Reserve Bank of Australia

RESEARCH DISCUSSION PAPER

A Small BVAR-DSGE Model for Forecasting the Australian Economy

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RDP 2008-04

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Research Discussion Paper
2008-04

September 2008

Economic Research Department
Reserve Bank of Australia

We thank Stéphane Adjemian, Adam Cagliarini, Richard Finlay, Hugo Gerard, Jamie Hall, Jarkko Jääskelä and Mariano Kulish for assistance. Adrian Pagan and Shaun Vahey provided comments on an earlier version of this paper. The views expressed herein are those of the authors and are not necessarily those of the Reserve Bank of Australia. This paper was revised in December 2008. Any errors are our own.

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Abstract

This paper estimates a small structural model of the Australian economy, designed principally for forecasting the key macroeconomic variables of output growth, underlying inflation and the cash rate. In contrast to models with purely statistical foundations, which are often used for forecasting, the Bayesian Vector Autoregressive Dynamic Stochastic General Equilibrium (BVAR-DSGE) model uses the theoretical information of a DSGE model to offset in-sample over-fitting. We follow the method of Del Negro and Schorfheide (2004) and use a variant of the small open economy DSGE model of Lubik and Schorfheide (2007) to provide prior information for the VAR. The forecasting performance of the model is competitive with benchmark models such as a Minnesota VAR and an independently estimated DSGE model.

JEL Classification Numbers: C11, C53, E37
Keywords: BVAR-DSGE, forecasting

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1. Introduction

Forecasting is hard. Forecasting is also a key aspect of central banking. Consequently, central banks devote considerable resources to forecasting and understanding the current state of the economy, of which econometric models are one component. Models can be used for a variety of purposes – for example, scenario analysis and forecasting – and these different roles may require different models. The purpose of this paper is to estimate a model for Australia specifically designed for forecasting key macroeconomic variables, namely a structural Bayesian Vector Autoregression (BVAR), with priors from a Dynamic Stochastic General Equilibrium (DSGE) model.

DSGE models are structural models, often with explicit microeconomic foundations, an example of which, for Australia, is Jääskelä and Nimark (forthcoming).[1] Consequently, these models have a strong emphasis on theory, which places many restrictions on the parameters, possibly at the expense of fitting the data. Alternatively, VARs are far less restrictive and therefore may fit the data better.[2] However, good in-sample fit does not necessarily translate into good out-of-sample forecasting performance; for example, an unrestricted VAR may have many parameters which are imprecisely estimated, particularly in small samples. The Bayesian framework is a way of introducing prior information and therefore producing more precise parameter estimates. A common prior used for VARs is that the series are very persistent, which is referred to as the Minnesota

1 Sometimes a distinction is made between DSGE and new-Keynesian models, with the former used to refer to relatively large models. We use the terms interchangeably.

2 The trade-off between theoretical coherence and fit is the basis of the Pagan diagram (Pagan 2003).

prior.[3] While the Minnesota prior has aided the forecasting ability of VAR models, it is a purely statistical device. As an alternative, we use a small DSGE model as the source of prior information for the VAR.

2. Methodology – Estimation

This section provides a brief overview of the methodology used to estimate the BVAR-DSGE; further details can be found in Del Negro and Schorfheide (2004), which we follow closely.

2.1 Some Notation

Let the parameters of the DSGE model, which we will describe further below, be denoted by the vector θ. Let the column vector of n observable variables be $\boldsymbol{y}_t$, which are also assumed to be the variables in the VAR. That is,

$$\boldsymbol{y}_t = \Phi_0 + \Phi_1 \boldsymbol{y}_{t-1} + \Phi_2 \boldsymbol{y}_{t-2} + \ldots + \Phi_p \boldsymbol{y}_{t-p} + \boldsymbol{u}_t, \tag{1}$$

where: Φ_0 is a vector of constants; $\Phi_{1..p}$ are matrices of VAR parameters; and $\boldsymbol{u}_t \sim N(\boldsymbol{0}, \Sigma_u)$.[4] This can be written more compactly as $Y = X\Phi + U$, where: Y and U are matrices with rows $\boldsymbol{y}'_t$ and $\boldsymbol{u}'_t$ respectively; X has rows $\boldsymbol{y}'_{t-1}$, $\boldsymbol{y}'_{t-2}$, ..., $\boldsymbol{y}'_{t-p}$ and $\Phi \equiv [\Phi_1, \Phi_2, \ldots, \Phi_p]'$. It is noteworthy that the number of parameters in the DSGE model is much smaller than that in the VAR, hence the greater ability of the VAR to fit the data.

2.2 Priors for the VAR Parameters

In this paper we want to use a DSGE model to provide information about the parameters of the VAR. Intuitively, one way of doing this is to simulate data from the DSGE and to combine it with the actual data when estimating the VAR. The relative share of simulated observations compared to the actual data, λ, governs the relative weight placed on the prior information. However, as the DSGE model specifies the stochastic process for $\boldsymbol{y}_t$, rather than simulating data we can instead

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3 The Minnesota prior was introduced by Litterman (1979), and extended by Doan, Litterman and Sims (1984); an intuitive description is in Todd (1984). For an overview of Bayesian forecasting, see Geweke and Whiteman (2006).

4 As we de-mean the data, we suppress Φ_0 in what follows.

use the solution to the log-linearised DSGE model to analytically compute the population moments of $\boldsymbol{y}_t$. The role of λ therefore is to scale these moments so as to be equivalent in magnitude to the (non-standardised) sample moments that would have been obtained through simulation. It is then possible to formulate the prior for the VAR parameters $p(\Phi,\Sigma_u|\theta)$ (for given DSGE model parameters θ), in Inverted-Wishart (IW)-Normal (N) form, that is, $\Sigma_u|\theta \sim IW$ and $\Phi|\Sigma_u,\theta \sim N$. The parameters of these prior densities are functions of the population moments calculated from the DSGE model.[5]

2.3 Priors for the DSGE Parameters

We also have prior beliefs about the parameters of the DSGE model, $p(\theta)$. The joint prior density of both sets of parameters is:

$$p(\Phi,\Sigma_u,\theta) = p(\Phi,\Sigma_u|\theta)p(\theta).$$

2.4 The VAR Posterior

The posterior distribution of the VAR parameters Φ and Σ_u, $p(\Phi,\Sigma_u|Y,\theta)$, from which we will draw parameters when forecasting, is obtained by combining the prior with information from the data, namely the likelihood function. The likelihood, reflecting the distribution of the innovations ($\boldsymbol{u_t}$), is multivariate normal, which is particularly useful as the priors described above for the VAR parameters are of Inverted-Wishart-Normal form, and these conjugate. Consequently, the posterior follows the same class of distributions as the prior, that is, $\Sigma_u|\theta,Y \sim IW$ and $\Phi|\Sigma_u,\theta,Y \sim N$.[6] Finally, we can simulate the posterior for the VAR parameters by first drawing a θ from the posterior of the DSGE parameters and then sampling from these distributions.

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5 See Equations (24) and (25) in Del Negro and Schorfheide (2004).

6 Once again we have suppressed the parameters of the posterior distributions – see Equations (30) and (31) in Del Negro and Schorfheide (2004).

