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The Quantitative Importance of News Shocks in Estimated DSGE Models

MEI surprise shock

We estimate a dynamic stochastic general equilibrium (DSGE) model with several frictions and both unanticipated and news shocks, using quarterly U.S. data from 1954 to 2004 and Bayesian methods. We find that unanticipated shocks dominate news shocks in accounting for the unconditional variance of output, consumption, and investment growth, interest rate, and the relative price of investment. The unanticipated shock to the marginal efficiency of investment is the dominant shock, accounting for over 45% of the variance in output growth. News shocks account for less than 15% of the variance in output growth. Within the set of news shocks, nontechnology sources of news dominate technology news, with wage markup news shocks accounting for about 60% of the variance share of both hours and inflation. We find that in the estimated DSGE model (i) the presence of endogenous countercyclical price and wage markups due to nominal frictions substantially diminishes the importance of news shocks relative to a model without these frictions, and (ii) while there is little change in the estimated contributions of technology news when we restrict wealth effects on labor supply, the contributions of nontechnology news shocks are relatively more sensitive.

JEL codes: E2, E3
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WE EXAMINE THE QUANTITATIVE importance of anticipated shocks, referred to as "news shocks" in the post–WW II U.S. data, using a dynamic stochastic general equilibrium (DSGE) model. Following the empirical work of Beaudry and Portier (2006), which suggests that an important fraction of aggregate

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fluctuations may be driven by news shocks, a rapidly growing literature has emerged. One strand of this literature, to which our paper contributes, uses the framework of estimated DSGE models to examine the role of news shocks in driving aggregate fluctuations. Early work includes Davis (2007), Schmitt-Grohé and Uribe (Forthcoming), and Fujiwara, Hirose, and Shintani (2011).

We consider a benchmark DSGE model that has elements from Smets and Wouters (2003, 2007), Christiano, Eichenbaum, and Evans (2005), Justiniano and Primiceri (2008), Justiniano, Primiceri, and Tambalotti (2010), and Altig et al. (2011). There are several features in the benchmark model that are worth highlighting. The model contains a variety of real and nominal frictions that are helpful in accounting for the conditional responses of macroeconomic variables to shocks. The driving forces in the model include permanent and stationary shocks to total factor productivity (TFP), and permanent and stationary investment shocks. The latter two are the investment-specific (INV) and the marginal efficiency of investment (MEI) shocks, respectively. Recently, Justiniano, Primiceri, and Tambalotti (2011) emphasize the distinction between these two types of investment shocks. In addition, we include five nontechnology shocks, namely, preference, price and wage markups, government spending, and monetary policy shocks. Our objective is to conduct a quantitative assessment of unanticipated shocks relative to news shocks when they all compete in a DSGE model. We therefore introduce news components in both technology (TFP, MEI, and INV) and nontechnology shocks, except the monetary policy shock. Following Jaimovich and Rebelo (2009), we introduce preferences which can mitigate the strong wealth effects of news shocks. In the presence of other real frictions, investment adjustment costs and capital utilization costs, the benchmark DSGE model we use in our analysis is equipped, in theory, to produce comovement among macroeconomic variables in response to news shocks. We estimate the model using Bayesian methods and quarterly U.S. data on eight observables from 1954:3 to 2004:4. These variables are log difference of real GDP, real consumption, real wage, real investment, the relative price of investment, and inflation, as well as the log level of hours worked and the federal funds rate.

Our main quantitative findings are as follows. First, unanticipated shocks dominate news shocks, and account for about 87% of the unconditional variance in output growth. The unanticipated MEI shock is quantitatively the most important, accounting for 46.7% of the total variance, followed by the unanticipated TFP shocks (about 24%). The total variance share of news shocks for output growth is 13.60%. Second, the unanticipated shocks also dominate news shocks in accounting for the variance of consumption, investment, wages, interest rate, and the relative price of investment. Third, in the set of news shocks, the nontechnology sources of news dominate technology news, and account for 64.3% of the variance of hours and 61% of the variance in inflation. The contribution of the wage markup news shock is the largest (accounting for nearly 60% of the variance in hours and inflation), and hence quantitatively the most important among all types of news shocks. Finally, restricting the wealth elasticity of labor supply to zero increases the variance share of TFP news shocks for all variables but the magnitudes remain small, in the range of 2–6%. And for nontechnology shocks the variance shares for real variables falls relative to those in the benchmark model. The dominant role of unanticipated shocks relative to news shocks in accounting for fluctuations, however, remains unchanged relative to the benchmark case where the estimated value of the wealth elasticity is 0.62, implying the presence of moderate wealth effects in the data.

The quantitative importance of the unanticipated MEI shock is consistent with the results of Justiniano, Primiceri, and Tambalotti (2010) who do not consider news shocks but find a large role for unanticipated MEI shocks in accounting for aggregate fluctuations in the U.S. economy. Our results indicate that the news component of the MEI shock has a negligible role. Our findings are consistent with those of Fujiwara, Hirose, and Shintani (2011) in that TFP news shocks contribute mainly toward the variance of consumption growth (with a variance share of about 10%). Moreover, the relative ranking of the importance of news shocks for output, consumption, investment growth, and hours remains similar to that in Fujiwara, Hirose, and Shintani (2011), despite the differences in model specifications noted in Section 3.5. The results reveal both similarities and differences relative to Schmitt-Grohé and Uribe (Forthcoming). Our result that TFP news shocks are quantitatively unimportant in an estimated DSGE model when both nominal and real frictions are present is consistent with the finding in Schmitt-Grohé and Uribe based on an estimated RBC model. The variance share of TFP news shocks for output, consumption, investment growth, and hours is below 4%, similar to what they find. This finding is not sensitive to changes in the wealth elasticity of labor supply. A second finding that is similar to theirs is the large role of the wage markup news shocks in accounting for the variance in hours (a variance share of almost 60% versus 67% in theirs). Previously, Justiniano, Primiceri, and Tambalotti (2010) show that wage markup shocks are important for hours accounting for 58% of the unconditional variance (i.e., only at very low frequencies). Our findings indicate that while this remains the case, it is the news component of wage markups that is more important for hours relative to the unanticipated component. At the business cycle frequency, however, the share of wage markup news shocks in accounting for the variance in hours is substantially smaller (10.5%) while that of unanticipated MEI shocks is 67%.

When Schmitt-Grohé and Uribe (Forthcoming) sum up the contribution of all types of news shocks (both technology and nontechnology), they find that news shocks also dominate in accounting for the variance in output, consumption, and investment growth. In contrast, we find that its the unanticipated shocks which dominate. We show that the main reason why the estimated sources of variance shift from news shocks to unanticipated shocks is the presence of nominal price and wage frictions. The variance share of news shocks falls when these nominal frictions are present, as in our benchmark model. Moreover, the role of unanticipated MEI increases substantially. The reason is that there is a change in the transmission mechanism that favors the unanticipated MEI shocks. Nominal frictions permit an endogenous countercyclical movement of markups to operate, which in turn causes positive shifts in the labor demand and supply and increase equilibrium hours. This improves the comovement properties of the unanticipated MEI shocks, and in the estimated DSGE model increases their variance shares relative to the case where nominal frictions are absent as in Schmitt-Grohé and Uribe (Forthcoming).

The rest of the paper is structured as follows. Section 1 describes the model set-up; Section 2 presents results, robustness, and comparisons with the literature; and Section 3 concludes.

1. THE MODEL

We consider a DSGE model with real and nominal frictions and a variety of shocks as the benchmark model. The recent literature has shown that a medium-scale model with a rich structure and set of shocks helps account for the variation in aggregate data, in understanding the effects of shocks, and in assessing the sources of business cycles. A few prominent examples of such models are Smets and Wouters (2003, 2007), Christiano, Eichenbaum, and Evans (2005), Justiniano and Primiceri (2008), Justiniano, Primiceri, and Tambalotti (2010), and Altig et al. (2011). There are several features in the benchmark model that are worth highlighting. First, the driving forces in the model include permanent and stationary shocks to TFP, and permanent and stationary shocks to investment. The latter two are INV and MEI shocks, respectively. Recently, Justiniano, Primiceri, and Tambalotti (2011) emphasize the distinction between these types of investment shocks and show that the MEI shock in particular is a quantitatively important source of fluctuations. In addition, we include a set of stationary shocks to price and wage markups, preferences, government spending, and monetary policy. Second, in the benchmark model we introduce anticipated (news) components in both technology (i.e., TFP, INV, and MEI) and nontechnology (i.e., price and wage markup, government spending, preference) shocks. Third, we consider preferences suggested by Jaimovich and Rebelo (2009) that can, in theory, help mitigate the strong wealth effects of news shocks on labor supply thereby helping to generate comovement among the key real macroeconomic variables.

The model economy consists of goods-producing firms, households, a government sector, and a central bank conducting monetary policy. We now briefly describe the structure and the shock processes of the model.

