Comparing DSGE-VAR Forecasting Models: How Big are the Differences?*

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Abstract

I generate priors for a VAR from a standard RBC model, a RBC model with capital-adjustment costs and habit formation, and a sticky-price model with an unaccommodating monetary authority. The response of hours worked to a TFP shock differs sharply across these models. I compare the accuracy of forecasts made from each of the resulting DSGE-VAR models. Despite having different structural characteristics, the DSGE-VARs are comparable in terms of forecasting performance. As in previous work, DSGE-VARs compare favorably with atheoretical VARs.

Key Words: Model Evaluation. Priors from DSGE Models. Economic Fluctuations. Hours Debate. Business Cycles.

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1 Introduction

One of the key roles of economic models is to help us in forecasting macroeconomic variables. As a number of recent papers have found, dynamic stochastic general equilibrium (DSGE) models can be quite helpful in this regard. What is less clear is what characteristics a DSGE model should have to produce reliable forecasts. One might argue that we should use the model that is most consistent with the data based on the results from structural vector autoregressions (SVARs): a common approach to testing DSGE models has been to look at the impulse response functions (IRFs) the economic model implies and then compare them with the ones estimated from the data using a SVAR.

However, a key question for the purposes of forecasting is the extent to which models that differ sharply in their theoretical impulse response functions produce different forecasts. To address this question, I use recently developed Bayesian econometric techniques to compare the performance of four contrasting models of economic fluctuations, two of which predict that hours decline following a technology shock and two that generate an increase in hours. Specifically, I evaluate a standard real business cycle (RBC) model with indivisible labor and one where Fisher's (2006) investment-specific technology shocks assume greater importance than the neutral technology shock, both of which generate an increase in hours following a technology shock. For the models predicting a decline in hours following a technology shock, I use an RBC model augmented with capital adjustment costs and habit formation and a sticky price model with an unaccommodating monetary authority.

I follow DeJong, Ingram, and Whiteman (1993), Ingram and Whiteman (1994), and Del Negro and Schorfheide (2004) in using these models to shrink the parameter space of an unrestricted VAR towards that of the restricted VAR implied by the economic model. A tightness parameter, λ, controls the weight placed on the model versus the unrestricted VAR. The VAR(λ, i), where i indexes the economic model, is then used to forecast output, investment, hours, and consumption. This is analogous to using λT artificial observations and T actual observations to estimate the parameters of the VAR. I also compare the forecasting performance of the VAR(λ, i) with a VAR that uses shrinkage from the uninformative Minnesota prior introduced by Doan, Litterman, and Sims (1984) and Litterman (1986). Since it is well-known that the OLS estimator is inadmissible when the loss function is mean squared forecast error (MSFE) and that many shrinkage estimators dominate OLS for this loss function (see, for example, Judge et al., 1985), it is a victory for the model only if the VAR(λ, i) outperforms the VAR with shrinkage using the Minnesota prior.

I find little difference in forecast accuracy for output, investment, hours worked, and consumption across the VAR(λ, i) models. While the investment specific technology shocks model gives slightly better forecasts for investment and hours, the improvement is slight and not very robust. The small differences in forecasting accuracy are in contrast to the models' very different implications for the effects of technology shocks.

However, all of the models considered often outperform the Minnesota prior and unrestricted VARs. The similarity in forecasting accuracy across models seems to come from the high autocorrelations the models imply, similar implied correlations between investment and output, and similar implied correlations between investment and consumption.

To my knowledge, this is the first paper to use a Bayesian approach to try to distinguish between the basic RBC model with that of seemingly distant competitors in forecasting real variables. Other work has used Bayesian techniques to compare alternative sticky price models: Korenok and Swanson (2005) compare the forecasting performance of a variety of sticky price models in predicting the output gap and inflation while Rabanal and Rubio-Ramirez (2005) compare the ability of several sticky price models to reproduce the observed persistence in inflation, output, and wages by computing posterior odds ratios. I also build on the literature contrasting the forecasting ability of priors from DSGE models with the Minnesota prior.

I choose the specific models to compare such as to have models that generate very different impulse response functions from one another. I selected these models from a recent literature which has come under the rubric of "the hours debate". Gali (1999) sparked this discourse when he found that, for the majority of the G7 countries, hours worked fall following a technology shock. He estimated a VAR of the first differences of hours and labor productivity and then restricted one of the shocks to have no effect on the long-run level of labor productivity identifying the other shock as the technology shock. However, Christiano, Eichenbaum, and Vigfusson (CEV) (2003) and Altig, Christiano, Eichenbaum, and Linde (ACEL) (2004) estimate similar empirical models but use hours in levels in their VARs. Despite the failure of augmented Dicky Fuller tests to reject the null of a unit root in hours per capita, they discuss several sensible reasons for this specification. Using this specification, both CEV and ACEL find that hours rise following a technology shock. Francis and Ramey (2005a) perform a series of robustness checks on the results in Gali (1999), including adding control variables and verifying that the technology shock identified is exogenous rather than capturing monetary shocks, oil shocks, or war dates. Consistent with the results above, they find that changing only how hours enter into the VAR changes the sign of the effect of technology shocks on hours. However, they find that the technology shock identified using the hours-in-differences specification is exogenous while the technology shock found using the hours-in-levels specification is Granger-caused by all three alternative shocks and thus conclude that their results corroborate Gali's.[1]

The remainder of the paper is organized as follows: Section 2 briefly describes the models under consideration. Section 3 describes how to generate priors for the VAR parameters from the models as well as the specification of the Minnesota prior. Section 4 contains the results and robustness exercises. Section 5 discusses the results briefly and concludes.

2 The Models

I consider four models: 1) Hansen's (1985) RBC model with indivisible labor, 2) a formulation of 1) augmented by habit formation and capital adjustment costs the exact specification of which follows Beaudry and Guay (1996), 3) a version of 1) where investment-specific technology shocks are of greater importance, and 4) a sticky price model with a fixed money supply. Models 2) and 4) are two of the models the hours' debate literature (see Gali, 1999 and Francis and Ramey, 2005) has found capable of generating a fall in hours worked following a neutral technology shock. The goal of the paper is not to generate the best possible forecasts possible but rather to compare models that have very different implications for the role of neutral technology shocks in business cycle fluctuations. I therefore choose prior distributions for the parameters in these models such that, at the mean of the priors, models 2) and 4) generate a decline in hours worked in the short run in responses to a neutral technology shock contrary to the prediction of models 1) and 3).[2] Furthermore, most of the mass of the priors is concentrated in regions that have the same directional implications for the reaction of hours worked.

[1] Recent contributions to this debate also include Fernald (2004), Pesavento and Rossi (2005), Francis and Ramey (2005b), and Basu, Fernald, and Kimball (2006).

[2] As noted by Manuelli (2003) and Rotemberg (2003), however, the rise in hours in models 1) and 3) depends crucially on the immediate diffusion of the technology shock; slow diffusion of the technology shock will instead generate a decline in hours.

The models each contain three structural shocks: neutral technology shocks, government spending shocks, and investment-specific technology shocks. Since there are four observables, to ensure the models are well specified as $\lambda \longrightarrow \infty$, I add an i.i.d. measurement error to the observation equation for output to generate the VAR(λ, i) models.

2.1 A Standard RBC Model with Indivisible Labor

Now a canonical specification of the RBC model, Hansen's (1985) model postulates that, treating government purchases exogenously, and adding investment-specific technology and government spending shocks, the social planner's problem is

$$\begin{aligned} & \max_{\{C_t, H_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t u\left(C_t, H_t, G_t\right) \\ = & \max_{\{C_t, H_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln C_t - \gamma H_t + v\left(G_t\right)\right], \quad \beta \in (0,1), \ \ \gamma > 0 \end{aligned} \tag{1}$$

subject to

$$Y_t = A_t K_t^{\theta} \left(\eta^t H_t\right)^{1-\theta}, \quad \theta \in (0,1) \tag{2}$$

$$K_{t+1} = (1-\delta) K_t + V_t I_t, \quad \delta \in (0,1) \tag{3}$$

$$Y_t = C_t + I_t + G_t \tag{4}$$

$$\ln A_t = (1-\rho_A) \ln A + \rho_A \ln A_{t-1} + \varepsilon_t^A, \quad \rho_A \in (-1,1), \quad A > 0, \quad \varepsilon_t^A \left(0, \sigma_A^2\right) \tag{5}$$

$$\ln g_t = (1-\rho_G) \ln g + \rho_G \ln g_{t-1} + \varepsilon_t^g, \quad \rho_g \in (-1,1), \quad g > 0, \quad \varepsilon_t^g \left(0, \sigma_g^2\right) \tag{6}$$

$$\ln V_t = (1-\rho_V) \ln V + \rho_V \ln V_{t-1} + \varepsilon_t^V, \quad \rho_V \in (-1,1), \quad V > 0, \quad \varepsilon_t^V \left(0, \sigma_V^2\right) \tag{7}$$

where C_t, H_t, Y_t, A_t, K_t, V_t, I_t, and G_t are consumption, hours worked, output, the level of neutral technology, capital, the level of investment-specific technology, investment, and government purchases of goods and services financed with lump-sum taxes. $g_t = \frac{G_t}{\eta^t}$ represents detrended government spending.

Table 1 summarizes the priors over the DSGE model parameters for the four models. As is standard in the literature , I assume the parameters are distributed independently of one another.[3]

[3] See, among others, Ingram and Whiteman (1994), Schorfheide (2000), Rabanal and Rubio-Ramirez (2005), An and Schorfheide (2007), and Del Negro, Schorfheide, Smets, and Wouters (2007).

I set the mean values of A, θ, δ, and β to 1, 0.36, 0.021, and 0.99 following Francis and Ramey (2005). The mean of η is set at 1.00055 to be consistent with the average growth rate of (logged) per capita output in the data. The mean values of ρ_A, ρ_G, and ρ_V are 0.95, 0.8, and 0.95 with the priors on and ρ_G and ρ_V being more diffuse than the one on ρ_A. The mean values for the standard deviations of the shocks, both the three structural shocks and the one measurement error, are all 0.0066. The Inverse-Gamma priors are of the form $p(\sigma|a,b) \propto \sigma^{-a-1}\exp\{-b/\sigma\}$ such that $E(\sigma) = \frac{b}{a-1}$ and $Var(\sigma) = \frac{b^2}{(a-1)^2(a-2)}$. The steady state ratio of government spending to output (which appears in the log-linearization of the model), g/y, has a mean value of 0.2. The shapes of the priors are similar to others used in the literature.

