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In this paper we examine how the forecasting performance of Bayesian VARs is affected by a number of specification choices. In the baseline case, we use a Normal-Inverted Wishart prior that, when combined with a (pseudo-) iterated approach, makes the analytical computation of multi-step forecasts feasible and simple, in particular when using standard and fixed values for the tightness and the lag length. We then assess the role of the optimal choice of the tightness, of the lag length and of both; compare alternative approaches to multi-step forecasting (direct, iterated, and pseudo-iterated); discuss the treatment of the error variance and of cross-variable shrinkage; and address a set of additional issues, including the size of the VAR, modeling in levels or growth rates, and the extent of forecast bias induced by shrinkage. We obtain a large set of empirical results, but we can summarize them by saying that we find very small losses (and sometimes even gains) from the adoption of specification choices that make BVAR modeling quick and easy. This finding could therefore further enhance the diffusion of the BVAR as an econometric tool for a vast range of applications.

Keywords: Bayesian VARs, forecasting, prior specification, lag length, marginal likelihood.

JEL Classifications: C11, C13, C33, C53.

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1 Introduction

Forecasting future developments in the economy is a key element of the decision process in policy making, consumption and investment decisions, and financial planning. For example, members of the Federal Open Market Committee (FOMC) often stress (in public comments) that, because monetary policy affects the economy with a lag, policy must be forward-looking. Looking ahead means relying on forecasts of GDP growth, inflation, and other key indicators.

The Federal Reserve Bank of Cleveland, like a number of other central bank institutions, makes use of Bayesian Vector Autoregressions ($BVARs$) in forecasting. $BVARs$ have a long history in forecasting, stimulated by their effectiveness documented in the seminal studies of Doan, Litterman, and Sims (1984) and Litterman (1986). In recent years, the models seem to be used even more systematically for policy analysis and forecasting macroeconomic variables (e.g., Kadiyala and Karlsson 1997, Koop 2010). At present, there is considerable interest in using BVARs for these purposes in a large dataset context (e.g., Banbura, Giannone, and Reichlin, 2010, Carriero, Kapetanios, and Marcellino 2009, 2010a).

Putting BVARs to use in practical forecasting raises a host of detailed questions about model specification and estimation. Under some approaches, estimating and forecasting with a BVAR can be technically and computationally demanding. In general, one of the major stumbling blocks that has sometimes limited the use of $BVARs$ as models for forecasting and policy analysis has been the large computational burden they can pose, especially when Markov Chain Monte Carlo (MCMC) simulation methods are used for estimation. In many cases, such as a BVAR with a Minnesota prior patterned after Litterman's (1986) specification, technically proper estimation requires MCMC methods. In particular, in a forecasting context, the natural point forecast from a BVAR is the mean of the posterior distribution of forecasts. In many instances, the posterior mean can only be computed by MCMC (e.g., Geweke and Whiteman 2006, Kadiyala and Karlsson 1997). The development of computing power has substantially alleviated this problem. However, in general the computation of nonlinear functions of the parameters such as impulse-response functions and multi-step forecasts still requires time consuming simulations, and the computing cost is particularly relevant when these exercises are recursively conducted over a long time span, or with models including more than a handful of variables.

Other approaches can make the use of the models much easier. Accordingly, the point of this paper is to examine approaches that make the computation of point forecasts from BVARs quick and easy, for example by making specific choices on the priors and by using direct rather than iterated forecasts (e.g., Marcellino, Stock and Watson, 2006). In most cases, the resulting forecasts represent approximations to the mean of the posterior distribution, but not necessarily the actual mean. Hence, we then assess whether alternative more complex and time demanding specification choices, which lead to forecasts theoretically closer to the mean of the posterior distribution, yield gains in terms of increased forecast precision, as measured by mean squared forecast error. We also address a set of other empirically relevant related issues, such as the choice of the lag length of the BVAR and whether or not to transform the variables to get stationarity.

Since it is difficult to rank the alternative modeling and forecasting choices from a purely theoretical point of view, given that their relative performance will be determined by the unknown data generating process, we take a more practical perspective. Specifically, we consider a set of variables whose future evolution is of key interest for central banks and more generally for economic policy making, and we evaluate the performance of different BVAR modeling choices in this context. In light of recent evidence of the success of larger models relative to smaller ones and interest in large datasets (e.g., Banbura, Giannone, and Reichlin 2010), we focus on mid-size models applied to monthly data: 18-variable BVARs for U.S. data. To assess the robustness of the results, we repeat the analysis for Canada, France and the UK.

We find that simple works. For an institution or forecaster interested in a simple and effective modeling and forecasting approach, we can recommend the following specification and method: a BVAR with variables transformed to the units usually thought stationary (e.g., growth rates of output and employment); a relatively long lag length (12 with monthly data); a Normal-Wishart prior; posterior mean coefficient estimates obtained from the conventional closed-form solution associated with the Normal-Wishart prior; and point forecasts for all horizons obtained (iteratively) using the posterior mean coefficients. We can summarize our large set of empirical results by saying that we find very small losses (and sometimes even gains) from the adoption of these BVAR modeling choices that make forecast computation quick and easy. For the accuracy of point forecasts, there proves to be essentially no payoff to using MCMC methods to obtain multi-step forecasts from the posterior distribution. Similarly, there is no payoff to using a Litterman (1986) prior that is tighter for lags of other variables than for lags of the dependent variable. This finding that simple methods work well could therefore further enhance the diffusion of the BVAR as an econometric tool for a vast range of applications.

The paper is structured as follows. In Section 2 we describe the US data and the design of the forecasting exercise. In Section 3 we present the baseline case. In Section 4 we consider optimal choice of the tightness, lag length and both. In Section 5 we compare alternative approaches to multi-step forecasting. In Section 6 we discuss the treatment of the error variance and of cross-variable shrinkage. In Section 7 we address a set of additional issues, including the size of the VAR, modeling in levels or growth rates, and the extent of forecast bias induced by shrinkage. In Section 8 we summarize the results for Canada, France and the UK, comparing them with those for the US. Finally, Section 9 concludes.

2 Data and design of the forecasting exercise

Our data set for the United States has monthly frequency and runs from January 1973 to March 2010. The data include 18 macroeconomic and financial series of major interest to policymakers and forecasters. If any series are very persistent, we take the growth rates. Table 1 lists the series and their transformations in our models.

The forecasting exercise is performed in pseudo real time, i.e. we never use information which is not available at the time the forecast is made. For all models, we use a recursive estimation window. We have data starting from 1973:1, but after differencing the first observation is missed. Moreover, as we plan to compare models featuring up to 12 lags, we start with the estimation sample 1974:2 to 1985:12 in order to have the same number of data points for each model. We produce forecasts for all the horizons up to 12-step ahead; for a horizon of h periods, the first available forecast is for 1986:1 + $h - 1$. Our last estimation sample is 1974:2 to 2009:3, yielding a forecast for horizon h for date 2009:4 + $h - 1$.

We evaluate our results in terms of Root Mean Squared Forecast Error ($RMSFE$) for a given model. Let $\hat{y}^{(i)}_{t+h}(M)$ denote the forecast of the i-th variable $y^{(i)}_{t+h}$ made by model M. The $RMSFE$ made by model M in forecasting the i-th variable at horizon h is:

$$RMSFE^{M}_{i,h} = \sqrt{\frac{1}{P}\sum\left(\hat{y}^{(i)}_{t+h}(M) - y^{(i)}_{t+h}\right)^2} \tag{1}$$

where the sum is computed over all the P forecasts produced.