2.5 Choosing the Lag Length and the Weight on the Prior, λ

The VAR posterior is conditional on a choice of λ, the relative weight given to the DSGE prior. Let the set of possible λ be Λ, where $\Lambda \equiv \{\lambda_1, \ldots, \lambda_i, \ldots, \lambda_q\}$, and for all i, $\lambda_i > 0$. The approach suggested by Del Negro and Schorfheide (2004) is to compare the model evaluated at each $\lambda \in \Lambda$, using the metric of the marginal data density, $p(Y|\lambda)$.[7] This is somewhat akin to an information criterion, and can be obtained by integrating out the parameters of the joint density of the data and the parameters

$$\begin{aligned} p(Y|\lambda) &\equiv \int_{\mathbf{\Sigma}_u,\mathbf{\Phi},\mathbf{\Theta}} p(Y,\theta,\Sigma_u,\Phi|\lambda)d(\Sigma_u,\Phi,\theta) \\ &= \int_{\mathbf{\Sigma}_u,\mathbf{\Phi},\mathbf{\Theta}} p(Y|\theta,\Sigma_u,\Phi)p(\theta,\Sigma_u,\Phi|\lambda)d(\Sigma_u,\Phi,\theta), \end{aligned}$$

where $\mathbf{\Sigma}_u$, $\mathbf{\Phi}$ and $\mathbf{\Theta}$ are the parameter spaces (that is, the sets of possible parameter values) for Σ_u, Φ and θ. As pointed out by Christiano (2007), the integration involved in calculating the marginal data density is computationally intensive. However, recall that the joint prior density of the VAR and DSGE parameters, $p(\Phi,\Sigma_u,\theta|\lambda)$, equals $p(\Phi,\Sigma_u|\theta,\lambda)p(\theta)$, and the prior of the VAR parameters given θ is of Inverted-Wishart-Normal form. The latter enables the integrals with respect to the VAR parameters to be calculated analytically, leaving only the integral with respect to θ to be calculated in order to approximate $p(Y|\lambda)$.[8] An 'optimal' λ, $\hat{\lambda}$, could then be chosen to maximise $p(Y|\lambda)$, that is,

$$\hat{\lambda} = \arg\max_{\lambda \in \Lambda} p(Y|\lambda). \tag{2}$$

As noted by Del Negro and Schorfheide (2004), we could also use the marginal data density to pick the lag length of the VAR, p.

However, as the primary purpose of this model is forecasting, an alternative approach is to choose λ and the lag length with respect to the out-of-sample forecasting performance, which we describe in Section 4.2.

7 The notation of the marginal data density follows Del Negro *et al* (2007). Also, previously we suppressed the fact that many of the densities (for example, the joint prior density for the VAR and DSGE parameters) are conditional on λ.

8 This is done using Geweke's harmonic mean estimator (Geweke 1999); see also An and Schorfheide (2007).

2.6 The DSGE Model

The DSGE model we use as the source of the prior information is a variant of the model by Lubik and Schorfheide (2007), which itself is a simplified version of Galí and Monacelli (2005). The Lubik and Schorfheide (2007) model has previously been used in the estimation of a BVAR-DSGE for New Zealand by Lees, Matheson and Smith (2007), and while not without criticism (for example, Fukač and Pagan forthcoming), as argued by Lees *et al* (2007) it probably represents the smallest possible DSGE model for a small open economy. It is worth noting that our model lacks many of the traditional features used in DSGE models to enhance their fit, such as habit persistence in consumption or indexation in price setting. The model has microeconomic foundations; however, as they are not our focus we only provide a brief overview of the key final log-linearised equations of the model which we will use.[9]

$$
\begin{aligned}
y_t &= E_t y_{t+1} - \chi\left(R_t - E_t \pi_{t+1}\right) + \chi\rho_z z_t + \alpha\chi E_t \Delta q_{t+1} + \left(\frac{\chi}{\tau} - 1\right) E_t \Delta y^*_{t+1}, && (3)\\
\pi_t &= \beta E_t \pi_{t+1} + \alpha\beta E_t \Delta q_{t+1} - \alpha\Delta q_t + \frac{\kappa}{\chi}\left(y_t - \bar{y}_t\right), && (4)\\
\Delta e_t &= \pi_t - (1-\alpha)\Delta q_t - \pi^*_t, && (5)\\
R_t &= \rho_R R_{t-1} + (1-\rho_R)\left(\psi_1 \pi_t + \psi_2 y_t\right) + \varepsilon_{R_t}, && (6)\\
\Delta q_t &= \rho_{\Delta q}\Delta q_{t-1} + \varepsilon_{\Delta q_t}, && (7)\\
y^*_t &= \rho_{y^*} y^*_{t-1} + \varepsilon_{y^*_t}, \text{ and} && (8)\\
\pi^*_t &= \rho_{\pi^*}\pi^*_{t-1} + \varepsilon_{\pi^*_t}, && (9)
\end{aligned}
$$

where: $\chi \equiv \tau + \alpha(2-\alpha)(1-\tau)$; $\bar{y}_t \equiv \left(1 - \frac{\chi}{\tau}\right) y^*_t$; Δ is the first difference operator; and E_t is the expectation operator conditional on period t information. An appealing feature of the model is that world (and hence domestic) technology, A_t, is assumed to follow a non-stationary process. A consequence of this is that some of the real variables (such as output) are normalised by technology before the log-linearisation. All variables are expressed as (approximate) per cent deviations from their steady-state values. Technology is assumed to grow at the rate z_t, that is, $z_t \equiv \ln A_t - \ln A_{t-1}$, which follows an AR(1) process, $z_t = \rho_z z_{t-1} + \varepsilon_{z_t}$. Output is denoted by y_t, R_t denotes the quarterly gross interest rate, q_t is the

[9] See Appendix A and the above references (particularly Galí and Monacelli 2005) for the derivations. Lubik and Schorfheide (2005) is also a useful reference.

terms of trade, π_t is inflation, e_t is the nominal exchange rate (defined so that a fall is an appreciation), $\bar{y}_t$ is the level of potential output (that is, the level of output consistent with flexible prices), and variables with a superscript $*$ are the equivalent world variables.

Equation (3) is the IS curve, which is derived from the consumers' Euler equation; the parameters α, β and τ are the import share of domestic consumption, the discount factor and the intertemporal elasticity of substitution, respectively. Output depends on the expectations of future output both at home and abroad, the real interest rate, expected changes in the terms of trade and technology growth.

Equation (4) is the open-economy Phillips curve, which can be derived from assuming a continuum of monopolistic firms which only use labour in production and set prices à la Calvo. Movements in the output gap affect inflation as they are associated with changes in real marginal costs; the parameter κ affects the slope of the Phillips curve and is a function of other deeper parameters, but here is taken to be structural. Changes in the terms of trade enter the Phillips curve reflecting the fact that some consumer goods are imported and also reflecting the assumption of relative purchasing power parity (PPP), as per Equation (5).

Monetary policy, as specified in Equation (6), is assumed to partially adjust the nominal rate (at rate $1-\rho_R$) to the level suggested by a Taylor rule, following Clarida, Galí and Gertler (2000). The weights on inflation and output in the Taylor rule are given by ψ_1 and ψ_2.[10]

The change in the terms of trade in this model is assumed to follow an AR(1) process, as are world output y_t^* and inflation π_t^*, with autoregression coefficients $\rho_{\Delta q}$, ρ_{y^*} and ρ_{π^*}, respectively. The structural shocks are denoted by $\varepsilon_{variable_t}$.