2.2 An RBC Model with Habit Formation and Capital Adjustment Costs

The second model is identical to that of section 2.1 except for the addition of habit formation and capital adjustment costs. The literature considers several particular forms for the habit formation and capital adjustment costs; the treatment here follows Beaudry and Guay (1996) with the functional form of the utility function that of section 2.1 and with a deterministic trend in the growth component of technology rather than the stochastic trend of Beaudry and Guay. The social planner's problem is thus identical to that of 2.1 with equations (1) and (4) replaced by

$$\max_{\{C_t,H_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln\left(C_t - \nu C_{t-1}\right) - \gamma H_t + v\left(G_t\right)\right] \tag{8}$$

$$Y_t = C_t + I_t + q\frac{\left(K_{t+1} - \eta K_t\right)^2}{2K_t} + G_t \tag{9}$$

The intuition behind the decline in hours following a technology shock in this model is as follows: with habit formation, individuals prefer a smoother consumption path than in the standard model and so increase consumption only gradually in response to an increase in expected income. In the absence of capital adjustment costs, individuals spend the increase in expected income on investment to take advantage of the temporarily higher productivity shock. However, with capital adjustment costs, this aperture is substantially less valuable and instead individuals spend the windfall on leisure.

The priors over ν and q reflect a compromise between the GMM estimates in Beaudry and Guay and the higher values for habit persistence and implied capital adjustment costs in Jermann (1998), Boldrin, Christiano, and Fisher (2001), and Francis and Ramey (2005a). Boldrin, Christiano, and Fisher estimate $\nu = 0.9$ conditional on their chosen parameter value for their capital adjustment costs; Jermann (1998) finds that $\nu = 0.82$ maximizes the model's ability to match selected moments in the data. I compromise and set the means of ν and q to 0.7 and 25.

2.3 Investment Specific Technology Shocks

Fisher (2006) studies the possibility that investment-specific technological change, first studied to explain long-run growth by, among others, Greenwood, Hercowitz, and Krusell (1997) and Hulten (1992), can drive business cycles. He finds that when investment-specific shocks are added to the model, neutral technology shocks account for little of the variation in hours worked over the business cycle. However, investment-specific technology shocks generate a significant rise in hours worked, consistent with traditional RBC models, and thus suggest that the technology-driven theory of the business cycle is alive and well.

The third model I consider is therefore the exact same model as in section 2.1 but the priors on the DSGE model parameters are now such that the investment-specific technology shock has three times as large a variance as the neutral shock, i.e., $\sigma_V = 3\sigma_A$. To guard against the possibility that the results are driven by simply having more overall variance, I scale down the variance of the neutral technology shock by 2/3rds and keep the variance of the remaining shocks in the system the same.

2.4 A Sticky Price Model with an Unaccommodating Monetary Authority

The sticky price model is relatively standard in the literature and is similar to the models of Yun (1996), King and Wolman (1996), and Chari, Kehoe, and McGrattan (2000). To be consistent with the models in 2.1-2.3, there is a trend in the labor-augmenting technology of intermediate goods firms as in Yun (1996). The demand for real balances arises through inserting money into the utility function, monopolistically competitive intermediate goods firms set their prices in Calvo (1983) -style staggering, and final goods firms behave perfectly competitively. I also include capital adjustment costs to be consistent with the sticky price model Francis and Ramey (2005) use.

Specifically, there is a continuum of intermediate goods firms on the interval $[0, 1]$, indexed by j, each of which produces $Y_{j,t}$. Perfectly competitive final goods producers produce the composite commodity consumed by households using

$$Y_t = \left[\int_0^1 (Y_{j,t})^{\frac{\xi-1}{\xi}} \, dj \right]^{\frac{\xi}{\xi-1}} \tag{10}$$

where ξ is the elasticity of substitution between goods. Profit maximization yields the demands for the intermediate goods and the zero profit condition implies the price of the composite good in terms of the price of the intermediate good prices.

The household's problem is

$$\max_{\{C_t, H_t, M_t^D\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln C_t + \omega \ln \left(\frac{M_t^D}{P_t} \right) - \gamma H_t + v(G_t) \right]$$

subject to

$$\frac{P_t}{V_t} K_t + M_t^D = (1-\delta) \frac{P_t}{V_t} K_{t-1} + r_t P_t K_{t-1} + P_t W_t H_t + M_{t-1}^D + T_t + PR_t - q \frac{(K_t - \eta K_{t-1})^2}{2K_{t-1}} - P_t C_t - P_t Tax_t$$

where M_t^D is the household's date t nominal balances, C_t is units of consumption of the composite good, W_t and r_t are the real wage and rental rates, T_t is transfers from the monetary authority, PR_t are the profits from household's ownership of firms, Tax_t is lump-sum taxes paid, g_t follows (6), and V_t follows (7).

Intermediate goods firms produce goods using $Y_{j,t} = A_t K_{j,t}^{\theta} \left(\eta^t H_{j,t} \right)^{1-\theta}$ where A_t follows the process given in (5). The price stickiness is modeled as simple Calvo price staggering following the finding of Korenok and Swanson (2005) that price indexation does not improve the performance of the sticky price model for real variables.[4] That is, each period a firm faces the probability $1-\alpha$ of being able to change its nominal price. This leads to the maximization problem

$$\max_{P_{j,t}} E_t \sum_{k=0}^{\infty} (\alpha\beta)^k m_{t+k} \left(P_{j,t} - mc_{t+k} P_{t+k} \right) Y_{j,t+k}^d \tag{11}$$

where mc_{t+k} is marginal cost and m_{t+k} is the current value of a dollar received by the household in period $t+k$ which the firm treats as exogenous.

[4] Note, however, that both Korenok and Swanson (2005) and Rabanal and Rubio-Ramirez (2005) find that price indexation improves the performance of the sticky price model for inflation.

The government runs a balanced budget every period, i.e., $G_t = Tax_t$ with the law of motion for g_t given by (6). The monetary authority follows a $k\%$ rule,

$$M^s_{t+1} = \mu M^s_t \tag{12}$$

and remits all seignorage revenue to the household. Since the value of μ does not affect the model's dynamics, μ is fixed at 1 for simplicity.

In this model, the proximate effect of a technology shock is to lower the intermediate good firm's marginal costs. With sticky prices, this drives a wedge between the real wage and its marginal revenue product. Since households expect the wedge to decrease over time as prices adjust, they increase their consumption of leisure now. With a Cobb-Douglas production function, labor and capital are complements such that the firm decreases its demand for capital and, in response to this decline in the return to capital, the household disinvests to satisfy its intertemporal Euler equation until prices adjust.

There is disagreement in the literature regarding the value of the elasticity of substitution between goods, ξ, which must be consistent with a steady-state markup of price over marginal cost equal to $\frac{\xi}{\xi-1}$: Korenok and Swanson (2005) set it at 11, Chari, Kehoe, and McGrattan (2000) set it at 10, Yun (1996), Ireland (2001), and Rabanal and Rubio-Ramirez (2005) set it at 6, while Christiano, Eichenbaum, and Evans (2005) and Eichenbaum and Fisher (2004) estimate to be around 3. In the benchmark specification I set its mean to 6. There is similarly some controversy regarding the value of $1 - \alpha$, the probability a firm can adjust its price: Bils and Klenow (2004), Eichenbaum and Fisher (2004), and Christiano, Eichenbaum, and Evans (2005) both suggest that firms reoptimize prices on average once every two quarters implying $\alpha = 0.5$ while Rabanal and Rubio-Ramirez (2005) and other earlier work cited by Bils and Klenow (2004) find that firms reoptimize only every four to seven quarters. I choose the prior such that the mean value of α is 0.8, implying that firms readjust prices every five quarters.

2.5 Impulse Response Functions at Means of Priors

Figures 1 presents the theoretical impulse responses for these models at the means of the priors to a neutral technology shock. The figures confirm the posited effects on hours of neutral technology shocks in each of the models. Furthermore, although of the models feature a positive response of output, the magnitude of the response in the first ten quarters differs sharply across the three models. Likewise, the responses of investment are dissimilar across the three models with only consumption showing a similar shape and magnitude across all three models.

Figure 2 shows the models' responses to a shock to government spending in the three models. Government spending shocks lead to an increase in hours worked and a fall in consumption due to a wealth effect: as the government is consuming more, there is less output available for households to consume. See Ramey (2007) for additional discussion of the role of government in the basic RBC model. While the responses are usually of the same sign (with the exception of investment), the magnitudes again differ sharply for hours worked and consumption.

Figure 3 shows the models' responses to the last structural shock in the model, an investment-specific technology shock. The large capital adjustment costs in HABIT make that model much less sensitive to investment-specific technology shocks than the other two models.

To summarize, the theoretical impulse response functions often differ in both sign and magnitude from one another such that the models imply very different economic dynamics from one another.

3 Incorporating Prior Information

3.1 Prior Information from DSGE Models

Let y_t, i_t, h_t, and c_t denote data on output, investment, hours worked, and consumption. We are interested in using the models above to generate forecasts from the model

$$x_t = \sum_{i=1}^{p} x_{t-i}\phi_i + \phi_0 + u_t$$

where $x_t = [y_t, i_t, h_t, c_t]$, each ϕ_i is a $4x4$ matrix, and ϕ_0 is $1x4$.

This system can be written in matrix form as

$$Y = X\Phi + u \tag{13}$$

where Y has rows x_t, $X = [\mathbf{1}, x_{-1}, x_{-2}, .., x_{-p}]$ and $\Phi = \left[\phi_0', \phi_1', .., \phi_p'\right]'$.

Now assume that

$$u \sim N(0, \Sigma_u).$$

Let $\hat{y}_t$, $\hat{\imath}_t$, $\hat{h}_t$, and $\hat{c}_t$ denote the percent deviations from steady state of output, investment, hours worked, and consumption as implied by the DSGE models and let ζ_i denote the vector of DSGE model parameters and the standard deviation of the measurement error in model i, $i = 1, 2, 3, 4$. i corresponds to the model discussed in section 2.i. If the DSGE model was precisely the data generating process, conditional on the parameter the observable data, once detrended, would relate to these quantities according to

$$Y^*_{i,t}|\zeta_i = \left[y^*_{i,t}, i^*_{i,t}, h^*_{i,t}, c^*_{i,t}\right] = \left[\hat{y}_t + \varepsilon_t^{MEAS}, \hat{\imath}_t, \hat{h}_t, \hat{c}_t\right]$$

where ε_t^{MEAS} is an i.i.d. measurement error.

In the benchmark version of the model, each data series is linearly detrended where the detrending is done using only the data available up to the time of the first forecasting period. To date, the more common detrending method used for DSGE-VARs has been to first difference the data (e.g., Del Negro and Schorfheide, 2004; Smets and Wouters, 2007) or to use models that do not imply anything about the trend and then add a trend to the VAR (e.g., De Jong, Ingram and Whiteman, 1993; Ingram and Whiteman, 1994).

The models do however imply what trend growth rates should be - consumption, output, and investment should be growing at rate $\eta - 1$ while hours should have no trend. However, the models were designed primarily to explain deviations from the trends rather than the trends themselves and so it is unclear they do a good job of explaining the trends in the data. My benchmark case is to use the models' implications for the deviations from trend and largely ignore the (erroneous) predictions the models make about the trends. In section 4.4.4, I consider the case where the trends are left in the data and the priors are adjusted accordingly.