3 Baseline case

3.1 Baseline specification

The baseline specification, against which we will compare alternative modeling choices, is a standard $BVAR$ with Normal-Inverted Wishart (N-IW) conjugate prior. Given N different variables grouped in the vector $y_t = (y_{1t}\ y_{2t}\ ...\ y_{Nt})'$, we consider the following Vector Autoregression (VAR):

$$y_t = \Phi_c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + ... + \Phi_p y_{t-p} + \varepsilon_t;\ \varepsilon_t \sim i.i.d.N(0, \Sigma), \tag{2}$$

where $t = 1, ..., T$. Each equation has $M = N \times P + 1$ regressors. By grouping the coefficient matrices in the $M\times\ N$ matrix $\Phi = [\Phi_c\ \Phi_1\ ...\ \Phi_p]$ and defining $x_t = (1\ y'_{t-1}\ ...\ y'_{t-p})'$ as a vector containing an intercept and p lags of y_t, the VAR can be written as:

$$y_t = \Phi x_t + \varepsilon_t. \tag{3}$$

An even more compact notation is:

$$Y = X\Phi + E, \tag{4}$$

where $Y = [y_1, .., y_T]'$, $X = [x_1, .., x_T]'$, and $E = [\varepsilon_1, .., \varepsilon_T]'$ are, respectively, $T \times N$, $T \times M$ and $T \times N$ matrices.

We use the conjugate N-IW prior:

$$\Phi|\Sigma \sim N(\Phi_0, \Sigma \otimes \Omega_0), \; \Sigma \sim IW(S_0, v_0). \tag{5}$$

As the N-IW prior is conjugate, the conditional posterior distribution of this model is also N-IW (Zellner 1973):

$$\Phi|\Sigma, Y \sim N(\bar{\Phi}, \Sigma \otimes \bar{\Omega}), \; \Sigma|Y \sim IW(\bar{S}, \bar{v}). \tag{6}$$

Defining $\hat{\Phi}$ and $\hat{E}$ as the OLS estimates, we have that $\bar{\Phi} = (\Omega_0^{-1} + X'X)^{-1}(\Omega_0^{-1}\Phi_0 + X'Y)$, $\bar{\Omega} = (\Omega_0^{-1} + X'X)^{-1}$, $\bar{v} = v_0 + T$, and $\bar{S} = \hat{\Phi}'X'X\hat{\Phi} + \Phi_0'\Omega_0^{-1}\Phi_0 + \Phi_0 + \hat{E}'\hat{E} - \hat{\Phi}'\bar{\Omega}^{-1}\hat{\Phi}$.

The $1-$step ahead forecast $\hat{y}_{t+1}$ is obtained by using the posterior mean $\bar{\Phi}$:

$$\hat{y}_{t+1} = \bar{\Phi}_c + \bar{\Phi}_1 y_t + \bar{\Phi}_2 y_{t-1} + ... + \bar{\Phi}_p y_{t-p+1}. \tag{7}$$

The h-step ahead forecasts are obtained by iteration:

$$\hat{y}_{t+h} = \bar{\Phi}_c + \bar{\Phi}_1 \hat{y}_{t+h-1} + \bar{\Phi}_2 \hat{y}_{t+h-2} + ... + \bar{\Phi}_p \hat{y}_{t+h-p}, \tag{8}$$

where $\hat{y}_{t+h} = y_{t+h-p}$ for $h \leq p$. Alternatively, by using the notation in (3), one can write:

$$\hat{y}_{t+h} = \bar{\Phi}^h x_t. \tag{9}$$

In our baseline specification we impose the prior expectation and variance of the coefficient matrices to be:

$$E[\Phi_k^{(ij)}] = \begin{cases} \Phi^* & \text{if } i = j, \; k = 1 \\ 0 & \text{otherwise} \end{cases}, \; Var[\Phi_k^{(ij)}] = \theta \frac{1}{k^2} \sigma_i^2 / \sigma_j^2, \; k = 1, ..., p, \tag{10}$$

where $\Phi_k^{(ij)}$ denotes the element in position (i, j) in the matrix Φ_k, and where the covariances among the coefficients in Φ_k are zero. The prior mean Φ^* is typically set to 1 in the traditional Minnesota prior to account for the persistence of the data, but if the VAR is estimated in first differences Φ^* should be set to 0. The shrinkage parameter θ measures the tightness of the prior: when $\theta \to 0$ the prior is imposed exactly and the data do not influence the estimates, while as $\theta \to \infty$ the prior becomes loose and the prior information does not influence the estimates, which will approach the standard OLS estimates. In the baseline specification we set $\theta = 0.1$. We will discuss in detail the choice of this parameter below. The factor σ_i^2/σ_j^2 is a scaling parameter which accounts for the different scale and variability of the data. To set the scale parameters σ_i^2 we follow common practice (see e.g. Litterman, 1986; Sims and Zha, 1998) and set it equal to the variance of the residuals from a univariate autoregressive model for the variables.

The prior specification is completed by assuming a diffuse normal prior on the intercepts Φ_c and by choosing v_0 and S_0 so that the prior expectation of Σ is equal to a fixed diagonal residual variance $E[\Sigma] = diag(\sigma_1^2, ..., \sigma_N^2)$. In particular, following Kadiyala and Karlsson (1997), we set the diagonal elements of S_0 to $s_{0ii} = (v_0 - N - 1)\sigma_i^2$ and $v_0 = N + 2$.

For the baseline case we set the lag length $p = 1$.

3.2 Baseline specification results

The upper panel of Table 2 reports, for each of the 18 variables under evaluation, the RMSFEs over the entire forecast sample 1986-2010. All the subsequent results will be expressed as values relative to these RMSFEs.

The lower panel of Table 2 presents the RMSFE from a classical VAR(1) relative to those of the benchmark BVAR, so that values lower than one indicate a lower loss from the classical VAR. The results are rather mixed, with the classical VAR doing better for variables such as unemployment, hours and capacity utilization and the BVAR for the federal fund rate and the yields on the 10-year bonds. Across variables and forecast horizons the differences are quite small, the average and median ratios are very close to one.

The outcome of this first comparison is not so surprising since the larger gains from the BVAR are expected from the use of a larger information set, when shrinkage matters more. Table 3 presents descriptive statistics (computed over all variables) of the RMSFE of a VAR of order p against a BVAR of order p. As is clear, the longer the lag length, the worse the classical VAR performance. We will also see below that increasing the lag length of the BVAR improves its own forecasting performance.

4 Choice of hyperparameters and lag length

4.1 Choice of hyperparameters (tightness)

To make the prior operational, one needs to choose the value of the hyperparameter θ, which controls the tightness of the prior. We follow Carriero, Kapetanios, and Marcellino (2010b) and at each point we choose θ by maximizing the marginal data density of the model:[1]

$$\theta_t^* = \arg\max_{\theta} \ln p(Y). \tag{11}$$

[1] Giannone, Lenza, and Primiceri (2010) propose the same strategy for forecasting a macroeconomic dataset.

The marginal data density (or marginal likelihood) $p(Y)$ can be obtained by integrating out all the coefficients of the model. Defining Θ as the set of all the coefficients of the model, we have:

$$p(Y) = \int p(Y|\Theta)p(\Theta)d\Theta. \tag{12}$$

Under our Normal-Inverted Wishart prior the density $p(Y)$ can be computed in closed form (Bauwens, Lubrano and Richard 1999) and it is given by:

$$\begin{aligned} p(Y) = \pi^{\frac{-TN}{2}} \times |(I + X\Omega_0 X')^{-1}|^{\frac{N}{2}} \times |S_0|^{\frac{v_0}{2}} \times \frac{\Gamma_N(\frac{v_0+T}{2})}{\Gamma_N(\frac{v_0}{2})} \\ \times |S_0 + (Y - X\Phi_0)'(I + X\Omega_0 X')^{-1}(Y - X\Phi_0)|^{-\frac{v_0+T}{2}} \end{aligned} \tag{13}$$

with $\Gamma_N(\cdot)$ denoting the N-variate gamma function. A derivation is provided in the Appendix.