[10] We deviate from Lubik and Schorfheide (2007) and assume that the Taylor rule does not include the exchange rate.

3. Data and DSGE Priors

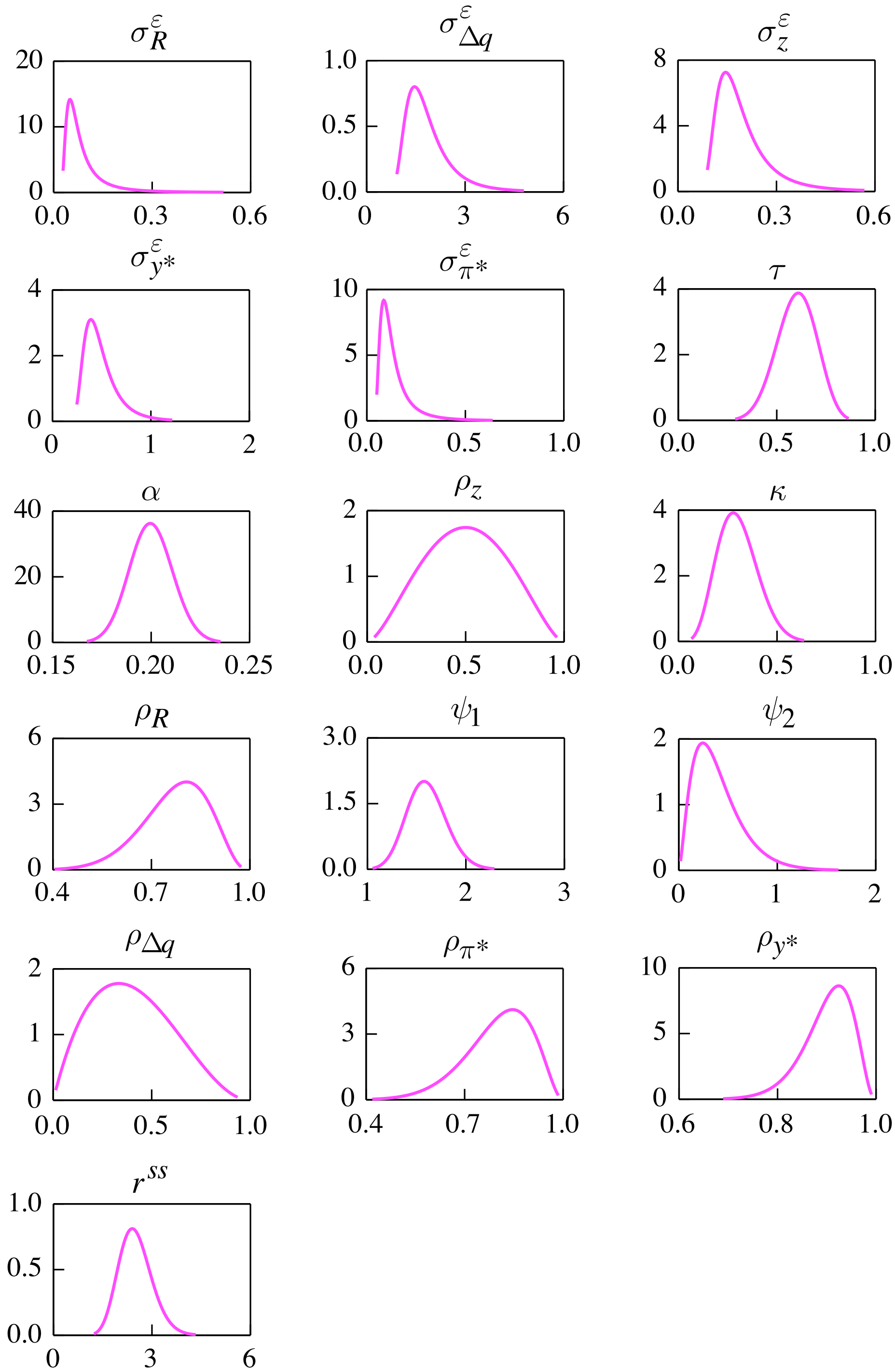
3.1 DSGE Priors

The priors for the DSGE parameters are given in Table 1 and Figure 1. These differ from those in Lubik and Schorfheide (2007), who apply their model to four countries, and vary only a small subset of the priors for each country. Our priors are selected in part by examining the results of recent DSGE modelling for Australia and by reference to economic theory. Additionally, we draw on past experience in modelling the Australian economy at the Reserve Bank of Australia. However, for many parameters, the differences between our priors and theirs are small. Rather than place a prior on the discount factor, we place a prior (and estimate) the steady-state (real) interest rate r^{ss}. Note that $\beta = e^{\frac{-r_{ss}}{400}}$. The standard deviations of the five structural shocks are denoted by $\sigma^{\varepsilon}_{variable}$.

Table 1: DSGE Parameter Priors

Parameter	Distribution	Mean	Standard deviation
Households and firms			
τ	Beta	0.6	0.1
α	Beta	0.2	0.011
r^{ss}	Gamma	2.5	0.5
Phillips curve			
κ	Beta	0.3	0.1
Taylor rule			
ρ_R	Beta	0.77	0.1
ψ_1	Gamma	1.6	0.2
ψ_2	Gamma	0.4	0.25
Exogenous persistence			
$\rho_{\Delta q}$	Beta	0.4	0.2
ρ_{π^*}	Beta	0.8	0.1
ρ_{y^*}	Beta	0.9	0.05
ρ_z	Beta	0.5	0.2
Exogenous shock standard deviations			
σ^{ε}_R	Inverse gamma	0.1	0.2
$\sigma^{\varepsilon}_{\Delta q}$	Inverse gamma	1.9	0.8
σ^{ε}_z	Inverse gamma	0.2	0.1
$\sigma^{\varepsilon}_{y^*}$	Inverse gamma	0.5	0.2
$\sigma^{\varepsilon}_{\pi^*}$	Inverse gamma	0.15	0.15

Figure 1: DSGE Parameter Priors



Note: Each panel shows the probability density function for the relevant parameter.

The priors we place on the standard deviations of the structural shocks are tighter and have lower mean values than those in Lubik and Schorfheide (2007).[11] This reflects our view that the structural shocks probably were quite moderate for much of the sample period for the Australian economy (1993 onwards; see Section 3.2). For example, we suspect that monetary policy shocks have generally been small in magnitude during the inflation-targeting regime. The mean of our prior on the standard deviation of terms of trade growth shocks is higher than that set for the other shocks, to account for the apparent volatility of this series.

Turning to the structural parameters of the DSGE model, our prior for the import share of consumption (α) has the same mean as used by Lubik and Schorfheide (2007), namely 0.2, but is considerably tighter, reflecting that over the estimation period the import share of GDP was around this value (and that output equals consumption in this model). The mean of the prior for the intertemporal elasticity of substitution (τ) is 0.6, which is larger than the mode used by Nimark (2007) (0.3), but less than the mean value of Justiniano and Preston (forthcoming) (0.8). The parameter κ, together with α and τ, determines the slope of the Phillips curve. We select the mean of the prior for κ so that (given the priors of these other parameters) it implies a similar slope to that estimated by Kuttner and Robinson (forthcoming) using GMM over the inflation-targeting period.