DeJong, Ingram, and Whiteman (1993) and Ingram and Whiteman (1994) originated the idea of using prior information from a DSGE model to induce shrinkage. However, I follow Del Negro and Schorfheide (2004) in using the expectation of the moments the model would generate, rather than simulating data from the models, a procedure that would introduce stochastic variation into the estimation, and in specifying the prior distribution for Σ_u.

Denote by $Y_i^* = \left[Y_{i,1}^{*\prime}, Y_{i,2}^{*\prime}, ..., Y_{i,T}^{*\prime}\right]'$ and define X_i^*analogously. Conditional on λ, a hyperparameter controlling the tightness of the prior, and the vector of DSGE model parameters for model i, which I will denote by ζ_i, the prior for Φ and Σ_u is of the Inverted-Wishart (IW) - Normal (N) form, i.e.,

$$
\begin{aligned}
&\Sigma_u|\zeta_i\tilde{\ } IW\left(\lambda T\Sigma_u^*\left(\zeta_i\right), \lambda T - k\right) \\
&\Phi|\zeta_i\tilde{\ } N\left(\Phi^*\left(\zeta_i\right), \Sigma_u \otimes \left(\lambda T \Gamma_{XX}^i\left(\xi_i\right)\right)^{-1}\right).
\end{aligned}
$$

where

$$
\begin{aligned}
\Sigma_u^*\left(\zeta_i\right) &= \Gamma_{YY}^i\left(\zeta_i\right) - \Gamma_{YX}^i\left(\zeta_i\right)\left[\Gamma_{XX}^i\left(\zeta_i\right)\right]^{-1}\Gamma_{XY}^i\left(\zeta_i\right), \\
\Phi^*\left(\zeta_i\right) &= \left[\Gamma_{XX}^i\left(\zeta_i\right)\right]^{-1}\Gamma_{XY}^i\left(\zeta_i\right), \\
\Gamma_{XX}^i\left(\zeta_i\right) &= E_{\zeta_i}\left(X_{i,t}^{*\prime}X_{i,t}^*\right), \\
\Gamma_{XY}^i\left(\zeta_i\right) &= E_{\zeta_i}\left(X_{i,t}^{*\prime}Y_{i,t}^*\right), \\
\Gamma_{YY}^i\left(\zeta_i\right) &= E_{\zeta_i}\left(Y_{i,t}^{*\prime}Y_{i,t}^*\right),
\end{aligned}
$$

n denotes the number of observed variables, and $k = np + 1$. $\Gamma_{XX}^i\left(\zeta_i\right)$, $\Gamma_{XY}^i\left(\zeta_i\right)$, and $\Gamma_{YY}^i\left(\zeta_i\right)$ are generated from the state-space representation of the DSGE models as described in appendix A.2 of Del Negro and Schorfheide.

The posterior distribution of the VAR parameters is thus

$$
p\left(\Phi, \Sigma_u|\zeta_i, Y\right) = p\left(\Phi|\zeta_i, \Sigma_u, Y\right)p\left(\Sigma_u|\zeta_i, Y\right)p\left(\zeta_i\right)
$$

where, because of the choice of the Inverted-Wishart - Normal prior,

$$
\begin{aligned}
&\Sigma_u|Y, \zeta_i\tilde{\ } IW\left(\left(\lambda + 1\right)T\tilde{\Sigma}_u\left(\zeta_i\right), \left(1 + \lambda\right)T - k\right) \\
&\Phi|Y, \Sigma_u, \zeta_i\tilde{\ } N\left(\tilde{\Phi}\left(\zeta_i\right), \Sigma_u \otimes \left(\lambda T \Gamma_{XX}^i\left(\zeta_i\right) + X'X\right)^{-1}\right)
\end{aligned}
$$

with

$$\tilde{\Sigma}(\zeta_i) = ((\lambda+1)T)^{-1} \begin{bmatrix} \left(\lambda T \Gamma^i_{YY}(\zeta_i) + Y'Y\right) \\ -\left(\lambda T \Gamma^i_{YX}(\zeta_i) + Y'X\right)\left(\lambda T \Gamma^i_{XX}(\zeta_i) + X'X\right)^{-1}\left(\lambda T \Gamma^i_{XY}(\zeta_i) + X'Y\right) \end{bmatrix}$$
$$\tilde{\Phi}(\zeta_i) = \left(\lambda T \Gamma^i_{XX}(\zeta_i) + X'X\right)^{-1}\left(\lambda T \Gamma^i_{XY}(\zeta_i) + X'Y\right)$$

I denote the resulting empirical VAR(λ, i) models as RBC, HABIT, ISHOCK, and STICKY.

Note that I follow DeJong, Ingram, and Whiteman (1993) here in drawing from the posterior distribution of the VAR parameters conditional on the prior distribution of the DSGE model parameters. If one were interested in indirectly estimating the DSGE model parameters via this method, one could follow the procedure Del Negro and Schorfheide describe to draw from the joint posterior of the DSGE model parameters and the VAR parameters. However, the interest of this paper is not in estimating the DSGE parameters but rather to compare models that differ exactly because of the restrictions they place on the DSGE model parameters. Section 4.4.5 does, however, consider the case where the DSGE parameters are estimated.

3.2 The Minnesota Prior

Since the OLS estimator is inadmissible for the loss function considered here (see, e.g., Robert 2001), I compare the forecasting performance of a shrinkage estimator using the Minnesota prior also known as the Litterman prior. Todd (1984) provides an excellent intuitive explanation why this estimator often outperforms an unrestricted and many kinds of structural VARs. Essentially, an unrestricted VAR puts equal likelihood on all values of the VAR parameters and so does not reflect even the most naive forecaster's true beliefs about the values of the parameters. Since the OLS parameter estimates are identical to the maximum likelihood estimates for the coefficients of an unrestricted VAR, the OLS procedure is identical to having a diffuse prior over the coefficients. To see this, let w, $p(\Phi)$, $p(\Phi|w)$, and $l(w|\Phi)$ denote a vector of data, the prior, the posterior, and the likelihood function. Then if the econometrician has a diffuse prior over Φ, i.e., $p(\Phi) \propto 1$ then

$$p(\Phi|w) \propto p(\Phi)\, l(w|\Phi).$$

Structural VARs similarly impose dogmatic priors on some parameters in their use of zero restrictions while again placing equal weight on all possible values for the remaining parameters of the model. Both of these procedures are at odds with common sense and so it is not surprising that professional forecasters using some judgment rather than formal econometric models were generally able to outperform econometric models until the advent of Bayesian VARs (Litterman, 1986).

While many priors not derived from economic theory perform well relative to unrestricted VARs[5], the Minnesota prior of Doan, Litterman, and Sims (1984) and Litterman (1986) has proven difficult to consistently outperform and remains the benchmark for many analyses (see, for example, Ingram and Whiteman, 1994, Kadiyala and Karlsson, 1997, Sims and Zha, 1998, and Del Negro and Schorfheide, 2004). This prior posits that a good first approximation of the data is that each series follows a univariate random walk. In particular, the coefficients are normally distributed with a variance that decreases with the order of the lag and a smaller variance for cross lags than for own lags. The idea behind this specification of the variance structure is that the variance should be higher for parameters that are likely to be more important in estimating the VAR so that an overly tight prior does not seriously bias the results. My implementation of this prior follows Litterman (1986) with the tightness parameters, θ and λ_{LIT}, set at 0.2 and 0.05 where the θ is that in the Litterman paper and not to be confused with the capital share parameter of section 2. The value of θ is set as in Litterman (1986) while $\lambda_{LIT} = 0.05$ yielded much better forecasts than Litterman's original choice of $\lambda_{LIT} = 0.2$.

4 Results

4.1 Data

The data are seasonally adjusted and cover 1947:1-2007:4. Consumption and investment, c_t and i_t, are NIPA series for personal consumption expenditures and gross private fixed investment retrieved from the Bureau of Economic Analysis website (BEA table 1.1.5) deflated by their price deflators (BEA table 1.1.4). Since none of the models considered here include export or import sectors, the empirical analog to output in the models, y_t, consists of real consumption, investment, and government purchases. I construct this output series using the divisia method Whelan (2002) outlines. The hours series, h_t, is an index (1992=100) for non-farm business employment which I take from the Bureau of Labor Statistics. The series ID is PRS85006033. All variables are used

[5] See Kadiyala and Karlsson (1997) for a review of some of these priors.

in natural logs and put on per capita terms by dividing by the US population, data which comes from the Global Financial Data (GFD) Database. The series ID is POPUSA. Population data is only available on an annual basis so quarterly values are obtained by linear interpolation. Finally, all variables ware linearly detrended using only data available prior to the first forecast.

4.2 Forecasting Scheme

The benchmark model uses four lags of output, investment, hours, and consumption, a common lag length for VAR analysis in macroeconomics, and a 160 quarter estimation window. Kim and Nelson (1999) and McConnell and Perez-Quiros (2000) document the structural instability in the real side of the US macroeconomy over the course of the dataset. It is beyond the scope of this paper to explicitly model such instability. Instead I follow the recommendations of West (2005) and Giacomini and White (2006) and use a rolling window forecasting scheme to minimize the effect of this instability such that the model is estimated anew at each forecasting date. I draw 5000 times from the posterior distribution of the VAR parameters and create forecasts 1 to 20 steps ahead. I then take the mean forecasts across all draws,

$$\hat{x}_{t+1}^{\Phi} = \frac{1}{5000} \sum_{j=1}^{5000} \hat{x}_{t+1} \left(\Phi_j \right),$$

as the one-step ahead forecast. I use $\hat{x}_{t+1}^{\Phi}$ to update the data matrices for the next forecasting horizon and then compute the forecast for that horizon by again averaging over the forecasts produced for each draw from the posterior distribution of Φ. The mean squared forecast errors shown for each horizon are the average squared forecast error across the periods in the data not used to estimate the model. I detrend and demean the data using only the data available prior to the first forecast.

4.3 Results for the Benchmark Model

Columns $3-8$ of tables $2-5$ report the results for several values of the tightness parameter. The most striking result is how similar the root mean squared forecast errors (MSFEs) are across the different models compared to how different the models appear based on their impulse response functions in figures $1-3$. While ISHOCK gives slightly better forecasts for investment and hours, the improvement is slight. HABIT seems to be the weakest performer of the four but otherwise the winner depends on which variable, which forecasting horizon, and which value for the tightness parameter.[6] Furthermore, the relatively poor performance of HABIT and relatively strong performance of ISHOCK is not robust to alternative choices for the estimation window as I discuss in section 4.4.2. The results for the higher tightness parameters seem to be better although there appears to be some small trade-offs between forecasting power at the one quarter horizon versus longer horizons for the higher values of lambda.