1.1 Firms

There are firms that operate in a perfectly competitive market to produce an aggregate final good, Y_t, using differentiated intermediate goods, $Y_t(m)$, supplied by a continuum of monopolistically competitive firms, $m \in [0, 1]$. The production process of the final good producing firms is described according to the technology

$$Y_t = \left[\int_0^1 Y_t(m)^{\frac{1}{1+\lambda_{p,t}}} dm\right]^{1+\lambda_{p,t}} \tag{1}$$

and $(1+\lambda_{p,t})/\lambda_{p,t}$ is the time-varying elasticity of substitution between the intermediate goods. The final good producing firms take the price of their output, P_t, and inputs $P_t(m)$ as given, along with the exogenous process for $\lambda_{p,t}$, to solve the profit maximization problem $\max_{Y_t(m)}[P_t Y_t - \int_0^1 P_t(m) Y_t(m) dm]$ subject to (1). The first-order necessary condition gives the intermediate good demand functions as

$$Y_t(m) = \left(\frac{P_t(m)}{P_t}\right)^{-\frac{1+\lambda_{p,t}}{\lambda_{p,t}}} Y_t, \quad m \in [0,1] \tag{2}$$

and implies a unit price of final good

$$P_t = \left[\int_0^1 P_t(m)^{-\frac{1}{\lambda_{p,t}}} dm\right]^{-\lambda_{p,t}}. \tag{3}$$

Each intermediate goods-producing monopolist uses the technology

$$Y_t(m) = \begin{cases} \left(\varepsilon_t^a\right)^{1-\alpha} K_t(m)^\alpha (Z_t L_t(m))^{1-\alpha} - V_t^{\frac{\alpha}{1-\alpha}} Z_t \phi \\ \qquad \text{if } \left(\varepsilon_t^a\right)^{1-\alpha} K_t(m)^\alpha (Z_t L_t(m))^{1-\alpha} \geq V_t^{\frac{\alpha}{1-\alpha}} Z_t \phi \\ 0 \qquad \text{otherwise,} \end{cases} \tag{4}$$

where $K_t(m)$ and $L_t(m)$ denote capital and labor services hired to produce the mth intermediate good, $0 < \alpha < 1$ is the capital share in production, Z_t denotes the nonstationary neutral (TFP) technology process, ε_t^a denotes the stationary neutral (TFP) technology process, and V_t denotes the INV nonstationary process. Equation (4) implies that production occurs only if the fixed costs of production, ϕ, are covered, subject to the scaling $V_t^{\frac{\alpha}{1-\alpha}} Z_t$, which ensures that a balanced growth path exists in the nonstochastic steady state of the model.

Intermediate good firms face a nominal friction in setting prices that follows the standard Calvo (1983) formulation. In each period a firm faces a probability $(1-\xi_p)$ to choose the optimal price and with probability ξ_p it cannot do so. And in that case, it uses an indexed-pricing rule to reset its price as

$$P_t(m) = P_{t-1}(m)\pi_{t-1}^{\iota_p}\pi^{1-\iota_p}, \tag{5}$$

where π_t denotes the aggregate (gross) inflation P_t/P_{t-1}, π is the steady-state inflation, and $0 \leq \iota_p \leq 1$ is the price indexation parameter.

Let $\tilde{P}_t(m)$ denote the optimally set price chosen by maximizing current and present discounted value of future profits. This price is chosen by solving

$$E_t\left[\sum_{s=0}^{\infty} \beta^s \xi_p^s \nu_{t+s}\left[P_t(m)\left(\Pi_{k=0}^s \pi_{t-1+k}^{\iota_p}\pi^{1-\iota_p}\right) Y_{t+s}(m) - W_{t+s}L_{t+s}(m) - R_{t+s}^k K_{t+s}(m)\right]\right] \tag{6}$$

subject to (2), where $\beta^s \xi_p^s \nu_{t+s}$ is the stochastic discount factor used by the firm owners (the households) for valuing nominal income stream accruing in period s, with $0 < \beta < 1$, and $\lambda_{p,t}$ in (2) corresponds to the time-varying price markup. W_t is the nominal wage and R_t^k is the nominal rental rate of capital.

1.2 Households

There is a continuum of households indexed by $j \in (0, 1)$. Each household consumes goods and services, supplies a specialized labor to labor market at marked-up wages, rents capital services to firms, and makes investment and capital utilization decisions. There are costs associated with adjusting the flow of investment and the capital utilization rate. We introduce the preference structure suggested by Jaimovich and Rebelo (2009) which conveniently nests two special cases which we describe later. The utility function of household $j \in [0, 1]$ is

$$E_t \sum_{s=0}^{\infty} \beta^s \frac{\varepsilon_{t+s}^b \left(C_{t+s} - hC_{t+s-1} - \chi L_{t+s}(j)^{1+\sigma_l} X_{t+s}\right)^{1-\sigma_c} - 1}{1 - \sigma_c}, \tag{7}$$

where

$$X_t = (C_t - hC_{t-1})^{\omega} X_{t-1}^{1-\omega} \tag{8}$$

is a geometric average of the current consumption level (net of internal habits), $(C_t - hC_{t-1})$, and the past consumption level, X_{t-1}, and $L_t(j)$ are labor services (hours) of household worker-type j supplied to firms in the production sector. The operator E_t denotes expectation conditional on the information available at time t, $0 < \beta < 1$ is the subjective discount factor, $\sigma_l > 0$ determines the elasticity of labor supply, $\chi > 0$ is the weight on the disutility of labor effort, $\sigma_c > 0$ determines the intertemporal elasticity of substitution, $0 \leq h \leq 1$ is the internal habit parameter, $0 < \omega \leq 1$, and ε_t^b is the preference shock.

Consider the case with no habits in consumption ($h = 0$). When $\omega = 1$ the preferences are the same as in King, Plosser, and Rebelo (1988) with the implication that the intertemporal substitution effect influences labor effort. When $\omega = 0$ the preferences are the same as in Greenwood, Hercowitz, and Huffman (1988), with the implication that intertemporal consumption-saving choice does not affect labor effort.

Interesting!

The budget constraint expressed in nominal terms is

$$\begin{aligned} P_t C_t + P_t V_t^{-1} I_t + \frac{B_t}{R_t} - T_t \leq W_t(j) L_t(j) + Q_t(j) + R_t^k U_t \overline{K}_{t-1} \\ - P_t a(U_t) \overline{K}_{t-1} V_{t-1}^{-1} + Div_t + B_{t-1} \end{aligned} \tag{9}$$

and the capital accumulation equation

$$\overline{K}_t = (1 - \delta)\overline{K}_{t-1} + \varepsilon_t^i \left[1 - S\left(\frac{I_t}{I_{t-1}}\right)\right] I_t. \tag{10}$$

Households rent capital services to firms and capital services are related to physical capital as follows,

$$K_t = U_t \overline{K}_{t-1}. \tag{11}$$

The notation is as follows: P_t is the price of one unit of consumption, I_t is investment, $\overline{K}_t$ is physical capital, K_t is capital services, B_t denotes nominal government bonds, R_t is the gross nominal interest rate, T_t denotes nominal lump-sum taxes, $W_t(j)$ is the wage of labor type j, $Q_t(j)$ denotes the net cash flow obtained from holding state-contingent securities, R_t^k is the nominal rental rate on capital, Div_t are the nominal dividends received from the ownership of firms, U_t is the utilization rate of capital, $a(U_t)$ is a convex function of the utilization rate. In the steady state, $U_t = 1$, with $a(1) = 0$ and $\psi \equiv a''(1)/a'(1)$ is the capital utilization elasticity. $P_{It}/P_t = V_t^{-1}$ is the relative price of investment in consumption units, where P_{It} is the price of a unit of investment good.[1] The term $S(\frac{I_t}{I_{t-1}})$ in (10) is a convex investment adjustment cost function. In the steady state it is assumed that $S = S' = 0$ and $S'' > 0$. ε_t^i in (10) denotes the shock to the marginal efficiency of capital (MEI). Note that while the households supply different types of labor services at different wages, the existence of state contingent securities ensures that in equilibrium all households have identical marginal utility of wealth, and hence the same level of consumption and asset holdings. This means that we can drop the index j from consumption, physical capital and investment, and bond holdings in (7) and (9).

