65	5.52	7.52	6.87
News about technology	12.66	-	14.93	-
Non-technology	71.68	94.48	77.55	93.13
	Investment		Wage	
Unanticipated technology	4.28	3.15	6.60	2.63
News about technology	3.44	-	14.13	-
Non-technology	92.28	96.85	79.27	97.37
	Output		Interest rate	
Unanticipated technology	11.70	6.40	7.26	3.87
News about technology	8.53	-	13.84	-
Non-technology	79.78	93.60	78.90	96.13
	Hours			
Unanticipated technology	5.70	3.86		
News about technology	5.58	-		
Non-technology	88.72	96.14		

Table 3: Log Marginal Data Densities and Variance Decompositions

	Baseline	No news	1-period only	2-period only	3-period only	4-period only	5-period only
$\ln p(Y^T)$	-438.67	-443.51	-444.59	-444.07	-446.86	-445.46	-443.10
				Output			
Unanticipated shock	11.70	6.40	7.75	8.30	6.51	7.62	8.69
News shocks (in total)	8.53	-	2.83	3.07	1.83	1.63	1.68
News 1 period ahead	3.11	-	2.83	-	-	-	-
News 2 periods ahead	2.10	-	-	3.07	-	-	-
News 3 periods ahead	1.12	-	-	-	1.83	-	-
News 4 periods ahead	0.93	-	-	-	-	1.63	-
News 5 periods ahead	1.23	-	-	-	-	-	1.68
				Inflation			
Unanticipated shock	7.52	6.87	7.16	7.69	6.93	7.41	7.19
News shocks (in total)	14.93	-	1.04	0.85	0.74	1.58	3.87
News 1 period ahead	0.68	-	1.04	-	-	-	-
News 2 periods ahead	1.05	-	-	0.85	-	-	-
News 3 periods ahead	1.95	-	-	-	0.74	-	-
News 4 periods ahead	3.69	-	-	-	-	1.58	-
News 5 periods ahead	7.56	-	-	-	-	-	3.87

Table 4: Log Marginal Data Densities and Variance Decompositions for Japan

|	Baseline	No news	1-period only	2-period only	3-period only	4-period only	5-period only
$\ln p(Y^T)$	-486.57	-477.75	-483.38	-483.39	-483.06	-481.81	-482.46
Output							
Unanticipated shock	45.68	52.64	48.22	48.54	48.95	49.04	50.80
News shocks (in total)	5.10	-	3.03	2.23	2.20	2.59	2.73
News 1 period ahead	1.21	-	3.03	-	-	-	-
News 2 periods ahead	0.92	-	-	2.23	-	-	-
News 3 periods ahead	0.92	-	-	-	2.20	-	-
News 4 periods ahead	1.04	-	-	-	-	2.59	-
News 5 periods ahead	1.01	-	-	-	-	-	2.73
Inflation							
Unanticipated shock	13.25	13.31	13.37	13.39	12.80	12.37	13.06
News shocks (in total)	5.77	-	0.93	2.04	3.82	4.53	4.70
News 1 period ahead	0.40	-	0.93	-	-	-	-
News 2 periods ahead	0.82	-	-	2.04	-	-	-
News 3 periods ahead	1.35	-	-	-	3.82	-	-
News 4 periods ahead	1.64	-	-	-	-	4.53	-
News 5 periods ahead	1.56	-	-	-	-	-	4.70

