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Forecasting Performance of an Open Economy Dynamic Stochastic General Equilibrium Model

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Abstract

This paper analyzes the forecasting performance of an open economy DSGE model, estimated with Bayesian methods, for the Euro area during 1994Q1-2002Q4. We compare the DSGE model and a few variants of this model to various reduced form forecasting models such as vector autoregressions (VAR) and vector error correction models (VECM), estimated both by maximum likelihood and two different Bayesian approaches, and traditional benchmark models, e.g. the random walk. The accuracy of point forecasts, interval forecasts and the predictive distribution as a whole are assessed in an out-of-sample rolling event evaluation using several univariate and multivariate measures. The results show that the open economy DSGE model compares well with more empirical models and thus that the tension between rigor and fit in older generations of DSGE models is no longer present. We also critically examine the role of Bayesian model probabilities and other frequently used low-dimensional summaries, e.g. the log determinant statistic, as measures of overall forecasting performance.

Keywords: Bayesian inference; Forecasting; Open economy DSGE model; Vector autoregressive models.
JEL classification: C11; C32; E37; E47.

*Adolfson: *Sveriges Riksbank, malin.adolfson@riksbank.se;* Lindé: *Sveriges Riksbank and IIES, jesper.linde@riksbank.se;* Villani: *Sveriges Riksbank and Stockholm University*, *mattias.villani@riksbank.se.* The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Executive Board of Sveriges Riksbank. Villani was partly financially supported by a grant from the Swedish Research Council (Vetenskapsrådet, grant no. 412-2002-1007).

1. Introduction

One of the objectives behind the formation of dynamic stochastic general equilibrium (DSGE) models is to explain and understand macroeconomic fluctuations using a coherent theoretical framework. The use of DSGE models in policy analysis, however, has been criticized by both academics and practitioners. The main argument has been the inability of DSGE models to - loosely speaking - fit the data. For instance, Pagan (2003) retains that there is a trade-off between theoretical and empirical coherence in DSGE models and VARs, the latter being more empirically than theoretically coherent relative to the former.

The new generation of DSGE models developed by Christiano, Eichenbaum and Evans (2005) among others, have shown great promise of improving the empirical properties by introducing nominal and real frictions into the model economy. Of course, the evaluation of fit can be assessed in various ways. For policy makers, the comparison of out-of-sample forecasting properties is of particular interest, as policy actions typically rely upon accurate assessments of the future development of the economy. Results in Smets and Wouters (2004) suggest that the new generation of closed economy DSGE models compare very well with vector autoregressive (VAR) models in terms of forecasting accuracy.

This paper evaluates the forecasting accuracy of an open economy DSGE model for the Euro area. This model enables us to predict several so called open economy variables such as, for example, the exchange rate, imports and exports. Evaluating the DSGE model for the latter variables are of particular interest, because previous research have demonstrated the difficulties to project these variables accurately. By opening up the model economy we hope to better capture the workings of the real world economy, but it could very well be that the added complexity by itself deteriorates the forecasting performance of the model. It is not uncommon to find that very small models are able to beat larger ones in forecasting. This motivates a thorough investigation of the model's forecasting performance with regard to both domestic and open economy macroeconomic variables.

A major difference between our analysis and Smets and Wouters' (2004), apart from the extension to the open economy setting, is that we include a unit-root stochastic technology shock, following Altig, Christiano, Eichenbaum and Lindé (2003). This induces a common stochastic trend in the variables and makes it possible to jointly model economic growth and business cycle fluctuations. In the empirical estimation and forecast evaluation we are hence not forced to detrend the data.

The DSGE model's forecasting properties are evaluated against a wide range of less theoretically oriented forecasting tools such as VARs, Bayesian VARs (BVARs), and naïve forecasts based on univariate random walks as well as on the simple means of the most recent data observations. Several authors have recently noted the theoretical connection between Bayesian model posterior probabilities and out-of-sample forecasting performance, e.g. Geweke (1999) and Del Negro, Schorfheide, Smets and Wouters (2004). Adding three alternative specifications of the benchmark DSGE model to the model set, allows us to study this link in some detail.

The forecasting performance of the models will be assessed in a rolling event forecast evaluation. We use the observations in $1994Q1-2002Q4$ to evaluate the forecasts. Several univariate and multivariate measures are employed to determine the accuracy of the point forecasts. Point forecasts are naturally the main concern of policy makers and has typically been the interest in the forecasting literature, see e.g. the M-competition in Makridakis et al. (1982). Recently, there has also been a growing interest in forecast uncertainty. The so called fan charts used by Bank of England and Sveriges Riksbank (the central bank of Sweden) to communicate the uncertainty in the inflation forecasts is one example. Using a Bayesian methodology we can derive the exact finite sample joint forecast distribution of all the endogenous variables in the system. We therefore also move beyond the evaluation of point forecasts to assess the reasonableness of, for example, predictive intervals.

The results indicate that the forecasting performance of the open economy DSGE model compares well with reduced form forecasting models such as VARs and BVARs. This holds true both in terms of the point forecast accuracy and when evaluating the accuracy of the whole forecast distribution. An empirical result with more of a methodological flavor is that frequently used measures of multivariate forecasting performance, such as the marginal likelihood and the log determinant MSE statistic, can be very sensitive to the choice of variables used in the forecast evaluation. We also show that such measures may be completely dominated by the forecasting accuracy of variables that the end user of the model cares very little about. Also, the often stated result that marginal likelihoods measure out-of-sample forecasting performance is shown to be a lot more problematic than is typically acknowledged among DSGE model developers.

The rest of the paper is organized as follows. Section 2 presents the theoretical DSGE model. The following section discusses inference and forecasting in DSGE models, and reports the estimation results of four different specifications of the DSGE model. In Section 4 we briefly discuss the alternative models used for forecasting such as vector autoregressive models and a couple of naïve setups. Section 5 reports the results from the forecast evaluation on Euro area data. Lastly, Section 6 summarizes and provides some conclusions.

2. The DSGE model

2.1. **Model.** This section gives an overview of the model economy and presents the key equations in the theoretical model. The model is an open economy version of the DSGE model in Christiano et al. (2005) and Altig et al. (2003), developed in Adolfson, Laséen, Lindé and Villani (2005) who we refer to for a more detailed description.

The final domestic good is a composite of a continuum of i differentiated goods, each supplied by a different firm, which follows the constant elasticity of substitution (CES) function

$$Y_t = \left[\int_0^1 (Y_{i,t})^{\frac{1}{\lambda_t^d}} \, di \right]^{\lambda_t^d}, 1 \leq \lambda_t^d < \infty, \tag{2.1}$$

where λ_t^d is the time-varying markup in the domestic goods market. The production function for intermediate good i is given by

$$Y_{i,t} = z_t^{1-\alpha} \epsilon_t K_{i,t}^{\alpha} H_{i,t}^{1-\alpha} - z_t \phi, \tag{2.2}$$

where z_t is a unit-root technology shock, ϵ_t is a covariance stationary technology shock, and $H_{i,t}$ denotes homogeneous labor hired by the i^{th} firm. $K_{i,t}$ denotes capital services which differ from the physical capital stock since we allow for variable capital utilization in the model. A fixed cost $z_t\phi$ is included in the production function and following Christiano et al. (2005) we set ϕ so that profits are zero in steady state.

We allow for working capital by assuming that a fraction ν of the intermediate firms' wage bill has to be financed in advance through loans from a financial intermediary. Cost minimization yields the following nominal marginal cost for intermediate firm i:

$$MC_t^d = \frac{1}{(1-\alpha)^{1-\alpha}} \frac{1}{\alpha^{\alpha}} (R_t^k)^{\alpha} \left[W_t (1 + \nu(R_{t-1} - 1)) \right]^{1-\alpha} \frac{1}{(z_t)^{1-\alpha}} \frac{1}{\epsilon_t}, \tag{2.3}$$

where R_t^k is the gross nominal rental rate per unit of capital services, R_{t-1} the gross nominal (economy wide) interest rate, and W_t the nominal wage rate per unit of aggregate, homogeneous, labor $H_{i,t}$.

Each of the domestic goods firms is subject to price stickiness through an indexation variant of the Calvo (1983) model. Thus, each intermediate firm faces in any period a probability $1-\xi_d$ that it can reoptimize its price.[1] Since we have a time-varying inflation target in the model we allow for partial indexation to the current inflation target, but also to last period's inflation rate in order to allow for a lagged pricing term in the Phillips curve. The first order condition of the profit maximization problem yields the following log-linearized Phillips curve:

$$(2.4)\qquad \begin{aligned}\left(\widehat{\pi}_t^d - \widehat{\bar{\pi}}_t^c\right) \;=\;& \frac{\beta}{1+\kappa_d\beta}\left(\mathrm{E}_t\widehat{\pi}_{t+1}^d - \rho_\pi\widehat{\bar{\pi}}_t^c\right) + \frac{\kappa_d}{1+\kappa_d\beta}\left(\widehat{\pi}_{t-1}^d - \widehat{\bar{\pi}}_t^c\right) \\ & - \frac{\kappa_d\beta\left(1-\rho_\pi\right)}{1+\kappa_d\beta}\widehat{\bar{\pi}}_t^c + \frac{(1-\xi_d)(1-\beta\xi_d)}{\xi_d\left(1+\kappa_d\beta\right)}\left(\widehat{mc}_t^d + \widehat{\lambda}_t^d\right),\end{aligned}$$

where a hat denotes log-linearized variables (i.e., $\hat{X}_t = dX_t/X$), $\widehat{\pi}_t^d$ denotes the inflation rate in the domestic sector, $\widehat{\bar{\pi}}_t^c$ the time-varying inflation target of the central bank and $\widehat{mc}_t^d$ the real marginal cost.

We now turn to the import and export sectors. There is a continuum of importing consumption and investment firms that buy a homogenous good at price P_t^* in the world market, and converts it into a differentiated good through a brand naming technology. The exporting firms buy the (homogenous) domestic final good at price P_t^d and turn this into a differentiated export good through the same type of brand naming technology. The nominal marginal cost of the importing and exporting firms are thus $S_tP_t^*$ and P_t^d/S_t, respectively, where S_t is the nominal exchange rate (domestic currency per unit of foreign currency). The differentiated import and export goods are subsequently aggregated by an import consumption, import investment and export packer, respectively, so that the final import consumption, import investment, and export good is each a CES composite according to the following:

$$(2.5)\qquad C_t^m = \left[\int_0^1 \left(C_{i,t}^m\right)^{\frac{1}{\lambda_t^{mc}}} di\right]^{\lambda_t^{mc}}, \qquad I_t^m = \left[\int_0^1 \left(I_{i,t}^m\right)^{\frac{1}{\lambda_t^{mi}}} di\right]^{\lambda_t^{mi}}, \qquad X_t = \left[\int_0^1 \left(X_{i,t}\right)^{\frac{1}{\lambda_t^{x}}} di\right]^{\lambda_t^{x}},$$

where $1 \leq \lambda_t^j < \infty$ for $j = \{mc, mi, x\}$ is the time-varying markup in the import consumption (mc), import investment (mi) and export (x) sector. By assumption the importers and exporters invoice in local currency. In order to allow for short-run incomplete exchange rate pass-through to import and export prices we introduce nominal rigidities in the local currency price, following for example Smets and Wouters (2002).[2] This is modeled through the same type of Calvo setup as described above. The price setting problems of the importing and exporting firms are completely analogous to that of the domestic firms. In total there are thus four specific Phillips curve relations determining inflation in the domestic, import consumption, import investment and export sectors, all having the same structure as equation (2.4). To allow for temporary different degrees of technological progress domestically and abroad,

[1] For the firms that are not allowed to reoptimize their price, we adopt the indexation scheme $P_{t+1}^d = \left(\pi_t^d\right)^{\kappa_d}\left(\bar{\pi}_{t+1}^c\right)^{1-\kappa_d}P_t^d$ where P_t^d is the domestic price, κ_d is an indexation parameter, and $\pi_t^d = P_t^d/P_{t-1}^d$ is gross domestic inflation. The process for the inflation target $(\bar{\pi}_{t+1}^c)$ is defined in equation (2.11)

[2] Since there are neither any distribution costs in the import and export sectors nor an endogenous pricing to market behaviour among the firms, there would be complete pass-through in the absence of nominal rigidities.

we introduce a stationary asymmetric technology shock $\tilde{z}_t^* = z_t^*/z_t$, where z_t^* is the permanent technology level abroad, when defining the aggregate demand for export goods. Foreign demand in turn follows a CES aggregate with elasticity η_f.