Following Erceg, Henderson, and Levin (2000) formulation to introduce imperfect competition and nominal wage rigidity in the model, we assume that each household is monopsonistic in the labor market and offers a differentiated labor service. Households sell their labor services to perfectly competitive firms who bundle them into an aggregate labor input, L_t, using the technology

$$L_t = \left[\int_0^1 L_t(j)^{\frac{1}{1+\lambda_{w,t}}} dj\right]^{1+\lambda_{w,t}}, \tag{12}$$

where $(1 + \lambda_{w,t})/\lambda_{w,t}$ is the time-varying elasticity of substitution between the differentiated labor services, and $\lambda_{w,t}$ is the time-varying wage markup. The profit maximization problem of the "labor services bundling" firms is $\max_{L_t(j)}[W_t L_t - \int_0^1 w_t(j)L_t(j)dj]$ subject to (12), which gives the demand curve for labor services as

$$L_t(j) = \left(\frac{W_t(j)}{W_t}\right)^{-\frac{1+\lambda_{w,t}}{\lambda_{w,t}}} L_t \tag{13}$$

1. The expression for the relative price of investment follows from the profit maximization problem of a perfectly competitive investment sector that purchases investment goods and transforms them to physical capital, which are then sold to households. The solution of this problem equates the price of investment goods, P_{It}, to the marginal cost, $P_t V_t^{-1}$. See Justiniano, Primiceri, and Tambalotti (2011) for a detailed exposition.

and implies an aggregate wage for a unit of bundled labor service as

$$W_t = \left[\int_0^1 W_t(j)^{-\frac{1}{\lambda_{w,t}}}\right]^{-\lambda_{w,t}}. \tag{14}$$

With probability $(1 - \xi_w)$ in each period, a household can optimally set its wage for providing a particular type of labor service. And with probability ξ_w it cannot, and updates its wage offer according to the wage-indexation rule

$$W_t(j) = W_{t-1}(j)\left(\pi_{t-1}\exp^{g^z_{t-1}+\frac{\alpha}{1-\alpha}g^v_{t-1}}\right)^{\iota_w}\left(\pi\exp^{g_z+\frac{\alpha}{1-\alpha}g_v}\right)^{1-\iota_w}, \tag{15}$$

where $0 \leq \iota_w \leq 1$ is the wage-indexation parameter, and g^z and g^v (to be defined in the following section) are the growth rates in nonstationary TFP and INV shock processes, respectively. The indexation rule (15) ensures that a balanced growth path exists in the nonstochastic steady state of the model.

The household chooses C_t, K_t, I_t, U_t, B_t, and $W_t(j)$ to maximize (7) subject to (8), (9), (10), and (13), taking as given the prices $\{P_t, W_t, R_t, R_t^k, P_t^I\}$ and L_t.

1.3 Monetary Policy and Fiscal Policy

The monetary policy is conducted via an interest rate rule. Following Smets and Wouters (2007), the specification of the interest rate rule is

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R_t}\right)^{\rho}\left[\left(\frac{\pi_t}{\pi}\right)^{r_\pi}\left(\frac{X_t}{X_t^*}\right)^{r_y}\right]^{(1-\rho)}\left[\frac{X_t/X_{t-1}}{X_t^*/X_{t-1}^*}\right]^{r_{\Delta y}}\varepsilon_t^r, \tag{16}$$

where $X_t = C_t + I_t + G_t$ denotes GDP and R is the steady state level of the interest rate. The parameter ρ in (16) determines the degree of interest rate smoothing in policy. Interest rate also responds to the level and the growth rate of GDP gap, $\frac{X_t}{X_t^*}$ (the difference between actual and the efficient level of GDP). Policy parameters r_π, r_y, and $r_{\Delta y}$ determine the extent to which the interest rate responds to the developments in inflation and GDP gap (level and growth) movements, respectively, and ε_t^r is the monetary policy shock.

The fiscal spending, G_t, is assumed to evolve exogenously as a time-varying proportion of output in each period as

$$G_t = \left(1 - \frac{1}{\varepsilon_t^g}\right)Y_t, \tag{17}$$

where ε_t^g is the government spending shock. The government finances G_t by issuing government bonds, B_t, and via lump-sum taxation.

1.4 Unanticipated and News Shocks

The stationary TFP shock process follows

$$\ln \varepsilon_t^a = \rho_a \ln \varepsilon_{t-1}^a + \eta_t^a, \tag{18}$$

where ρ_a is the persistence parameter and η_t^a is the innovation discussed later. The nonstationary TFP shock process follows

$$\ln Z_t = \ln Z_{t-1} + g_t^z \tag{19}$$

with the

$$g_t^z = \rho_z g_{t-1}^z + (1 - \rho_z)\, g_z + \eta_t^z. \tag{20}$$

why?

Similar to (18)–(20), the two investment shocks follow a stationary process (MEI shock) and a nonstationary INV shock, respectively. The MEI shock process is

$$\ln \varepsilon_t^i = \rho_i \ln \varepsilon_{t-1}^i + \eta_t^i \tag{21}$$

and the INV shock process is

$$\ln V_t = \ln V_{t-1} + g_t^v \tag{22}$$

with

$$g_t^v = \rho_v g_{t-1}^v + (1 - \rho_v) g_v + \eta_t^v. \tag{23}$$

We introduce news shocks in the model in the same way as in Davis (2007), Schmitt-Grohé and Uribe (Forthcoming), and Fujiwara, Hirose, and Shintani (2011). Consider, for example, the innovation η_t^a in (18). We split this innovation into two components. An unanticipated component, $\eta_t^{a,0}$, and an anticipated component, $\eta_t^{a,\text{news}}$, written as

$$\eta_t^a = \eta_t^{a,0} + \eta_t^{a,\text{ news}}, \tag{24}$$

well-described

where $\eta_t^{a,\text{news}} \equiv \sum_{h=1}^{H} \eta_{t-h}^{a,h}$ and $\eta_{t-h}^{a,h}$ is the h-period-ahead news about TFP received by the agents at period $t-h$. H denotes the longest horizon over which the shocks are anticipated by the agents. The innovations to ε_t^a, $\eta_{t-h}^{a,h}$, are i.i.d. normal with variance $\sigma_{a,h}^2$, for $h = 0, 1, \ldots, H$, and assumed to be uncorrelated across time and horizons. To clarify this information structure, suppose we consider a one-quarter-ahead news horizon so $H = 1$ and $\eta_t^a = \eta_t^{a,0} + \eta_{t-1}^{a,1}$. Now in period t rational agents can form expectations about one period ahead TFP as follows

$$\ln \varepsilon_t^a = \rho_a \ln \varepsilon_{t-1}^a + \eta_t^{a,0} + \eta_{t-1}^{a,1} \tag{25}$$

$$\ln \varepsilon_{t+1}^a = \rho_a \ln \varepsilon_t^a + \eta_{t+1}^{a,0} + \eta_t^{a,1} \tag{26}$$

$$\ln \varepsilon^a_{t+1} = \rho_a \left(\rho_a \ln \varepsilon^a_{t-1} + \eta^{a,0}_t + \eta^{a,0}_{t+1} + \eta^{a,1}_{t-1} \right) + \eta^{a,1}_t \tag{27}$$

$$E_t \left[\ln \varepsilon^a_{t+1} \right] = \rho^2_a \ln \varepsilon^a_{t-1} + \rho_a \eta^{a,0}_t + \rho_a \eta^{a,1}_{t-1} + \eta^{a,1}_t . \tag{28}$$

A similar news shocks structure applies to the innovations in all other shocks (except the monetary shock). That is, to the stationary and nonstationary investment shock processes (20), (21), and (23). And the remaining shocks are assumed to follow only stationary processes as follows: the preference (b) shock follows a stationary $AR(1)$ process of the form

$$\ln \varepsilon^b_t = \rho_b \ln \varepsilon^b_{t-1} + \eta^b_t . \tag{29}$$

The government spending shock follows

$$\ln \varepsilon^g_t = (1 - \rho_g) \ln \bar{g} + \rho_g \ln \varepsilon^g_{t-1} + \eta^g_t , \tag{30}$$

where $\bar{g}$ is the steady state level of government spending. The price (p) and wage (w) markup shocks follow ARMA (1,1)

$$\ln \varepsilon^j_t = \rho_j \ln \varepsilon^j_{t-1} + \eta^j_t - \mu_j \eta^s_{t-1}, \quad j \in \{p, w\}, \tag{31}$$

where the innovations η^j_t follow a structure similar to (24), that is, i.i.d. normal with standard deviation σ_j, $j \in \{p, w\}$. Finally, the monetary policy (r) shock is i.i.d.,

$$\ln \varepsilon^r_t = \eta^r_t . \tag{32}$$

As in Beaudry and Portier (2006), TFP news shocks may represent technological innovations that affect the level of productive capacity with a delay. Agents learn about a new technology that has been invented but will be implemented in the future at which time they expect TFP to rise. For example, agents may respond to news about future technology or patenting of a product. Alternatively, agents may respond to future gains in productivity due to the commercialization of products or processes (see Alexopoulos 2011). Similarly, agents may receive news that capital goods will be produced with greater efficiency or will incorporate significant quality improvements in the future. News components in nontechnology shocks may capture anticipated shifts in the market structure for goods and labor services (e.g., changes in regulation, shifts in bargaining power), and anticipated changes in public spending. The news formulation we adopt, however, allows for revisions in expectations so that news shocks could also potentially fail to be realized.