We now present the results obtained when rather than keeping $\theta = 0.1$ through all the sample, in each time period we set it equal to the value maximizing the marginal likelihood. We optimize over a discrete grid $\theta \in \{0.01, 0.025, 0.050, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.45, 0.50, 0.75, 1, 2, 5\}$. It turns out that the value of the tightness does not change substantially over time, with the optimal values being 0.3 and 0.25.

Table 4 contains the ratio of the RMSFE obtained by selecting θ with marginal likelihood maximization to the RMSFE of the baseline model. In some cases optimizing does help, with gains in the range of 5%, however in other instances there are no benefits or even losses. Across variables and horizons the average and median ratios are very close to one, and the fraction of cases for which fixed tightness is better is close to 50%.

These results are not surprising given that even the classical VAR(1) (which corresponds to the case $\theta \longrightarrow \infty$) and the benchmark were equivalent. However, as we also noted above, the lag length matters, in the sense that the amount of shrinkage becomes more relevant the longer the lag length. We will come back to this issue in Section 4.3 below.

4.2 Choice of the lag length

Up to now we have assumed a given lag length p. However, the researcher needs to determine the lag length as well.

As a first step, we check whether a very long lag length specification yields improved forecast accuracy. The results are reported in Table 5 (panel A), which provides the RMSFE of the baseline specification with $p = 12$ against the same specification with $p = 1$. It emerges that adding extra dynamics can be significantly beneficial for some variables, such as weekly hours, industrial production and capacity utilization, and in general does not harm. The average gains across variables and horizons are about 4%, with maximum gains of about 25% (for some horizons for the variable hours) and maximum losses of about 13% (for some horizons for the federal funds rate).

Next, we consider selecting the lag length by maximizing the marginal likelihood, as we did before for the hyperparameter θ. We set:

$$p^* = \arg\max_p \ln p(Y), \tag{14}$$

where we optimize over the grid $p \in \{1, 2, 3, 6, 12\}$. The optimal lag length chosen with this method is equal to 1 for the very first part of the sample (until 1989), then it becomes 2 and remains fixed until the end of the sample. The results for this case are reported in panel B of Table 5. On average, the gains with respect to the benchmark shrink to about 1-2%. Interestingly, for those variables that were particularly benefitting from a 12-lag specification, the gains are reduced, even though they remain positive compared to the fixed 1-lag case. Instead, for the remaining variables that did not benefit from a 12-lag length, there are now either some small positive gains or some smaller losses. As a consequence, the maximum gain is reduced from 25% to about 10%, but the maximum loss is also reduced from about 13% to less than 4%. Hence, optimal lag selection seems to provide more robustness across variables than using a long lag length, but the average gains with respect to the benchmark are smaller.

4.3 Simultaneous choice of tightness and lag length

Finally, we assess whether maximizing the marginal likelihood with respect to both the tightness parameter θ and the lag length p can produce some additional gains. For comparison, we use the same grids as when separately optimizing over θ or p. Figure 1 graphs the value of the marginal likelihood as a function of the hyperparameter θ over time, where the lag length is chosen optimally. The marginal likelihood is always maximized by $\theta = 0.3$ or $\theta = 0.25$, as in the $p = 1$ case. The variation in 1989 is related to the switch in the optimal lag length from 1 to 2 lags.

The forecasting results for this case are presented in Table 6. Comparing the figures with those in Table 4, there are clear gains with respect to only optimizing θ with $p = 1$. There are also on average gains, though much smaller, with respect to the case where $\theta = 0.1$ and p is optimally selected (Table 5 panel B), though the fraction of cases where the ratio of the RMSFE with respect to the benchmark is smaller than one decreases from about 77% to 64%.

Overall, the results suggest that optimizing over the lag length matters more than doing it over the tightness parameter, though the joint optimization produces some additional but very small average gains. However, in our results, the simple approach of fixing the lag length at 12 and shrinkage hyperparameter at 0.1 (for models of the size considered here) is hard to beat.

5 Multi-step forecasting approach

5.1 Full simulation vs approximation (iterated vs pseudo-iterated approach)

As mentioned above, for the standard N-IW prior closed form solutions are available for the marginal posterior of the VAR coefficients. These would naturally provide closed form solutions for the 1-step ahead forecasts. However, for multi-step forecasting (and also for impulse-response analysis) the fact that coefficients enter nonlinearly implies that simulation methods are needed. The posterior distribution of the h-step ahead forecast is a nonlinear function of Φ and therefore can only be obtained by simulation. For example, the posterior mean of the forecasts would be given by:

$$\hat{y}_{t+h} = \frac{1}{m}\Sigma_{l=1}^{m}\left[\Phi_l^h x_t\right], \tag{15}$$

where $\Phi_l^h x_t$ $l = 1, ...m$ is a collection of m simulated forecasts based on m draws from the marginal of Φ. We label this the "iterated" approach. Alternatively, the researcher can choose to approximate the result by just integrating out the uncertainty in the coefficients and then using the posterior mean of the coefficients to produce posterior means of the forecasts. This is what happens in our baseline specification, i.e.:

$$\hat{y}_{t+h} = \bar{\Phi}^h x_t. \tag{16}$$

Of course this has a computational benefit but it is, strictly speaking, inaccurate as it ignores the nonlinearity inherent in multistep forecasting. We label this method "pseudo-iterated".

We now compare the results obtained by using the baseline pseudo-iterated approach with those resulting from the proper simulation-based iterated approach, using in both cases the benchmark BVAR(1) specification with fixed tightness. The results contained in Table 7 clearly indicate that the gains from the simulation-based approach are negligible: in all the cases there are only third digit differences in the RMSFE ratios. While not reported in the interest of brevity, we obtained the same result for lag lengths of 2 and 3 (the longest orders that can reasonably be considered in a model with 18 variables and monthly data): at these longer lags, the accuracy of point forecasts was essentially the same under the iterated and pseudo-iterated approaches.

5.2 Direct forecasting approach

A way to overcome the problem of nonlinearity in the multistep forecasts is to use the so-called direct approach. Consider the following VAR:

$$y_t = \Phi_{c,h} + \Phi_{1,h} y_{t-(h-1)-1} + \Phi_{2,h} y_{t-(h-1)-2} + ... + \Phi_{1,h} y_{t-(h-1)-p} + \varepsilon_t \tag{17}$$

Note that in the above model the vector y_t is regressed directly onto y_{t-h} and p lags, and that for each forecast horizon h a different model is employed. Such an approach is known as "direct" forecasting, and it focuses on minimizing the relevant loss function for each forecast horizon, i.e. the h-step ahead forecast error. The approach of our baseline specification, namely, regress y_t onto y_{t-1} and p lags and then compute recursively the h-step ahead forecasts, is known as "iterated" or "powering up". For a discussion and a comparison of these alternative methods see, e.g., Marcellino, Stock, and Watson (2006) and Pesaran, Pick, and Timmerman (2010).