In the model economy there is a continuum of households which maximize utility subject to a standard budget constraint. The preferences of household j are given by

$$\text{(2.6)} \qquad \mathrm{E}_0^j \sum_{t=0}^{\infty} \beta^t \left[\zeta_t^c \ln\left(C_{j,t} - bC_{j,t-1}\right) - \zeta_t^h A_L \frac{(h_{j,t})^{1+\sigma_L}}{1+\sigma_L} + A_q \frac{\left(\frac{Q_{j,t}}{z_t P_t^d}\right)^{1-\sigma_q}}{1-\sigma_q} \right],$$

where $C_{j,t}$, $h_{j,t}$ and $Q_{j,t}/P_t^d$ denote the j^{th} household's levels of aggregate consumption, labor supply and real cash holdings, respectively. Consumption is subject to habit formation through $bC_{j,t-1}$, such that the household's marginal utility of consumption today is affected by the quantity of goods consumed last period. ζ_t^c and ζ_t^h are persistent preference shocks to consumption and labor supply, respectively. To make real cash balances stationary when the economy is growing these are scaled by the unit root technology shock z_t. Aggregate consumption is assumed to be given by a CES function consisting of domestically produced goods and imported products:

$$\text{(2.7)} \qquad C_t = \left[(1-\omega_c)^{1/\eta_c} \left(C_t^d\right)^{(\eta_c-1)/\eta_c} + \omega_c^{1/\eta_c} \left(C_t^m\right)^{(\eta_c-1)/\eta_c} \right]^{\eta_c/(\eta_c-1)},$$

where C_t^d and C_t^m are consumption of the domestic and imported good, respectively. ω_c is the share of imports in consumption, and η_c is the elasticity of substitution across consumption goods.

The households can increase their capital services (K_t) by investing (I_t) in additional physical capital ($\bar{K}_t$), taking one period to come in action, or by directly increasing the utilization rate of the physical capital stock at hand ($K_t = u_t \bar{K}_t$). Both operations undertake a cost. We also allow for a stationary investment-specific technology shock (Υ_t). Total investment is assumed to be given by a CES aggregate of domestic and imported investment goods (I_t^d and I_t^m, respectively) according to

$$\text{(2.8)} \qquad I_t = \left[(1-\omega_i)^{1/\eta_i} \left(I_t^d\right)^{(\eta_i-1)/\eta_i} + \omega_i^{1/\eta_i} \left(I_t^m\right)^{(\eta_i-1)/\eta_i} \right]^{\eta_i/(\eta_i-1)},$$

where ω_i is the share of imports in investment, and η_i is the elasticity of substitution across investment goods.

In addition to accumulating physical capital and holding cash, the households can save in domestic and foreign bonds. The choice between domestic and foreign bond holdings balances into an arbitrage condition pinning down expected exchange rate changes (i.e., an uncovered interest rate parity condition). To ensure a well-defined steady-state in the model, we assume that there is a premium on the foreign bond holdings which depends on the aggregate net foreign asset position of the domestic households, following, e.g., Lundvik (1992), and Schmitt-Grohé and Uribe (2001):

$$\text{(2.9)} \qquad \Phi(a_t, \tilde{\phi}_t) = \exp(-\tilde{\phi}_a(a_t - \bar{a}) + \tilde{\phi}_t),$$

where $A_t \equiv (S_t B_t^*)/(P_t z_t)$ is the net foreign asset position, and $\tilde{\phi}_t$ is a shock to the risk premium. Note also that $\Phi(a_t, \tilde{\phi}_t)$ is not a 'traditional' risk premium associated with variances and covariances in a stochastic environment.

Further, along the lines of Erceg, Henderson and Levin (2000), each household is a monopoly supplier of a differentiated labor service which implies that they can set their own wage. Wage stickiness is introduced through the Calvo (1983) setup, with partial indexation to last period's CPI inflation rate, the current inflation target and the current permanent technology growth rate.[3]

Following Smets and Wouters (2003), monetary policy is approximated with the following instrument rule (expressed in log-linearized terms)

$$\begin{aligned}\widehat{R}_t &= \rho_R \widehat{R}_{t-1} + (1-\rho_R)\left[\widehat{\bar{\pi}}_t^c + r_\pi\left(\hat{\pi}_{t-1}^c - \widehat{\bar{\pi}}_t^c\right) + r_y \hat{y}_{t-1} + r_x \hat{x}_{t-1}\right] \\ &\quad + r_{\Delta\pi}\left(\hat{\pi}_t^c - \hat{\pi}_{t-1}^c\right) + r_{\Delta y}\Delta\hat{y}_t + \varepsilon_{R,t},\end{aligned} \tag{2.10}$$

where $\varepsilon_{R,t}$ is an uncorrelated monetary policy shock. Thus, the central bank is assumed to adjust the short term interest rate in response to the CPI inflation rate $\hat{\pi}_t^c$, the time-varying inflation target $\widehat{\bar{\pi}}_t^c$, the output gap ($\hat{y}_t$, measured as actual minus trend output)[4], the real exchange rate $\left(\hat{x}_t \equiv \hat{S}_t + \hat{P}_t^* - \hat{P}_t^c\right)$, and the lagged interest rate.

The structural shock processes in the model is given in log-linearized form by the univariate representation

$$\hat{x}_t = \rho_x \hat{x}_{t-1} + \varepsilon_{x,t}, \qquad \varepsilon_{x,t} \overset{iid}{\sim} N\left(0, \sigma_x^2\right) \tag{2.11}$$

where $x = \{\ \mu_{z,t},\ \epsilon_t, \lambda_t^j,\ \zeta_t^c,\ \zeta_t^h,\ \Upsilon_t,\ \tilde{\phi}_t,\ \varepsilon_{R,t}, \bar{\pi}_t^c,\ \tilde{z}_t^*\}$ and $j = \{d, mc, mi, x\}$.

Lastly, to simplify the analysis we adopt the assumption that the foreign prices, output (HP-detrended) and interest rate are exogenously given by an identified VAR(4) model.[5] The fiscal policy variables - taxes on capital income, labour income, consumption, and the pay-roll, together with (HP-detrended) government expenditures - are assumed to follow an identified VAR(2) model.[6]

3. Bayesian Inference and Forecasting with DSGE Models

3.1. **The likelihood function.** Bayesian inference combines a prior distribution with a likelihood function to arrive at the posterior distribution of the structural parameters conditional on the available data. In order to efficiently compute the likelihood function, the DSGE model is log-linearized and the reduced form of the model is obtained by the AIM algorithm (Anderson and Moore, 1985). As a first step, we cast the log-linearized model on matrix form as

$$\mathrm{E}_t\left\{\alpha_0 \tilde{z}_{t+1} + \alpha_1 \tilde{z}_t + \alpha_2 \tilde{z}_{t-1} + \beta_0 \theta_{t+1} + \beta_1 \theta_t\right\} = 0, \tag{3.1}$$

where $\tilde{z}_t$ is a vector with log-linearized endogenous variables and θ_t contains the exogenous variables which follows the process

$$\theta_t = \rho\theta_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \Sigma). \tag{3.2}$$

Note that since some of the processes for the exogenous variables are given by more than one lag, we expand θ_t with lags of the relevant exogenous variable.

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[3] $1-\xi_w$ is the probability that a household is allowed to reoptimize its wage. For the households that are not allowed to reoptimize, the indexation scheme is $W_{j,t+1} = (\pi_t^c)^{\kappa_w}\left(\bar{\pi}_{t+1}^c\right)^{(1-\kappa_w)}\mu_{z,t+1}W_{j,t}^{new}$, where κ_w is the indexation parameter, and $\mu_{z,t} = z_t/z_{t-1}$ is the growth rate of the technology level.

[4] This measure has an empirical advantage over the more theoretically consistent flexible-price output gap, see Adolfson et al. (2005) for further details.

[5] The reason why we include foreign output HP-detrended in the VAR is that the (stationarized) level of foreign output enters the model.

[6] It should be noted that Adolfson et al. (2005) report that the fiscal shocks have small dynamic effects in the model. This is because households are Ricardian and infinitely lived. Moreover, these shocks are transitory and thus do not generate any permanent wealth effects.

The solution of the fundamental difference equation in (3.1) can then be written as

$$\tilde{z}_t = A\tilde{z}_{t-1} + B\theta_t \tag{3.3}$$

where A and B are the so called feedback and feed-forward matrices, respectively.

The solution of the model given by (3.3) and (3.2) can compactly be written as

$$\xi_t = F_\xi \xi_{t-1} + v_t, \tag{3.4}$$

where $\xi_t = (z_t, \theta_t)'$ and $v_t \overset{iid}{\sim} N(0, Q)$, and Q is a singular covariance matrix. The states in ξ_t are then connected to a vector of observed variables y_t via a set of measurement equations of the form

$$y_t = C'x_t + H'\xi_t + \zeta_t, \tag{3.5}$$

where x_t a vector with exogenous variables (e.g., a constant) and $\zeta_t \overset{iid}{\sim} N(0, R)$ are measurement errors. Equations (3.4) and (3.5) constitute a linear state-space model and the likelihood function is then easily evaluated by the Kalman filter (see e.g. Hamilton, 1994). We assume for simplicity that R is a diagonal matrix with 0.1 on the diagonal, with the exception of the three foreign variables which are assumed to be measured without errors.

In order to facilitate identification of the various shocks and parameters that we estimate (we estimate 11 shocks that follow AR(1) processes, and 2 shocks that are assumed to be i.i.d. The three foreign and the five fiscal shocks are estimated prior to the analysis), we include the following set of 15 observable variables in y_t: the domestic inflation rate, the short-run interest rate, employment, consumption, investment, GDP, the real wage, exports, imports, the consumption deflator and the investment deflator, the real exchange rate, foreign inflation, the foreign interest rate, and foreign output.[7] Despite the fact that the foreign variables are exogenous, we still include them as observable variables as they enable identification of the asymmetric technology shock and are informative about the parameters governing the transmission of foreign impulses to the domestic economy.

To make the data stationary we experiment with two different strategies. In the first strategy, all real variables enter y_t in first differences. It is important to note that the unit root technology shock in the theoretical model induces a common stochastic trend in the levels of the real variables. In the second strategy, we therefore exploit the cointegration structure of the theoretical model and all real variables except GDP enter y_t as deviations from the GDP level, while GDP itself enters in first difference form. In Figure 1 the data series are depicted with real variables in yearly growth rates. Note that employment and the real exchange rate are measured as percentage deviations around the mean.

3.2. **Bayesian Inference.** Prior to the Bayesian estimation of the model, we calibrate a subset of parameters which are likely to be weakly identified by the variables that we include in y_t. These parameters are mostly related to the steady-state values of the variables (i.e., the great ratios) and are therefore relatively easy to calibrate (see Adolfson et al. (2005) for details). The remaining 51 model parameters are estimated. The estimated parameters pertain mostly to the nominal and real frictions in the model as well as to the exogenous shock processes described above.

[7]The data set employed here was first constructed by Fagan et al. (2001). The Fagan data set includes foreign (i.e., rest of the world) output and inflation, but not a foreign interest rate. We therefore use the Fed funds rate as a proxy for this series. Note also that there is no (official) data on aggregate hours worked, $\hat{H}_t$, available for the euro area. Therefore, we use employment in our estimations. Since employment is likely to respond more slowly to shocks than hours worked, we model employment using Calvo-rigidity (following Smets and Wouters, 2003). For reasons discussed in greater detail in Adolfson et al. (2005), we take out a linear trend in employment and the excess trend in imports and exports relative to the trend in GDP prior to estimation.