I didn't see that

We detrend the endogenous variables in the model by removing the joint stochastic trend, $Z^*_t = Z_t V_t^{\frac{\alpha}{1-\alpha}}$, and then log-linearize the resulting stationary model equations around the steady state.[2] The vector of observables we use in the estimation, denoted

2. The details of model solution, data, and estimation methodology are provided in an online appendix on the authors' websites.

as $\mathbf{Y}_t$, is

$$\mathbf{Y}_t = \left[\Delta \log Y_t, \Delta \log C_t, \Delta \log I_t, \Delta \log \frac{W_t}{P_t}, \log L_t, \pi_t, r_t, \Delta \log \frac{P_{It}}{P_t}\right],$$

where Δ denotes the first-difference operator. We use the Bayesian methodology to estimate model parameters (see An and Schorfheide 2007, and Fernández-Villaverde 2009, and references therein, for recent overviews). All estimations are done using DYNARE.[3]

2. RESULTS

In this section, we present the parameter estimates and variance decompositions of the benchmark model. We then discuss the role of the wealth elasticity of labor supply in assessing news shocks, and contrast the findings with Fujiwara, Hirose, and Shintani (2011) and Schmitt-Grohé and Uribe (Forthcoming) to help understand the reasons behind the similarities and differences in the results.

2.1 Parameter Estimates

The last three columns of Table 1 report the estimated values of the structural parameters, and the persistence and the standard deviations of the shocks in the benchmark model. Overall, our estimates are in line with those in previous work of Smets and Wouters (2007) and Justiniano, Primiceri, and Tambalotti (2010, 2011) that have estimated similar specifications of the sticky price-wage framework that we adopt here. The Calvo wage and price stickiness estimates imply approximately three and four quarter contract durations, respectively. The indexation parameter suggests a small degree (under 20%) of price and wage indexation to previous period's inflation. The magnitude of the investment adjustment cost parameter is 2.77, in between the value 5.74 estimated in Smets and Wouters (2007) and 2.65 estimated in Justiniano, Primiceri, and Tambalotti (2011). The estimate of the consumption habit parameter is 0.81 which is somewhat less than the estimate of 0.91 (median) in Schmitt-Grohé and Uribe (Forthcoming).

The estimates of parameters in the monetary policy rule, that is, the coefficients for inflation, GDP gap, the growth in GDP gap, the interest rate smoothing parameter, and the standard deviations of the eight unanticipated disturbances, are also broadly in line with values reported in previous studies. The estimates of the AR and MA parameters for the price markup shock are 0.95 and 0.75, respectively, whereas for

3. http://www.cepremap.cnrs.fr/dynare/

TABLE 1

BENCHMARK MODEL: PRIOR AND POSTERIOR DISTRIBUTIONS

	Description	Distribution	Prior Mean	Prior Std. dev.	Posterior Mean	Posterior 10th	Posterior 90th
σ_c	Inverse intertemporal elasticity	Normal	1.00	0.37	1.08	0.79	1.36
ω	Wealth elasticity	Beta	0.50	0.20	0.62	0.32	0.90
σ_l	Inverse labor elasticity	Gamma	2.00	0.75	2.83	1.55	4.10
ξ_w	Calvo wages	Beta	0.66	0.10	0.66	0.56	0.76
ξ_p	Calvo prices	Beta	0.66	0.10	0.74	0.69	0.78
ι_w	Wage indexation	Beta	0.50	0.15	0.19	0.07	0.31
ι_p	Price indexation	Beta	0.50	0.15	0.14	0.05	0.22
ψ	Capital utilization elasticity	Gamma	5.00	1.00	5.08	3.40	6.74
S''	Investment adjustment cost	Gamma	4.00	1.00	2.77	1.70	3.80
h	Consumption habit	Beta	0.50	0.10	0.81	0.75	0.85
α	Share of capital	Normal	0.30	0.05	0.17	0.15	0.18
r_π	Taylor rule inflation	Normal	1.70	0.30	2.10	1.81	2.38
ρ	Taylor rule smoothing	Beta	0.60	0.20	0.85	0.82	0.88
r_y	Taylor rule GDP	Normal	0.12	0.05	0.08	0.04	0.12
$r_{\Delta y}$	Taylor rule GDP growth	Normal	0.12	0.05	0.19	0.15	0.23
$100(\pi - 1)$	Steady state quarterly inflation	Normal	0.50	0.10	0.32	0.17	0.46
$100(\beta^{-1} - 1)$	Discount factor	Gamma	0.25	0.10	0.18	0.07	0.30
$\log L^{SS}$	Steady state hours	Normal	0.00	0.15	0.00	-0.24	0.25
	Unanticipated shocks						
	Trends						
g_a	TFP trend	Normal	0.20	0.05	0.25	0.18	0.32
g_v	Investment-specific technology trend	Normal	0.50	0.05	0.43	0.37	0.49
	Persistence						
ρ_a	Stationary TFP	Beta	0.60	0.20	0.97	0.95	0.99
ρ_z	TFP growth	Beta	0.40	0.20	0.51	0.38	0.64
ρ_v	Investment-specific technology growth	Beta	0.20	0.10	0.21	0.11	0.31
ρ_I	Marginal efficiency of investment (MEI)	Beta	0.60	0.20	0.74	0.66	0.82
ρ_b	Preference	Beta	0.60	0.20	0.16	0.04	0.28
ρ_g	Government spending	Beta	0.60	0.20	0.99	0.98	0.99
ρ_p	Price markup	Beta	0.60	0.20	0.95	0.93	0.99
ρ_w	Wage markup	Beta	0.60	0.20	0.94	0.86	0.99
μ_p	Price markup MA	Beta	0.50	0.20	0.75	0.58	0.92
μ_w	Wage markup MA	Beta	0.50	0.20	0.95	0.89	0.99
	Volatilities						
σ_a	Stationary TFP	InvGamma	0.50	2.00	0.57	0.45	0.69
σ_z	TFP growth	InvGamma	0.50	2.00	0.54	0.38	0.71
σ_v	Investment-specific technology growth	InvGamma	0.50	2.00	0.57	0.47	0.67
σ_I	MEI	InvGamma	0.50	2.00	6.38	4.34	8.31
σ_b	Preference	InvGamma	0.10	2.00	1.97	1.30	2.62
σ_g	Government spending	InvGamma	0.50	2.00	0.27	0.21	0.33
σ_r	Monetary policy	InvGamma	0.10	2.00	0.21	0.19	0.23
σ_p	Price markup	InvGamma	0.10	2.00	0.18	0.15	0.21
σ_w	Wage markup	InvGamma	0.10	2.00	0.27	0.24	0.29

(Continued)

TABLE 1
Continued

	Description	Distribution	Prior Mean	Prior Std. dev.	Posterior Mean	Posterior 10th	Posterior 90th
	News shocks						
	Volatilities						
σ_{a4}	Stationary TFP 4qt ahead	InvGamma	0.35	2.00	0.15	0.09	0.21
σ_{a8}	Stationary TFP 8qt ahead	InvGamma	0.35	2.00	0.14	0.08	0.21
σ_{z4}	TFP growth 4qt ahead	InvGamma	0.35	2.00	0.14	0.08	0.20
σ_{z8}	TFP growth 8qt ahead	InvGamma	0.35	2.00	0.15	0.08	0.21
σ_{v4}	Investment-specific technology growth 4qt ahead	InvGamma	0.35	2.00	0.21	0.09	0.33
σ_{v8}	Investment-specific technology growth 8qt ahead	InvGamma	0.35	2.00	0.19	0.08	0.31
σ_{I4}	MEI 4qt ahead	InvGamma	0.35	2.00	0.25	0.08	0.43
σ_{I8}	MEI 8qt ahead	InvGamma	0.35	2.00	0.30	0.08	0.55
σ_{b4}	Preference 4qt ahead	InvGamma	0.07	2.00	0.05	0.02	0.10
σ_{b8}	Preference 8qt ahead	InvGamma	0.07	2.00	0.05	0.02	0.10
σ_{g4}	Government spending 4qt ahead	InvGamma	0.35	2.00	0.14	0.09	0.20
σ_{g8}	Government spending 8qt ahead	InvGamma	0.35	2.00	0.16	0.10	0.23
σ_{p4}	Price markup 4qt ahead	InvGamma	0.07	2.00	0.04	0.02	0.05
σ_{p8}	Price markup 8qt ahead	InvGamma	0.07	2.00	0.04	0.02	0.05
σ_{w4}	Wage markup 4qt ahead	InvGamma	0.07	2.00	0.02	0.01	0.03
σ_{w8}	Wage markup 8qt ahead	InvGamma	0.07	2.00	0.03	0.01	0.03

NOTES: Posterior distributions are obtained via the Metropolis-Hastings algorithm using 300,000 draws, with the first 60,000 draws discarded. The abbreviation "qt" indicates "quarters."

the wage markup shock they are 0.94 and 0.95.[4] We found that the ARMA(1,1) specification for both markup shocks provides a relatively better fit compared to alternative shock process specifications of either AR(1) or i.i.d.[5]

A new parameter which we estimate is, ω, which controls the wealth elasticity of labor supply. The estimated value (the posterior mean) is 0.62 (see Table 1) and is relatively tightly estimated. This value indicates that the data support a preference structure that implies an intermediate range of wealth effects, in between no wealth effect (Greenwood, Hercowitz, and Huffman 1988) and full wealth effect (King,

4. For comparison, the estimates in Smets and Wouters (2007) for the ARMA(1,1) price and wage markup processes are 0.89 (AR) and 0.69 (MA) and 0.96 (AR) and 0.84 (MA), respectively. The estimates in Justiniano, Primiceri, and Tambalotti (2011) are 0.97 (AR) and 0.98 (MA) for the price markup process, and 0.96 (AR) and 0.82 (MA).