Figure 1: Impulse Responses to Productivity Shocks
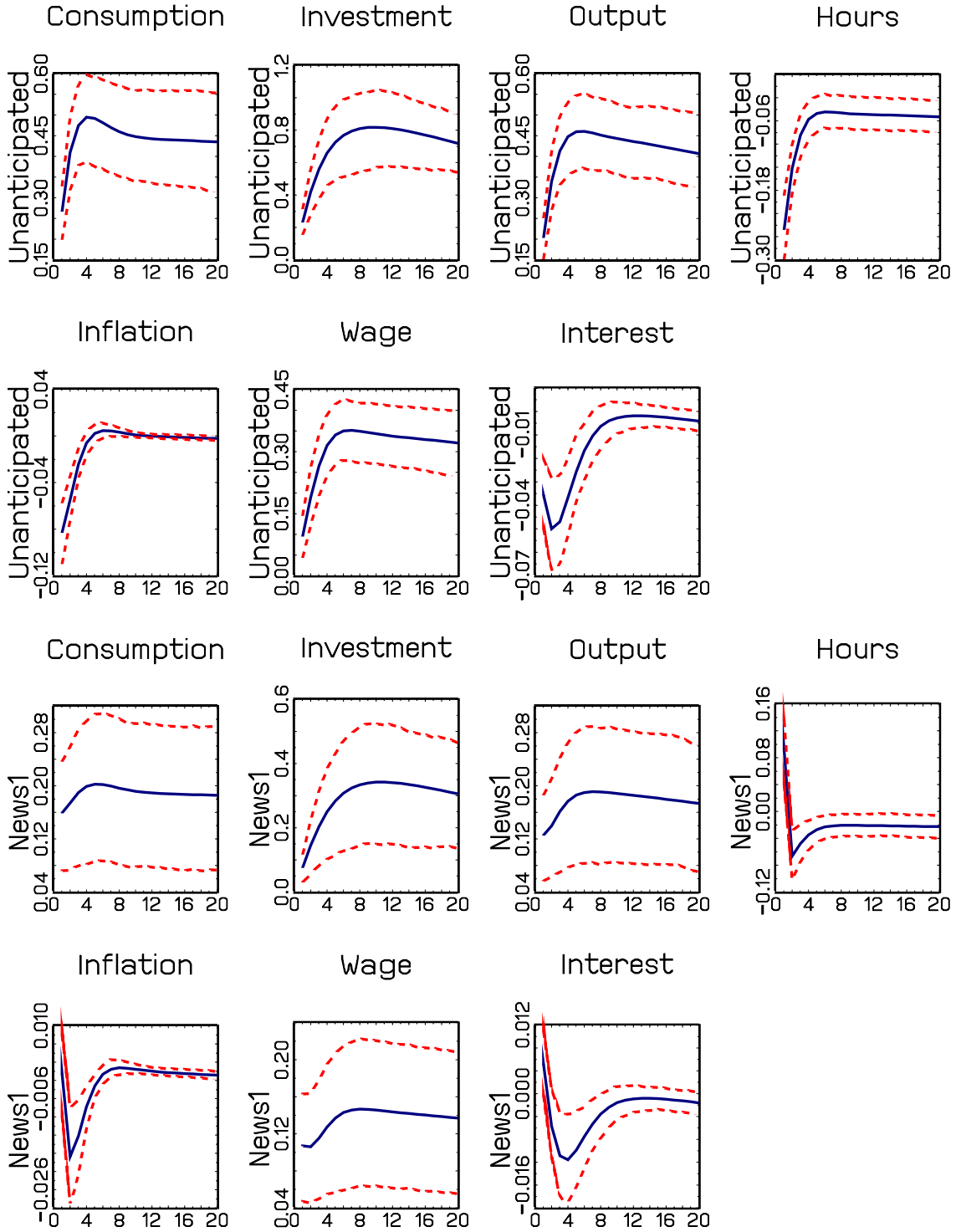
Note: The Figure depicts posterior means (solid lines) and pointwise 90% posterior probability intervals (dashed lines) for the impulse responses to one-standard deviation shocks.
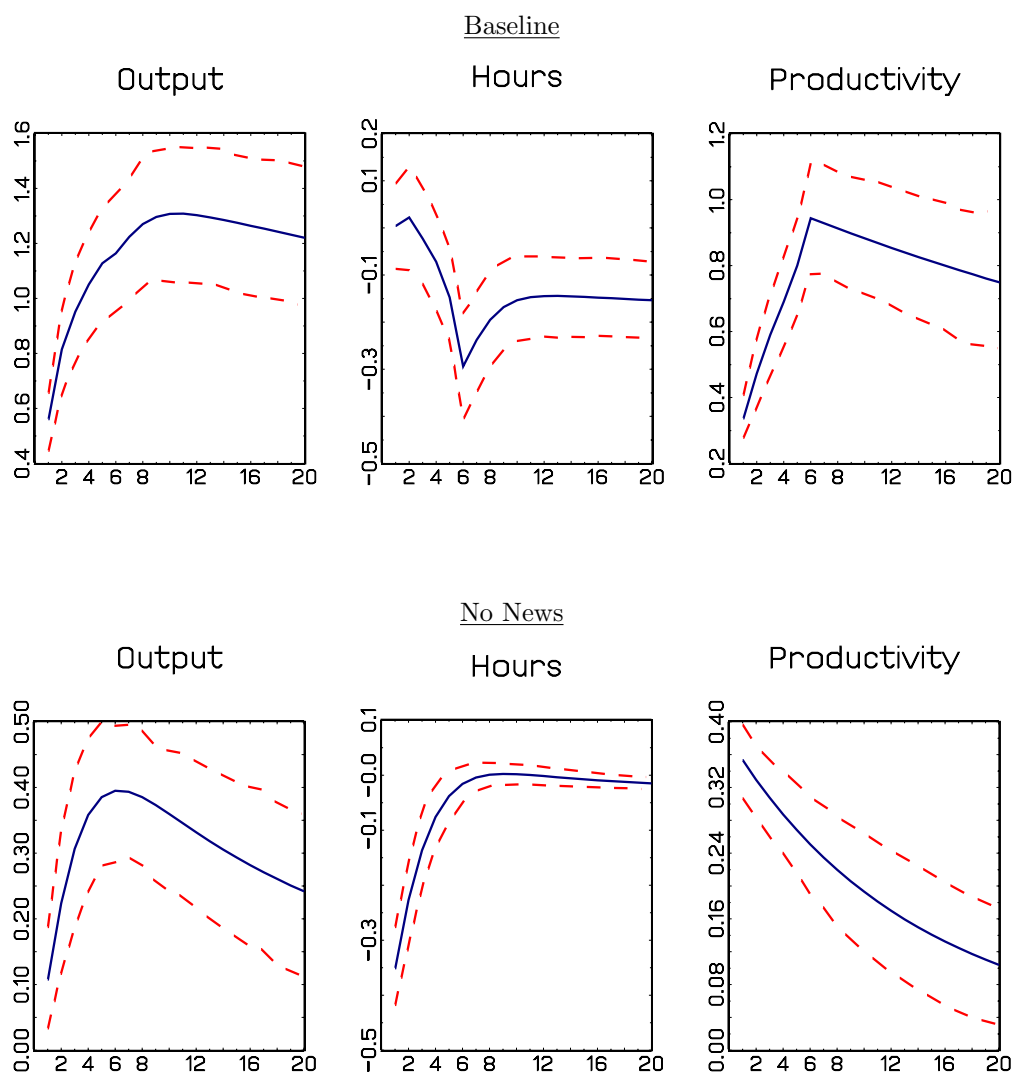