In brief, generally, the powering up approach is more efficient, as the used estimators are equivalent to maximum likelihood, under correct model specification. But it is dangerous in the presence of misspecification, because in general the misspecification will inflate with the forecast horizon when the forecasts are computed recursively. On the other side, the direct approach is less efficient but is more robust to misspecification. In addition, the direct approach implies that the h-step ahead forecast is still a linear function of the coefficients (because a different model is used for each forecast horizon), while in the traditional powering up approach the multi-step forecasts are highly nonlinear functions of the estimated coefficients. As a result, there is an exact closed form solution for the distribution of the h-step ahead forecasts computed using (17), while computing the forecasts resulting from the powering up strategy requires the use of time-demanding simulation methods, as discussed above.[2]

The outcome of the comparison of the pseudo-iterated approach with the direct forecasting method in the context of the baseline specification is reported in Table 8, Panel A. Panel B of Table 8 repeats the comparison with optimally selected tightness and lag length.

Overall, there is no clear ranking of the two approaches when the tightness and lag length are kept fixed: the average and median RMSFE ratios are very close to one, and the percentage of ratios smaller than one is close to 50%. However, there are variables for which the choice between the direct and iterated approaches makes a sizable difference. For example, for the inflation variables the direct method performs much better than the iterated

[2] Admittedly, however, the closed form solution obtained with a direct forecasting approach assumes the error terms of the model are serially uncorrelated, which will not actually be the case with forecast horizons of more than one period. We follow other studies such as Jacobson and Karlsson (2004) and Wright (2009) in applying direct methods to multi-step forecast horizons.

approach, when $p = 1$, in particular at longer horizons. As discussed in Marcellino, Stock, and Watson (2006), these results are likely due to misspecification of a model with one lag for some variables. Moreover, when the lag length and tightness are chosen optimally, the direct approach seems to fare quite well at long forecast horizons, which again can be explained by the fact that the direct approach reduces the effects of possible misspecification. So when specific variables and horizons are of special interest, it can pay to assess the relative merits of both forecasting methods.

6 Treatment of error variance and cross-variable shrinkage

The baseline model we have considered so far is a Normal-Inverted Wishart prior which features the same sample mean of the prior proposed by Doan, Litterman, and Sims (1984) and Litterman (1986) and that is known as Minnesota prior. However, the N-IW prior of our baseline specification differs in two respects. First, in Litterman's approach the error covariance matrix is treated as fixed and diagonal. This assumption means that the model can be estimated with ridge regression on an equation-by-equation basis. In contrast, in our N-IW prior (Kadiyala and Karlsson, 1997), we treat as fixed and diagonal the mean of the error covariance matrix, while the covariance matrix itself is not treated as diagonal and is sampled from an inverse Wishart with scale matrix equal to the error variance matrix of the VAR. The second difference is in the values of the hyperparameters in the coefficients variance matrix. In the original Litterman implementation, the prior variance is

$$Var[\Phi_k^{(ij)}] = \begin{cases} \theta \frac{1}{k^2} \text{ if } i = j \\ \lambda\theta \frac{1}{k^2}\sigma_i^2/\sigma_j^2 \text{ otherwise} \end{cases}, \qquad (18)$$

where the additional parameter λ controls the shrinkage on the lags on all the variables other than the dependent variable of the i-th VAR equation. Typically this parameter is set to a number smaller than one to impose a stronger shrinkage on these lags, which captures the idea that, at least in principle, these lags should be less relevant than the lag of the dependent variable itself.

We now study what happens when the baseline N-IW prior along the lines of Kadiyala and Karlsson (1997) is replaced by the original Minnesota prior of Doan, Litterman, and Sims (1984) and Litterman (1986), which permits estimation by ridge regression applied to each equation separately. We set the additional hyperparameter of cross-variable shrinkage to either $\lambda = 0.5$ or $\lambda = 0.2$. We present results for this model against our baseline specification in Table 9.

Under the pseudo-iterated approach, the N-IW and Minnesota priors seem to be broadly comparable (of course, as the cross-variable shrinkage moves toward 1, the forecasts will become even more similar). A relevant exception is the federal funds rate, for which the forecasts from the VAR with Minnesota prior are considerably more accurate than the N-IW forecasts. On balance, accuracy is slightly better with cross-variable shrinkage of 0.5 than 0.2 (again with the exception of the federal funds rate).

We have also computed the same ratios using the direct approach for both VARs and a richer lag specification. We do not report these results for brevity, but we note that at shorter horizons and lag lengths, the Minnesota prior with direct approach fares a little better than the pseudo-iterated approach (in the sense that the median ratios against the N-IW prior are slightly smaller than 1 for horizons between 2 and 6 months, and about 60% of these ratios are smaller than 1). At longer horizons, there doesn't seem to be a clear advantage to either approach. With tight cross-variable shrinkage the results obtained with the two methods are pretty similar, on average.

Finally, we have considered specifically the role of restricting the variance matrix of the residuals to be fixed and diagonal, rather than leaving it full and free to vary randomly. Table 10 contains the ratios of the Minnesota prior forecasts computed using the random variance matrix and the iterated method (which requires Gibbs sampling, as in Kadiyala and Karlsson 1997) against the forecasts produced using the fixed diagonal variance matrix and pseudo-iterated approach (which does not involve simulation). In general, the RMSFE ratios are close to 1, signaling that both choices yield very similar forecast. However it is worth noting that there is a slight predominance of cases in which the simpler model (the one with fixed diagonal matrix) performs better. The differences in RMSFEs tend to be larger for greater cross-variable shrinkage (i.e., the differences are larger when the shrinkage is set at 0.2 than when it is set at 0.5). While not reported in the interest of brevity, we obtained a similar result on the simulation vs. no-simulation approach with the Minnesota prior with a lag order of 2. On balance, for the accuracy of point forecasts, there is no consistent advantage to cross-variable shrinkage, with or without MCMC simulation.

7 Additional Issues

We now discuss a set of additional features related to the specification of a BVAR that can influence its forecasting performance

7.1 VAR size

After the spreading of methods to handle large datasets, there is now a re-consideration of whether more data is always beneficial for forecasting. For example, Boivin and Ng (2006) suggest that pre-selecting the variables that are included in a factor model according to their relationship with the target variable of interest can improve the forecasting precision.

Similarly, Banbura, Giannone, and Reichlin (2010) show that a medium scale BVAR of about 20 variables delivers often more accurate forecasts than large BVARs. Koop (2010) shows that the forecasting performance increases with the size, but only up to about 20 variables.

Given this evidence, we now also assess whether a smaller scale BVAR for a subset of the variables of interest has worse forecasting performance than our medium sized VAR including all the variables under analysis. In particular, we focus on the following 7 variables: unemployment rate (UR), core PCE price index (PCEXFEPI), nonfarm payroll employment (PAYROLLS), nominal retail sales (RETAILSALES), single-family housing starts (STARTS), industrial production (IP), and the federal funds rate (FFR).

Table 11 presents the results obtained by using the smaller VAR system, as a ratio with respect to the RMSFE obtained using the 18 variables system. The table contains results for both the N-IW baseline specification, and for the Minnesota specification with $\lambda = 0.5$, for a lag length of either 1 or 12, and using the pseudo-iterated approach. Table 12 reports the same results when the direct approach is used. We have also experimented with the iterated case, i.e. with full simulation of the posterior forecast. Results are similar to the pseudo-iterated case and therefore we do not report them for brevity.

In the pseudo-iterated case, the 18-variable model generally yields more accurate forecasts – in keeping with the recent results in the literature mentioned above. For most of the 7 variables, the RMSFEs are lower for the forecasts from the 18 variable model than the 7 variable model. The advantage is bigger at longer lags than shorter. The one exception is the federal funds rate, at short horizons: in this case, the forecast from the 18-variable model tends to be less accurate than the forecast from the 7-variable model, and larger with the N-IW prior than with the Minnesota prior.