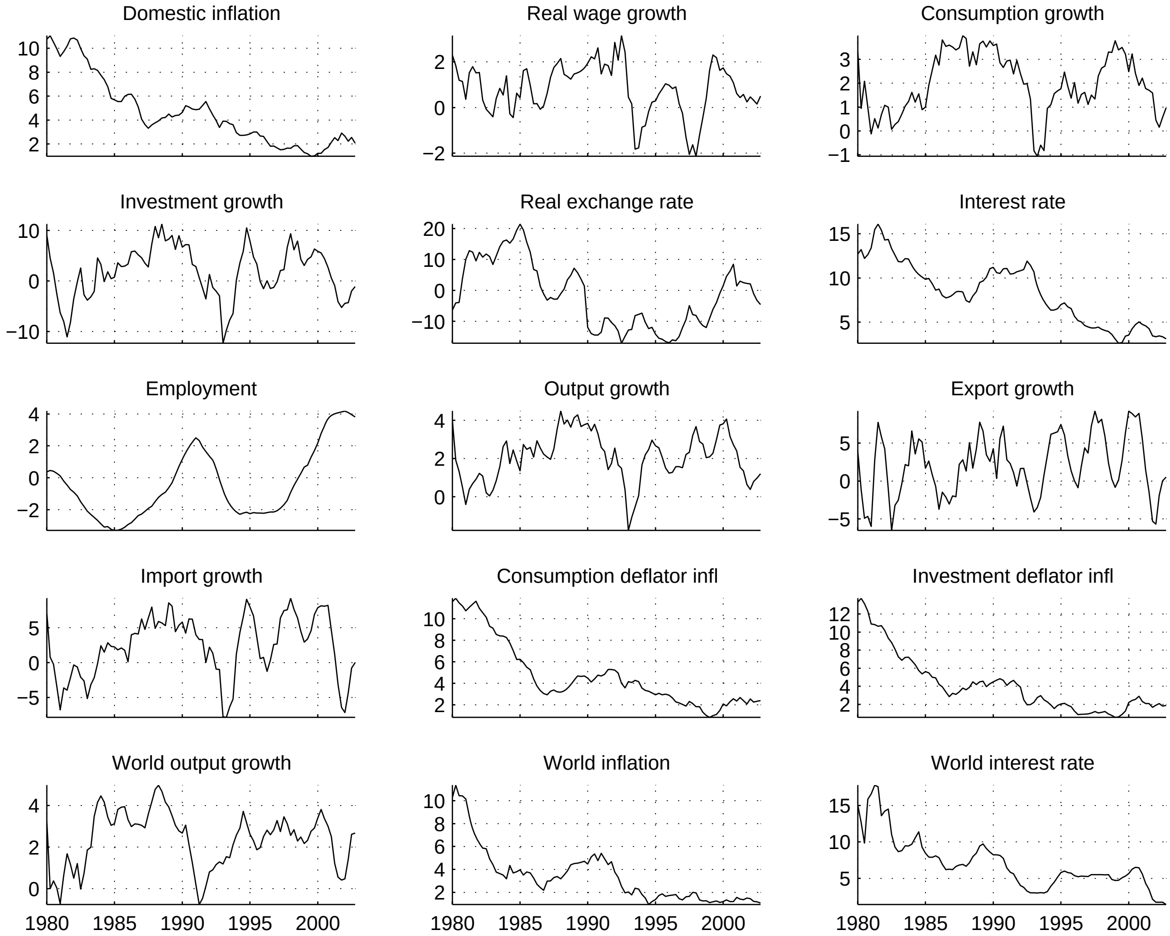

FIGURE 1. Euro area data 1980Q1-2002Q4, yearly growth rates.

Table 1 shows the assumptions for the prior distribution of the estimated parameters. The location of the prior distribution of the 51 estimated parameters corresponds to a large extent to those in Smets and Wouters (2003) and the findings in Altig et al. (2003) on U.S. data. See Adolfson et al. (2005) for a more detailed discussion about our choice of prior distributions. We use the first 10 years of the full sample $1970Q1-2002Q4$ to obtain a prior on the unobserved state variables in $1979Q4$, and use the subsample $1980Q1 - 2002Q4$ for inference.

The joint posterior distribution of all estimated parameters is obtained in two steps. First, the posterior mode and Hessian matrix evaluated at the mode is computed by standard numerical optimization routines. Second, draws from the joint posterior are generated using the random walk Metropolis algorithm (see Schorfheide (2000) for details).[8] In Table 1 we report the posterior mode estimates of the parameters.

Table 1 also report estimation results for the following alternative specifications of the benchmark model: *i*) with variable capital utilization, *ii*) with persistent domestic markup shocks, and *iii*) with IID markup shocks. We have chosen these specifications since a high or a low cost of varying the capital utilization has rather large effects on the impulse response

[8]A posterior sample of $500,000$ post burn-in draws was generated. Convergence was checked using standard diagnostics such as CUSUM and potential scale reduction factors (PSRF) on parallel simulation sequences.

functions. For example, with variable capital utilization, marginal cost is smoother after a monetary policy shock which in turn also makes the response of inflation more smooth. For case *ii*) we find that allowing for persistent domestic markup shocks implies that the domestic price stickiness is estimated to a much lower number, see Table 1. Similarly, if all markup shocks are assumed to be independently distributed, the source of variation as well as the price stickiness parameters (ξ:s) are completely different. We interpret this as that the model needs either a high degree of price stickiness or highly correlated markup shocks to explain the high inflation inertia seen in the data. We also find a larger role for indexation to past inflation in this case, so that when less of the persistence is generated by correlated shocks there must be a larger role for intrinsic persistence (i.e. lagged inflation) to account for the inflation dynamics. Note that these alternative specifications are estimated using the data in first differences.

Figures 2 and 3 show the sequential estimates (posterior mode) of the different DSGE models' parameters when extending the data set year-by-year from 1994 and onwards. For each specification of the model most of the parameters appear to be relatively stable over time (scales considered) which is encouraging given that the parameters are updated according to this scheme in the subsequent rolling forecast evaluation. However, the model estimated with cointegration constraints shows somewhat less stability. First of all, there is negative correlation between the habit formation parameter (b) and the persistence of the consumption preference shock (ρ_{ζ_c}). Second, the parameters related to investment (investment adjustment costs (SS'') and the persistence (ρ_Υ) and standard deviation (σ_Υ) of the investment-specific technology shock) are correlated over time and unstable. It should be noted that these parameters tend to have bimodal posteriors and the large changes in posterior mode estimates from time to time simply reflect that sometimes one of the two local modes happens to be slightly larger than the other. In other words, the instability in the posterior mode estimates are more dramatic than the instability in the posterior distribution as a whole. Nevertheless, the instability is larger in the model with cointegration imposed in the estimation. This is probably an effect of the rather large persistent movements in the cointegrating relations, in combination with a relatively short sample period (the shortest is 1980Q1-1993Q4 and the longest 1980Q1-2001Q4). All in all, it seems reasonable to start the evaluation of the forecasts as early as 1994, which leaves us with a relatively large sample to evaluate the forecasts.

3.3. **Forecasting with DSGE models.** Standing at time T, the predictive distribution of the next h observations can be expressed as

$$p_T(y_{T+1}, ..., y_{T+h}) = \int p(y_{T+1}, ..., y_{T+h}|\theta)p_T(\theta)d\theta, \tag{3.6}$$

where θ is a vector of structural parameters in the DSGE model and $p_T(\theta)$ is the posterior distribution of θ based on all available information at time T. The multi-dimensional integral in (3.6) cannot be evaluated analytically. The following algorithm uses the state space form of the model in (3.4) and (3.5) to simulate $N = N_1 \cdot N_2$ future paths for the observed variables and the unobserved states from the joint predictive distribution.

(1) Simulate a parameter vector θ from the posterior distribution.
(2) Simulate the current state vector from $\xi_T \sim N(\hat{\xi}_{T|T}, P_{T|T})$, where the posterior mean vector $\hat{\xi}_{T|T} = E_T(\xi_T)$ and the posterior covariance matrix $P_{T|T} = Cov_T(\xi_T)$ are obtained in the final step of the Kalman filter.
(3) Simulate a sequence of future state vectors $\xi_{T+1}, ..., \xi_{T+h}$ from the transition equation (3.4) using the ξ_T generated in step 2 and an iid sequence of future shocks $v_{T+1}, ..., v_{T+h}$ from $N(0, Q)$.

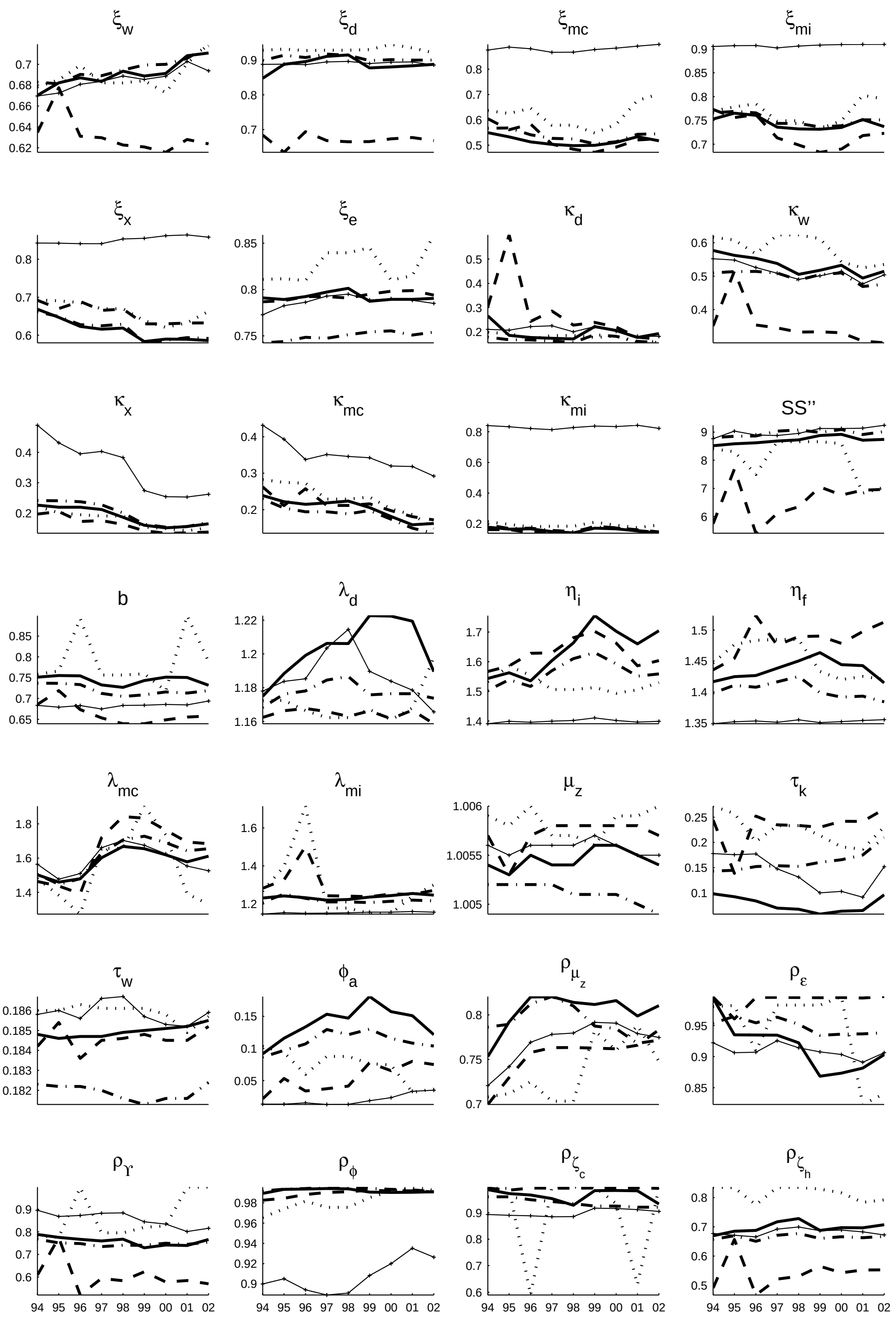

FIGURE 2. Sequential posterior mode estimates of the DSGE models' parameters using a year-by-year extended data set. DSGE diff. (—), DSGE coint. (···), Corr. mkup. (- - -), Var. cap. util. (– · –) and IID Markup (–+–).