The second thing to remark from tables $2-5$ is that all of the economic models are very competitive with the VAR-MINN and the unrestricted VAR at shorter horizons for all variables except for hours worked. This is particularly true for the higher values of λ in the DSGE models. Both the VAR-MINN and VAR(λ, i) models have the difficulty forecasting hours worked.

The last panels of table $2-5$ show the forecasting results when $\lambda = \infty$ such that there is no weight on the data. The best forecasts for the furthest out horizons actually come with this choice for the tightness parameter although this choice yields the worst forecasting performance at shorter horizons. Here, we do see larger differences in forecasting performance and all of the DSGE models do quite poorly at the short horizons. STICKY performs notably badly in forecasting output, investment, and hours worked.

4.4 Sensitivity Analysis

4.4.1 An Accommodating Monetary Authority

The sticky price model considered has an unaccommodating monetary authority, such that the model generates a decline in hours following a technology shock. However, King and Wolman (1996) document that the dynamics in sticky price models are highly sensitive to the specification of the monetary rule as monetary economists would expect. Further, Clarida, Gali, and Gertler (1999) and Gali, Lopez-Salido, and Valles (2003) present evidence that the Federal Reserve Board optimally responded to technology shocks during the Volcker-Greenspan era but followed a constant money growth rule in the pre Volcker era, suggesting that the model of section 2.4 may be the right model to consider for many of the estimation periods but a poor approximation for the forecasting

[6] As discussed in Giacomini and White (2006), the commonly used Diebold and Mariano (1995) tests for differences in MSFEs are inappropriate for Bayesian estimation schemes because asymptotic irrelevance does not apply. While the tests proposed by Giacomini and White (2006) can be implemented for testing differences in one-step ahead forecasting ability, practical implementation of the Giacomini and White tests at further than one quarter ahead has no precedent in the literature and, to my knowledge, no computationally convenient algorithm exists at this time.

periods, all of which are in the Volcker-Greenspan era. I therefore consider a specification of the sticky price model that allows the central bank to respond to technology shocks. This model is the same as that in 2.4 but with (12) replaced by

$$\ln M_{t+1}^{S} = \rho_M \ln M_t^S + (1-\rho_M) \ln M + E_t \ln A_{t+1}. \tag{14}$$

That is, the monetary authority matches any increase in the expected level of technology with an immediate increase in the money supply in the period following the shock. I use a $\beta\,(50, 50)$ prior for ρ_M; the mean of the distribution is 0.5 and its standard deviation is 0.05.

The final columns of tables $2-5$ report the results for this specification of STICKY (denoted STICKY-ACC). Despite this model perhaps being a more accurate description of monetary policy, the root mean squared forecast errors are not substantially better than the benchmark specification of STICKY.

4.4.2 Alternative Estimation Windows

The choice of 160 quarters as the length of the estimation window is somewhat arbitrary. I also considered windows of 120, 140, and 180 quarters. The forecasting accuracy across models remained similar and the relatively poor performance of HABIT and good performance of ISHOCK was not robust to using a 120 or 140 quarter window. The full tables with the results are available in an appendix on the author's webpage. ISHOCK does continue to perform well for hours relative to the other VAR(λ, i) models when I use alternative estimation windows. Furthermore, the notably poor performance of STICKY when $\lambda = \infty$ is consistent across all estimation windows.

4.4.3 Alternative Specifications of the Minnesota Prior

There may be concern that the success of the economic models relative to VAR-MINN owes to a poor specification of the Minnesota prior: there are many ways of specifying the Minnesota prior and the performance is often sensitive to the choice of the tightness parameter (Ni and Sun, 2003). I therefore also consider a looser Litterman priors ($\lambda_{LIT} = 0.1$) and a tighter Litterman prior ($\lambda_{LIT} = 0.03$). Table 6 reports these results and compares them with the results for the DSGE models using $\lambda = 10$ as the tightness parameter.

4.4.4 Forecasts in Levels

Without detrending the observable data, the model implied observations would be

$$Y_{i,t}^{*}|\zeta_i = \left[y_{i,t}^{*}, i_{i,t}^{*}, h_{i,t}^{*}, c_{i,t}^{*}\right] = \left[\eta^t \left(y_0 + \hat{y}_t + \varepsilon_t^{MEAS}\right), \eta^t \left(i_0 + \hat{\imath}_t\right), h_0 + \hat{h}_t, \eta^t \left(c_0 + \hat{c}_t\right)\right] \tag{15}$$

where y_0, i_0 , h_0, and c_0 are the steady state values of output, investment, hours worked, and consumption at the beginning of the sample. Since we do not observe initial values, I proxy for them using the actual values for the first observation in the sample divided by η such that $y_1 = \eta y_0$.

The scaling of the population moments differs slightly from that in section 3 as the data is no longer covariance stationary. After detrending, we defined population moments in section 3 as $\Gamma_{YY}^{i}(\zeta_i)$ as $\Gamma_{YY}^{i}(\zeta_i) = E_{\zeta_i}\left(Y_{i,t}^{*\prime}Y_{i,t}^{*}\right)$ because the models were all covariance stationary. The population moments here use all of the data that the DSGE model would generate in levels with the trend defined by the parameter η. To be consistent with the earlier notation, I scale the matrices by $1/T$.

Table 7 present the results of this specification. The DSGE models perform spectacularly badly. The root mean squared forecast errors are orders of magnitude greater than those from the VAR-MINN and the unrestricted VAR. Consistent with the earlier results, however, the DSGE models all perform similarly disastrously relative to the differences in their impulse response functions.

Why do the DSGE models yield such awful forecasts when the data is not detrended? The problem lies in the models' specification of the trend. Over the full 1947Q1 - 2007Q4 sample, logged per capita output, investment, hours, and consumption grew at rates of 0.055%, 0.058%, 0.087%, and 0.003%. However, according to the DSGE models, output, investment, and consumption grew at rate $\eta - 1$ while hours experienced no growth. With the DSGE model in levels, investment ends up growing far too slowly such that the data the DSGE model implies bears little resemblance to the data - the trend component dominates the simulated data and so the cross-correlations from the DSGE models do not take the differences in the trends into account. To accurately capture both the trend and the fluctuations around the trend, the models would need to find a better job of modeling the individual trends rather than imposing the common trend. Simply put, the priors for the data in levels are bad illustrating Clive Granger's (1986) adage that "a good Bayesian will beat a non-Bayesian who will do better than a bad Bayesian".

4.4.5 Estimating the DSGE parameters

Among other improvements, Del Negro and Schorfheide (2004) modify the methodologies of DeJong, Ingram, and Whiteman (1993) and Ingram and Whiteman (1994) to allow both the VAR parameters and the DSGE parameters to be estimated from the VAR. I therefore also consider how the forecasts change when the forecasts are made using the posterior estimates of both the DSGE model parameters and the VAR parameters. The technical details closely follow Del Negro and Schorfheide (2004) which in turn builds on Schorfheide (2000).

I draw 100,000 times from the posterior distribution of the DSGE parameters and discard the first 90,000 as burn-in draws. The remaining 10,000 draws are then used to draw from the VAR parameters and compute the forecasts. The choice to discard a larger than usual number of draws reduces the computational time substantially while allowing enough draws to ensure convergence of the Markov Chain.

Table 9 illustrates that the main results of the paper are robust to estimating the DSGE parameters: when one $VAR(\lambda, i)$ model outperforms the VAR-MINN model, all of them tend to more often than not. Furthermore, the relatively weak performance of HABIT is overturned when the DSGE parameters are estimated. The improvement of HABIT when the DSGE parameters are estimated appears to be due to allowing for a higher degree of habit formation than implied by the mean of the prior: while the mean value of the prior for ν, which controls the degree of habit formation, is 0.7, the estimated values of ν are 0.79, 0.90, and 0.90 for $\lambda = 0.25$, 1, and 10.

4.5 Forecast Combinations

That the mean of the squared forecast errors is similar does not necessarily indicate that the models all yield similar results; it may be the case that the models make mistakes in opposite directions of one another, with one model over-predicting a variable and another under-predicting, and yet the average forecast error is the same. If this were the case, there may be gains from combining the forecasts from different models.

This section explores whether there are gains from model averaging. Table 8 shows the results using a simple average of the four models with $\lambda = 10$ and using and the 160 quarter estimation window. There appears to be little improvement from combining forecasts.

5 Discussion and Conclusions

The main finding of the paper that all of the models generate similar forecasting results, despite their different implications for the effects of technology shocks. As in previous work, the DSGE-VAR models perform quite favorably relative to atheoretical models. However, the results in this paper suggest that, at least for the purposes of forecasting, it does not matter all that much which DSGE model is chosen to serve as the prior. An important exception is that, when no weight is placed on the data, the sticky price model performs significantly worse than the other DSGE models in forecasting output, investment, and hours worked.

Given its simplicity, it is somewhat surprising that the basic RBC model performs so well; the more sophisticated models do not yield better forecasts in general. What might explain the similarity of the forecasts? Table 10 reports the cross-correlations that the models generate. All models have high autocorrelations and positive correlations between output and investment and between output and consumption. This suggests that the improvements in forecasting performance that using DSGE model priors yield may come from their implications for the correlation structure for the variables in the VAR rather than the dynamics *per se* that the models imply.

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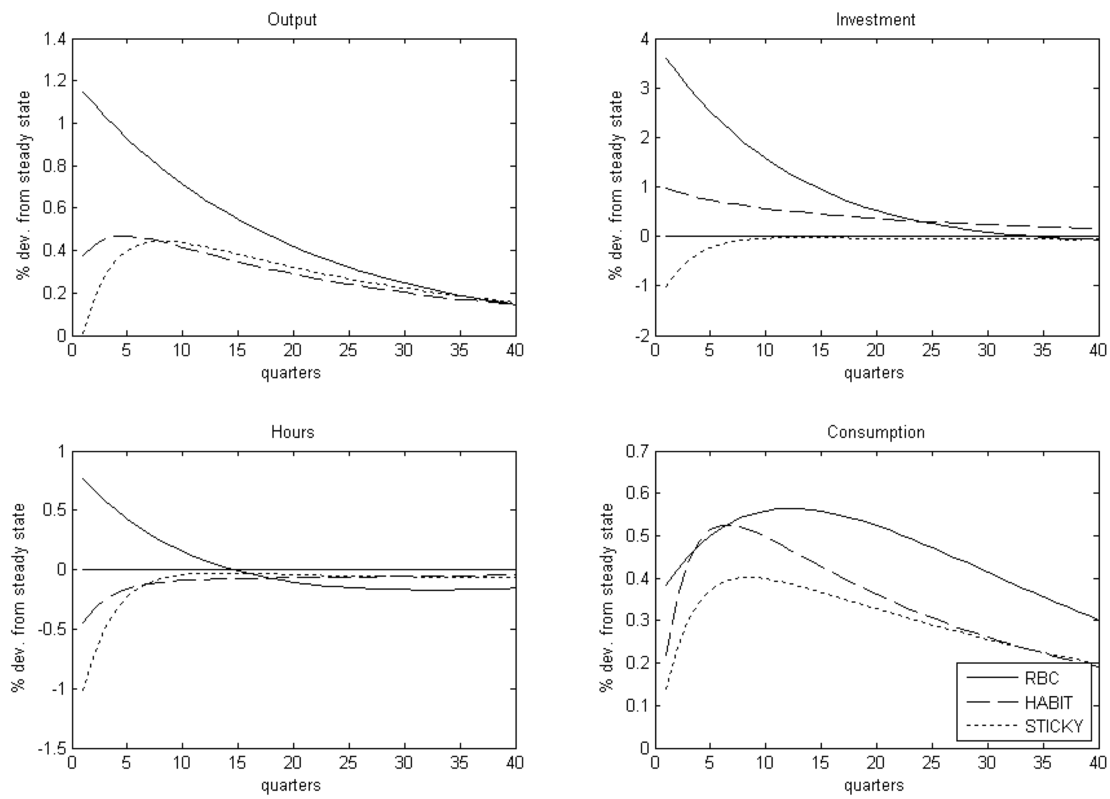