For the parameter ψ_1 in the Taylor rule (Equation (6)), which describes the monetary policy reaction to deviations of inflation from its steady state, the probability mass is distributed over values greater than one. This ensures that the real interest rate increases in response to higher inflation (that is, the Taylor principle is satisfied). Further, consistent with previous studies – which tend to find a considerable degree of interest rate smoothing (for example, de Brouwer and Gilbert 2005) – we place a large prior on the parameter ρ_R.

[11] Note that this, in part, reflects our shorter estimation period.

3.2 Data

There are five observable variables in the model: growth in chain-volume non-farm GDP (Δy_{obs_t}); the quarterly average cash rate (R_{obs_t}); trimmed-mean consumer price index (CPI) inflation (π_{obs_t}); the change in the inverse of the nominal trade-weighted exchange rate (Δe_{obs_t}) (consequently, negative values correspond to an appreciation); and growth in the terms of trade (Δq_{obs_t}) – that is, the ratio of export to import prices. The data sources are given in Appendix B. We multiply log differences (for example, non-farm output) by 100, so as to approximate percentages.[12] We de-mean all of the data as the DSGE model variables are in terms of log deviations from steady state. The estimation sample is from 1993:Q1, when inflation targeting began in Australia, until 2007:Q4.

3.3 Measurement Equations

The measurement equations, given below, map the observed data ($\boldsymbol{y}_t$, which are also the variables in the VAR and are on the left-hand side below) into the model variables (shown on the right-hand side):

$$\Delta y_{obs_t} = \Delta y_t + z_t \tag{10}$$
$$R_{obs_t} = 4R_t \tag{11}$$
$$\pi_{obs_t} = \pi_t \tag{12}$$
$$\Delta e_{obs_t} = \Delta e_t \tag{13}$$
$$\Delta q_{obs_t} = \Delta q_t. \tag{14}$$

Recall that in the DSGE model, output has been normalised by technology. Consequently, observed output growth is related to both output and technology growth as per Equation (10). The cash rate is expressed on a per annum basis, whereas the model interest rate is the gross one-period return. Also, as we have log-linearised the model (about its steady state), R_t more precisely is the log deviation of the gross rate from its steady state.

[12] Unlike Lubik and Schorfheide (2007), we do not annualise observable quarterly inflation.

4. Results – Estimation

4.1 DSGE

Table 2 presents the mean of the posterior distributions of the DSGE parameters; the posterior densities are shown in Figure C1 in Appendix C.[13,14]

Examples of parameters where the data shift the posterior distribution away from the prior include the intertemporal elasticity of substitution (τ), for which we find a posterior mean of 0.5. This indicates that consumers are less willing than expected to change their consumption decisions in response to interest rate shocks. For the persistence of technology shocks (ρ_z), we find a posterior mean of 0.29, which is broadly similar to the 0.4 estimate of Lubik and Schorfheide (2007).

We obtain 0.8 as our posterior mean for the nominal interest rate smoothing parameter ρ_R, which is comparable to the estimates from other recent DSGE studies, such as the posterior mode of 0.87 obtained by Nimark (2007). Our posterior mean estimates of ψ_1 and ψ_2 suggest that monetary policy responds more aggressively to deviations of inflation from steady state than output, consistent with Nimark.

Also interesting is that we find that the posterior mean of the persistence of foreign inflation (ρ_{π^*}) is lower than expected and that the posterior mean of the standard deviation of foreign inflation shocks ($\sigma^{\varepsilon}_{\pi^*}$) is considerably larger than expected. This reflects the fact that the foreign inflation shock π_t^* captures deviations from the rather strict assumption of PPP (a point noted by Lubik and Schorfheide 2007).

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13 We construct the posteriors using the Metropolis-Hastings algorithm with a Markov chain 500 000 observations long. To ensure convergence we drop the first 250 000 simulations and simulate a second chain for comparison. All estimation was conducted using Dynare 4, in Matlab R2007b and R2008a. Dynare is developed by S Adjemian, M Juillard and O Kamenik; see <http://www.cepremap.cnrs.fr/juillard/mambo/index.php> for further information. We manage Dynare 4 with TortoiseSVN, available from <http://tortoisesvn.net/>.

14 These posterior densities depend on λ via the marginal likelihood, $P(Y|\theta)$ (see Equation (A.2) in Del Negro and Schorfheide (2004)). They are for $\lambda = 1.75$, which is selected in Section 4.2.

Table 2: DSGE Estimation Results

Parameter	Prior mean	Posterior mean	90 per cent interval
		Households and firms	
τ	0.6	0.50	[0.36, 0.66]
α	0.2	0.20	[0.18, 0.21]
r^{ss}	2.5	2.48	[1.66, 3.26]
		Phillips curve	
κ	0.3	0.42	[0.28, 0.58]
		Taylor rule	
ρ_R	0.77	0.81	[0.75, 0.87]
ψ_1	1.6	1.62	[1.31, 1.94]
ψ_2	0.4	0.40	[0.07, 0.67]
		Exogenous persistence	
$\rho_{\Delta q}$	0.4	0.57	[0.49, 0.65]
ρ_{π^*}	0.8	0.53	[0.36, 0.70]
ρ_{y^*}	0.9	0.92	[0.86, 0.98]
ρ_z	0.5	0.29	[0.05, 0.74]
		Exogenous shock standard deviations	
σ_R^{ε}	0.1	0.08	[0.06, 0.10]
$\sigma_{\Delta q}^{\varepsilon}$	1.9	1.23	[1.01, 1.43]
σ_z^{ε}	0.2	0.35	[0.10, 0.47]
$\sigma_{y^*}^{\varepsilon}$	0.5	0.54	[0.25, 0.82]
$\sigma_{\pi^*}^{\varepsilon}$	0.15	2.91	[2.33, 3.50]

4.2 Selection of λ and Lag Length

We consider lag lengths of 2, 3 and 4 for the VAR component of the BVAR-DSGE. To determine the relative weight on the DSGE model, we let the set of possible λ be $\Lambda = [0.75, 1, 1.25, 1.5, 1.75, 2, 5, 10, 100000]$.[15] Using the marginal data density measure of Equation (2), which focuses on in-sample fit, we find the best combination to be a VAR(3) with $\lambda = 1$.[16] This implies that we place

[15] Placing a large weight on λ is akin to estimating the DSGE model. The unrestricted VAR we estimate separately in Section 5.1 is effectively $\lambda = 0$, since it places zero weight on the DSGE model.

[16] The means of the posterior distributions of the DSGE parameters when $\lambda = 1$ are similar to those presented in Table 2.

equal weight on the DSGE model and the VAR, which was also found for New Zealand by Lees *et al* (2007). Alternatively, a lower weighting of 0.6 was used by Del Negro and Schorfheide (2004).

To select λ with reference to the out-of-sample forecasting performance, we estimate BVAR-DSGE models corresponding to each possible value of λ over the grid Λ, at each lag length. We truncate the sample to end in 2001:Q4, estimate the model, construct the forecasts, advance the end-date by one quarter and repeat the process, until the last end-date of 2007:Q3. To construct the forecasts we first draw a matrix of VAR parameters Φ and a variance-covariance matrix Σ_u from their posterior distributions. Given Σ_u we draw a vector of innovations $\boldsymbol{u}_{t+1}$ from the multivariate-normal distribution $N(\mathbf{0}, \Sigma_u)$, and compute $\boldsymbol{y}_{t+1}$ using the VAR with parameters Φ. Further draws of innovations enable us to compute the sequence of forecasts $\boldsymbol{y}_{t+2}$, $\boldsymbol{y}_{t+3}$, ..., $\boldsymbol{y}_{t+h}$, using previous forecasts for the lags in the VAR (that is, the forecasts are dynamic). By repeating this entire process 1 000 times we construct a distribution of forecasts, which we summarise by calculating the mean forecast at each horizon. As we do this for each estimation end-date, we obtain a sequence of forecasts for each horizon; for example, we construct 24 one-quarter-ahead forecasts (the last being those made in 2007:Q3 for 2007:Q4) and 17 eight-quarter-ahead forecasts. We then evaluate the forecasts by calculating the Root-Mean-Squared Error (RMSE).