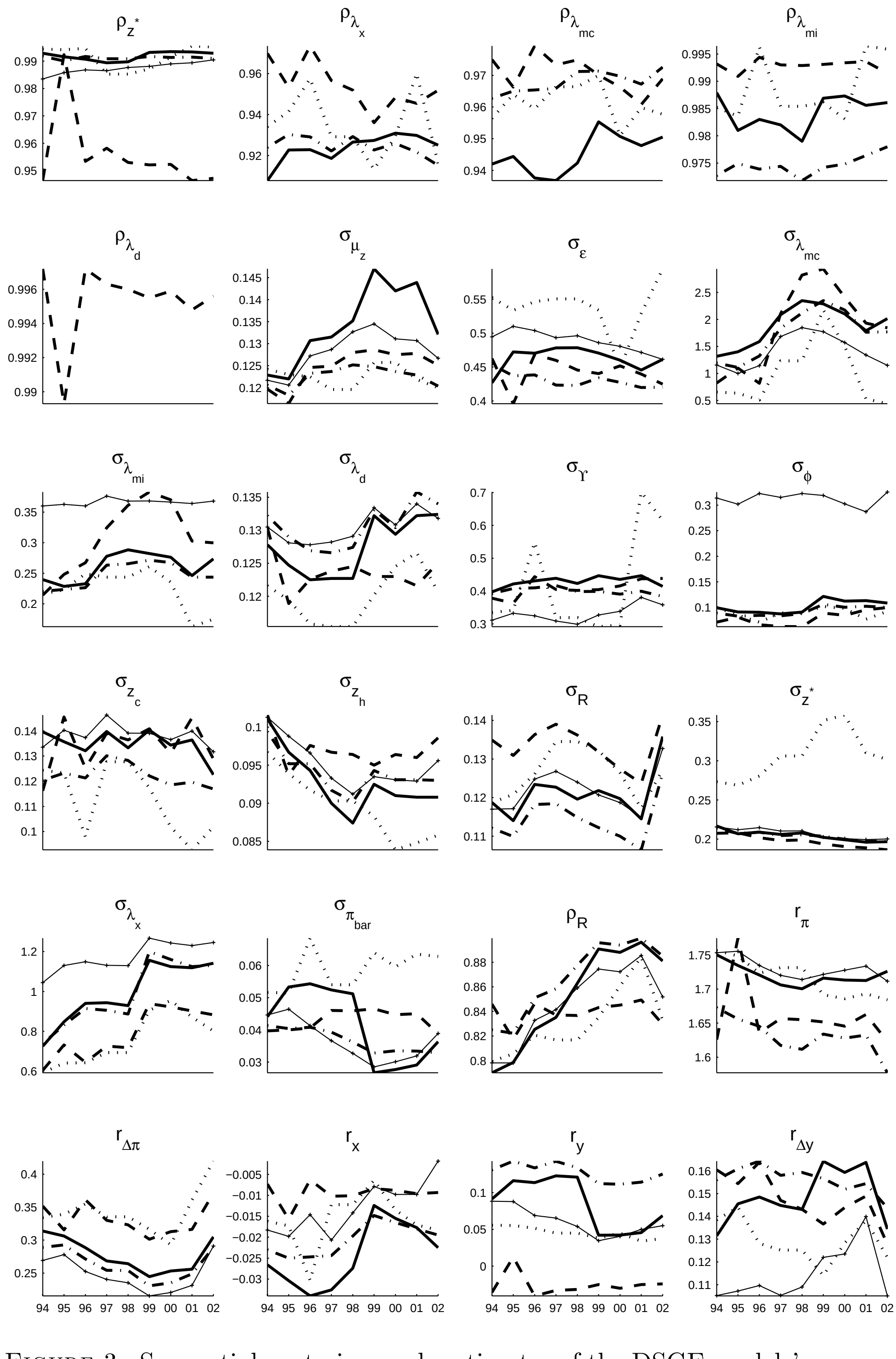

FIGURE 3. Sequential posterior mode estimates of the DSGE models' parameters using a year-by-year extended data set. DSGE diff. (—), DSGE coint. (· · ·), Corr. mkup. (- - -), Var. cap. util. (– · –) and IID Markup (–+–).

(4) Simulate an iid sequence of measurement errors $\zeta_{T+1},...,\zeta_{T+h}$ from $N(0,R)$ and compute the observed variables from the measurement equation (3.5).
(5) Repeat steps 2-4 N_1 times for the same θ.
(6) Repeat steps 1-5 N_2 times.

The above algorithm makes it clear that the uncertainty in the forecasts comes from four sources: parameter uncertainty (θ), uncertainty about the current state (ξ_T), uncertainty about future shocks (v), and measurement errors (ζ). One way to quantify the size of these four sources is by decomposing the h-step ahead forecast covariance matrix $Cov(y_{T+h}|y^{(T)})$. To this end, we write

$$Cov(y_{T+h}|y^{(T)}) = E_T[Cov(y_{T+h}|\theta, y^{(T)})] + Cov_T[E(y_{T+h}|\theta, y^{(T)})], \tag{3.7}$$

where E_T and Cov_T denotes the expectation and covariance with respect to the posterior of θ at time T, $p_T(\theta)$. The first term $E_T[Cov(y_{T+h}|\theta, y^{(T)})]$ represents the average uncertainty in the forecast when parameters are assumed to be known. The second term $Cov_T[E(y_{T+h}|\theta, y^{(T)})]$ therefore represents the additional uncertainty that comes from parameter uncertainty. It is straightforward to show that

$$E(y_{T+h}|\theta, y^{(T)}) = H'F^h\hat{\xi}_{T|T} + C'x_{T+h}. \tag{3.8}$$

We now decompose the first term of (3.7) further as

$$Cov(y_{T+h}|\theta, y^{(T)}) = H'F^hP_{T|T}(F^h)'H + H'[\textstyle\sum_{i=1}^h F^{i-1}Q(F^{i-1})']H + R. \tag{3.9}$$

The first term of $Cov(y_{T+h}|\theta, y^{(T)})$ comes from not knowing the current state ξ_T at time T. The second term of represents shock uncertainty and the last term is the covariance matrix of the measurement errors. Inserting (3.8) and (3.9) in (3.7) thus gives us the following decomposition of the h-step ahead prediction covariance matrix

$$\begin{aligned} & Cov(y_{T+h}|y^{(T)}) \\ = \; & E_T[H'F^hP_{T|T}(F^h)'H] + E_T\left\{H'[\textstyle\sum_{i=1}^h F^{i-1}Q(F^{i-1})']H\right\} + R + Cov_T(H'F^h\hat{\xi}_{T|T} + C'x_{T+h}) \\ = \; & \xi_T\text{-uncertainty} + v\text{-uncertainty} + \zeta\text{-uncertainty} + \theta\text{-uncertainty}. \end{aligned}$$

These four components of $Cov(y_{T+h}|y^{(T)})$ may be estimated by averaging over the posterior draws in the usual simulation consistent way. Figure 4 displays the relative contribution to the observed variables' predictive variance (diagonal elements of $Cov(y_{T+h}|y^{(T)})$) from the four different sources in the benchmark DSGE model. It is apparent from Figure 4 that v-uncertainty dominates, especially at longer forecast horizons, but for some variables the ξ_T-uncertainty is substantial at shorter horizons. It is also seen that parameter uncertainty contributes only a tiny part of the total forecast uncertainty.

4. Alternative forecasting models

The DSGE model is compared to several vector autoregressive (VAR) models, using both maximum likelihood estimates of the parameters and Bayesian posterior distributions. In addition, naïve forecasts based on univariate random walks as well as the means of the most recent data observations are calculated.

The VAR systems consist of either seven or thirteen variables, with trending variables modelled in first differences. The first is a closed economy specification composed of the seven domestic variables: the domestic inflation rate, the short-run interest rate, employment, consumption, investment, GDP, and the real wage. The second is an open economy specification which additionally includes exports, imports, the real exchange rate, foreign inflation, the foreign interest rate, and foreign output. Note that the consumption and investment deflators

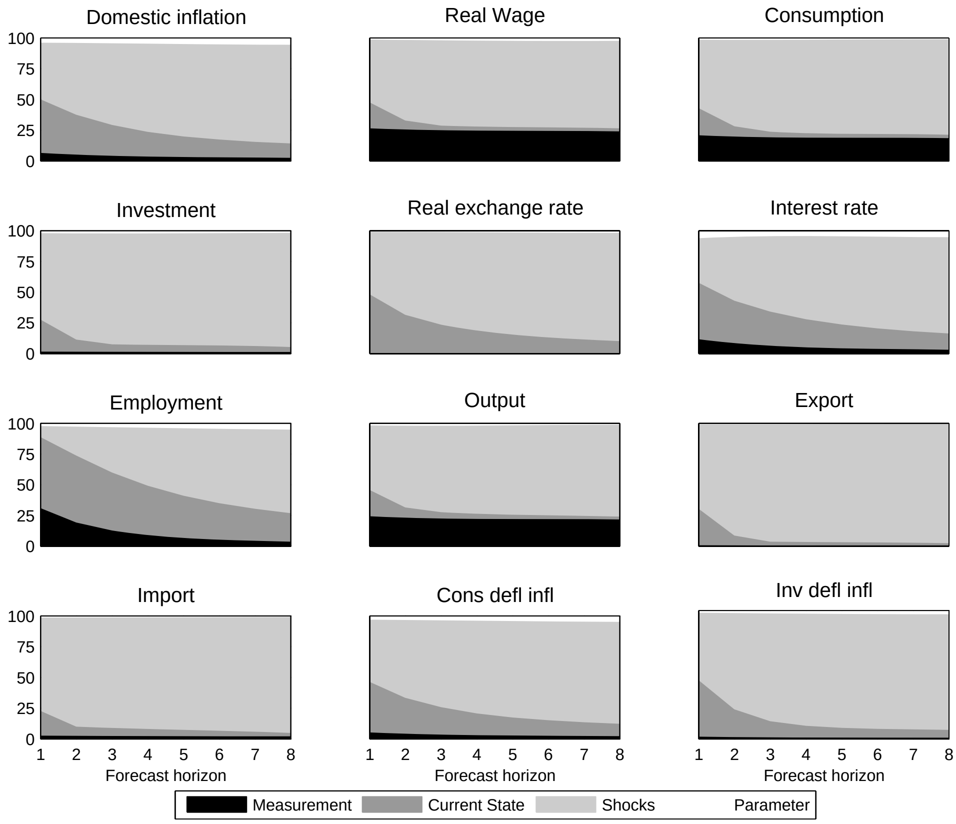

FIGURE 4. Decomposition of the forecast uncertainty. The subgraphs display the relative contribution to the predictive variances of the observed variables at different forecast horizons.

have been excluded in the VARs for reasons of parsimony. We will consider both VAR models where the trending variables are modelled in first differences and VECM models with the DSGE model's cointegration restrictions imposed on the cointegrating space. Estimating the VARs in first differences may suffer from misspecification since we do not allow for any cointegration vectors. However, if the cointegrating relations are not stable over time, differencing may play a robustifying role, see e.g. Clements and Hendry (1998).

The usual parametrization of the VAR model reads

$$\Pi(L)y_t = \Phi d_t + \varepsilon_t, \tag{4.1}$$

where y_t is a p-dimensional vector of time series, $\Pi(L) = I_p - \Pi_1 L - ... - \Pi_k L^k$, and L the usual back-shift operator with the property $Ly_t = y_{t-1}$. The disturbances $\varepsilon_t \sim N_p(0, \Sigma)$, $t = 1, ..., T$, are assumed to be independent across time. $d_t = (1, d_{MP,t})'$ is a vector of deterministic variables. As noted in Section 2, the DSGE model embodies a time-varying inflation target which enables it to capture the downward shift in the nominal variables over the sample period. In the VAR, we approximate this by including the following dummy variable in the model

$$d_{MP,t} = \begin{cases} 1 \text{ if } t \leq t^* \\ 0 \text{ if } t > t^* \end{cases},$$

where t^* is set to $1992Q4$ based on the posterior distribution of t^* presented in Villani (2005).

A problem with the standard VAR representation in (4.1) is that the unconditional mean, $\mu_y = E(y_t)$, of the process is given by a non-linear function of the model's parameters. This makes it difficult to specify a prior on the VAR-coefficients which implies a reasonable prior distribution on μ_y. This has in turn consequences for the forecasting performance since the long run forecasts from a stationary process converge to μ_y. Moreover, the lack of a decent prior on the unconditional mean in the VAR makes the comparison with the DSGE model unbalanced as the DSGE model enjoys the benefit of having a well defined prior on its steady state. We will therefore also consider an alternative parametrization of the VAR model of the form

$$\Pi(L)(y_t - \Psi d_t) = \varepsilon_t. \tag{4.2}$$

This somewhat non-standard parametrization of the VAR model in (4.2) is non-linear in its parameters, but has the advantage that the unconditional mean, or steady state, of the process is directly specified by Ψ as $\mu_y = \mathrm{E}_0(y_t) = \Psi d_t$. This allows us to put the BVAR and DSGE models more on par by using a prior on the steady state of the BVAR which is comparable to the steady state prior used in the DSGE models. To formulate a prior on Ψ, note that the specification of d_t implies the following parametrization of the unconditional mean

$$\mathrm{E}_0(y_t) = \begin{cases} \psi_1 + \psi_2 & \text{if } t \leq 1992Q4 \\ \psi_1 & \text{if } t > 1992Q4 \end{cases},$$

where ψ_i is the ith column of Ψ. The prior on ψ_1 thus determines the steady state in the second regime. The elements in Ψ are assumed to be independent and normally distributed *a priori*. The 95% prior probability intervals for the yearly steady state growth rates are given in Table 2. We will refer to specifications (4.1) and (4.2) as the BVAR and MBVAR (mean-adjusted Bayesian VAR), respectively.

The prior proposed by Litterman (1986) will be used on the dynamic coefficients in Π, with the following default values on the hyperparameters: overall tightness is set to 0.3, cross-equation tightness to 0.2 and a harmonic lag decay with a hyperparameter equal to one. See Litterman (1986) and Doan (1992) for details. Litterman's prior was designed for data in levels and has the effect of shrinking the process towards the univariate random walk model. We therefore modify the original Litterman prior by setting the prior mean on the first own lag to zero for all variables in growth rates. The two interest rates, employment and the real exchange rate are assigned a prior which centers on the AR(1) process with a coefficient on the first lag equal to 0.9. In all VAR models we impose the small open economy restriction that the foreign variables are exogenously given, i.e., block exogenity of (π_t^*, y_t^*, R_t^*). Finally, the usual non-informative prior $|\Sigma|^{-(p+1)/2}$ is used for Σ.