In the direct case, the advantage of the 18 variable model over the 7 variable model is smaller. On average, the larger model is more accurate, but the difference between the two models is smaller than under the pseudo-iterated approach. In fact, at longer forecast horizons, for many variables, the smaller model becomes slightly more accurate than the larger model. This might indicate that the 7 variable VAR is somewhat misspecified with respect to the 18 variable VAR, therefore the direct approach is better suited to deal with such misspecification.

7.2 Levels vs Growth rates

It is in principle unclear whether transforming variables into their growth rates can enhance the forecasting performance of the BVAR. The level specification can better take into consideration the existence of long run (cointegrating) relationships across the variables, which are omitted in a VAR in differences. On the other hand, Clements and Hendry (1996) show that in a classical framework differencing can improve the forecasting performance in the presence of instability. Hence, this is another issue to be considered from an empirical perspective. As far as we know, there has been little effort in the BVAR forecasting literature to compare specifications in levels versus differences. Following the Litterman (1986) tradition, some BVAR forecasting work uses models with variables in levels or log levels (e.g., Banbura, Giannone, and Reichlin 2010, Giannone, Lenza, Momferatou, and Onorante 2010, and Giannone, Lenza, and Primiceri 2010), while other work uses models in differences or growth rates (e.g., Clark and McCracken 2008 and Del Negro and Schorfheide 2004).

In light of recent work based on models in log levels, we revisit the levels versus growth rates question. Table 13 provides results for our baseline specification, but with 12 lags (unreported results with 6 lags are very similar), and all variables in levels or log levels. For the log levels model, we use a prior with a mean of 1 for those variables that are differenced in the baseline specification (see Table 1 for a listing of the differenced variables). The table reports the RMSFE ratios for the levels model vs. growth rate model (where forecasts from the levels model are transformed to the units/transformations of the growth rate model forecasts).

The figures confirm that the model in growth rates generally yields forecasts more accurate than those from the model in levels. On average across variables and horizons, the losses from the levels specification are about 11%, but some losses can be much larger, while the maximum gain is about 18%. Perhaps most tellingly, across all variables and horizons, the forecast from the model in growth rates is more accurate than the forecast from the model in levels in 74% of the cases.

7.3 Bias

The shrinkage towards the prior underlying Bayesian estimation reduces parameter estimation uncertainty and therefore the variance of the forecast error. On the other hand, when the true value of the parameters is different from the prior, it introduces a systematic bias. Typically the latter is not explicitly considered in BVAR applications, but an evaluation of its size and statistical significance can provide a better understanding of the pros and cons of BVAR forecasts.

The upper panel of Table 14 reports the mean errors for the BVAR with the N-IW prior, 12 lags, and tightness at its baseline value of 0.1. The lower panel presents p-values of t-tests for the null hypothesis of zero mean errors (i.e., unbiased forecasts). For forecast horizons longer than 1, the underlying standard errors are based on the Newey-West estimator, with bandwidth $2(h-1)$.

For a few variables, since they are measured in levels rather than growth rates, it is complex to assess the size of the mean errors. As an example, the mean errors of new claims for unemployment insurance look large in an absolute sense, but the level of claims varies between about 300 and 500 over the forecast sample. Hence, the tests for forecast unbiasedness are more informative. They show that for about half of the variables under evaluation we have a significant bias at pretty much all horizons. In light of other results in the literature (see, e.g., Clark 2011), it is not surprising that the inflation forecasts are biased. Qualitatively, the biases of forecasts generated with the direct approach are pretty similar.

In summary, it is worth keeping in mind that the shrinkage underlying Bayesian estimation can introduce a bias in the estimated VAR coefficients and in the resulting forecasts.[3] However, the extent of the average bias appears in general quite limited.

8 Results for other countries

To assess the robustness of our results, we extend our analysis to three more countries: Canada, France and the UK. For each country we have collected a dataset composed of nine variables since the entire set of variables used for the US analysis is not available for each country, or at least not for a sufficiently long time span. The variables are described in Table 15, together with their transformations.

The estimation and forecast samples are comparable to those for the US. Specifically,for Canada and France we use data ranging from January 1971 to May 2010. The first estimation sample is February 1972 to December 1983, and then the estimation sample expands within the recursive scheme, ending in May 2009. Forecasts are produced recursively after each estimation, therefore the forecast period for these countries ranges from January 1984 to May 2010. For the UK the sample is slightly shorter, starting in January 1975 and ending in March 2010. The first estimation window is February 1976 to December 1987, the last is January 1975 to March 2009, and the forecast sample is January 1988 to March 2010.

In the interest of space, the tables containing the results for these countries are not presented here but can be found in the Table Appendix. Here we briefly discuss the results, focusing especially on the comparison with the findings obtained for the US. For this reason, the tables in the Table Appendix are numbered as their counterparts for the US.

The results on the choice of the lag length and the tightness parameter are broadly in line with those for the US. In particular, choosing optimally the tightness seems to

[3] In results not reported in the interest of brevity, we found biases to be smaller with two alternative approaches: (1) estimation by OLS, and (2) intercept correction (as in Clements and Hendry 1996) of the BVAR forecasts. But both approaches to bias reduction elevate the RMSFEs.

produce only slight gains. Occasionally, for example for policy rates and the 10-year yield, optimizing the tightness improves forecast accuracy, but on average the gains are limited. The gains are also small for lag length selection, mainly because the selected lag length is often equal to the baseline lag length of 1. Also, many of the gains disappear when results are compared with a richer lag length specification of 12 lags. Detailed results are in Tables A3-A6 (corresponding to Tables 4-6 for US) in the Table Appendix.

Turning to the results for the iterated versus the pseudo-iterated approach, for the U.S. we found clear evidence that the two methods produce virtually the same results, supporting the use of the much quicker pseudo-iterated approach. These results are resoundingly confirmed. For Canada and France the ratios are never larger/smaller than 1 by more than 1%. Similar results are obtained for the UK, with the only exception of the forecasts of the bond yields at very long horizons, where the iterated approach performs slightly better. We obtained the same basic result (of iterated and pseudo-iterated RMSFEs being basically the same) for these countries using a lag order of 3. Detailed results are in Table A7 in the Table Appendix.

As for the comparison between the direct and pseudo-iterated approach, the direct approach seems to fare a little worse than in the US results. For France and the UK, the direct approach seems to be clearly outperformed by the pseudo-iterated approach, though the average gains are small, in the 2-4% range. Detailed results are in Tables A8.1-A8.2 in the Table Appendix.

With regards to the comparison between the Minnesota prior and the baseline specification we confirm that the cross-variable shrinkage does not pay a lot, since the fraction of cases in which the simpler baseline specification forecasts better is often above 60%, and reaches even 80% for the UK. However, it is remarkable that the good forecasting performance of the Minnesota prior for policy rates detected in the US BVAR is confirmed for the other countries. Interestingly, and in line with Table 10 for the US, results show that using a non-fixed variance matrix seems to reduce the accuracy of the forecasts (in relative terms). Detailed results are in Tables A9.1, A9.2, A10.1, and A10.2 in the Table Appendix.

The results for the comparison of the model estimated in levels versus growth rates confirm those obtained for the US, with the model in levels producing worse forecasts in most of the cases. Finally, also for these three countries the size of the forecast bias is rather limited, though statistically significant in a few cases. Detailed results are in Tables A13, A14.1, and A14.2. in the Table Appendix.