5. The marginal data density for the ARMA(1,1) case is −1435.36; for the i.i.d. case it is −1463.18, and for the AR(1) case it is −1469.58.

Plosser, and Rebelo 1988).[6] Our estimate of ω is in between the 0.53–0.81 range recently estimated by Khan and Tsoukalas (2011) using a New Keynesian model with only stationary shocks. By contrast, in a real business cycle (RBC) environment with fewer data series used as observables, Schmitt-Grohé and Uribe (Forthcoming) find ω close to zero. While it is not straightforward to pinpoint the exact source of why the estimates of ω are large in medium-scale models estimated with both real and nominal data relative to the parsimonious RBC structure, in Section 2.3 we examine the sensitivity of our quantitative conclusions when the elasticity is calibrated to be zero (i.e., $\omega = 0$).

2.2 Variance Decompositions

To assess the quantitative importance of news shocks relative to unanticipated shocks, we examine the contribution of all shocks to the unconditional variance of the observables. We compute the unconditional variance using the posterior distribution of the estimated parameters and report the median, and 10% and 90% probability bands. Tables 2 and 3 present the variance decompositions for the benchmark model for the set of technology and nontechnology shocks, respectively. Several results stand out. First, the unanticipated MEI shock accounts for the largest share (46.7%) of the variance in output growth, followed by the combined unanticipated stationary and nonstationary TFP shocks (about 24%). By contrast, the news shocks contribute little to the output growth variance. The combined contribution of TFP news and investment news (both INV and MEI) shocks is below 2%. Among the set of nontechnology news shocks, the share of variance in output growth accounted for by government spending news and wage markup news shocks is slightly higher at 3.8% and 7.5%, respectively. These results suggest that U.S. output fluctuations are primarily driven by unanticipated investment shocks of the MEI variety. The MEI shock also accounts for approximately four-fifths of investment growth variance, and about 18% of the hours variance. The important role for the unanticipated MEI shocks for output and investment that we find corroborates the evidence in Justiniano, Primiceri, and Tambalotti (2011) who estimate a DSGE model without news shocks.

Second, about four-fifths of the total consumption growth variance is accounted for by the unanticipated shocks, with shares of about 40% due to unanticipated TFP shocks and 26% due to preference shocks. The TFP news shocks account for only 4% and the nontechnology news shocks all together contribute about 16% to the consumption growth variance.

Third, while news shocks have a limited contribution to the variance shares of output, investment, and consumption growth, their dominant role arises in accounting for the variance of total hours. Here the nontechnology news sources account for approximately two-thirds of the hours variance, with the largest share (60% of the

6. The nonzero wealth effect on labor supply we estimate based on aggregate data is consistent with the findings of Imbens, Rubin, and Sacerdote (2001) based on a survey data of lottery players, and Kimball and Shapiro (2010) based on a survey implemented in the Health and Retirement Study. Both sets of studies provide evidence in favor of wealth effects on labor supply from unearned income.

TABLE 2

Benchmark Results with Estimated ω: Contribution of Each Shock to the Unconditional Variance of Variables (in %), the Median and 10–90th Percentiles

	Technology shocks							
Variable	TFP^{S}	TFP^{NS}	MEI^{S}	INV^{NS}	TFP^{S}_{news}	TFP^{NS}_{news}	MEI^{S}_{news}	INV^{NS}_{news}
Output growth	4.10	19.70	46.70	1.20	0.30	1.35	0.00	0.00
	[3.50, 5.90]	[13.25, 26.15]	[34.70, 54.75]	[0.70, 1.90]	[0.15,0.40]	[0.60, 3.00]	[0.00, 0.00]	[0.00, 0.00]
Consumption growth	2.85	36.20	11.10	0.65	1.00	2.45	0.00	0.00
	[1.80, 4.00]	[25.90, 44.10]	[6.05, 18.30]	[0.40, 1.05]	[0.40,1.60]	[1.60, 3.80]	[0.00, 0.00]	[0.00, 0.00]
Investment growth	4.10	6.50	79.75	1.40	0.20	0.50	0.00	0.00
	[2.20, 6.90]	[4.15, 9.60]	[72.00, 84.60]	[0.70, 2.30]	[0.10,0.45]	[0.30, 0.70]	[0.00, 0.00]	[0.00, 0.00]
Hours	2.45	2.20	18.20	0.50	0.20	1.20	0.00	0.00
	[1.15, 5.50]	[1.35, 3.70]	[7.80, 29.90]	[0.30, 1.00]	[0.10,0.55]	[0.90, 2.90]	[0.00, 0.00]	[0.00, 0.00]
Wage growth	7.40	31.40	1.40	0.40	0.40	2.20	0.00	0.00
	[5.30, 9.35]	[25.50, 39.05]	[0.85, 2.30]	[1.25, 2.65]	[0.20,0.50]	[1.00, 3.80]	[0.00, 0.00]	[0.00, 0.00]
Inflation	4.80	4.10	13.50	0.50	0.30	0.40	0.00	0.00
	[2.75, 8.85]	[2.30, 7.60]	[7.35, 20.50]	[0.10, 0.70]	[0.20,0.45]	[0.10, 1.10]	[0.00, 0.00]	[0.00, 0.00]
Interest rate	5.00	2.10	49.90	1.70	0.60	0.90	0.00	0.50
	[3.15, 11.00]	[0.90, 4.30]	[40.10, 62.75]	[0.60, 2.25]	[0.10,0.95]	[0.50, 2.35]	[0.00, 0.00]	[0.40, 0.90]
RPI	0.00	0.00	0.00	89.40	0.00	0.00	0.00	10.60
	[0.00,0.00]	[0.00, 0.00]	[0.00, 0.00]	[88.00, 90.20]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[9.80,12.00]

Notes: News shocks are the sum of four- and eight-quarter-ahead components. S and NS denote stationary and nonstationary, respectively. Entries decompose the forecast error variance in each variable into percentages due to each shock. Entries may not sum to 100 due to rounding.

TABLE 3

BENCHMARK RESULTS WITH ESTIMATED ω: CONTRIBUTION OF EACH SHOCK TO THE UNCONDITIONAL VARIANCE OF VARIABLES (IN %), THE MEDIAN AND 10–90TH PERCENTILES

	Nontechnology shocks								
Variable	ε^b	$\varepsilon^b_{\text{news}}$	ε^g	$\varepsilon^g_{\text{news}}$	ε^r	ε^p	$\varepsilon^p_{\text{news}}$	ε^w	$\varepsilon^w_{\text{news}}$
Output growth	4.80	0.00	5.60	3.80	2.80	1.00	0.60	0.50	7.50
	[2.60, 8.40]	[0.00, 0.00]	[2.55, 8.10]	[2.40, 6.00]	[1.20, 4.20]	[0.65, 1.30]	[0.30, 0.90]	[0.25, 0.80]	[4.40, 11.90]
Consumption growth	26.00	0.00	0.85	1.60	2.15	0.45	0.70	0.50	13.50
	[16.70, 35.10]	[0.00, 0.00]	[0.35, 1.20]	[1.00, 3.00]	[1.20, 2.95]	[0.20, 1.20]	[0.40, 1.20]	[0.30, 1.50]	[7.70, 19.00]
Investment growth	0.00	0.00	0.00	0.15	2.30	1.20	0.60	0.00	3.30
	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.10, 0.20]	[1.30, 3.00]	[0.80, 2.60]	[0.40, 1.45]	[0.00, 0.00]	[1.50, 4.65]
Hours	0.30	0.00	7.60	3.40	1.25	1.00	1.00	0.80	59.90
	[0.10, 0.50]	[0.00, 0.00]	[3.30, 15.50]	[1.80, 5.90]	[0.75, 2.20]	[0.20, 2.65]	[0.45, 1.75]	[0.40, 1.60]	[38.60, 73.50]
Wage growth	0.00	0.00	0.00	0.00	0.00	13.00	4.40	36.90	2.50
	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[11.10, 18.50]	[2.70, 7.95]	[30.10, 42.15]	[1.35, 3.30]
Inflation	0.00	0.00	0.25	0.00	3.70	9.20	1.60	2.30	59.40
	[0.00, 0.00]	[0.00, 0.00]	[0.10, 0.35]	[0.00, 0.00]	[1.90, 5.85]	[6.70, 18.80]	[1.20, 2.80]	[1.40, 4.90]	[36.50, 74.30]
Interest rate	1.00	0.00	0.60	0.50	4.90	1.00	0.30	0.00	31.00
	[0.60, 2.50]	[0.00, 0.00]	[0.20, 1.55]	[0.30, 1.65]	[2.00, 9.50]	[0.40, 2.35]	[0.10, 1.75]	[0.00, 0.00]	[25.00, 49.20]
RPI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]