Figure 1: Impulse Responses for a Neutral Technology Shock

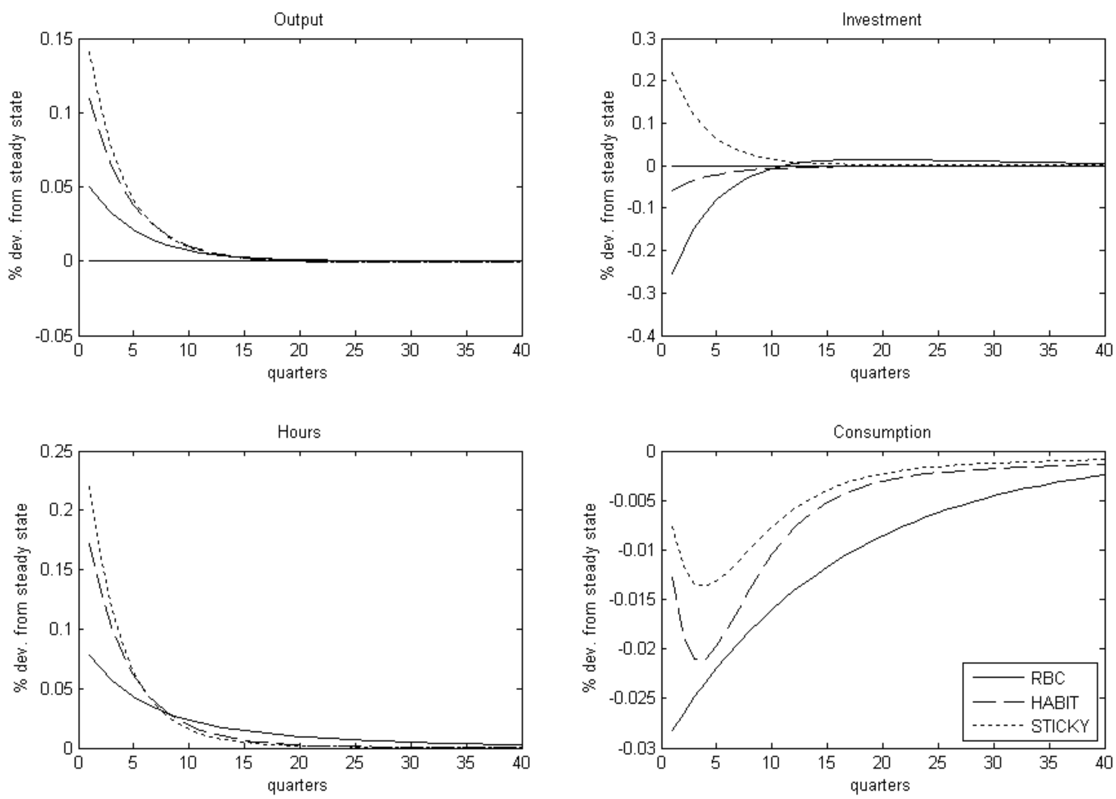

Figure 2: Impulse Responses for a Government Spending Shock

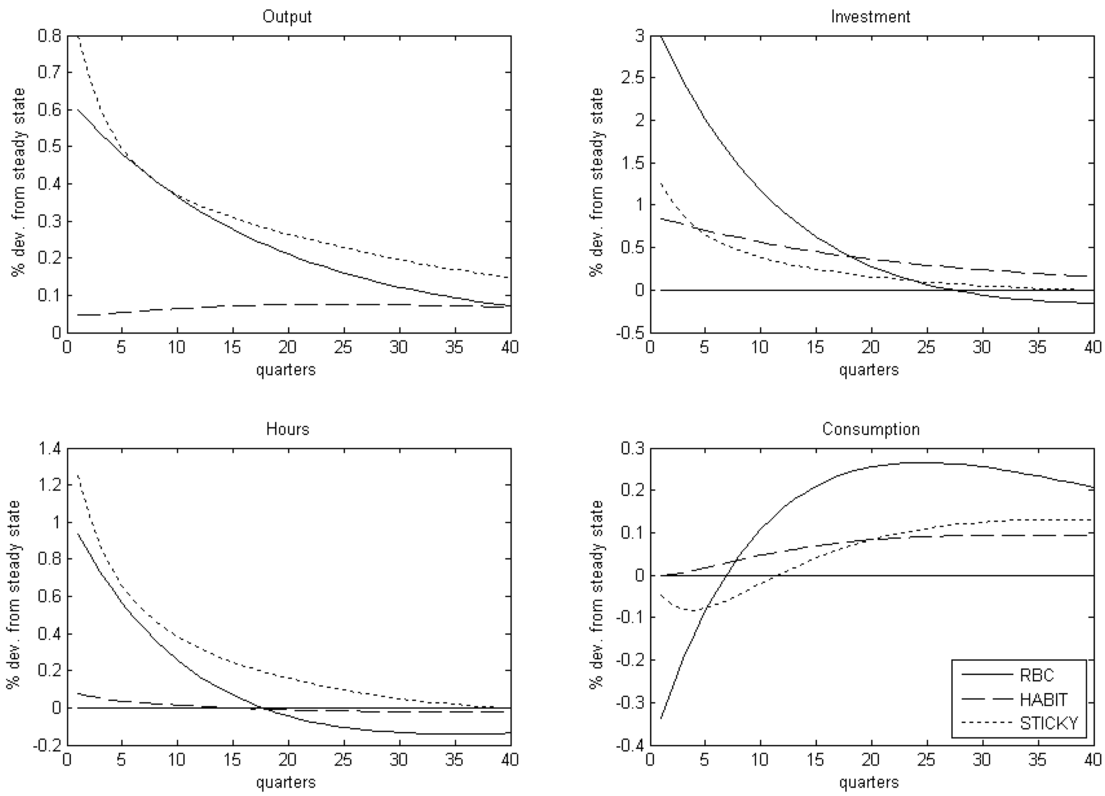

Figure 3: Impulse Responses for an Investment-Specific Technology Shock

Table 1: Priors for DSGE Model Parameters

Param.	Description	Model(s)	Dist.	Mean	Par. 1	Par. 2	Std. Dev.
β	Discount Factor	All	Fixed	0.99			
γ	Disutility from Labour	All					
θ	Capital Share	All	Beta	0.36	18	32	0.067
η	Growth of Labour-Augmenting Tech.	All	Normal	1.00055	1.00055	0.0001	0.0001
δ	Depreciation Rate	All	Beta	0.021	12.6	587.4	0.006
ρ_A	Persistence of Neutral Shocks	All	Beta	0.95	95	5	0.022
ρ_g	Persistence of Gov't Spending Shocks	All	Beta	0.8	32	8	0.062
ρ_V	Persistence of Investment Specific Shocks	All	Beta	0.95	47.5	2.5	0.031
g/y	Steady State Gov't Share of Output	All	Beta	0.2	20	80	0.040
σ_A	Std. Dev. of Neutral Shocks	RBC, HABIT, STICKY	Inv. Gamma	0.0066	3.74	0.0181	0.005
σ_A	Std. Dev. of Neutral Shocks	ISHOCK	Inv. Gamma	0.0044	2.77	0.0078	0.005
σ_g	Std. Dev. of Gov't Spending Shocks	RBC, HABIT, STICKY	Inv. Gamma	0.0066	3.74	0.0181	0.005
σ_g	Std. Dev. of Gov't Spending Shocks	ISHOCK	Inv. Gamma	0.0044	2.77	0.0078	0.005
σ_V	Std. Dev. of Investment Specific Shocks	RBC, HABIT, STICKY	Inv. Gamma	0.0066	3.74	0.0181	0.005
σ_V	Std. Dev. of Investment Specific Shocks	ISHOCK	Inv. Gamma	0.0132	8.97	0.1052	0.005
σ_{MEAS}	Measurement Error	RBC, HABIT, STICKY	Inv. Gamma	0.0066	3.74	0.0181	0.005
σ_{MEAS}	Measurement Error	ISHOCK	Inv. Gamma	0.0044	2.77	0.0078	0.005
ν	Degree of Habit Formation	HABIT	Beta	0.7	14	6	0.100
q	Size of Capital Adjustment Costs	HABIT	Truncated Normal	25	25	5	5
q	Size of Capital Adjustment Costs	STICKY	Truncated Normal	10	10	5	5
ω	Utility from Real Balances	STICKY					
ξ	Elasticity of Substitution between Goods	STICKY	Truncated Normal	6	6	2	2
α	Fraction of Firms not Adjusting Prices	STICKY	Beta	0.8	2	0.5	0.21