In the results that follow, we focus on the models' ability to forecast output growth, inflation and interest rates. These are the key policy variables, and the other variables are difficult to forecast (particularly the exchange rate; see Meese and Rogoff 1983).

Table 3 presents the RMSE of the forecasts for each variable one quarter ahead, and for their year-ended changes four and eight quarters ahead, except for interest rates, where we report its value at these horizons. These forecasts are computed for different values of λ in the manner just described, using a VAR with three lags. It suggests that by moderately increasing the weight on the DSGE prior from that recommended by the marginal data density – to between 1.5 and 2 – we generally improve the model's forecasting performance, particularly for output growth and inflation one quarter ahead. Placing an even larger weight on the prior further improves the year-ahead interest rate forecasts, but at the expense of some deterioration in the near-term growth and interest rate forecasts.

Table 3: RMSE of BVAR-DSGE over Different Values of λ
2002:Q1–2007:Q4, VAR(3), percentage points

λ	One quarter ahead	Four quarters ahead	Eight quarters ahead
	Quarterly	Year-ended	Year-ended
		Output	
0.75	0.338	0.629	0.742
1	0.333	0.622	0.756
1.25	0.329	0.618	0.766
1.5	0.326	0.614	0.796
1.75	0.326	0.613	0.789
2	0.324	0.609	0.801
5	0.337	0.588	0.812
10	0.354	0.607	0.779
		Interest rates	
0.75	0.201	0.709	0.713
1	0.197	0.665	0.687
1.25	0.195	0.631	0.662
1.5	0.196	0.585	0.624
1.75	0.196	0.581	0.619
2	0.196	0.560	0.603
5	0.210	0.472	0.519
10	0.216	0.439	0.502
		Inflation	
0.75	0.167	0.332	0.341
1	0.163	0.335	0.337
1.25	0.160	0.337	0.330
1.5	0.155	0.344	0.339
1.75	0.156	0.345	0.324
2	0.150	0.339	0.328
5	0.150	0.373	0.350
10	0.149	0.383	0.365

Note: The interest rate forecasts are for its level at all horizons.

It is also possible to compare the forecasting performance at different lag lengths for the VAR (Table E1 in Appendix E). In general, the interest rate forecasts are most accurate when only two lags are used, whereas for the other variables the one-year-ahead forecasts are improved by using three lags. We place a greater weight on the accuracy of the inflation and output forecasts relative to those for interest rates, and consequently the BVAR-DSGE results in the remainder of this paper are computed with a VAR(3) and $\lambda = 1.75$.[17]

5. Forecasting Performance Comparison

5.1 The Benchmarks

In order to examine the forecasting gain from using priors from a DSGE model, we need some benchmark models. There are several natural candidates. The first is an unrestricted (reduced-form) VAR, which makes no attempt to identify the structural shocks.[18] The second is a Bayesian reduced-form VAR with Minnesota-style priors. Minnesota BVARs historically have proven to be a useful forecasting tool (for a recent Australian example see Gerard and Nimark 2008). Briefly, a Minnesota VAR prior usually assumes that the *level* of each series is highly persistent, that is, they follow a unit root (possibly with drift). Consequently, the mean of the prior for the coefficient on the first own lag is one, and the mean of the priors for the coefficients on other lags are zero, and these priors are held more tightly for longer lags.[19] To make them comparable, the unrestricted and Minnesota VARs were estimated using the same variables as were observable for the BVAR-DSGE. As some of these series (such as output) are already expressed as growth rates rather than levels, the Minnesota prior was modified so as to have

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17 Ideally, the latter results would be constructed over a separate sample than that used to select λ. However, as we wished to only use the inflation-targeting period, this was impractical.

18 The UVAR was estimated in EViews 6.0.

19 More precisely, the standard deviation of the prior on coefficient $\Phi_{p_{jk}}$ (recall p denotes the lag length) is $\pi_1^{-1}\pi_2^{1-I(j,k)}p^{-\pi_3}$, where $I(j,k)$ is an indicator function that equals 1 if $j = k$, and 0 otherwise. π_1 is the overall tightness of the prior, which we set at 0.2. π_2 enables the prior to be tighter on lags of other variables, however, as we use an Inverted-Wishart Normal prior and Gibbs sampling we impose $\pi_1 = \pi_2$ (see Kadiyala and Karlsson 1997). Finally, $\pi_3 > 0$ imposes a tighter prior on longer lags, and we set this to 0.5 (this is known as harmonic decay). Estimation was conducted in WinRATS 7.0 by Estima, using code by Tom Doan available on the Estima website (<www.estima.com>). One thousand observations were discarded as burn-in.

a mean of zero for their first own lag.[20] For simplicity we impose the same lag length of three across the models. Finally, another natural benchmark is the DSGE model itself, which we approximate by setting $\lambda = 100\,000$. The forecasts from these benchmark models were constructed in the same way as those for the BVAR-DSGE.

5.2 Forecast Comparisons

To evaluate the forecasting performance of the models we construct out-of-sample forecasts and compute their RMSE. Table 4 presents the forecasting performance of the BVAR-DSGE relative to the benchmark models.

Table 4: RMSE of BVAR-DSGE

2002:Q1–2007:Q4, VAR(3)

Variable	**One quarter ahead**	**Four quarters ahead**	**Eight quarters ahead**
	Quarterly	Year-ended	Year-ended
		Relative to unrestricted VAR	
Output growth	0.84	0.89	1.08
Nominal cash rate	0.80	0.61	0.79
Underlying inflation	0.84	1.08	0.99
		Relative to DSGE	
Output growth	0.88	0.94	1.05
Nominal cash rate	0.88	1.44	1.24
Underlying inflation	1.06	0.87	0.79
		Relative to Minnesota VAR	
Output growth	0.92	0.74	0.96
Nominal cash rate	0.44	0.89	1.02
Underlying inflation	1.00	1.13	0.96

Note: The interest rate forecasts are for its level at all horizons.

To interpret this table, note that if the entry in a particular cell is less than one, then the BVAR-DSGE outperforms the corresponding benchmark model. Focusing initially on the UVAR, this is always the case for the one-quarter-ahead forecasts. It is also true for output one year ahead, but not for inflation. Compared to the

20 By using the same variables we may, to some extent, make the benchmark models 'straw men'; for example, if one was independently constructing a Minnesota BVAR then possibly a larger or different set of variables could be used.

DSGE model alone, the BVAR-DSGE performs well at forecasting inflation at long horizons. The gain in forecasting performance may reflect the tendency for DSGE models to be under-parameterised. The combination of a DSGE with a VAR model increases the number of free parameters, allowing for better fitting of the data. However, the DSGE outperforms in forecasting the cash rate, apart from one quarter ahead. This was expected since when we selected the relative weighting on the DSGE model we placed more importance on the output and inflation forecasting accuracy, partly at the cost of interest rates.