Table 2: 95% prior probability intervals of Ψ

	π	$\triangle w$	$\triangle c$	$\triangle i$	R
ψ_1	$(1.54, 2.33)$	$(2.02, 2.83)$	$(2.02, 2.83)$	$(2.02, 2.83)$	$(4.93, 6.39)$
ψ_2	$(4, 7)$	$(-0.05, 0.05)$	$(-0.05, 0.05)$	$(-0.05, 0.05)$	$(3, 5)$
	$\widehat{E}$	Δy	x	$\Delta\widetilde{X}$	$\Delta\widetilde{M}$
ψ_1	$(-10, 10)$	$(2.02, 2.83)$	$(-10, 10)$	$(2.02, 2.83)$	$(2.02, 2.83)$
ψ_2	$(-0.05, 0.05)$	$(-0.05, 0.05)$	$(-0.05, 0.05)$	$(-0.05, 0.05)$	$(-0.05, 0.05)$
	Δy^*	π^*	R^*		
ψ_1	$(2.02, 2.83)$	$(1.54, 2.33)$	$(4.93, 6.39)$		
ψ_2	$(-0.05, 0.05)$	$(4, 7)$	$(3, 5)$		

Note: The prior on the steady state is specified in terms of yearly rates for the domestic and foreign inflation and interest rates (π, R, π^*, R^*) and in yearly growth rates for all real variables except employment and the real exchange rate (i.e., Δw, Δc, Δi, Δy, $\Delta\widetilde{X}$, $\Delta\widetilde{M}$, and Δy^*).

The posterior distribution of the model parameters and the forecast distribution of the endogenous variables are computed numerically using the Gibbs sampling algorithm in Kadiyala and Karlsson (1997) for the parameterization in (4.1) and the Gibbs sampler in Villani (2005) for the specification in (4.2).

To sum up, we analyze two different VAR-systems (7 and 13 variables) with 1 to 4 lags. Both VAR systems are analyzed in first differences for the real variables as well as using a VECM representation with the cointegration vectors taken from the DSGE model. For each of these models, we employ two different specifications of the deterministic part of the process, given by eq. (4.1) and eq. (4.2), respectively. In addition to this we also estimate the 7- and 13-variables system with maximum likelihood. To save space we choose only to report the results from models with four lags in the 7-variable systems and, for reasons of parsimony, with two lags in the 13-variable models. However, the forecasting results are similar across lag lengths. All VAR systems are estimated on data beginning in $1980Q1$.

5. Evaluating Forecast Accuracy on Euro Area Data 1994Q1-2002Q4

5.1. **The rolling forecast evaluation scheme.** The performance of the forecasting models will be assessed using a standard rolling forecast procedure where the models' parameters are estimated using data up to a specified time period T where the dynamic forecast distribution of $x_{T+1}, ..., x_{T+h}$ is computed. The estimation sample is then extended to include the observed data at time $T+1$ and the dynamic forecast distribution of $x_{T+2}, ..., x_{T+h+1}$ is computed. This is prolonged until no data are longer available to evaluate the one-step ahead forecast. Notice that the VARs are re-estimated at a quarterly frequency while the DSGE models are re-estimated only yearly. We start the rolling forecasts in $1993Q4$, with the first out-of-sample forecast produced for $1994Q1$. The final estimation period is $2002Q3$ which provides one 1-step ahead forecast to be evaluated against the final data point in our sample which is dated $2002Q4$. We consider the forecast horizons 1 to 8 quarters ahead. This gives us 36 hold-out observations for the 1-step ahead forecast and 28 observations on the longest horizon.

5.2. **Point forecasts - a univariate view.** Figure 5 shows the root mean squared forecast errors (RMSE) in yearly percentage terms at 1 to 8 quarters horizon from the baseline DSGE model, two VAR systems (open and closed economy specifications), and two naïve setups (univariate random walk and the mean of the eight most recent data observations). The mean absolute forecast errors (MAE) give similar results and to save space we have chosen only to report the RMSEs. We see from the figure that the DSGE model does very well in terms of forecasts on the real exchange rate, exports and imports, at both short and long horizons, suggesting that the open-economy aspects of the DSGE model are satisfactory modeled. The DSGE model also seems to project consumption, employment, and the consumption deflator inflation very well. For output and domestic inflation the DSGE model does slightly better forecasts than the MBVARs at shorter horizons (1 and 2 quarters) but looses somewhat in the medium run. Note also that the one- and two-step-ahead forecasts from the DSGE model beat the random walk for most variables with the exception of the real wage, the interest rate and the investment deflator inflation. In addition, the DSGE model's forecasts outperform those of the MLVAR model on most variables and horizons. However, at the eight quarter horizon the baseline DSGE model's forecast error for domestic inflation is a lot larger compared to the ones for the two Bayesian VAR systems. The DSGE model misses with about 1.25% on average while the forecast errors for domestic inflation in the MBVARs stay around 0.65%. It should be noted that the long-run properties of the DSGE and MBVARs are similar since the latter has a prior on the unconditional mean that is comparable to the steady state prior in the DSGE model. It is thus not obvious that the DSGE model's theoretical structure should matter more in the long run, and therefore has an advantage over the MBVARs in the forecasting performance at those particular horizons.

Figure 6 depicts the RMSEs for the four different specifications of the DSGE model estimated with data in first differences, together with the benchmark specification estimated with the DSGE model's cointegration restrictions imposed. The figure shows that the accuracy of the domestic inflation forecasts from the baseline DSGE model is a lot worse than the ones generated by the DSGE model with correlated markup shocks, which in turn is more in line with the MBVAR evidence. The problem is that the baseline model on average overpredicts both inflation and the real wage more often at longer horizons than the model with correlated markup shocks (not shown). By way of some simple experiments, we found that the main reason for this is the higher price stickiness parameter in the baseline DSGE which induces more inflation inertia than the model with correlated markup shocks. The baseline DSGE model consequently has more difficulties capturing upturns and downturns in the inflation series than, for example, the model with correlated markup shocks.[9]

Note also that imposing the model's cointegration restrictions in the estimation on the baseline specification leads to inferior forecasting performance on almost all variables and horizons (see Figure 6). One explanation for this behavior is that the cointegrating relations implied by the DSGE model display a large degree of persistence during the sample period. In order to capture this feature of the data, the cointegration model is estimated to have both more intrinsic persistence (i.e., larger nominal frictions) and a higher correlation in the exogenous shock processes, compared to the baseline model estimated on data in first differences (see Table 1). This in turn causes the cointegration model to generate more persistent forecasts, which are generally not a feature of the actual outcome in the forecasting evaluation period where, for example, inflation is consistently low and less persistent than in the earlier part of the sample. A similar, but not as dramatic, deterioration in forecasting performance is obtained also in the VARs when the DSGE's cointegrating relations are included in the model (compare the RMSE from the BVAR and the BVECM in Figure 7). Including highly persistent

[9]However, also other parameters contribute to the inflation persistence, such as a higher wage indexation and larger responses to the output gap in the monetary policy rule (cf. Table 1).

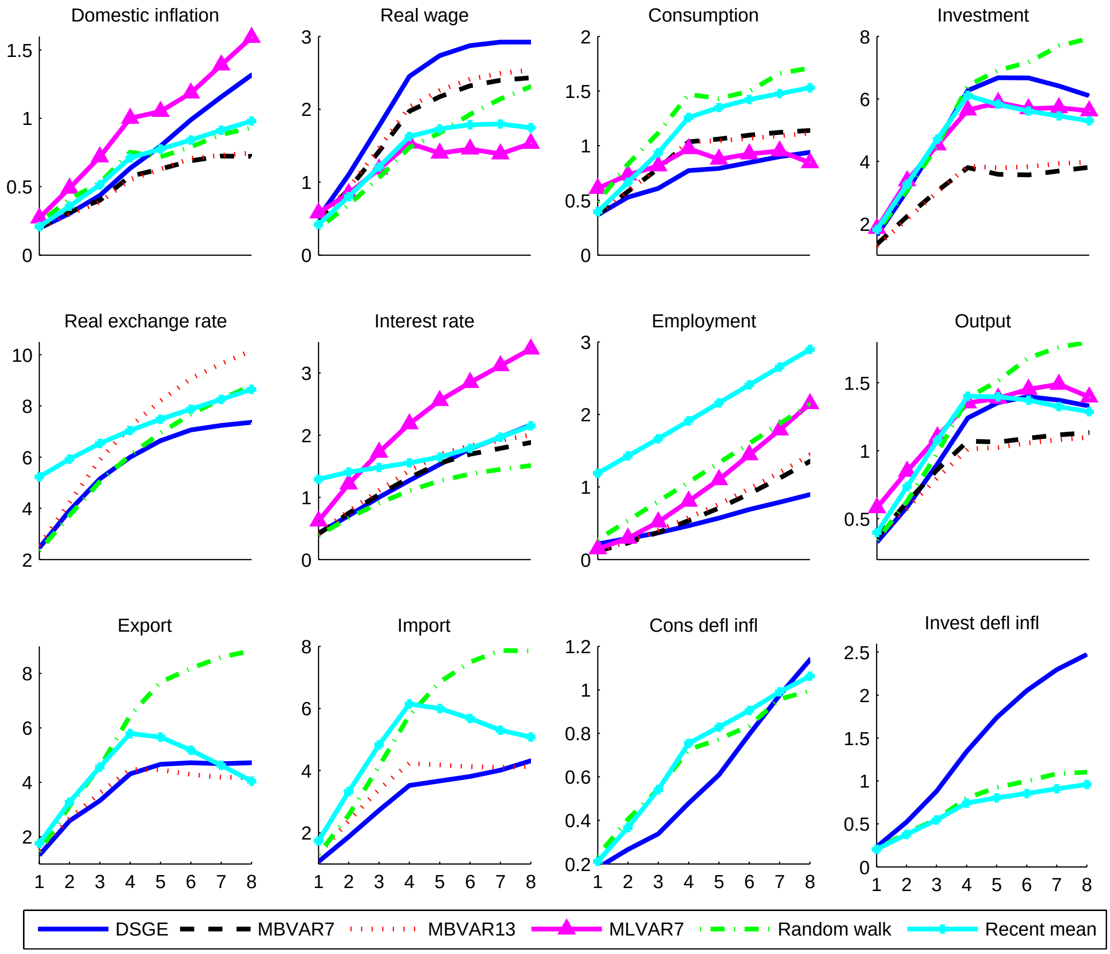

FIGURE 5. Root mean squared forecast errors for a subset of the models.

cointegrating restrictions in a first difference VAR is expected to be less problematic than imposing cointegration in the DSGE estimation as the VAR model always has the possibility to exclude a possibly inappropriate (non-stationary) cointegrating relation by estimating the adjustment coefficients to be close to zero.

In Figure 7 we display the RMSEs for the various VAR systems. We see that the MBVARs with a prior on the steady state seems to do better in terms of the forecasts on inflation at longer horizons. On the other hand, the MBVAR models seem instead to perform worse on some of the real variables such as e.g. the real wage. The difference between the Bayesian VARs at longer horizons is to a large extent explained by the MBVARs' prior on the steady state in Table 2. The average inflation rate during the evaluation period turned out to be near the center of the steady state prior which explains the good long run forecasts of inflation from the MBVAR models. Likewise, the poor real wage forecasts are explained by the lack of correspondence between the realized real wage growth in the evaluation period and the steady state prior (compare Figure 1 and Table 2).