Table 2: Root MSFEs for Output

λ	Horizon	Unrestricted RMSFE	VAR-MINN	RBC	HABIT	ISHOCK	STICKY	STICKY-ACC
0.25	1	0.01	1.02	**0.95**	**0.95**	**0.94**	**0.95**	**0.95**
0.25	2	0.02	0.92	**0.91**	0.94	**0.91**	0.95	0.95
0.25	4	0.03	0.86	0.92	0.96	0.91	0.97	0.98
0.25	8	0.06	0.85	0.94	0.98	0.93	0.98	0.99
0.25	12	0.08	0.86	0.96	0.98	0.95	0.98	0.98
0.25	16	0.11	0.88	0.97	0.98	0.96	0.97	0.97
0.5	1	0.01	1.02	**0.93**	**0.93**	**0.93**	**0.93**	**0.94**
0.5	2	0.02	0.92	**0.89**	**0.92**	**0.89**	0.93	0.93
0.5	4	0.03	0.86	0.89	0.94	0.88	0.95	0.95
0.5	8	0.06	0.85	0.92	0.96	0.91	0.96	0.97
0.5	12	0.08	0.86	0.94	0.97	0.93	0.96	0.96
0.5	16	0.11	0.88	0.95	0.97	0.95	0.95	0.96
1	1	0.01	1.02	**0.92**	**0.91**	**0.93**	**0.91**	**0.91**
1	2	0.02	0.92	**0.86**	**0.89**	**0.87**	**0.90**	**0.90**
1	4	0.03	0.86	0.86	0.92	0.86	0.92	0.92
1	8	0.06	0.85	0.89	0.94	0.90	0.94	0.94
1	12	0.08	0.86	0.92	0.95	0.92	0.94	0.94
1	16	0.11	0.88	0.93	0.95	0.93	0.93	0.94
5	1	0.01	1.02	**0.88**	**0.89**	**0.90**	**0.83**	**0.85**
5	2	0.02	0.92	**0.78**	**0.84**	**0.81**	**0.80**	**0.80**
5	4	0.03	0.86	**0.78**	0.87	**0.81**	**0.83**	**0.83**
5	8	0.06	0.85	**0.82**	0.89	0.85	0.86	0.86
5	12	0.08	0.86	0.86	0.91	0.88	0.87	0.87
5	16	0.11	0.88	0.88	0.92	0.90	0.88	0.88

Table 2 (Cont.): Root MSFEs for Output

λ	Horizon	Unrestricted RMSFE	VAR-MINN	RBC	HABIT	ISHOCK	STICKY	STICKY-ACC
10	1	0.01	1.02	**0.88**	**0.89**	**0.89**	**0.82**	**0.84**
10	2	0.02	0.92	**0.74**	**0.82**	**0.78**	**0.75**	**0.75**
10	4	0.03	0.86	**0.75**	**0.84**	**0.78**	**0.78**	**0.78**
10	8	0.06	0.85	**0.79**	0.87	**0.82**	**0.82**	**0.82**
10	12	0.08	0.86	**0.83**	0.89	**0.85**	**0.84**	**0.84**
10	16	0.11	0.88	**0.87**	0.91	0.88	**0.86**	**0.85**
20	1	0.01	1.02	**0.91**	**0.90**	**0.88**	**0.84**	**0.88**
20	2	0.02	0.92	**0.71**	**0.79**	**0.75**	**0.71**	**0.71**
20	4	0.03	0.86	**0.71**	**0.81**	**0.75**	**0.74**	**0.72**
20	8	0.06	0.85	**0.77**	**0.84**	**0.80**	**0.79**	**0.78**
20	12	0.08	0.86	**0.81**	0.87	**0.83**	**0.82**	**0.81**
20	16	0.11	0.88	**0.85**	0.89	**0.86**	**0.83**	**0.83**
∞	1	0.01	1.02	5.65	5.00	5.65	94.20	3.10
∞	2	0.02	0.92	2.91	2.43	2.91	31.04	1.54
∞	4	0.03	0.86	1.17	0.92	1.17	39.67	**0.72**
∞	8	0.06	0.85	**0.58**	**0.59**	**0.57**	26.85	**0.61**
∞	12	0.08	0.86	**0.57**	**0.66**	**0.57**	24.30	**0.69**
∞	16	0.11	0.88	**0.64**	**0.72**	**0.64**	24.59	**0.74**

The entries in the column "Unrestricted" are Root MSFEs. The entries in the five other columns are MSFEs relative to "Unrestricted". Notes: 1) Bold entries are those for which a DSGE-VAR outperforms both the unrestricted VAR and the VAR-MINN. 2) Results are for a rolling forecasting scheme with a window of 160 quarters starting in 1947:1. 3) Results are shown for VARs with four lags.

Table 3: Root MSFEs for Investment

λ	Horizon	Unrestricted RMSFE	VAR-MINN	RBC	HABIT	ISHOCK	STICKY	STICKY-ACC
0.25	1	0.04	1.00	**0.92**	**0.96**	**0.90**	**0.95**	**0.95**
0.25	2	0.07	0.91	**0.89**	0.95	**0.85**	0.95	0.95
0.25	4	0.11	0.84	0.88	0.96	0.83	0.97	0.97
0.25	8	0.18	0.81	0.90	0.97	0.85	0.97	0.97
0.25	12	0.23	0.83	0.91	0.97	0.87	0.95	0.96
0.25	16	0.26	0.84	0.91	0.96	0.88	0.93	0.94
0.5	1	0.04	1.00	**0.91**	**0.94**	**0.89**	**0.94**	**0.94**
0.5	2	0.07	0.91	**0.87**	0.93	**0.84**	0.94	0.94
0.5	4	0.11	0.84	0.85	0.94	**0.81**	0.95	0.95
0.5	8	0.18	0.81	0.87	0.95	0.83	0.95	0.96
0.5	12	0.23	0.83	0.89	0.95	0.85	0.93	0.94
0.5	16	0.26	0.84	0.89	0.94	0.85	0.91	0.92
1	1	0.04	1.00	**0.91**	**0.92**	**0.89**	**0.94**	**0.94**
1	2	0.07	0.91	**0.86**	**0.91**	**0.83**	0.93	0.93
1	4	0.11	0.84	**0.83**	0.91	**0.79**	0.93	0.94
1	8	0.18	0.81	0.85	0.93	0.82	0.93	0.94
1	12	0.23	0.83	0.86	0.93	0.83	0.91	0.92
1	16	0.26	0.84	0.86	0.92	**0.83**	0.89	0.90
5	1	0.04	1.00	**0.93**	**0.88**	**0.91**	**0.92**	**0.93**
5	2	0.07	0.91	**0.86**	**0.85**	**0.83**	**0.90**	**0.91**
5	4	0.11	0.84	**0.81**	0.85	**0.78**	0.88	0.89
5	8	0.18	0.81	0.82	0.86	**0.80**	0.88	0.89
5	12	0.23	0.83	**0.82**	0.88	**0.80**	0.87	0.87
5	16	0.26	0.84	**0.82**	0.88	**0.79**	0.85	0.85

Table 3 (Cont.): Root MSFEs for Investment

λ	Horizon	Unrestricted RMSFE	VAR-MINN	RBC	HABIT	ISHOCK	STICKY	STICKY-ACC
10	1	0.04	1.00	**0.94**	**0.87**	**0.92**	**0.91**	**0.93**
10	2	0.07	0.91	**0.87**	**0.84**	**0.84**	**0.88**	**0.89**
10	4	0.11	0.84	**0.81**	**0.82**	**0.79**	0.85	0.87
10	8	0.18	0.81	**0.81**	0.84	**0.79**	0.86	0.86
10	12	0.23	0.83	**0.81**	0.86	**0.79**	0.85	0.85
10	16	0.26	0.84	**0.80**	0.87	**0.78**	0.84	**0.84**
20	1	0.04	1.00	**0.96**	**0.87**	**0.93**	0.90	0.93
20	2	0.07	0.91	**0.88**	**0.83**	**0.85**	0.86	0.88
20	4	0.11	0.84	**0.81**	**0.80**	**0.79**	0.83	0.84
20	8	0.18	0.81	**0.80**	0.82	**0.78**	0.83	0.84
20	12	0.23	0.83	**0.80**	0.84	**0.78**	0.83	0.83
20	16	0.26	0.84	**0.79**	0.86	**0.77**	0.82	0.82
∞	1	0.04	1.00	1.13	1.02	1.11	10.08	**0.99**
∞	2	0.07	0.91	1.01	**0.89**	0.98	10.56	0.92
∞	4	0.11	0.84	0.86	**0.76**	**0.83**	5.63	**0.84**
∞	8	0.18	0.81	**0.73**	**0.71**	**0.70**	2.80	**0.81**
∞	12	0.23	0.83	**0.68**	**0.72**	**0.67**	2.30	**0.82**
∞	16	0.26	0.84	**0.67**	**0.72**	**0.68**	1.71	**0.83**

See notes to table 2.

Table 4: Root MSFEs for Hours

λ	Horizon	Unrestricted RMSFE	VAR-MINN	RBC	HABIT	ISHOCK	STICKY	STICKY-ACC
0.25	1	0.01	1.19	1.01	1.00	**1.00**	1.07	1.05
0.25	2	0.01	1.20	**0.99**	**1.00**	**0.97**	1.08	1.05
0.25	4	0.02	1.13	**0.96**	**0.99**	**0.93**	1.06	1.03
0.25	8	0.04	1.09	**0.94**	**0.98**	**0.90**	1.02	1.00
0.25	12	0.05	1.12	**0.93**	**0.98**	**0.90**	1.00	**0.99**
0.25	16	0.05	1.12	**0.92**	**0.97**	**0.89**	**0.99**	**0.98**
0.5	1	0.01	1.19	1.01	1.01	**1.00**	1.10	1.07
0.5	2	0.01	1.20	**0.99**	**1.00**	**0.96**	1.11	1.06
0.5	4	0.02	1.13	**0.95**	**0.98**	**0.91**	1.07	1.03
0.5	8	0.04	1.09	**0.92**	**0.97**	**0.88**	1.02	1.00
0.5	12	0.05	1.12	**0.91**	**0.96**	**0.86**	1.00	**0.98**
0.5	16	0.05	1.12	**0.89**	**0.95**	**0.85**	**0.99**	**0.97**
1	1	0.01	1.19	1.02	1.01	**0.99**	1.12	1.08
1	2	0.01	1.20	**0.99**	1.00	**0.95**	1.13	1.08
1	4	0.02	1.13	**0.94**	**0.98**	**0.89**	1.08	1.04
1	8	0.04	1.09	**0.90**	**0.96**	**0.85**	1.02	**0.99**
1	12	0.05	1.12	**0.88**	**0.95**	**0.82**	1.00	**0.97**
1	16	0.05	1.12	**0.86**	**0.94**	**0.80**	**0.99**	**0.96**
5	1	0.01	1.19	1.07	1.04	1.01	1.17	1.13
5	2	0.01	1.20	1.04	1.02	**0.96**	1.18	1.13
5	4	0.02	1.13	**0.96**	**0.98**	**0.88**	1.12	1.07
5	8	0.04	1.09	**0.88**	**0.95**	**0.82**	1.04	**1.00**
5	12	0.05	1.12	**0.83**	**0.93**	**0.76**	1.01	**0.97**
5	16	0.05	1.12	**0.79**	**0.91**	**0.72**	**1.00**	**0.95**

Table 4 (Cont.): Root MSFEs for Hours

λ	Horizon	Unrestricted RMSFE	VAR-MINN	RBC	HABIT	ISHOCK	STICKY	STICKY-ACC
10	1	0.01	1.19	1.10	1.05	1.03	1.19	1.16
10	2	0.01	1.20	1.07	1.03	**0.99**	1.22	1.16
10	4	0.02	1.13	**0.98**	**0.99**	**0.90**	1.14	1.10
10	8	0.04	1.09	**0.88**	**0.95**	**0.82**	1.05	1.01
10	12	0.05	1.12	**0.82**	**0.93**	**0.75**	1.02	**0.97**
10	16	0.05	1.12	**0.77**	**0.91**	**0.70**	1.01	**0.96**
20	1	0.01	1.19	1.13	1.07	1.06	1.22	1.18
20	2	0.01	1.20	1.11	1.05	1.02	1.25	1.20
20	4	0.02	1.13	1.01	1.01	**0.93**	1.18	1.13
20	8	0.04	1.09	**0.89**	**0.96**	**0.83**	1.08	1.03
20	12	0.05	1.12	**0.82**	**0.94**	**0.75**	1.04	**0.99**
20	16	0.05	1.12	**0.76**	**0.91**	**0.69**	1.02	**0.98**
∞	1	0.01	1.19	1.40	1.55	1.41	29.88	1.53
∞	2	0.02	1.20	1.48	1.65	1.50	30.95	1.66
∞	4	0.03	1.13	1.34	1.45	1.38	8.62	1.54
∞	8	0.06	1.09	1.12	1.18	1.15	2.96	1.31
∞	12	0.08	1.12	1.05	1.10	1.07	5.54	1.23
∞	16	0.11	1.12	1.05	1.07	1.07	5.06	1.19

See notes to table 2.