Compared to the Minnesota VAR we see some moderate forecasting gains. The BVAR-DSGE forecasts more accurately both output growth at any horizon and the cash rate one year ahead. The inflation forecasts of the BVAR-DSGE are competitive. These results suggest that the theoretical information in the DSGE prior is a useful complement to the purely statistical Minnesota prior.

Overall, the results show that the BVAR-DSGE is competitive at forecasting inflation and output. Table 5 presents the absolute forecasting performance of the BVAR-DSGE model.

Table 5: RMSE of BVAR-DSGE
2002:Q1–2007:Q4, VAR(3), percentage points

Variable	**One quarter ahead**	**Four quarters ahead**	**Eight quarters ahead**
	Quarterly	Year-ended	Year-ended
Output growth	0.33	0.61	0.79
Nominal cash rate	0.20	0.58	0.62
Underlying inflation	0.16	0.34	0.32
Change in nominal TWI	3.07	8.79	8.81
Change in terms of trade	1.34	4.68	7.01

Note: The interest rate forecasts are for its level at all horizons.

The RMSEs of the three key variables – output growth, underlying inflation and the cash rate – are noticeably lower than those for the exchange rate and terms of trade growth, which is unsurprising given the volatility in the latter series, as mentioned previously.

6. Conclusions

With the principal objective of macroeconomic forecasting, we have used a simple, small open economy DSGE model to provide prior information for a structural Bayesian VAR model. The performance of the BVAR-DSGE model in forecasting the key variables of output growth and inflation is competitive with the three benchmark models we have considered; for example, its inflation forecasts outperform those from the DSGE alone at most horizons. However, the DSGE model we have used as the source of prior information is particularly simple. Future work could extend the BVAR-DSGE model in at least two ways: introducing common features used to improve the fit of DSGE models (such as habit persistence in consumption); and improving its open economy aspects. The main result we take from our analysis is that the BVAR-DSGE methodology is a useful way of balancing theoretical and data coherence, particularly when the aim is to build a model for forecasting.

Appendix A: Deriving the IS Equation

In this appendix, to be explicit, we change the notation slightly, and distinguish variables which have been log-linearised. We denote log deviations from steady state as lower-case variables with a superscript ~.[21]

A.1 The Consumer's Problem

Let the consumer's utility be of the form in Lubik and Schorfheide (2005), namely

$$U = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{(C_t/A_t)^{1-\frac{1}{\tau}}}{1-\frac{1}{\tau}} - N_t \right]. \tag{A1}$$

Compared to Lubik and Schorfheide (2005), a few minor modifications have been made: τ is now the intertemporal elasticity of substitution (rather than the coefficient of relative risk aversion); habits in aggregate consumption (C_t) have been removed; and technology is assumed to be common across all countries (A_t). N_t denotes the labour input.

We specify the consumer's budget constraint as:

$$P_t C_t + B_{t+1} \leq W_t N_t + R_{t-1} B_t, \tag{A2}$$

where: P_t is the price of aggregate consumption; and W_t is the wage rate. For simplicity we have expressed the budget constraint in terms of bond holdings B_t and their return R_t.

A.2 First-order Conditions

We express the consumer's problem above as a Lagrangian, $\mathscr{L}$:

$$\mathscr{L}_0 = \mathbb{E}_0 \sum_{t=0}^{\infty} \left(\beta^t \left[\frac{(C_t/A_t)^{1-\frac{1}{\tau}}}{1-\frac{1}{\tau}} - N_t \right] - \lambda_t \left(P_t C_t + B_{t+1} - W_t N_t - R_{t-1} B_t \right) \right) \tag{A3}$$

The relevant first-order conditions are:

$$\begin{aligned} \frac{\partial \mathscr{L}_t}{\partial B_{t+1}} &= -\lambda_t + \mathbb{E}_t R_t \lambda_{t+1} &= 0 \\ \frac{\partial \mathscr{L}_t}{\partial C_t} &= \beta^t \frac{1}{A_t^{1-\frac{1}{\tau}}} C_t^{-\frac{1}{\tau}} - \lambda_t P_t &= 0. \end{aligned}$$

21 This appendix draws on work by Jamie Hall. We also thank Adam Cagliarini for his assistance.

Eliminating λ_t yields

$$\frac{C_t^{-\frac{1}{\tau}}}{P_t A_t^{1-\frac{1}{\tau}}} = \mathbb{E}_t \left(R_t \frac{\beta C_{t+1}^{-\frac{1}{\tau}}}{P_{t+1} A_{t+1}^{1-\frac{1}{\tau}}} \right).$$

If $c_t \equiv \frac{C_t}{A_t}$, then this can be expressed as

$$c_t^{-\frac{1}{\tau}} = \beta \mathbb{E}_t \left(c_{t+1}^{-\frac{1}{\tau}} \frac{P_t}{P_{t+1}} \frac{A_t}{A_{t+1}} R_t \right), \tag{A4}$$

which is the Euler equation.

A.3 Log-linearisation

We log-linearise Equation (A4) using the steady-state condition that $\beta^{-1} = R$ (assuming no steady-state inflation):

$$\tilde{c}_t = \mathbb{E}_t \tilde{c}_{t+1} - \tau \left(\tilde{r}_t - \mathbb{E}_t \tilde{\pi}_{t+1} \right) + \tau \mathbb{E}_t \tilde{z}_{t+1}. \tag{A5}$$

A.4 The IS Equation

In order to obtain the IS equation we use two results from Galí and Monacelli (2002), namely their Equations (25) and (16):

$$\tilde{y}_t = \tilde{y}_t^* - \chi \tilde{q}_t, \text{ and} \tag{A6}$$

$$\tilde{c}_t = \tilde{c}_t^* - \tau(1-\alpha)\tilde{q}_t. \tag{A7}$$

Note that these have been modified to take into account differences in notation; they define the terms of trade as the price of imports relative to exports (and denote it by s_t), whereas q_t is defined inversely to this. Similarly, they define the coefficient of relative risk aversion as σ, so $\tau = \sigma^{-1}$. Also, output (y_t) has been normalised by technology, which is not necessary in their paper as technology is assumed to be stationary. From Equations (A6) and (A7), and using the market-clearing condition $\tilde{c}_t^* = \tilde{y}_t^*$, yields their Equation (27):

$$\tilde{c}_t = \frac{\chi - \tau(1-\alpha)}{\chi} \tilde{y}_t^* + \frac{\tau(1-\alpha)}{\chi} \tilde{y}_t. \tag{A8}$$

We can substitute Equation (A8) into Equation (A5) for $\tilde{c}_t$ and $\mathbb{E}_t\tilde{c}_{t+1}$, which yields:

$$\begin{aligned}\frac{\chi-\tau(1-\alpha)}{\chi}\tilde{y}_t^* + \frac{\tau(1-\alpha)}{\chi}\tilde{y}_t &= \mathbb{E}_t\left(\frac{\chi-\tau(1-\alpha)}{\chi}\tilde{y}_{t+1}^* + \frac{\tau(1-\alpha)}{\chi}\tilde{y}_{t+1}\right) \\ &\quad -\tau\left(\tilde{r}_t - \mathbb{E}_t\tilde{\pi}_{t+1}\right) + \tau\mathbb{E}_t\tilde{z}_{t+1}.\end{aligned}$$