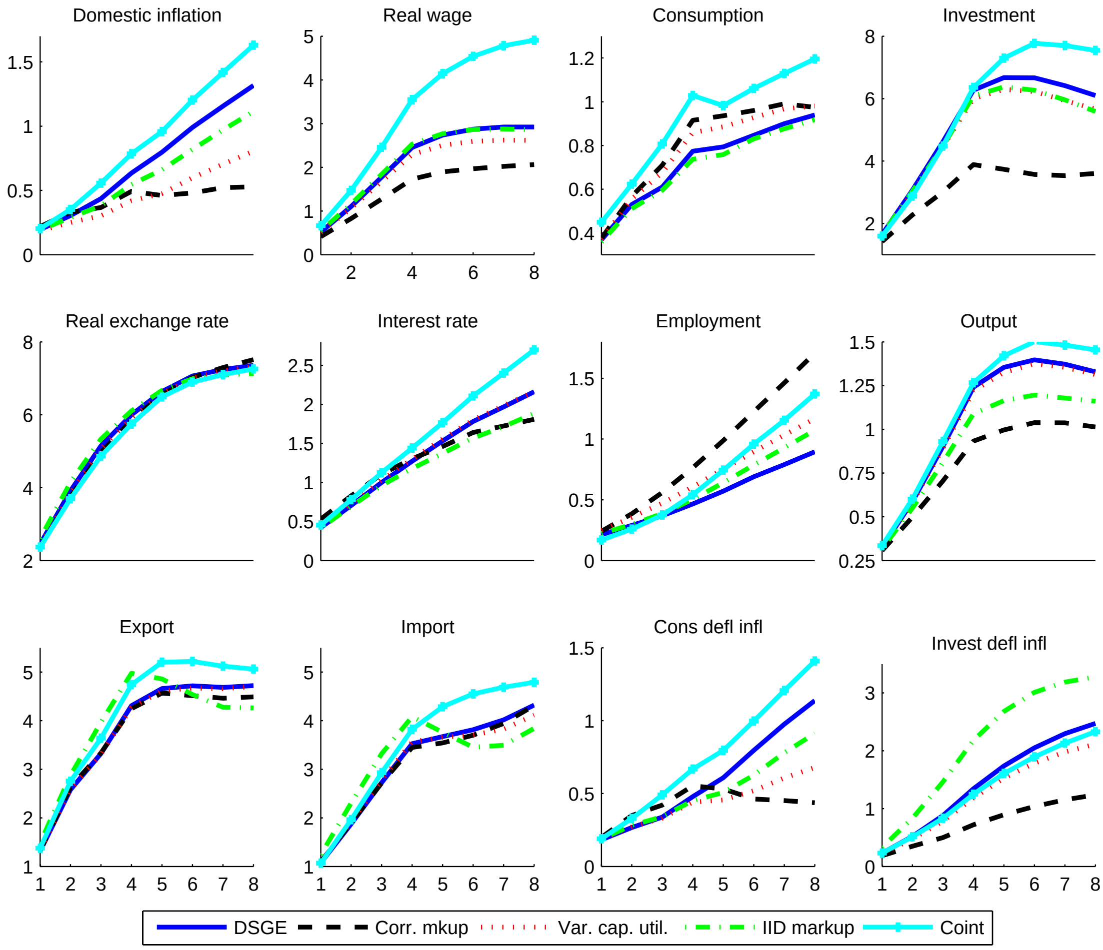

FIGURE 6. Root mean squared forecast errors for the DSGE models.

5.3. **Point forecasts - a multivariate view.** We also consider two multivariate measures of point forecast accuracy based on the scaled h-step-ahead Mean Squared Error (MSE) matrix

$$\Omega_M(h) = N_h^{-1} \sum_{t=T}^{T+N_h-1} \tilde{e}_t(h)\tilde{e}'_t(h), \tag{5.1}$$

where $\tilde{e}_t(h) = M^{-1/2}e_t(h)$, $e_t(h)$ is the h-step-ahead forecast error vector from the forecast produced at time t, M is a positive definite scaling matrix, and N_h is the number of evaluated h-step-ahead forecasts. Commonly used scalar valued multivariate measures of point forecast accuracy are the log determinant statistic $\ln|\Omega_M(h)|$ and the trace statistic $\mathrm{tr}[\Omega_M(h)]$. Note the relations $\ln|\Omega_M(h)| = \ln|\Omega_I(h)| - \ln|M|$ and $\mathrm{tr}[\Omega_M(h)] = \mathrm{tr}[M^{-1}\Omega_I(h)]$, so that the log determinant statistic is invariant to the choice of scaling matrix, whereas the trace statistic is not. Because of this, and to simplify the interpretation of the trace statistic, we set M equal to a diagonal matrix with the sample variances of the time series based on data from $1993Q1-2002Q4$ as diagonal elements. With M equal to a diagonal matrix, the trace statistic reduces to a simple weighted average of the MSEs of the individual series.

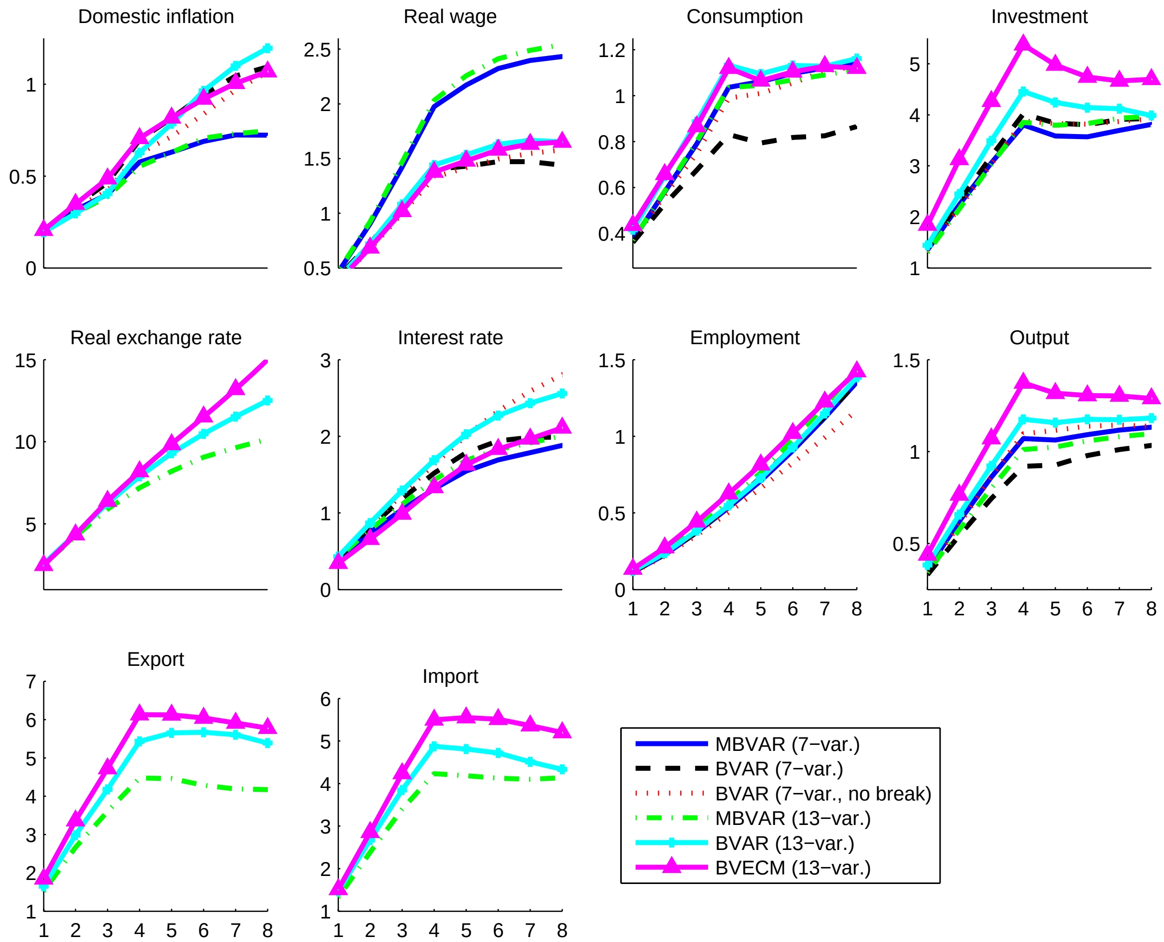

FIGURE 7. Root mean squared forecast errors for the VAR models.

Table 3 shows the log determinant and the trace of the MSE matrix (the log predictive score statistic will be discussed in Section 5.5). In order to be able to compare the multivariate measures across the different models, we have in the first set chosen to include only the variables that are common to all models. The first set of multivariate measures are therefore based on the matrix of forecast errors from domestic inflation, the real wage, consumption, investment, employment, the interest rate and output. According to both the log determinant and the trace statistics, the Bayesian VAR models appear overall to have better accuracy on the one and four quarter ahead forecasts than the ones generated from the different DSGE specifications. However, at the 8 quarter horizon the forecasts from the DSGE model outperforms those of the BVARs, at least judging from the log determinant statistic.

The RMSE results in Figures 5-7 appear incompatible with the multivariate measures in Table 3. As an example, the substantially worse multivariate performance of the DSGE models at the one quarter horizon is hard to understand simply by looking at the univariate RMSEs. To investigate the multivariate measures in more detail we perform a singular value decomposition of Ω (M and h is dropped here for notational convenience): $\Omega = V\Lambda V'$,where $V = (v_1, ..., v_k)$, $V'V = I_k$, is the matrix of eigenvectors, Λ=diag$(\lambda_1, \lambda_2, ..., \lambda_k)$ is the diagonal matrix with eigenvalues in descending order. The eigenvalues are the variances of the

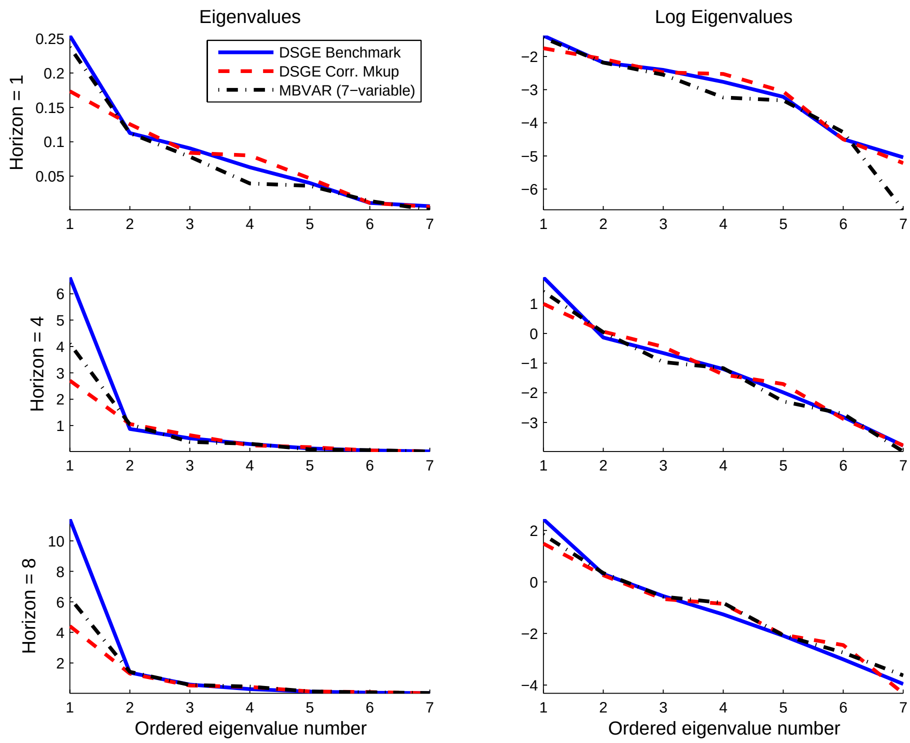

FIGURE 8. Eigenvalues (left column) and log of eigenvalues (right column) of the MSE matrix at different horizons.

principal components $y_{i,t} = v_i'\tilde{e}_t$. λ_1 (λ_k) is thus the variance of the least (most) predictable linear combination of the time series. Since $\ln|\Omega| = \sum_{i=1}^{k} \ln\lambda_i$ and $\mathrm{tr}(\Omega) = \sum_{i=1}^{k} \lambda_i$, it is clear that $\mathrm{tr}(\Omega)$ will to a large extent be determined by the forecasting performance of the least predictable dimensions (largest eigenvalues), whereas $\ln|\Omega| = \sum_{i=1}^{k} \ln\lambda_i$ also takes into account the most predictable dimensions (smallest eigenvalues), sometimes to the extent of being dominated by them. To see the latter point, note that as $\lambda_k \to 0$ we have $\mathrm{tr}(\Omega) \to \sum_{i=1}^{k-1} \lambda_i$, but $\ln|\Omega| \to -\infty$, for any values of λ_i, $i = 1, ..., k-1$.