Table 5: Root MSFEs for Consumption

λ	Horizon	Unrestricted RMSFE	VAR-MINN	RBC	HABIT	ISHOCK	STICKY	STICKY-ACC
0.25	1	0.01	1.06	**0.99**	1.00	**0.97**	1.00	1.00
0.25	2	0.01	0.98	**0.97**	0.99	**0.95**	0.98	0.99
0.25	4	0.03	0.91	0.96	0.99	0.95	0.97	0.98
0.25	8	0.05	0.88	0.96	0.98	0.96	0.96	0.98
0.25	12	0.08	0.88	0.97	0.98	0.97	0.96	0.97
0.25	16	0.11	0.89	0.98	0.98	0.98	0.95	0.96
0.5	1	0.01	1.06	**0.99**	1.01	**0.97**	1.00	1.00
0.5	2	0.01	0.98	**0.96**	0.99	**0.95**	**0.97**	**0.98**
0.5	4	0.03	0.91	0.95	0.98	0.94	0.96	0.97
0.5	8	0.05	0.88	0.95	0.97	0.96	0.95	0.96
0.5	12	0.08	0.88	0.96	0.97	0.97	0.94	0.95
0.5	16	0.11	0.89	0.97	0.97	0.97	0.94	0.95
1	1	0.01	1.06	**0.99**	1.01	**0.97**	1.00	1.01
1	2	0.01	0.98	**0.95**	0.98	**0.95**	**0.96**	**0.97**
1	4	0.03	0.91	0.94	0.97	0.94	0.94	0.95
1	8	0.05	0.88	0.94	0.96	0.96	0.93	0.94
1	12	0.08	0.88	0.95	0.96	0.97	0.92	0.93
1	16	0.11	0.89	0.96	0.96	0.98	0.92	0.93
5	1	.01	1.06	**0.99**	1.01	**0.98**	1.00	1.01
5	2	0.01	0.98	**0.94**	**0.97**	**0.96**	**0.93**	**0.94**
5	4	0.03	0.91	**0.91**	0.95	0.95	**0.89**	**0.90**
5	8	0.05	0.88	0.92	0.93	0.95	**0.87**	0.88
5	12	0.08	0.88	0.92	0.93	0.96	**0.87**	**0.88**
5	16	0.11	0.89	0.93	0.94	0.97	**0.87**	**0.88**

Table 5 (Cont.): Root MSFEs for Consumption

λ	Horizon	Unrestricted RMSFE	VAR-MINN	RBC	HABIT	ISHOCK	STICKY	STICKY-ACC
10	1	0.01	1.06	**0.99**	1.01	**0.98**	1.00	1.01
10	2	0.01	0.98	**0.93**	**0.96**	**0.96**	**0.91**	**0.93**
10	4	0.03	0.91	**0.91**	0.94	0.94	**0.87**	**0.88**
10	8	0.05	0.88	0.90	0.92	0.95	**0.85**	**0.86**
10	12	0.08	0.88	0.91	0.92	0.95	**0.85**	**0.86**
10	16	0.11	0.89	0.92	0.93	0.96	**0.85**	**0.86**
20	1	0.01	1.06	**0.98**	1.00	**0.99**	1.00	1.02
20	2	0.01	0.98	**0.93**	**0.95**	**0.96**	**0.90**	**0.92**
20	4	0.03	0.91	**0.90**	0.93	0.94	**0.85**	**0.87**
20	8	0.05	0.88	0.89	0.91	0.94	**0.84**	**0.84**
20	12	0.08	0.88	0.90	0.92	0.94	**0.83**	**0.83**
20	16	0.11	0.89	0.91	0.92	0.95	**0.84**	**0.84**
∞	1	0.01	1.06	1.17	1.07	1.22	1.12	1.10
∞	2	0.02	0.98	**0.84**	**0.84**	**0.87**	**0.83**	**0.88**
∞	4	0.03	0.91	**0.64**	**0.76**	**0.65**	**0.82**	**0.75**
∞	8	0.06	0.88	**0.62**	**0.74**	**0.61**	**0.78**	**0.71**
∞	12	0.08	0.88	**0.64**	**0.75**	**0.62**	**0.76**	**0.71**
∞	16	0.11	0.89	**0.67**	**0.76**	**0.65**	**0.82**	**0.74**

See notes to table 2.

Table 6: Alternative Specifications of the Litterman Prior

Variable	Horizon	VAR-MINN λ_{LIT} = 0.05	VAR-MINN λ_{LIT} = 0.03	VAR-MINN λ_{LIT} = 0.10	RBC λ= 10	HABIT λ= 10	ISHOCK λ= 10	STICKY λ= 10
Output	1	1.02	1.03	1.00	**0.88**	**0.89**	**0.89**	**0.82**
Output	2	0.92	0.90	0.97	**0.74**	**0.82**	**0.78**	**0.75**
Output	4	0.86	0.81	0.96	**0.75**	**0.84**	**0.78**	**0.78**
Output	8	0.85	0.79	0.95	0.79	0.87	0.82	0.82
Output	12	0.86	0.81	0.95	0.83	0.89	0.85	0.84
Output	16	0.88	0.83	0.94	0.87	0.91	0.88	0.86
Inv.	1	1.00	0.99	1.04	**0.94**	**0.87**	**0.92**	**0.91**
Inv.	2	0.91	0.88	1.00	**0.87**	**0.84**	**0.84**	**0.88**
Inv.	4	0.84	0.78	0.97	0.81	0.82	0.79	0.85
Inv.	8	0.81	0.75	0.95	0.81	0.84	0.79	0.86
Inv.	12	0.83	0.77	0.93	0.81	0.86	0.79	0.85
Inv.	16	0.84	0.79	0.92	0.80	0.87	0.78	0.84
Hours	1	1.19	1.23	1.11	1.10	1.05	1.03	1.19
Hours	2	1.20	1.22	1.12	1.07	1.03	**0.99**	1.22
Hours	4	1.13	1.13	1.10	**0.98**	**0.99**	**0.90**	1.14
Hours	8	1.09	1.06	1.11	**0.88**	**0.95**	**0.82**	1.05
Hours	12	1.12	1.08	1.16	**0.82**	**0.93**	**0.75**	1.02
Hours	16	1.12	1.07	1.18	**0.77**	**0.91**	**0.70**	1.01
Cons.	1	1.06	1.07	1.04	**0.99**	1.01	**0.98**	1.00
Cons.	2	0.98	0.94	1.04	**0.93**	0.96	0.96	**0.91**
Cons.	4	0.91	0.85	1.01	0.91	0.94	0.94	0.87
Cons.	8	0.88	0.82	0.98	0.90	0.92	0.95	0.85
Cons.	12	0.88	0.83	0.96	0.91	0.92	0.95	0.85
Cons.	16	0.89	0.84	0.96	0.92	0.93	0.96	0.85

$\lambda_{LIT} = 0.05$ corresponds to the benchmark Litterman prior. See also notes to table 2.

Table 7: Root MSFEs when Forecasts are Made in Levels

Variable	λ	Horizon	Unrestricted RMSFE	VAR-MINN	RBC	HABIT	ISHOCK	STICKY
Output	0.25	1	0.01	0.97	9.42	9.90	9.24	10.21
Output	0.25	2	0.02	0.90	13.25	16.71	13.90	15.16
Output	0.25	4	0.03	0.80	27.28	44.29	35.88	35.73
Output	1	1	0.01	0.97	9.82	10.83	9.60	11.44
Output	1	2	0.02	0.90	12.99	19.60	14.21	18.67
Output	1	4	0.03	0.80	29.05	70.83	40.62	66.13
Output	10	1	0.01	0.97	9.32	11.42	9.05	13.06
Output	10	2	0.02	0.90	11.06	25.70	11.08	28.70
Output	10	4	0.03	0.80	16.10	133.10	16.33	149.09
Inv.	0.25	1	0.05	1.01	2.01	2.09	1.98	2.17
Inv.	0.25	2	0.07	0.93	4.92	6.07	4.92	6.31
Inv.	0.25	4	0.11	0.82	11.72	17.96	13.84	15.68
Inv.	1	1	0.05	1.01	2.10	2.25	2.06	2.43
Inv.	1	2	0.07	0.93	4.89	7.11	5.14	7.91
Inv.	1	4	0.11	0.82	11.98	26.73	15.25	27.60
Inv.	10	1	0.05	1.01	2.11	2.36	2.05	2.85
Inv.	10	2	0.07	0.93	3.64	7.78	3.86	11.10
Inv.	10	4	0.11	0.82	6.02	41.88	6.61	60.02
Hours	0.25	1	0.01	1.21	1.08	1.06	1.06	1.07
Hours	0.25	2	0.01	1.20	1.97	2.54	2.03	3.01
Hours	0.25	4	0.02	1.09	7.14	10.93	8.34	10.23
Hours	1	1	0.01	1.21	1.09	1.06	1.07	1.09
Hours	1	2	0.01	1.20	1.92	3.11	2.11	4.13
Hours	1	4	0.02	1.09	6.47	15.08	8.48	16.83
Hours	10	1	0.01	1.21	1.19	1.09	1.14	1.15
Hours	10	2	0.01	1.20	1.37	3.42	1.60	6.69
Hours	10	4	0.02	1.09	2.73	22.97	3.81	38.21

Table 7 (Cont.): Root MSFEs when Forecasts are Made in Levels

Variable	λ	Horizon	Unrestricted RMSFE	VAR-MINN	RBC	HABIT	ISHOCK	STICKY
Cons.	0.25	1	0.01	1.03	11.61	12.23	11.38	12.58
Cons.	0.25	2	0.01	0.95	16.43	20.55	17.11	18.10
Cons.	0.25	4	0.02	0.82	31.79	51.81	41.89	40.77
Cons.	1	1	0.01	1.03	12.06	13.34	11.76	14.03
Cons.	1	2	0.01	0.95	16.56	24.55	17.92	22.64
Cons.	1	4	0.02	0.82	35.39	85.83	49.11	77.85
Cons.	10	1	0.01	1.03	11.51	14.17	11.10	16.16
Cons.	10	2	0.01	0.95	15.09	33.50	14.92	35.87
Cons.	10	4	0.02	0.82	21.23	169.25	21.17	180.07

See notes to table 2.