NOTES: News shocks are the sum of four- and eight-quarter-ahead components. Entries decompose the forecast error variance in each variable into percentages due to each shock. ε^b (preference), ε^g (government spending), ε^r (monetary policy), ε^p (price markup), and ε^w (wage markup). Entries may not sum to 100 due to rounding.

total variance) due to wage markup news shocks alone. Justiniano, Primiceri, and Tambalotti (2010) show that wage markup shocks are important for hours, accounting for 58% of the unconditional variance (i.e., only at very low frequencies). Our findings indicate that while this remains the case, it is the news component of wage markups that is more important for hours relative to the unanticipated component. At the business cycle frequency, however, the share of wage markup news shocks in accounting for the variance in hours is substantially smaller (10.5%).[7] By contrast, technology news shocks seem unimportant with the TFP news shocks' share of under 2% and investment news shocks' share of zero.

Fourth, turning to the nominal variables, the unanticipated wage and price markup shocks accounts for about half of the variance in wage growth, followed by the unanticipated TFP shocks (about 40%). For inflation and the nominal interest rate, the news components in the wage markup shocks account for a substantial variance shares nearly 60% and 31%, respectively. The MEI shock accounts for about 50% of the variance of nominal interest rate.

2.3 Role of the Wealth Elasticity of Labor Supply

The estimate of the posterior mean of the wealth elasticity of labor supply, ω, in the benchmark model is 0.62, implying a relatively important wealth effect on labor supply. This wealth effect in turn mitigates the comovement property of news shocks embedded in the model. We consider a special case to explore how the wealth elasticity influences the quantitative results. In the benchmark model we calibrate this elasticity to nearly zero ($\omega = 0.001$), and reestimate the model parameters. This calibrated value is similar to that estimated in Schmitt-Grohé and Uribe (Forthcoming) based on the RBC model. The low value of ω implies the preference structure as in Greenwood, Hercowitz, and Huffman (1988) with minimal wealth effect on labor supply. When combined with other model features, especially high investment adjustment costs and high elasticity of capital utilization, the low ω facilitates comovement following a TFP news shock. Tables 4 and 5 present the quantitative results for technology and nontechnology shocks, respectively.[8] As expected, the contribution of TFP news shocks to the variance of output, investment growth, and hours increases, but only by a small magnitude.[9] Note that the contribution of nonstationary TFP news to hours increases from 1.2% in the benchmark model to 4.50% when ω is restricted to be near zero, consistent with an expansion of hours in response to TFP news. When the wealth elasticity is near zero, the contribution of the wage markup news shock to hours falls from about 60% to 42.5%, however, for the interest rate and inflation, it increases

7. These shares are obtained from a variance decomposition based on the spectral density of the observables at business cycle frequencies focusing on periodic components that encompass cycles between 6 and 32 quarters.

8. For space considerations we do not report the re-estimated parameters.

9. In this restricted version, the estimated investment adjustment cost parameter is equal to 2.30, while the elasticity of utilization is equal to 4.88. Both estimated parameters are slightly lower compared to the estimated values in the benchmark.

TABLE 4

Benchmark Results with Calibrated $\omega = 0.001$: Contribution of Each Shock to the Unconditional Variance of Variables (in %), the Median and 10–90th Percentiles

Variable	Technology shocks							
	TFP^{S}	TFP^{NS}	MEI^{S}	INV^{NS}	TFP^{S}_{news}	TFP^{NS}_{news}	MEI^{S}_{news}	INV^{NS}_{news}
Benchmark model with $\omega = 0.001$								
Output growth	4.10	24.70	45.50	1.00	0.50	2.00	0.00	0.40
	[2.15, 7.95]	[19.30, 31.15]	[29.90, 58.40]	[0.70, 1.30]	[0.35,1.00]	[1.35, 3.40]	[0.00, 0.00]	[0.20, 0.80]
Consumption growth	2.90	41.00	9.80	0.40	0.70	3.50	0.00	0.00
	[1.45, 4.80]	[29.00, 52.70]	[5.85, 12.90]	[0.20, 0.90]	[0.30,1.25]	[2.10, 8.10]	[0.00, 0.00]	[0.00, 0.00]
Investment growth	3.80	8.70	76.80	1.20	0.40	1.40	0.00	0.30
	[2.20, 5.90]	[5.15, 14.90]	[68.10, 85.15]	[0.70, 2.30]	[0.10,0.75]	[0.50, 2.70]	[0.00, 0.00]	[0.20, 0.70]
Hours	0.80	34.25	8.00	1.00	0.50	4.50	0.00	0.60
	[0.45, 1.50]	[22.35, 46.70]	[5.00, 12.90]	[0.50, 1.60]	[0.20,0.85]	[2.90, 10.60]	[0.00, 0.00]	[0.20, 1.00]
Wage growth	6.70	30.30	1.80	0.20	0.40	2.40	0.00	0.00
	[3.95, 11.65]	[23.50, 40.50]	[0.85, 3.30]	[0.15, 0.35]	[0.20,0.50]	[1.00, 3.80]	[0.00, 0.00]	[0.00, 0.00]
Inflation	3.65	3.70	12.00	0.40	0.30	0.50	0.00	0.00
	[1.75, 6.45]	[1.90, 5.60]	[7.35, 19.50]	[0.20, 1.00]	[0.20,0.45]	[0.10, 1.10]	[0.00, 0.00]	[0.00, 0.00]
Interest rate	4.40	2.60	40.00	1.40	0.80	1.20	0.00	0.50
	[2.15, 8.10]	[1.70, 3.40]	[35.40, 55.55]	[0.70, 2.55]	[0.30,1.95]	[0.90, 3.00]	[0.00, 0.00]	[0.30, 0.80]
RPI	0.00	0.00	0.00	89.40	0.00	0.00	0.00	10.60
	[0.00,0.00]	[0.00, 0.00]	[0.00, 0.00]	[88.40, 90.80]	[0.00, 0.00]	[0.00,0.00]	[0.00,0.00]	[9.20,11.60]

Notes: News shocks are the sum of four- and eight-quarter-ahead components. S and NS denote stationary and nonstationary, respectively. Entries decompose the forecast error variance in each variable into percentages due to each shock. Entries may not sum to 100 due to rounding.

TABLE 5

Benchmark Results with Calibrated $\omega = 0.001$: Contribution of Each Shock to the Unconditional Variance of Variables (in %), the Median and 10–90th Percentiles

Variable	Nontechnology shocks ε^b	$\varepsilon^b_{\text{news}}$	ε^g	$\varepsilon^g_{\text{news}}$	ε^r	ε^p	$\varepsilon^p_{\text{news}}$	ε^w	$\varepsilon^w_{\text{news}}$
Benchmark model with $\omega = 0.001$									
Output growth	4.40	0.00	4.10	3.00	2.70	1.00	0.90	0.40	6.00
	[2.50, 6.10]	[0.00, 0.00]	[2.15, 6.60]	[1.70, 5.20]	[1.40, 4.40]	[0.65, 1.70]	[0.40, 2.60]	[0.00, 0.60]	[2.60, 8.70]
Consumption growth	24.40	0.00	1.00	2.00	1.70	0.50	0.60	0.50	11.00
	[17.00, 31.50]	[0.00, 0.00]	[0.85, 1.30]	[1.10, 3.60]	[1.10, 2.45]	[0.30, 1.20]	[0.20, 1.45]	[0.20, 1.00]	[7.00, 16.50]
Investment growth	0.00	0.00	0.00	0.25	2.30	1.25	0.60	0.30	3.00
	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.10, 0.50]	[1.00, 3.60]	[0.40, 2.60]	[0.40, 1.55]	[0.10, 0.60]	[1.50, 4.75]
Hours	0.30	0.00	2.80	1.40	0.60	0.80	0.60	0.50	42.50
	[0.00, 0.50]	[0.00, 0.00]	[1.30, 4.50]	[1.10, 2.60]	[0.45, 1.20]	[0.50, 1.25]	[0.45, 1.15]	[0.20, 1.20]	[24.60, 54.10]
Wage growth	0.00	0.00	0.00	0.00	0.00	14.15	5.00	36.60	2.50
	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[12.70, 25.95]	[3.20, 8.75]	[30.60, 42.70]	[1.15, 5.40]
Inflation	0.00	0.00	0.25	0.00	3.00	8.20	1.80	2.50	63.70
	[0.00, 0.00]	[0.00, 0.00]	[0.10, 0.35]	[0.00, 0.00]	[1.30, 5.00]	[5.70, 19.20]	[1.20, 3.90]	[1.20, 4.50]	[49.50, 77.90]
Interest rate	0.40	0.00	0.70	1.10	4.80	1.00	0.40	0.00	40.70
	[0.20, 0.60]	[0.00, 0.00]	[0.50, 1.65]	[0.60, 1.75]	[2.40, 6.90]	[0.40, 1.65]	[0.30, 1.85]	[0.00, 0.00]	[34.00, 65.15]
RPI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]	[0.00, 0.00]

Notes: News shocks are the sum of four- and eight-quarter-ahead components. Entries decompose the forecast error variance in each variable into percentages due to each shock. ε^b (preference), ε^g (government spending), ε^r (monetary policy), ε^p (price markup), and ε^w (wage markup). Entries may not sum to 100 due to rounding.

from 59.4% to 63.7%, and 31% to about 41%, respectively. Thus, the nontechnology news shocks are slightly more sensitive to the wealth elasticity although the shares remain relatively large in both cases. With the wealth effect shut down, the permanent unanticipated TFP shock accounts for a larger share of variance of output growth, consumption growth, and hours relative to the benchmark model.