Figure 1(continued): Impulse Responses to Productivity Shocks
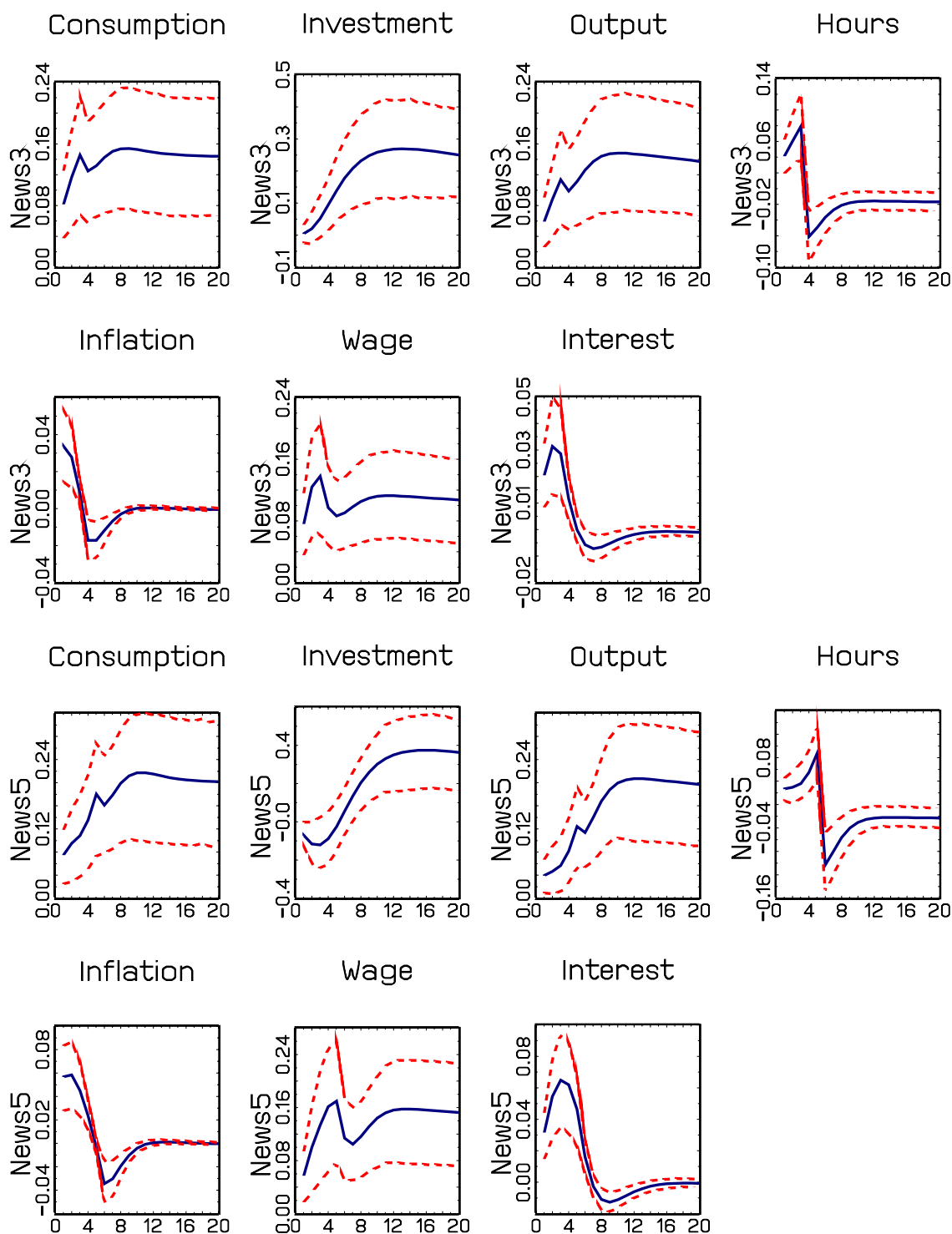
Note: The Figure depicts posterior means (solid lines) and pointwise 90% posterior probability intervals (dashed lines) for the impulse responses to one-standard deviation shocks.

Figure 2: Impulse Responses of Output, Hours and Productivity to Simultaneous Shocks on Unanticipated and News Components

Note: The Figure depicts posterior means (solid lines) and pointwise 90% posterior probability intervals (dashed lines) for the impulse responses to one-standard deviation shocks.