Figure 8 displays the eigenvalues of the MSE matrix, both on original and log scale, at the 1, 4 and 8 quarter horizons for four of the models. The log determinant statistic equals the sum of the log eigenvalues of the MSE matrix. It is therefore clear from the right column of Figure 8 that the large difference in forecasting performance between the DGSEs and BVARs captured by this statistic at the first quarter horizon is driven by the smallest eigenvalue. The DSGE models inferior forecast performance at the one quarter horizon therefore comes from their inability to predict those variables which account for the major part of the last principal component at the shortest horizon. Looking at the subgraphs in the right column of Figure 9, which depicts the relative weight on the variables in the eigenvector with smallest eigenvalue (v_{jk}^2 for the jth variable), it is clear that this principal component at the shorter horizons is essentially the forecast errors of the employment series. The one-quarter ahead RMSEs of the employment series in Figure 5 are small for all models, but the relative difference between the DSGE models and the BVARs are substantial: the RMSE of employment at the first horizon in the benchmark DSGE is almost twice those of the two BVARs. Since the log determinant measure is very sensitive to the performance on the most predictable dimensions, this minor

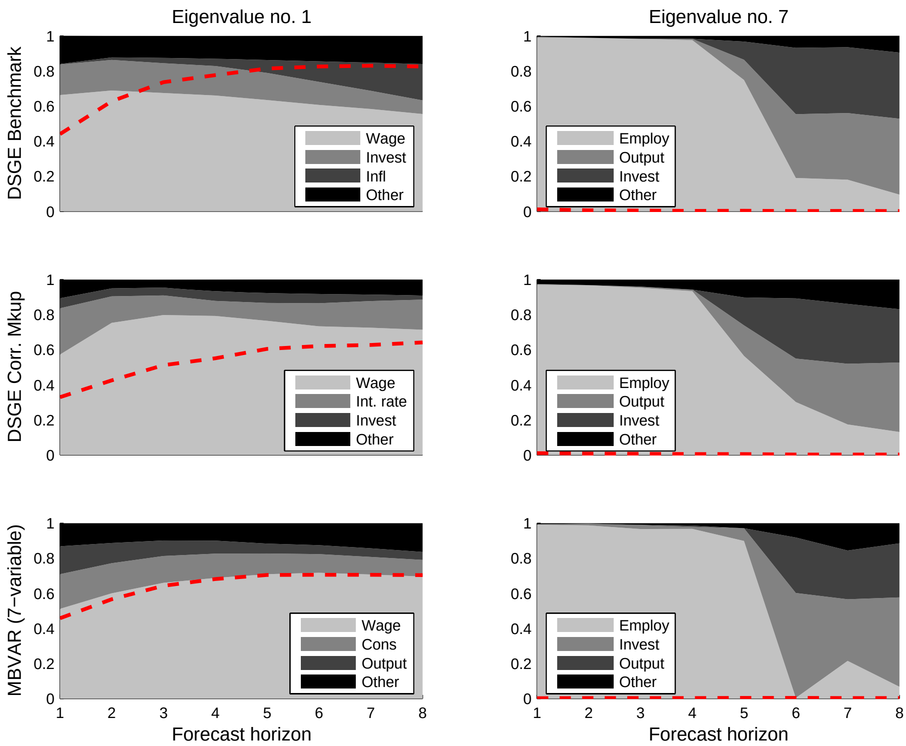

FIGURE 9. Relative contribution to the smallest and largest eigenvalue of the MSE matrix (square of the elements in the eigenvector). The superimposed dashed line depicts the percentage of total variation explained by the eigenvector, $\lambda_i / \sum_{j=1}^{k} \lambda_j$ where λ_i is the ith largest eigenvalue.

difference between the models receives a very large weight in the log determinant measure. Note also that the forecast errors of employment is still the driving force of the smallest eigenvalue at horizon 4 (see Figure 9), but here the difference in log determinant statistic across models is no longer dominated by this eigenvalue (see Figure 8). At the four quarter horizon it is mainly the largest eigenvalue which is dominating the comparison. The determinants of this eigenvector are given in the left hand column of Figure 9. The relatively good multivariate performance of the DSGE model with correlated markup shocks and the seven variable BVAR is in part explained by the fairly large weight on real wage, a variable which these two models predict more accurately than the benchmark DSGE. Finally, on the eight quarter horizon the picture is more complicated, but the poor performance of the benchmark DSGE on the long run forecasts of the real wage (which drives the largest eigenvalue, see Figure 9) is more than compensated by its good forecasts of the variables contributing to the smallest eigenvalues.

Since the multivariate measures run the risk of being dominated by a specific variable which may be of minor interest (e.g., employment), Table 3 also shows the log determinant and trace of the MSE matrix from two other sets of variables. One is based on the forecast errors of domestic inflation, output and the interest rate, and another on these three variables together with the real exchange rate, exports and imports. Looking only at the three domestic variables it appears as if the DSGE models have a better chance of replicating the forecasting performance of the BVARs also at shorter horizons. The same holds true when adding the performance in terms of the open economy variables (i.e., the real exchange rate, exports and

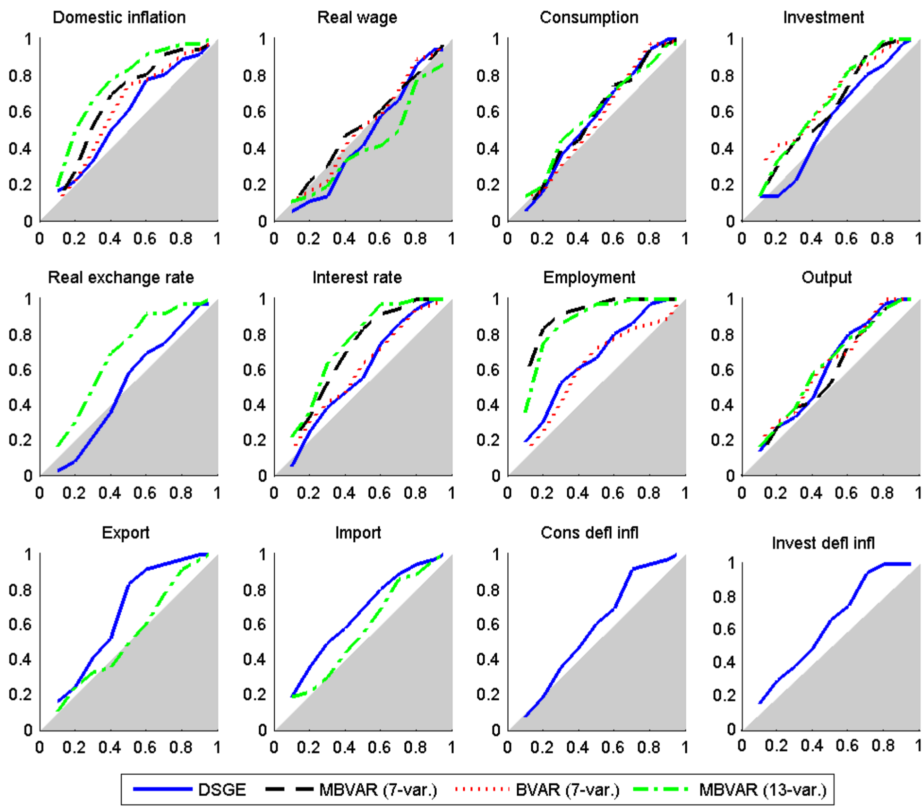

FIGURE 10. Empirical coverage probability, DSGE and BVARs, 1 quarter horizon.

imports) to these three variables. Both the log determinant and the trace statistic indicate that the DSGE models have better forecast accuracy for this set of variables on the 1, 4 and 8 quarter horizons.

5.4. **Interval forecasts.** A forecast interval[10] is said to be well calibrated if the long run relative frequency of realized observations included in the forecast interval equals the pre-specified coverage probability of the interval (Dawid, 1982). Formally, define the sequence of hit indicators of an h-step-ahead forecast interval with coverage probability as

$$I_t^\alpha(h) = \begin{cases} 1 \text{ if } x_t \in [L_t^\alpha(h), H_t^\alpha(h)] \\ 0 \text{ if } x_t \notin [L_t^\alpha(h), H_t^\alpha(h)] \end{cases}$$

where $L_t^\alpha(h), H_t^\alpha(h)$ are the lower and upper limits of the interval at time t. The relative frequency of interval hits in the evaluation sample, $\hat{\alpha}_h = N_h^{-1} \sum_{t=T}^{T+N_h-1} I_t^\alpha(h)$, may then be compared to the pre-specified coverage rate α.

Figure 10 shows the accuracy of the one quarter ahead forecast intervals in terms of the empirical coverage probabilities for the baseline DSGE model and three BVAR specifications. The horizontal axis depicts the (intended) coverage probability of the interval and the vertical axis the empirical coverage rate obtained in the hold-out sample. The ideal forecasting model

[10]There are many ways to construct a forecast interval with predetermined coverage probability, e.g. highest posterior density (HPD) intervals. We shall here restrict attention to forecast intervals with equal tail probabilities.

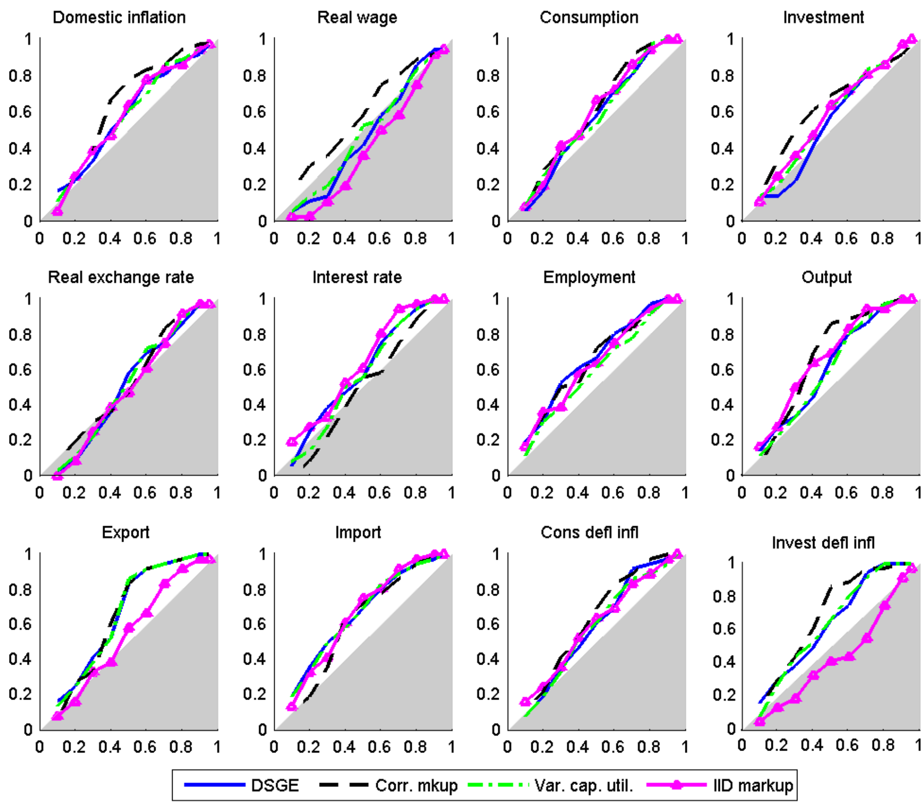

FIGURE 11. Empirical coverage probability, DSGE , 1 quarter horizon.

should thus have an empirical coverage rate which is located on the 45 degree line.[11] The empirical coverage probabilities of the forecast intervals for the DSGE model and the BVAR model are rather equal across variables, with a few exceptions. The MBVARs tend to deliver too wide forecast intervals for most variables.

A more formal analysis of the accuracy of forecast intervals may be based on the observation that the hit sequence from a correct one step-ahead forecast interval follows an iid Bernoulli process with success probability. Christoffersen (1998) suggests using asymptotic likelihood ratio tests to test the Bernoulli hypothesis against several alternatives. As a Bayesian alternative to these tests we compute posterior probabilities of the following three hypotheses

$$\begin{aligned} H_0 &: \quad \{I_t^{\alpha}(1)\}_{t=T+1}^{T+N_1} \overset{iid}{\sim} Bern(\alpha) \\ H_1 &: \quad \{I_t^{\alpha}(1)\}_{t=T+1}^{T+N_1} \overset{iid}{\sim} Bern(\pi) \\ H_2 &: \quad \{I_t^{\alpha}(1)\}_{t=T+1}^{T+N_1} \sim Markov(\pi_{01}, \pi_{11}), \end{aligned} \tag{5.2}$$

where π in H_1 and π_{01}, π_{11} in H_2 are estimated freely. The notation $Markov(\pi_{01}, \pi_{11})$ is here used to denote a general two-state Markov chain with transition probabilities $\pi_{01} = \Pr(0 \to 1)$ and $\pi_{11} = \Pr(1 \to 1)$. If H_0 is supported, the forecast intervals are correct, both in terms

[11]The one-step ahead empirical coverage probabilities are based on 36 hit indicators. The uncertainty in estimating percentiles of the predictive density is expected to be fairly large, especially in the tail of the distribution, and the exact numbers in Figure 10 should therefore not be over-emphasized.

of coverage and independence of interval hits. If data supports H_1, the hit indicators are independent, but do not generate the intended coverage α. A large posterior probability of H_2 suggests a violation of the independence property of the interval. Note that even if H_2 receives the largest posterior probability, the coverage of the interval may still be correct. Whether or not the interval has the correct coverage when the evidence is in favor of H_2 is indicated by the relative distribution of the remaining probability mass on H_0 and H_1.[12]

Table 4 shows the posterior probabilities of the three hypotheses in equation (5.2) for the 70% forecast interval. From the table follows that the baseline DSGE model has most probability mass on H_0. From Table 4 also follows that the benchmark DSGE model has somewhat better calibrated forecast intervals than the other DSGE specifications. As mentioned above, the model with correlated markup shocks does a lot better in terms of the point forecast accuracy of domestic inflation at longer horizons but on 1 and 2 quarters ahead the inflation forecast accuracy in the different DSGE specifications are about the same. However, from Figure 11 follows that the inflation forecast intervals are a lot wider in the model with correlated markups than in the baseline DSGE model. The empirical coverage rate is hence too large.