We conclude that even with restricting the wealth elasticity to zero the unanticipated MEI shock remains dominant in accounting for the variance in output and investment growth. And its contribution to the interest rate variance remains large at 40%, the same as that of the wage markup news shocks. The contribution of technology news shocks, although increases a little, remains quite small. This is an interesting finding since the low wealth elasticity in calibrated models was originally considered to deliver comovement following technology news shocks (specifically TFP news) as in Jaimovich and Rebelo (2009). It is, however, important to note that the absence of a wealth effect on labor supply is only a necessary but not sufficient condition for a significant role of news shocks to emerge in estimated DSGE models. While in theory a low ω value facilitates comovement among macroeconomic aggregates in line with the data, its role arises in combination with other model features (large investment adjustment costs and elastic capacity utilization).

2.4 Summary of Results

Table 6 provides a summary of the benchmark results. From the perspective of an estimated DSGE model, the unanticipated shocks dominate in accounting for the variance in six of the eight observables considered in estimating the benchmark model. The news shocks play only a limited role with the exception of hours and inflation where the nontechnology news shocks are dominant (shown in Panel A). When the wealth elasticity of labor supply is restricted to nearly zero, the contribution of nontechnology news shocks (in particular wage markup news) in accounting for the variance in hours decreases relative to the benchmark (shown in Panel B), and the variance share is split between both unanticipated and news shocks. The contribution of technology news shocks rises by a small magnitude, but their overall importance remains limited.

Does the presence of both unanticipated and news shocks improve the fit of the DSGE model relative to the case when only unanticipated shocks are present? We compare the log marginal data densities of the benchmark model with the latter case where the news shocks are absent to assess the relative fit of the estimated models. The values for the log marginal data densities (computed using the modified harmonic mean estimator suggested by Geweke 1999) are -1435.36 and -1436.34, respectively. Thus, the higher marginal data density indicates that the benchmark model has a superior fit relative to the model with only unanticipated shocks. The relatively superior fit of the benchmark model is not surprising as the news components in wage markups (and to a lesser extent price markups and government spending) help account for the dynamics in the data, especially for hours, inflation, and the interest rate. The log marginal data density of the model with ω restricted to 0.001

TABLE 6

Benchmark Model: Total Contribution of Unanticipated versus News Shocks to the Unconditional Variance of Variables (in %)

	Unanticipated shocks		News shocks	
Variable	Technology	Nontechnology	Technology	Nontechnology[a]
Panel A. Estimated $\omega = 0.62$				
Output growth	71.70	14.70	1.70	11.90
Consumption growth	50.80	29.95	3.45	15.80
Investment growth	91.75	3.50	0.70	4.05
Hours	23.35	10.95	1.40	64.30
Wage growth	40.60	49.90	2.60	6.90
Inflation	22.90	15.45	0.70	61.0
Interest rate	58.70	7.50	1.50	31.80
RPI	89.40	0.00	10.60	0.00
Panel B. Calibrated $\omega = 0.001$				
Output growth	75.30	12.60	2.90	9.90
Consumption growth	54.10	28.10	4.20	13.60
Investment growth	90.50	3.70	2.10	3.70
Hours	44.05	5.00	5.60	44.50
Wage growth	39.00	50.75	2.80	7.45
Inflation	19.75	13.95	0.80	65.50
Interest rate	48.40	6.90	2.50	42.20
RPI	89.40	0.00	10.60	0.00

Notes: Technology includes TFP, INV, and MEI shocks. Nontechnology includes ε^b (preference), ε^g (government spending), ε_r (monetary), ε^p (price markup), and ε^w (wage markup) .
[a]Nontechnology news shocks except ε_r (monetary).

is −1442.20, which is lower compared to both the benchmark model and the model with only unanticipated shocks.

2.5 Comparison with Fujiwara, Hirose, and Shintani (2011)

Fujiwara, Hirose, and Shintani (2011) find a relatively small contribution of the news component in a single shock (stationary TFP shock) with multiple horizons under nominal price and wage stickiness. Panel A in Table 7, sixth column, shows their estimated variance shares for output, consumption, investment growth, and hours. We find relatively small contribution of stationary TFP news shocks even when multiple news shocks (stationary versus nonstationary shocks, and technology versus nontechnology news shocks) are present under nominal price and wage stickiness.[10]

10. The four differences in the model specification relative to Fujiwara, Hirose, and Shintani (2011) are: (i) we consider stationary and nonstationary sources of news in both TFP and investment shocks while they consider only stationary TFP news, (ii) we consider news components in nontechnology shocks, (iii) our estimation also includes the relative price of investment as an observable whereas theirs does not, and (iv) we consider the Jaimovich and Rebelo (2009) preference structure whereas they consider the standard preferences as in Smets and Wouters (2007). Based on the marginal data density, we select four- and eight-quarters ahead news horizon similar to that in Schmitt-Grohé and Uribe (Forthcoming) under the nonstationary shock specification, whereas Fujiwara, Hirose, and Shintani (2011) select a five-quarter-ahead news horizon under the stationary shock specification. This difference in the news shock horizons, however, has little effect on the variance shares.

TABLE 7

VARIANCE SHARES OF TECHNOLOGY VERSUS NONTECHNOLOGY NEWS SHOCKS (IN %)

Variable	Benchmark model				Fujiwara et al. (2011)	Schmitt-Grohé and Uribe (Forthcoming)	
Panel A. Technology news shocks							
	TFP news[a]		Investment news[b]		TFP news[c]	TFP news[a]	Investment news[b]
	$\omega = 0.62$	$\omega = 0.001$	$\omega = 0.62$	$\omega = 0.001$	$\omega = 1$	$\omega = 0.00$	
Output	1.65	2.50	0.00	0.40	8.53	3.00	7.00
Consumption	3.45	4.20	0.00	0.00	12.66	2.00	1.00
Investment	0.70	1.80	0.00	0.30	3.44	1.00	19.00
Hours	1.40	5.00	0.00	0.60	5.58	1.00	2.00
Panel B. Nontechnology news shocks							
	Non-technology news[d]		Wage markup news			Nontechnology news[d]	Wage markup news
	$\omega = 0.62$	$\omega = 0.001$	$\omega = 0.62$	$\omega = 0.001$		$\omega = 0.00$	
Output	11.90	9.90	7.50	6.00	-	31.00	17.00
Consumption	15.80	13.60	13.50	11.00	-	49.00	18.00
Investment	4.05	3.70	3.30	3.00	-	12.00	12.00
Hours	64.30	44.50	59.90	42.50	-	71.00	67.00

[a] TFP news $= TFP^{S}_{\text{news}} + TFP^{NS}_{\text{news}}$.

[b] $MEI^{S}_{\text{news}} + INV^{NS}_{\text{news}}$.

[c] TFP news $= TFP^{S}_{\text{news}}$.

[d] The benchmark model nontechnology news is $\varepsilon^{b}_{\text{news}} + \varepsilon^{g}_{\text{news}} + \varepsilon^{p}_{\text{news}} + \varepsilon^{w}_{\text{news}}$ and in Schmitt-Grohé and Uribe (Forthcoming) it is $\varepsilon^{b}_{\text{news}} + \varepsilon^{g}_{\text{news}} + \varepsilon^{w}_{\text{news}}$.

In both, the benchmark model and the case with ω restricted to 0.001, the variance share of stationary TFP news shocks remains about 1% or less for consumption, output, investment growth, and hours.