9 Conclusions

For an institution or forecaster interested in developing a macroeconomic forecasting framework, the results of this study lead us to recommend easy-to-use Bayesian VAR methods. Past research has shown that this class of models can yield forecasts that are as accurate as forecasts from structural models and judgmental forecasts. The point of this paper is to compare the accuracy of such forecasts obtained with simple methods to the accuracy of BVAR forecasts obtained with more computationally demanding, if sometimes more technically proper, methods.

We find that simple works. Accordingly, we can recommend the following specification and method: a BVAR with variables transformed to the units usually thought stationary (e.g., growth rates of output and employment); a relatively long lag length (12 with monthly data); a Normal-Wishart prior; posterior mean coefficient estimates obtained from the conventional closed-form solution associated with the Normal-Wishart prior; and point forecasts for all horizons obtained using the posterior mean coefficients.

Our conclusion is based on an extensive evaluation of how a range of specification choices affect the forecasting performance of Bayesian VARs. In the baseline case, we use a Normal-Inverted Wishart (N-IW) prior that, when combined with a (pseudo-) iterated approach, makes the analytical computation of h-step ahead forecasts feasible, fast and simple, in particular when using standard and fixed values for the tightness and the lag length.

We then assess whether speed and simplicity have a cost in terms of decreased (point) forecast precision with respect to more general BVAR specifications and alternative forecasting methods. Specifically, we consider optimal choice of the tightness, of the lag length and of both; compare alternative approaches to h-step ahead forecasting (direct, iterated and pseudo-iterated); discuss the treatment of the error variance and of cross-variable shrinkage; and address a set of additional issues, including the size of the VAR, modeling in levels or growth rates, and the extent of forecast bias induced by shrinkage.

We obtain a large set of empirical results, for the United States but also, as a robustness check, for Canada, France and the UK. We can summarize them by saying that, while for few variables and forecast horizons a more careful specification can pay, on average across variables and horizons we find very small losses (and sometimes even gains) from the adoption of quick and easy BVAR modeling choices — specifically, the settings we described above.

10 Appendix: derivation of the marginal likelihood

First, we note that the likelihood is (matricvariate) normal:

$$Y|\Phi, \Sigma \sim N(X\Phi, \Sigma \otimes I) \tag{19}$$

To obtain the marginal data density we need to integrate out Φ and Σ. First, we integrate out Φ. Using (5) we can derive the distribution of the expected value $X\Phi$ given Σ:

$$X\Phi|\Sigma \sim N(X\Phi_0, \Sigma \otimes X\Omega_0 X') \tag{20}$$

Noting that $Y = X\Phi + E$, where $E|\Sigma \sim N(0, \Sigma \otimes I)$ is independent from $X\Phi$, we can write $Y|\Sigma$ as:

$$Y|\Sigma = X\Phi|\Sigma + E|\Sigma \sim N(X\Phi_0, \Sigma \otimes (I + X\Omega_0 X')) \tag{21}$$

Second, we integrate out the Σ. To do so it is sufficient to note that $Y|\Sigma$ and Σ are a N-IW, and invoke the theorem A 19 in Bauwens, Lubrano and Richard (1999). As a result, the marginal of Y is a matricvariate t:

$$Y \sim MT(X\Phi_0, (I + X\Omega_0 X')^{-1}, S_0, v_0). \tag{22}$$

Using the definition of matricvariate t (Dickey 1967), the expression for the p.d.f. of Y is:

$$p(Y) = k^{-1} \times |S_0 + (Y - X\Phi_0)'(I + X\Omega_0 X')^{-1}(Y - X\Phi_0)|^{-\frac{v_0+T}{2}} \tag{23}$$

with:

$$k = \pi^{\frac{TN}{2}} \times |(I + X\Omega_0 X')^{-1}|^{-\frac{N}{2}} \times |S_0|^{-\frac{v_0}{2}} \times \prod_{i=1}^{N} \frac{\Gamma(\frac{v_0+1-i}{2})}{\Gamma(\frac{v_0+T+1-i}{2})}, \tag{24}$$

where $\Gamma(\cdot)$ is the univariate gamma function. An alternative notation is $\prod_{i=1}^{N} \frac{\Gamma(\frac{v_0+1-i}{2})}{\Gamma(\frac{v_0+T+1-i}{2})} = \frac{\Gamma_N(\frac{v_0}{2})}{\Gamma_N(\frac{v_0+T}{2})}$, with $\Gamma_N(\cdot)$ denoting the N-variate gamma function. The expression above coincides with Giannone, Lenza, and Primiceri (2010), because it is easily shown that $|X\Omega_0 X' + I| = |\Omega_0||X'X + \Omega_0^{-1}|$, while the last term is the posterior moment $\bar{S}$.

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Tables

Table 1: Description of dataset and transformations

Code	Series	Transformation
UR	unemployment rate	*none*
PCEPI	PCE price index	$1200 \ln (y_t/y_{t-1})$
PCEXFEPI	core PCE price index (ex food and energy)	$1200 \ln (y_t/y_{t-1})$
PAYROLLS	nonfarm payroll employment	$1200 \ln (y_t/y_{t-1})$
WEEKLYHRS	weekly hours worked	*none*
CLAIMS	new claims for unemployment insurance	*none*
RETAILSALES	nominal retail sales	$1200 \ln (y_t/y_{t-1})$
CONSCONF	index of consumer confidence	*none*
STARTS	single-family housing starts	$100 \ln (y_t/y_{t-1})$
IP	industrial production	$1200 \ln (y_t/y_{t-1})$
CU	index of capacity utilization	*none*
PMISUPDELIV	Purchasing Managers Index of supplier delivery times	*none*
PMIORDERS	Purchasing Managers Index of new orders	*none*
POIL	price of oil (West Texas Intermediate)	$100 \ln (y_t/y_{t-1})$
SP500	S&P 500 index of stock prices	$100 \ln (y_t/y_{t-1})$
ITB10y	yield on 10-year Treasury bonds	*none*
FFR	federal funds rate	*none*
REALXR	real exchange rate	$100 \ln (y_t/y_{t-1})$

Table 2. Comparison of classical VAR(1) vs benchmark BVAR

Panel A. RMSFE of benchmark BVAR

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	0.15	0.19	0.24	0.29	0.35	0.42	0.49	0.57	0.65	0.73	0.81	0.89
PCEPI	2.07	2.47	2.56	2.60	2.64	2.67	2.74	2.76	2.80	2.86	2.89	2.93
PCEXFEPI	1.47	1.52	1.60	1.67	1.76	1.78	1.86	1.89	1.93	1.98	2.02	2.06
PAYROLLS	1.27	1.31	1.47	1.59	1.75	1.90	1.99	2.10	2.19	2.25	2.30	2.33
WEEKLYHRS	0.26	0.33	0.38	0.43	0.47	0.50	0.53	0.56	0.58	0.61	0.62	0.64
CLAIMS	17.25	24.84	31.71	37.70	43.35	48.59	53.59	58.10	62.16	65.60	68.60	71.33
RETAILSALES	14.08	14.68	14.72	14.65	14.73	14.88	14.92	14.91	14.95	14.53	14.09	14.06
CONSCONF	6.59	10.07	12.55	14.60	16.43	18.07	19.39	20.66	21.99	23.20	24.24	25.20
STARTS	6.43	6.48	6.43	6.40	6.44	6.44	6.45	6.45	6.46	6.45	6.45	6.43
IP	7.23	7.16	7.38	7.60	7.75	7.88	7.94	8.02	8.05	8.06	8.10	8.11
CU	0.52	0.79	1.05	1.31	1.57	1.82	2.08	2.31	2.53	2.74	2.93	3.11
PMISUPDELIV	1.85	2.34	2.72	3.08	3.49	3.72	3.95	4.08	4.21	4.29	4.31	4.32
PMIORDERS	3.28	4.56	5.41	6.05	6.43	6.62	6.77	6.88	6.93	6.97	6.94	6.88
POIL	8.85	9.19	8.93	8.81	8.81	8.72	8.64	8.57	8.43	8.45	8.45	8.47
SP500	3.85	3.98	3.95	3.91	3.93	3.93	3.93	3.93	3.90	3.89	3.89	3.90
ITB10Y	0.26	0.42	0.52	0.60	0.68	0.75	0.79	0.83	0.87	0.90	0.95	0.99
FFR	0.37	0.56	0.70	0.81	0.92	1.02	1.12	1.21	1.30	1.39	1.48	1.57
REALXR	1.75	1.85	1.82	1.79	1.77	1.76	1.75	1.74	1.74	1.74	1.76	1.76