Solving for $(1-\alpha)\tilde{y}_t$:

$$(1-\alpha)\tilde{y}_t = \mathbb{E}_t\left(\frac{\chi-\tau(1-\alpha)}{\tau}\Delta\tilde{y}_{t+1}^* + (1-\alpha)\tilde{y}_{t+1}\right) - \chi\left(\tilde{r}_t - \mathbb{E}_t\tilde{\pi}_{t+1}\right) + \chi\mathbb{E}_t\tilde{z}_{t+1}.$$

Hence,

$$\tilde{y}_t = \mathbb{E}_t\left(\frac{\chi-\tau(1-\alpha)}{\tau}\Delta\tilde{y}_{t+1}^* + \tilde{y}_{t+1} - \alpha\Delta\tilde{y}_{t+1}\right) - \chi\left(\tilde{r}_t - \mathbb{E}_t\tilde{\pi}_{t+1}\right) + \chi\mathbb{E}_t\tilde{z}_{t+1}.$$

We can first difference Equation (A6) to obtain an expression for $\Delta\tilde{y}_{t+1}$; substituting this into the equation above yields the IS equation:

$$\tilde{y}_t = \mathbb{E}_t\tilde{y}_{t+1} - \chi\left(\tilde{r}_t - \mathbb{E}_t\tilde{\pi}_{t+1}\right) + \chi\mathbb{E}_t\tilde{z}_{t+1} + \alpha\chi\mathbb{E}_t\Delta\tilde{q}_{t+1} + \left(\frac{\chi}{\tau} - 1\right)\mathbb{E}_t\left(\Delta\tilde{y}_{t+1}^*\right). \tag{A9}$$

In contrast to the IS equation in Lubik and Schorfheide (2007), the coefficients on the expected growth in the terms of trade and technology are positive (and the latter is not unity).

Appendix B: Data Sources

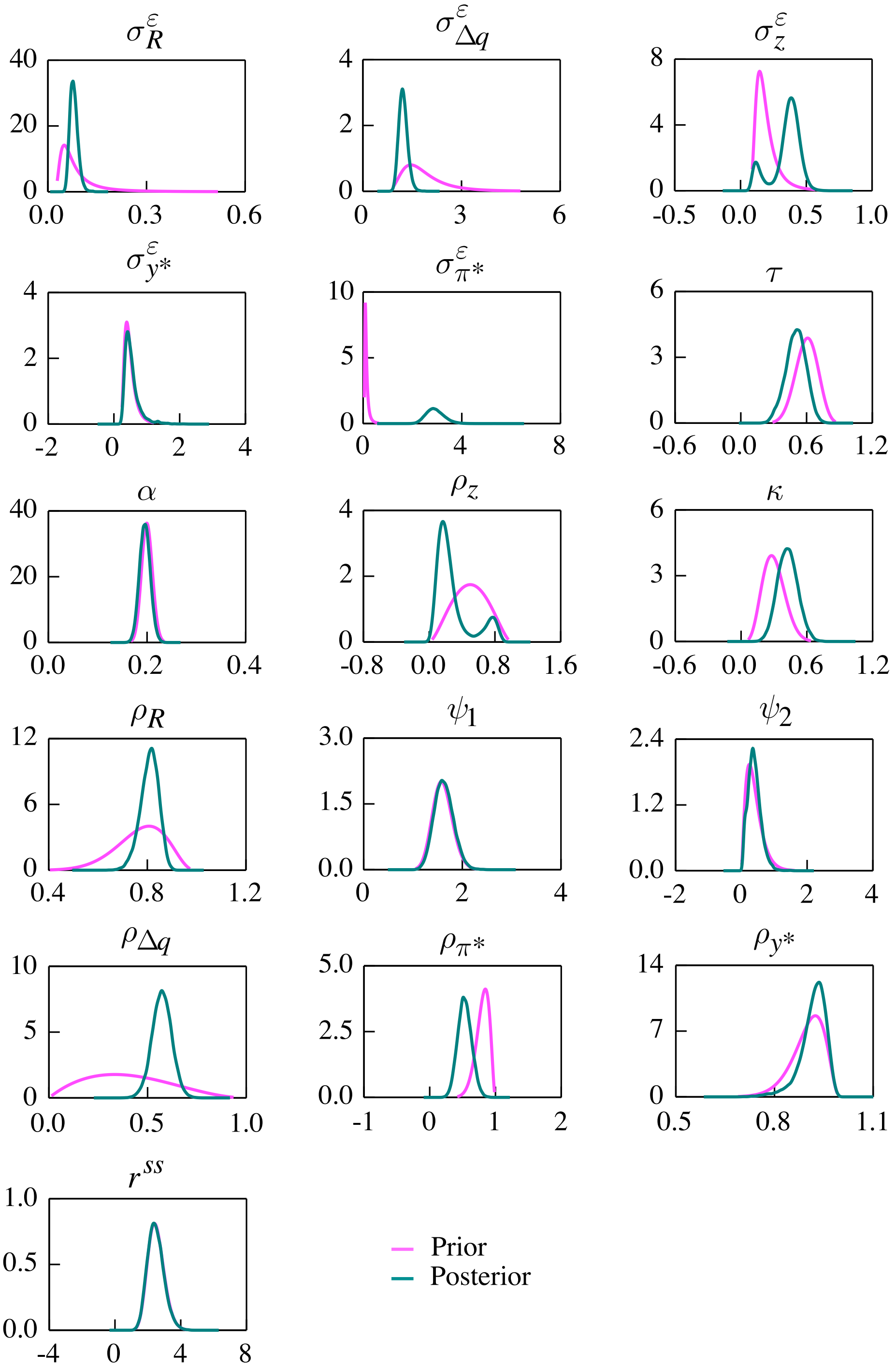
Data sources are listed in Table B1 below. All data are available upon request.

Table B1: Data Sources

Series	Source(s)
Chain-volume non-farm GDP	December 2007 National Accounts; ABS Cat No 5204.0
Terms of trade	As above
Nominal cash rate	RBA *Bulletin* Table 'F.1 Interest Rates and Yields – Money Market'
Trimmed-mean CPI	December 2007 Consumer Price Index, ABS Cat No 6401.0; RBA
Nominal trade-weighted exchange rate	RBA *Bulletin* Table 'F.11 Exchange Rates'

Appendix C: DSGE Posterior Distributions

Figure C1: DSGE Parameter Priors and Posteriors



Note: Each panel shows the prior and posterior probability density functions for the relevant parameter.