2.6 Comparison with Schmitt-Grohé and Uribe (Forthcoming)

As noted earlier, Schmitt-Grohé and Uribe (Forthcoming) consider news shocks in a RBC model with real frictions and imperfect competition in the labor market. Their central result is that anticipated (news) shocks account for more than half of predicted aggregate fluctuations in the postwar U.S. data. The results from their baseline model indicate that while TFP news shocks are relatively less important, the role of news resides in nontechnology sources. Table 7, columns 7 and 8, show the split between technology news (Panel A) and nontechnology news (Panel B) as reported in Schmitt-Grohé and Uribe. Note that wage markup news accounts for over two-thirds of the variance in hours, with the total share of nontechnology news of about 71%. We emphasize that our findings (Tables 2 and 3) of (i) relatively less important TFP news shocks and (ii) a large share of wage markup news shocks in contributing to total hours variance agree with those in Schmitt-Grohé and Uribe. The main difference is in terms of the relatively large role of news shocks for output, consumption, and investment growth that they find compared to the large role for unanticipated shocks that we find in accounting for the variances in these three variables.[11]

Why does the variance share of news shocks fall for output, consumption, and investment growth in our benchmark model relative to Schmitt-Grohé and Uribe (Forthcoming)? This question is of interest to researchers studying the role of news shocks in DSGE models. To answer this question, we estimate the Schmitt-Grohé and Uribe model after incorporating the two additional shocks that we have in our benchmark model but are absent in theirs, namely, the price markup (unanticipated and news components) shocks and monetary shocks (only unanticipated). In this intermediate model specification, prices and wages are perfectly flexible just as in Schmitt-Grohé and Uribe. It is important to note that the intermediate model specification has the same structural features as Schmitt-Grohé and Uribe, namely, consumption habits, Jaimovich and Rebelo (2009) preferences, capacity utilization, investment adjustment costs, and imperfect competition in the labor market. Thus, the only change is the addition of price markup (unanticipated and news components) shocks and monetary shocks (only unanticipated). To remain close to the Schmitt-Grohé and Uribe specification, we introduce only a small degree of imperfect competition in the goods market with a steady state markup $\lambda_p = 0.01$. We implement this specification by setting $\xi_w = \xi_p = \iota_w = \iota_p = 0.01$, in the benchmark model presented in Section 2, which imply flexible prices and wages, and no indexation. This is a judicious way to proceed as intermediate specification spans the distance between their RBC model with real frictions and imperfectly competitive labor market and

11. Relative to Schmitt-Grohé and Uribe (2010), we consider a medium-scale model with both real and nominal frictions, and include price markup and monetary policy shocks in the model. We include both real and nominal variables (price and wage inflation, and the nominal interest rate) in the estimation whereas they use only real variables for model estimation.

TABLE 8

Unanticipated versus News Shocks: a Comparison of Variance Shares (in %) across Specifications

Variable	Schmitt-Grohé and Uribe (Forthcoming)		Schmitt-Grohé and Uribe (Forthcoming) + $\{\varepsilon^p, \varepsilon^p_{\text{news}}\} + \varepsilon^r$		Schmitt-Grohé and Uribe (Forthcoming) + $\{\varepsilon^p, \varepsilon^p_{\text{news}}\} + \varepsilon^r$ + nominal frictions[a]	
	Unanticipated	News	Unanticipated	News	Unanticiapted	News
Output growth	59.00	41.00	61.45	38.55	86.40	13.60
Consumption growth	50.00	50.00	47.10	52.90	80.75	19.25
Investment growth	67.00	33.00	64.30	35.70	92.25	4.75
Hours	23.00	77.00	22.50	87.50	34.30	65.70

[a]This model specification is the same as our benchmark model in Section 2.

our benchmark model in Section 2. We use data on eight observables, namely, real output, real consumption, real investment, total hours worked, wage inflation, price inflation, nominal interest rate, and the relative price of investment.

Table 8 shows the variances shares split between the unanticipated and news shocks. Columns 2 and 3 show the results of Schmitt-Grohé and Uribe (Forthcoming). Columns 4 and 5 show the results for the intermediate specification. The key thing to note is that the overall importance of news shocks remains similar to Schmitt-Grohé and Uribe when the price markup and monetary shocks are included in the estimation. News shocks account for about 38%, 53%, 36%, and 87% of the variance in output, consumption, investment growth, and hours, respectively, relative to 41%, 50%, 33%, and 77% in the same variables in Schmitt-Grohé and Uribe, respectively. Thus, we conclude that the inclusion of price markup (unanticipated and news) shocks and monetary shocks is not the reason behind the differences in our findings relative to theirs. These shocks essentially account for the variation in nominal variables and have no bearing on the quantitative assessment of the real variables that are common across specifications.[12]

Next, we add nominal price and wage frictions to the specification considered earlier. Note that this case is the same as the benchmark model in Section 2.[13] Indeed, nominal frictions have a sharp effect on the results. As shown in the last two columns of Table 8, the contribution of news shocks to the variance in output, consumption, and investment growth falls substantially relative to Schmitt-Grohé and Uribe (Forthcoming). Unanticipated sources dominate in accounting for the variance in output, consumption, and investment growth. The share of news shocks, in particular the wage markup shock, in accounting for the variance in hours, however, remains

12. Schmitt-Grohé and Uribe (Forthcoming) use data on real output, real consumption, real investment, real government expenditure, total hours, TFP, and the relative price of investment in their estimation. To estimate the intermediate specification, we substitute real government expenditure and TFP with the nominal variables, price and wage inflation and the nominal interest rate. As shown above, the variance shares of news shocks do not change in the intermediate specification which suggests that our conclusion is robust to the presence of nominal data in the estimation.

13. The relative fit of the benchmark model is superior to that of the intermediate specification, which has the marginal data density of –1676.17.

substantial (almost 60%) as shown in Table 3. The unanticipated MEI shock now accounts for a large share of output (46.7%) and investment growth (79.75%) (see Table 2). For consumption growth, the unanticipated TFP shocks and the unanticipated preference shocks combine to account for 60% of the variance share (Tables 2 and 3). So the presence of nominal frictions is the key reason that diminishes the quantitative importance of news shocks relative to Schmitt-Grohé and Uribe.

Why do nominal frictions matter for the quantitative assessment of unanticipated MEI shocks in the benchmark model? The reason is that there is a change in the transmission mechanism that favors the unanticipated MEI shocks. Nominal frictions give rise to endogenous countercyclical markups. And in the presence of countercyclical markups, investment shocks can propagate relatively strongly. This point has been emphasized by Justiniano, Primiceri, and Tambalotti (2010). The reason is that following an unanticipated MEI shock, both price and wage markups fall, which in turn act as positive shifts to labor demand and labor supply such that equilibrium hours can expand. Moreover, the stronger response of hours coupled with changes in utilization facilitates a strong output response. This transmission mechanism helps improve the comovement properties of MEI shocks for investment, output, and hours. And in the estimated model, this mechanism substantially increases the variance share of unanticipated MEI shocks for output and investment, relative to news shocks.

3. CONCLUSION

We undertook a quantitative assessment into the role of news shocks in generating macroeconomic fluctuations in the U.S. economy using estimated DSGE models. The benchmark model is based on recent contributions of Smets and Wouters (2007), Altig et al. (2011), and Justiniano, Primiceri, and Tambalotti (2010), which have both real and nominal frictions, and is augmented to include Jaimovich and Rebelo (2009) preferences with habits which allow for a range of wealth elasticity of labor supply. The model is driven by stationary and nonstationary shocks, with both unanticipated and news components. The main findings are that unanticipated shocks (in particular the shock to the MEI) dominate news shocks in accounting for the unconditional variance in both real and nominal variables, with the exception of hours and inflation. The unanticipated shocks and news shocks account for about 87% and 13% of the variance in output growth, respectively. While news shocks to the TFP (both stationary and nonstationary) contribute under 4% of the variance in the real variables (output, consumption, investment growth, and hours), the contribution of investment news is essentially zero. The small contribution of stationary TFP news shocks is in line with the findings of Fujiwara, Hirose, and Shintani (2011). The dominant role for unanticipated shocks to the MEI is consistent with the findings of Justiniano, Primiceri, and Tambalotti (2010, 2011) who estimate a model without news shocks. When the size of the wealth elasticity of labor supply is restricted to essentially zero, unanticipated shocks continue to dominate as major sources of aggregate fluctuations. We find that the presence of endogenous countercyclical price and wage markups due to nominal frictions substantially diminishes the importance of news shocks relative to a model without these frictions. This turns out to be the key reason why Schmitt-Grohé and Uribe (Forthcoming) find that that news shocks dominate unanticipated shocks in a model without nominal frictions. Among the news shocks, the variance shares of nontechnology news shocks dominate the variance shares of technology news for all the observables used in estimation except the relative price of investment. In particular, the unconditional variance share of the wage markup news shock is the largest for hours, inflation, and interest rate.

Overall, our findings suggest that while news shocks have limited quantitative importance relative to unanticipated shocks, investigating the sources of nontechnology news (in particular, the wage markup news shocks) manifesting via anticipated shifts in the labor market may be a useful direction for future work in this literature.

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