Panel B. RMSFE ratios: classical VAR(1) / benchmark BVAR

		2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	0.96	0.92	0.91	0.92	0.93	0.94	0.94	0.95	0.95	0.96	0.96	0.96
PCEPI	0.99	0.98	0.97	0.96	0.96	0.95	0.95	0.94	0.95	0.96	0.97	0.97
PCEXFEPI	1.00	0.97	0.94	0.93	0.93	0.93	0.93	0.92	0.93	0.93	0.93	0.94
PAYROLLS	1.10	1.02	0.99	0.98	0.97	0.97	0.96	0.95	0.95	0.95	0.96	0.95
WEEKLYHRS	0.93	0.94	0.95	0.97	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.98
CLAIMS	0.98	0.98	0.99	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.00	1.00
RETAILSALES	1.00	1.01	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CONSCONF	0.95	0.95	0.95	0.94	0.94	0.94	0.94	0.94	0.94	0.95	0.95	0.95
STARTS	1.03	1.02	1.01	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IP	1.05	1.05	1.04	1.02	1.02	1.01	1.00	1.00	1.00	1.00	1.00	1.00
CU	0.94	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92
PMISUPDELIV	1.03	1.04	1.07	1.08	1.09	1.09	1.10	1.11	1.13	1.14	1.15	1.16
PMIORDERS	0.98	0.99	1.00	1.01	1.01	1.02	1.02	1.02	1.03	1.03	1.03	1.03
POIL	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.00	1.01	1.01	1.01	1.01
SP500	1.02	1.01	1.01	1.01	1.00	1.00	1.01	1.01	1.00	1.00	1.00	1.00
ITB10Y	1.06	1.06	1.07	1.07	1.07	1.08	1.09	1.08	1.07	1.07	1.07	1.06
FFR	1.08	1.19	1.25	1.26	1.26	1.25	1.23	1.21	1.19	1.17	1.15	1.12
REALXR	1.01	1.02	1.02	1.02	1.01	1.01	1.01	1.00	1.00	1.00	1.01	1.01

	all horizons	horz<=6	horz>6
average	1.004	1.005	1.004
median	1.000	1.003	1.000
min	0.906	0.906	0.915
max	1.264	1.264	1.231
% < 1	0.486	0.481	0.491
%>1	0.514	0.519	0.509

Table 3. Descriptive statistics for the RMSFE of classical VAR (p) vs benchmark BVAR (p) for alternative values of p

		all horizons	horz<=6	horz>6
p=1	**average**	1.00	1.00	1.00
	median	1.00	1.00	1.00
	min	0.91	0.91	0.92
	max	1.26	1.26	1.23
	% < 1	0.49	0.48	0.49
	%>1	0.51	0.52	0.51
p=2	**average**	1.02	1.03	1.01
	median	1.00	1.02	0.99
	min	0.82	0.82	0.88
	max	1.36	1.36	1.25
	% < 1	0.43	0.30	0.56
	%>1	0.57	0.70	0.44
p=3	**average**	1.15	1.11	1.18
	median	1.11	1.09	1.14
	min	0.95	0.95	1.00
	max	1.59	1.48	1.59
	% < 1	0.05	0.09	0.01
	%>1	0.95	0.91	0.99
p=6	**average**	1.37	1.34	1.40
	median	1.31	1.29	1.32
	min	1.12	1.12	1.12
	max	2.14	1.99	2.14
	% < 1	0.00	0.00	0.00
	%>1	1.00	1.00	1.00
p=12	**average**	2.04	2.03	2.06
	median	1.93	1.97	1.91
	min	1.44	1.44	1.45
	max	3.88	3.32	3.88
	% < 1	0.00	0.00	0.00
	%>1	1.00	1.00	1.00

Table 4. RMSFE ratios: optimised tightness / fixed tightness (fixed lag length)

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	0.96	0.92	0.91	0.92	0.93	0.94	0.95	0.95	0.96	0.96	0.96	0.96
PCEPI	0.99	0.98	0.97	0.96	0.96	0.96	0.96	0.95	0.96	0.96	0.97	0.97
PCEXFEPI	1.00	0.97	0.94	0.94	0.94	0.94	0.94	0.93	0.94	0.93	0.94	0.95
PAYROLLS	1.08	1.01	0.99	0.98	0.97	0.97	0.96	0.96	0.96	0.96	0.96	0.96
WEEKLYHRS	0.93	0.94	0.96	0.97	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99
CLAIMS	0.97	0.98	0.99	1.00	1.00	1.01	1.01	1.01	1.01	1.00	1.00	1.00
RETAILSALES	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CONSCONF	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.96
STARTS	1.03	1.01	1.00	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IP	1.04	1.04	1.03	1.02	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00
CU	0.94	0.92	0.92	0.92	0.92	0.93	0.93	0.93	0.93	0.92	0.92	0.92
PMISUPDELIV	1.02	1.03	1.05	1.06	1.07	1.07	1.08	1.09	1.10	1.11	1.12	1.12
PMIORDERS	0.98	0.99	0.99	1.00	1.01	1.01	1.01	1.02	1.02	1.03	1.03	1.03
POIL	1.01	1.01	1.01	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.01
SP500	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ITB10Y	1.04	1.04	1.05	1.05	1.06	1.07	1.07	1.06	1.05	1.05	1.05	1.04
FFR	1.06	1.15	1.20	1.21	1.21	1.19	1.18	1.16	1.14	1.12	1.10	1.09
REALXR	1.00	1.02	1.02	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.01	1.01

	all horizons	horz<=6	horz>6
average	1.000	1.000	1.000
median	1.000	1.001	1.000
min	0.907	0.907	0.922
max	1.209	1.209	1.175
% < 1	0.505	0.500	0.509

Table 5. RMSFE ratios for different lag lengths of the benchmark BVAR

PANEL A. RMSFE ratios: BVAR(12) / BVAR (1)