Turning to the four quarter horizon we see from Figure 12 that the forecast interval accuracy of the DSGE seems to deteriorate in comparison to the BVARs. A reason for the worse properties of the DSGE model could be the internal propagation of the disturbances hitting the economy. The processes for the disturbances are generally highly correlated, which implies that the uncertainty induced by these shocks amplify over the horizon and generate wider uncertainty bands.

5.5. **Density forecasts and marginal likelihood.** In this section we move beyond the evaluation of point and interval forecast to evaluate the predictive density as a whole. A natural measure of density forecast performance is the log predictive density score (LPDS) of the h-step-ahead predictive density in the evaluation sample

$$S_h = \sum_{t=T}^{T+N_h-1} \log p_t(y_{t+h}).$$

Note that

(5.3)

$$S_1 = \log[p_T(y_{T+1}) \cdots p_{T+N_1-1}(y_{T+N_1})] = \log[p_T(y_{T+1}, ..., y_{T+N_1})] = \log m(T+N_1) - \log m(T),$$

where

$$m(t) = p_0(y_1, ..., y_t) = \int p(y_1, ..., y_t|\theta) p_0(\theta) d\theta,$$

is the marginal likelihood of the observed data up to time t, and $p_0(\theta)$ is the prior density. It is important to note that no data are consumed to estimate the parameters of the model when

[12]The posterior probabilities of H_0, H_1 and H_2 are computed as follows. Let n_0 and n_1 denote the number of zeros and ones, respectively, in the hit sequence. Let further n_{ij} denote the number of transitions from state i to state j in the Markov chain under hypothesis H_2, so that for example n_{01} is the number of zeros in the sequence which are followed by ones. Assuming independent priors $\pi \sim Beta(\gamma, \delta)$ in H_1, $\pi_{01} \sim Beta(\gamma_{01}, \delta_{01})$ and $\pi_{11} \sim Beta(\gamma_{11}, \delta_{11})$ in H_2, the marginal likelihoods of the three hypotheses are easily shown to be

$$\begin{aligned} m_0 &= \alpha^{n_0}(1-\alpha)^{n_1} \\ m_1 &= \frac{B(n_0+\gamma, n_1+\delta)}{B(\gamma,\delta)} \\ m_2 &= \frac{B(n_{01}+\gamma_{01}, n_{00}+\delta_{01})B(n_{11}+\gamma_{11}, n_{10}+\delta_{11})}{B(\gamma_{01},\delta_{01})B(\gamma_{11},\delta_{11})}, \end{aligned}$$

where $B(\cdot,\cdot)$ is the Beta function. We will present results for uniform priors on π, π_{01} and π_{11}, i.e. we set $\gamma = \delta = \gamma_{01} = \delta_{01} = \gamma_{11} = \delta_{11} = 1$.

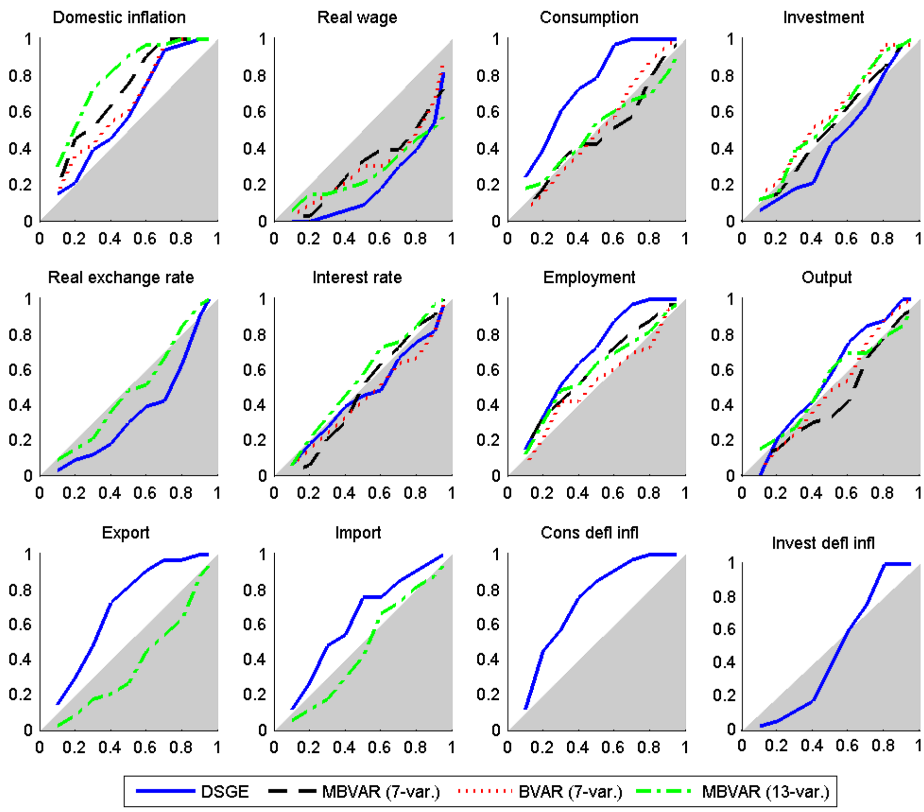

FIGURE 12. Empirical coverage probability, DSGE and BVARs, 4 quarter horizon.

computing the marginal likelihood (i.e. the prior density is used to average the likelihood values). This makes it possible to interpret the marginal likelihood as a measure of out-of-sample predictive density performance, rather than in-sample fit.

Equation (5.3) thus establishes an intimate connection between the marginal likelihood and the LPDS for the one-step-ahead forecasts. This connection breaks down for $h > 1$, however. While it *is* possible to decompose the marginal likelihood into terms which evaluate the LPDS for intermediate non-overlapping h-steps forecasts *paths*, i.e. a decomposition in terms of the form $p_t(y_{t+1}, ..., y_{t+h})$ (Geweke, 1999), it is *not* possible to decompose it in terms of the h-step-ahead forecasts densities, i.e $p_t(y_{t+h})$. This means that the marginal likelihood cannot detect that some models perform well on certain forecast horizons while other models do better on other horizons.

Computing S_h for $h > 1$ is not an easy task since $p_t(y_{t+h})$ does not have a closed form expression. One approach is to estimate $p_t(y_{t+h})$ from the predictive draws using e.g. a kernel density estimator. This is not practical unless the dimension of y_t is small, however. We shall instead assume that $p_t(y_{t+h})$ is a multivariate normal density, and estimate the mean vector and covariance matrix from the predictive sample. S_h will here be computed on yearly growth rates of the variables (with the exception of the real exchange rate and employment), as in all previously reported measures of forecasting accuracy.

The second column of Table 5 displays the marginal likelihood of the four DSGE models for the full sample $1980Q1 - 2002Q4$. This is the measure usually reported in DSGE applications.

According to this measure, the benchmark model is substantially better than the models with variable capital utilization and correlated markup shocks. The model where all markup shocks are iid has a dramatically lower marginal likelihood than the other models.[13] It is well-known that the marginal likelihood can be sensitive to the choice of prior distribution. One way around this is to use the first part of the sample to update the prior into a posterior which is subsequently used to compute the marginal likelihood of the second part of the data. The third column of Table 5 therefore presents the marginal likelihoods for the evaluation sample $1994Q1 - 2002Q4$ conditional on data up to $1993Q4$. Here the ranking of the four models has changed: the benchmark model and the model with variable capital utilization are essentially equally good, the model with correlated markup shocks is roughly two units worse on the log scale, while the model with iid markup shocks is still clearly the most inferior model.[14]

The last three columns of Table 5 show the LPDS of the four models at the $1, 4$ and 8 quarter horizons. The ranking of the four models is exactly the same for all three considered forecast horizons. The model with correlated markup shocks outperforms its competitors and the LPDS is much smaller for the model with iid markup shocks than for the other models, a results which holds for all forecast horizons. The relative differences between the LPDS of the first three models is much smaller at the 8 quarter horizon than at the 1 and 4 quarter horizons. Note that the marginal likelihood measures (column 2 and 3 in Table 5) are based on the data transformation which is used in the estimation of the model (first differences), whereas the LPDS measures use the same data transformation as in the other forecast performance measures (fourth differences). The choice of data transformation is clearly important even for the relative ranking of the model, as judged by the differences between $\log(m_{02:4}/m_{93:4})$ and S_1 in Table 5.[15]

Table 5: Evaluating predictive densities

	$\log m(02Q4)$	$\log[m(02{:}4)/m(93{:}4)]$	S_1	S_4	S_8
DSGE, Benchmark	**-1909.34**	-802.06	-634.09	-963.75	-943.05
DSGE, var. cap. util.	-1917.39	**-801.93**	-624.73	-958.04	-940.06
DSGE, corr. markup	-1915.53	-804.11	**-619.11**	**-945.65**	**-935.54**
DSGE, iid markup	-1975.50	-816.88	-681.32	-1061.28	-1014.30

Note: Numbers in bold indicate the best model for each measure.

The LPDS reported in Table 5 is based on the full set of 15 variables. Reducing this high-dimensional set to a scalar clearly runs the risk of being dominated by (linear combinations of) variables which the end user of the forecast cares very little about (cf. the discussion of the multivariate measures of point forecast accuracy in Section 5.3). Table 3 therefore reports the LPDS for certain subsets of variables. Here the picture is less clear-cut. In the case with the three and six variable subsets, the model with correlated markup shocks is inferior to the other DSGE models at all horizons, the exception being the 1 quarter horizon for the six-variable subset. The performance of the model with iid markup shocks, which was clearly inferior

[13]The posterior probabilities on the four DSGE models are 0.9975, 0.0003, 0.002 and 0.

[14]The posterior probabilities of the four DSGE models based on the subsample $1994Q1$-$2002Q4$ are 0.441, 0.502, 0.057 and 0.

[15]There are also two other reasons for the discrepancy between the marginal likelihood (1994Q1-2002Q4) and S_1. First, S_1 is in Table 5 computed using a normal approximation of the predictive distribution. Second, S_1 is based on a posterior sample which is updated only once a year. Given the fairly good normal approximation (not shown) and the stability of the posterior distribution over the evaluation sample (see Figure 2 and 3), it is expected that these two sources account for a smaller part of the discrepancy.

to the other models when all 15 variables were evaluated, is from Table 3 seen to be more in line with the other models when it comes to predicting smaller subsets of the variables. The performance of the iid markup shock model is particularly good on the important subset containing domestic inflation, the interest rate and output growth. Moreover, the previously reported measures of forecasting performance (e.g. RMSE) do not single out the iid markup model as dramatically worse than the other DSGE models.

6. Conclusions

This paper has evaluated the forecasting performance of an open economy dynamic stochastic general equilibrium model for the Euro area against a wide range of reduced form forecasting models such as VARs, BVARs, univariate random walks and naïve forecasts based on the means of the most recent data observations.

The DSGE model performs very well in terms of univariate point forecasts on the open economy variables such as the real exchange rate, exports and imports. The RMSEs speak in favour of the DSGE model for these variables at both long and short horizons, suggesting that the open economy aspects are reasonably modeled. In terms of the domestic variables, the DSGE model also seems to forecast output, consumption and employment very well, but has some difficulty with the long run projections of domestic inflation and the real wage.

The multivariate point forecast accuracy measures, which take the joint forecasting performance of the domestic variables into account, indicate that the DSGE models give more accurate forecasts than the BVARs at the medium- to long-term horizons (4 - 8 quarters ahead).

Turning to the overall density forecast accuracy, the differences between the models appear to be relatively small. Again, the baseline DSGE model seems to produce a somewhat better multivariate forecast density at longer horizons, while the BVARs have an overall forecasting advantage predominately at shorter horizons.

A caveat with the analysis in this paper is that we are using ex post data and not real-time data. The latter could perhaps change the ranking of the models, even if the same data are used in both the DSGE and the BVAR models. Another important issue for future work is to include more shocks with permanent effects in the model. The poor forecasting performance of the DSGE when imposing the model-implied cointegration properties suggests that it would be fruitful to incorporate more shocks with long-run effects than just the unit-root shock in total factor productivity considered here.

Future work may also want to consider an even broader set of competing forecasting models, e.g. the DSGE-VARs in Del Negro and Schorfheide (2004) or the large scale dynamic factor models in Stock and Watson (1999), and Giannone, Reichlin and Sala (2004).

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Visiting address: Brunkebergs torg 11
Mail address: se-103 37 Stockholm

Website: www.riksbank.se
Telephone: +46 8 787 00 00, Fax: +46 8 21 05 31
E-mail: registratorn@riksbank.se

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