Appendix D: Impulse Responses

D.1 Identification of the Structural Model

While it is not necessary to identify the structural VAR for the purpose of forecasting, Del Negro and Schorfheide (2004) demonstrate how it is possible to do so. This enables us to compute impulse responses that can be used to provide economic interpretation of the forecasts. Briefly, the mapping between the reduced-form and structural model is

$$\boldsymbol{u}_t = \Sigma_{tr}\Omega\boldsymbol{\varepsilon}_t, \tag{D1}$$

where: Σ_{tr} is the Cholesky decomposition of Σ_u (that is, $\Sigma_{tr}\Sigma_{tr}' = \Sigma_u$, with Σ_{tr} lower triangular); Ω is an orthonormal matrix and $\boldsymbol{\varepsilon}_t$ is a vector of structural shocks. Essentially, the Cholesky decomposition allows us to identify the structural model, but only up to a rotation (Ω). The insight from Del Negro and Schorfheide (2004) is that we can use the DSGE to pick Ω by equating the instantaneous effects of the structural shocks from the DSGE and the VAR. To do this, note that for the DSGE model there exists a matrix $A_0(\theta)$ that gives this contemporaneous effect, that is, $\frac{\partial \boldsymbol{y}_t}{\partial \boldsymbol{\varepsilon}_t'} = A_0(\theta)$. Applying a LQ transformation (akin to a QR transformation) to $A_0(\theta)$ yields $A_0(\theta) = LQ$, where L is a lower-triangular matrix and Q is orthonormal. Alternatively, from the VAR, Equations (1) and (D1), $\frac{\partial \boldsymbol{y}_t}{\partial \boldsymbol{\varepsilon}_t'} = \Sigma_{tr}(\theta)\Omega(\theta)$. Consequently, we set $\Omega = Q$.

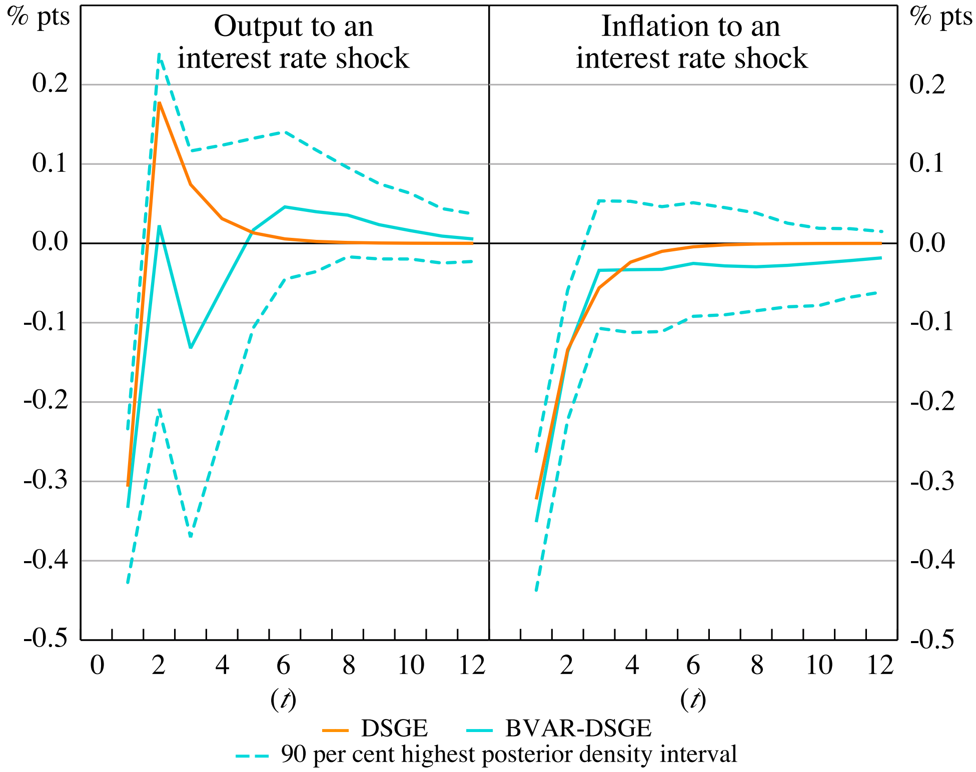
D.2 BVAR-DSGE Impulse Responses

Figure D1 shows the DSGE impulse responses (orange lines) and the BVAR-DSGE impulse responses (blue lines, with the corresponding 90 per cent highest posterior density intervals) for a shock to the cash rate of 25 basis points.[22] In the BVAR-DSGE, the maximum reduction in inflation is around 0.35 percentage points, which is somewhat larger than the 0.1 percentage point reduction reported in Nimark (2007) or the 0.05 percentage point reduction found by Jääskelä and Nimark (forthcoming). We also estimate the peak impact of a 25 basis point monetary policy shock on output growth to be around 0.3 percentage points, which is larger than in Jääskelä and Nimark (0.1 percentage points). Relative to the

[22] A 1 standard deviation shock is approximately equal to 8 basis points.

DSGE model, the BVAR-DSGE suggests that the impact of a monetary policy shock on output growth is more prolonged.

Figure D1: Selected Impulse Responses to a 25 Basis Point Cash Rate Shock



Appendix E: Varying Lag Length

Table E1 shows the impact of varying the lag length and λ on the forecast performance.

Table E1: RMSE of BVAR-DSGE over Different Lags and Values of λ
2002:Q1–2007:Q4, percentage points

λ	One quarter ahead			Four quarters ahead			Eight quarters ahead		
	Quarterly			Year-ended			Year-ended		
	Lag 2	Lag 3	Lag 4	Lag 2	Lag 3	Lag 4	Lag 2	Lag 3	Lag 4
				Output					
0.75	0.364	0.338	0.389	0.753	0.629	0.759	0.811	0.742	0.758
1	0.358	0.333	0.373	0.739	0.622	0.730	0.822	0.756	0.759
1.25	0.354	0.329	0.362	0.729	0.618	0.710	0.835	0.766	0.765
1.5	0.352	0.326	0.353	0.714	0.614	0.690	0.847	0.796	0.771
1.75	0.348	0.326	0.347	0.700	0.613	0.676	0.841	0.789	0.780
2	0.347	0.324	0.342	0.688	0.609	0.663	0.840	0.801	0.789
5	0.356	0.337	0.340	0.627	0.588	0.589	0.798	0.812	0.829
10	0.365	0.354	0.346	0.631	0.607	0.598	0.792	0.779	0.789
				Interest rates					
0.75	0.167	0.201	0.208	0.545	0.709	0.786	0.575	0.713	0.784
1	0.166	0.197	0.204	0.514	0.665	0.741	0.552	0.687	0.757
1.25	0.166	0.195	0.200	0.491	0.631	0.706	0.532	0.662	0.731
1.5	0.167	0.196	0.200	0.477	0.585	0.677	0.523	0.624	0.709
1.75	0.170	0.196	0.201	0.458	0.581	0.655	0.504	0.619	0.687
2	0.173	0.196	0.201	0.450	0.560	0.634	0.495	0.603	0.670
5	0.200	0.210	0.211	0.417	0.472	0.527	0.478	0.518	0.564
10	0.214	0.216	0.215	0.415	0.439	0.466	0.485	0.502	0.523
				Inflation					
0.75	0.154	0.167	0.178	0.348	0.332	0.354	0.297	0.341	0.374
1	0.152	0.163	0.171	0.357	0.335	0.351	0.304	0.337	0.374
1.25	0.151	0.160	0.166	0.363	0.337	0.350	0.312	0.330	0.370
1.5	0.149	0.155	0.162	0.373	0.344	0.349	0.338	0.339	0.368
1.75	0.149	0.156	0.159	0.377	0.345	0.350	0.332	0.324	0.364
2	0.148	0.150	0.157	0.379	0.339	0.349	0.338	0.328	0.363
5	0.148	0.150	0.150	0.395	0.373	0.361	0.370	0.350	0.374
10	0.141	0.149	0.149	0.392	0.383	0.362	0.380	0.365	0.362

Note: The interest rate forecasts are for its level at all horizons.

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