Table 8: Model Averaging Forecasts

Variable	Horizon	Model Averaging Forecast	RBC	HABIT	ISHOCK	STICKY
Output	1	0.85	0.88	0.89	0.89	0.82
Output	2	0.76	*0.74*	0.82	0.78	0.75
Output	4	0.78	*0.75*	0.84	0.78	0.78
Output	8	0.82	*0.79*	0.87	0.82	0.82
Output	12	0.85	*0.83*	0.89	0.85	0.84
Output	16	0.87	0.87	0.91	0.88	*0.86*
Inv.	1	0.90	0.94	*0.87*	0.92	0.91
Inv.	2	0.85	0.87	*0.84*	0.84	0.88
Inv.	4	0.81	0.81	0.82	*0.79*	0.85
Inv.	8	0.82	0.81	0.84	*0.79*	0.86
Inv.	12	0.82	0.81	0.86	*0.79*	0.85
Inv.	16	0.82	0.80	0.87	*0.78*	0.84
Hours	1	1.07	1.10	1.05	*1.03*	1.19
Hours	2	1.04	1.07	1.03	*0.99*	1.22
Hours	4	0.98	0.98	0.99	*0.90*	1.14
Hours	8	0.91	0.88	0.95	*0.82*	1.05
Hours	12	0.87	0.82	0.93	*0.75*	1.02
Hours	16	0.83	0.77	0.91	*0.70*	1.01
Cons.	1	0.99	0.99	1.01	*0.98*	1.00
Cons.	2	0.94	0.93	0.96	0.96	*0.91*
Cons.	4	0.91	0.91	0.94	0.94	*0.87*
Cons.	8	0.90	0.90	0.92	0.95	*0.85*
Cons.	12	0.91	0.91	0.92	0.95	*0.85*
Cons.	16	0.91	0.92	0.93	0.96	*0.85*

The entries in the table show the results for $\lambda = 10$ using the 160 quarter estimation window. The entries in the table are the root mean squared errors relative to those from the unrestricted VAR and italics denote the best forecasting model among those shown. See also notes to table 2.

Table 9: Root MSFEs when DSGE Parameters Estimated

Variable	λ	Horizon	Unrestricted RMSFE	VAR-MINN	RBC	HABIT	ISHOCK	STICKY
Output	0.25	1	0.01	0.97	0.97	0.93	0.96	0.95
Output	0.25	2	0.02	0.90	0.95	0.94	0.94	0.95
Output	0.25	4	0.03	0.80	0.96	0.95	0.95	0.96
Output	1	1	0.01	0.97	0.99	0.90	0.98	0.93
Output	1	2	0.02	0.90	0.97	0.87	0.96	0.94
Output	1	4	0.03	0.80	0.97	0.90	0.97	0.96
Output	10	1	0.01	0.97	1.23	0.93	1.10	0.97
Output	10	2	0.02	0.90	0.90	0.82	0.86	0.96
Output	10	4	0.03	0.80	0.82	0.80	0.81	0.97
Inv.	0.25	1	0.05	1.01	0.93	0.87	0.92	0.90
Inv.	0.25	2	0.07	0.93	0.87	0.80	0.85	0.84
Inv.	0.25	4	0.11	0.82	0.87	0.81	0.85	0.85
Inv.	1	1	0.05	1.01	0.94	0.84	0.93	0.87
Inv.	1	2	0.07	0.93	0.89	0.78	0.88	0.85
Inv.	1	4	0.11	0.82	0.85	0.73	0.85	0.81
Inv.	10	1	0.05	1.01	0.96	0.90	0.86	0.91
Inv.	10	2	0.07	0.93	0.89	0.80	0.81	0.87
Inv.	10	4	0.11	0.82	0.84	0.72	0.79	0.84
Hours	0.25	1	0.01	1.21	1.00	1.00	1.00	1.00
Hours	0.25	2	0.01	1.20	0.97	0.97	0.97	0.97
Hours	0.25	4	0.02	1.09	0.96	0.96	0.96	0.96
Hours	1	1	0.01	1.21	1.06	1.05	1.05	1.03
Hours	1	2	0.01	1.20	1.05	1.03	1.03	1.02
Hours	1	4	0.02	1.09	0.99	0.99	0.98	0.98
Hours	10	1	0.01	1.21	1.20	1.09	1.03	1.04
Hours	10	2	0.01	1.20	1.18	1.07	1.00	1.03
Hours	10	4	0.02	1.09	1.08	1.00	0.95	0.98

Table 9 (Cont.): Root MSFEs when DSGE Parameters Estimated

Variable	λ	Horizon	Unrestricted RMSFE	VAR-MINN	RBC	HABIT	ISHOCK	STICKY
Cons.	0.25	1	0.01	1.03	1.01	1.01	1.00	1.01
Cons.	0.25	2	0.01	0.95	1.00	1.01	0.99	1.01
Cons.	0.25	4	0.02	0.82	1.00	1.01	0.99	1.01
Cons.	1	1	0.01	1.03	1.02	1.00	1.01	1.01
Cons.	1	2	0.01	0.95	1.04	1.02	1.03	1.04
Cons.	1	4	0.02	0.82	1.02	1.03	1.02	1.03
Cons.	10	1	0.01	1.03	1.00	0.99	0.91	1.00
Cons.	10	2	0.01	0.95	1.00	1.00	0.93	1.01
Cons.	10	4	0.02	0.82	0.98	1.01	0.97	1.00

The results shown are those based on estimates from the model when the DSGE model parameters are estimated alongside the VAR parameters such that the draws for the DSGE model parameters are from the posterior distribution rather than the prior. See also notes to table 2 and the text.

Table 10: Theoretical Cross-Correlations

Variables	RBC	HABIT	ISHOCK	STICKY	Variables	RBC	HABIT	ISHOCK	STICKY
y(t), y(t-1)	0.92	0.98	0.94	0.95	h(t), y(t-1)	0.45	-0.61	0.55	0.42
y(t), y(t-2)	0.88	0.96	0.89	0.92	h(t), y(t-2)	0.36	-0.56	0.45	0.38
y(t), y(t-3)	0.83	0.93	0.84	0.89	h(t), y(t-3)	0.27	-0.53	0.37	0.34
y(t), y(t-4)	0.79	0.90	0.79	0.85	h(t), y(t-4)	0.20	-0.51	0.29	0.30
y(t), i(t-1)	0.84	0.81	0.83	0.91	h(t), i(t-1)	0.74	-0.36	0.82	0.53
y(t), i(t-2)	0.80	0.79	0.79	0.87	h(t), i(t-2)	0.63	-0.32	0.71	0.47
y(t), i(t-3)	0.75	0.78	0.75	0.84	h(t), i(t-3)	0.54	-0.30	0.62	0.42
y(t), i(t-4)	0.71	0.76	0.71	0.80	h(t), i(t-4)	0.45	-0.29	0.53	0.38
y(t), h(t-1)	0.52	-0.69	0.62	0.39	h(t), h(t-1)	0.86	0.83	0.89	0.81
y(t), h(t-2)	0.49	-0.69	0.58	0.34	h(t), h(t-2)	0.77	0.72	0.80	0.68
y(t), h(t-3)	0.46	-0.67	0.55	0.29	h(t), h(t-3)	0.69	0.64	0.71	0.59
y(t), h(t-4)	0.44	-0.66	0.52	0.26	h(t), h(t-4)	0.62	0.58	0.63	0.51
y(t), c(t-1)	0.66	0.95	0.37	0.72	h(t), c(t-1)	-0.21	-0.64	-0.44	-0.14
y(t), c(t-2)	0.63	0.93	0.35	0.71	h(t), c(t-2)	-0.24	-0.60	-0.44	-0.11
y(t), c(t-3)	0.60	0.90	0.33	0.70	h(t), c(t-3)	-0.27	-0.57	-0.44	-0.10
y(t), c(t-4)	0.57	0.87	0.31	0.69	h(t), c(t-4)	-0.30	-0.55	-0.44	-0.09

Table 10 (Cont.): Theoretical Cross-Correlations

Variables	RBC	HABIT	ISHOCK	STICKY	Variables	RBC	HABIT	ISHOCK	STICKY
i(t), y(t-1)	0.80	0.77	0.79	0.89	c(t), y(t-1)	0.73	0.98	0.45	0.73
i(t), y(t-2)	0.72	0.73	0.71	0.84	c(t), y(t-2)	0.75	0.97	0.51	0.73
i(t), y(t-3)	0.65	0.69	0.63	0.80	c(t), y(t-3)	0.76	0.96	0.56	0.73
i(t), y(t-4)	0.58	0.66	0.56	0.75	c(t), y(t-4)	0.78	0.94	0.60	0.73
i(t), i(t-1)	0.91	0.95	0.91	0.93	c(t), i(t-1)	0.37	0.74	0.00	0.57
i(t), i(t-2)	0.83	0.90	0.82	0.87	c(t), i(t-2)	0.41	0.75	0.07	0.58
i(t), i(t-3)	0.75	0.85	0.74	0.82	c(t), i(t-3)	0.44	0.75	0.14	0.58
i(t), i(t-4)	0.68	0.81	0.67	0.77	c(t), i(t-4)	0.47	0.74	0.19	0.58
i(t), h(t-1)	0.78	-0.40	0.85	0.48	c(t), h(t-1)	-0.13	-0.73	-0.36	-0.19
i(t), h(t-2)	0.71	-0.37	0.78	0.39	c(t), h(t-2)	-0.08	-0.74	-0.28	-0.19
i(t), h(t-3)	0.66	-0.35	0.71	0.32	c(t), h(t-3)	-0.04	-0.74	-0.22	-0.19
i(t), h(t-4)	0.60	-0.33	0.64	0.27	c(t), h(t-4)	-0.01	-0.73	-0.15	-0.18
i(t), c(t-1)	0.29	0.68	-0.09	0.57	c(t), c(t-1)	0.99	0.99	0.98	0.98
i(t), c(t-2)	0.25	0.64	-0.10	0.57	c(t), c(t-2)	0.98	0.98	0.95	0.97
i(t), c(t-3)	0.21	0.61	-0.11	0.55	c(t), c(t-3)	0.96	0.96	0.93	0.96
i(t), c(t-4)	0.18	0.58	-0.12	0.53	c(t), c(t-4)	0.95	0.94	0.91	0.95