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	0.94	0.94	0.93	0.93	0.95	0.95	0.96	0.96	0.95	0.95	0.94	0.94
PCEPI	0.99	0.98	0.97	0.96	0.95	0.96	0.95	0.95	0.95	0.95	0.96	0.96
PCEXFEPI	0.96	0.93	0.91	0.90	0.89	0.89	0.89	0.88	0.88	0.89	0.89	0.89
PAYROLLS	0.93	0.91	0.88	0.89	0.90	0.89	0.89	0.88	0.88	0.88	0.88	0.88
WEEKLYHRS	0.85	0.77	0.75	0.76	0.78	0.79	0.80	0.82	0.84	0.85	0.86	0.87
CLAIMS	0.97	0.93	0.93	0.93	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94
RETAILSALES	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99
CONSCONF	0.98	0.96	0.95	0.94	0.93	0.92	0.91	0.91	0.90	0.90	0.90	0.90
STARTS	0.99	1.01	1.00	0.99	0.99	0.98	0.98	0.99	0.99	0.99	0.99	1.00
IP	0.92	0.93	0.96	0.97	0.98	0.97	0.97	0.96	0.96	0.96	0.96	0.97
CU	0.91	0.85	0.84	0.84	0.84	0.85	0.85	0.85	0.86	0.86	0.85	0.85
PMISUPDELIV	1.03	1.03	1.01	1.01	1.02	1.03	1.03	1.04	1.05	1.04	1.04	1.03
PMIORDERS	0.99	0.97	0.98	0.99	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.01
POIL	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.00	1.01	1.00	1.01	1.01
SP500	0.99	1.00	1.00	0.99	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00
ITB10Y	1.04	1.05	1.05	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.03	1.02
FFR	1.09	1.13	1.13	1.11	1.10	1.10	1.09	1.08	1.08	1.08	1.07	1.06
REALXR	0.98	0.99	1.00	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01

	all horizons	horz<=6	horz>6
average	0.964	0.965	0.962
median	0.981	0.981	0.975
min	0.748	0.748	0.805
max	1.129	1.129	1.090
% < 1	0.667	0.676	0.657

PANEL B. RMSFE ratios: BVAR(optimal lag length) / BVAR (1)

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	0.97	0.97	0.97	0.97	0.98	0.98	0.99	0.99	0.99	0.99	0.98	0.98
PCEPI	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00
PCEXFEPI	0.99	0.99	0.97	0.98	0.97	0.98	0.98	0.98	0.98	0.98	0.99	0.99
PAYROLLS	0.99	0.97	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.97	0.97
WEEKLYHRS	0.94	0.90	0.90	0.92	0.93	0.94	0.96	0.96	0.97	0.98	0.99	0.99
CLAIMS	0.99	0.96	0.97	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99
RETAILSALES	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CONSCONF	1.00	0.98	0.97	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96
STARTS	1.01	1.01	1.00	1.00	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00
IP	0.96	0.96	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
CU	0.96	0.92	0.92	0.93	0.93	0.93	0.94	0.94	0.95	0.95	0.95	0.95
PMISUPDELIV	1.02	1.01	1.00	1.01	1.01	1.02	1.02	1.03	1.03	1.04	1.04	1.04
PMIORDERS	0.99	0.97	0.98	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01
POIL	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SP500	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ITB10Y	0.98	0.99	0.98	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.96	0.96
FFR	1.01	1.03	1.01	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.98
REALXR	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

	all horizons	horz<=6	horz>6
average	0.984	0.982	0.987
median	0.989	0.988	0.990
min	0.895	0.895	0.939
max	1.036	1.028	1.036
% < 1	0.769	0.787	0.750

Table 6. RMSFE ratios: BVAR(optimal tightness and lag length)/ benchmark BVAR(fixed tightness and lag length)

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	0.95	0.91	0.89	0.90	0.91	0.93	0.94	0.94	0.95	0.95	0.95	0.95
PCEPI	0.99	0.98	0.96	0.96	0.95	0.95	0.95	0.94	0.95	0.95	0.96	0.97
PCEXFEPI	1.00	0.96	0.93	0.93	0.92	0.92	0.92	0.92	0.92	0.92	0.93	0.93
PAYROLLS	1.06	0.99	0.94	0.93	0.93	0.93	0.91	0.91	0.91	0.91	0.91	0.91
WEEKLYHRS	0.86	0.79	0.79	0.82	0.85	0.87	0.89	0.91	0.93	0.95	0.96	0.97
CLAIMS	0.99	0.95	0.95	0.97	0.97	0.98	0.98	0.98	0.98	0.98	0.98	0.98
RETAILSALES	0.99	0.99	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
CONSCONF	0.95	0.94	0.93	0.91	0.91	0.91	0.90	0.89	0.90	0.90	0.91	0.91
STARTS	1.04	1.04	1.01	0.99	0.99	0.99	0.98	0.99	0.99	0.99	0.99	1.00
IP	0.98	0.96	0.99	1.00	1.00	0.99	0.99	0.99	0.98	0.99	0.98	0.99
CU	0.89	0.83	0.83	0.84	0.85	0.86	0.87	0.88	0.88	0.88	0.88	0.88
PMISUPDELIV	1.07	1.09	1.09	1.09	1.10	1.11	1.12	1.13	1.14	1.14	1.15	1.15
PMIORDERS	1.00	0.96	0.97	0.99	1.00	1.01	1.01	1.01	1.01	1.01	1.02	1.02
POIL	1.01	1.01	1.01	1.01	1.02	1.01	1.01	1.00	1.00	1.01	1.01	1.01
SP500	1.00	1.03	1.02	1.01	1.01	1.01	1.00	1.01	1.01	1.00	1.00	1.01
ITB10Y	1.01	1.05	1.04	1.01	1.00	1.02	1.02	1.02	1.02	1.01	1.00	0.99
FFR	1.01	1.18	1.21	1.17	1.15	1.13	1.12	1.11	1.09	1.08	1.07	1.05
REALXR	0.99	1.00	1.00	1.00	1.01	1.01	1.01	1.01	1.00	1.01	1.01	1.01

	all horizons	horz<=6	horz>6
average	0.980	0.979	0.981
median	0.989	0.989	0.989
min	0.790	0.790	0.871
max	1.205	1.205	1.152
% < 1	0.639	0.648	0.630

Table 7. RMSFE ratios: iterated (simulation) / pseudo-iterated (no simulation), benchmark BVAR.

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	1.001	0.999	0.999	0.999	0.999	0.998	0.998	0.997	0.997	0.996	0.996	0.996
PCEPI	0.999	1.000	1.000	1.000	0.998	0.998	0.996	0.997	0.996	0.995	0.996	0.995
PCEXFEPI	1.000	0.999	0.999	0.998	0.998	0.997	0.995	0.996	0.994	0.993	0.994	0.992
PAYROLLS	0.999	1.000	0.999	0.998	0.996	0.995	0.995	0.996	0.995	0.995	0.995	0.994
WEEKLYHRS	0.999	0.998	0.998	0.997	0.997	0.997	0.997	0.997	0.997	0.998	0.998	0.997
CLAIMS	0.999	1.000	0.999	0.998	0.998	0.997	0.996	0.996	0.996	0.996	0.996	0.996
RETAILSALES	1.002	1.000	1.000	1.000	0.999	1.000	1.000	1.000	0.999	1.000	0.998	0.998
CONSCONF	1.001	0.999	0.998	0.997	0.997	0.997	0.996	0.996	0.995	0.995	0.995	0.995
STARTS	0.999	1.001	1.000	1.000	1.001	1.001	0.999	1.000	0.999	1.001	1.000	1.000
IP	0.999	1.000	0.999	0.999	0.998	0.997	0.998	0.998	0.998	0.997	0.999	0.997
CU	0.999	0.999	0.999	0.998	0.998	0.997	0.997	0.996	0.995	0.995	0.994	0.994
PMISUPDELIV	1.002	1.003	1.002	1.003	1.001	1.001	1.001	1.001	0.999	0.999	0.999	1.000
PMIORDERS	1.002	1.001	1.000	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998
POIL	1.000	1.000	1.001	1.000	1.000	1.000	1.001	1.000	1.000	1.000	1.001	1.000
SP500	1.000	1.001	0.999	1.000	0.999	1.000	1.001	0.999	1.000	1.000	1.001	1.001
ITB10Y	1.002	1.001	1.000	1.001	1.000	1.000	1.001	1.000	1.000	1.000	0.999	0.998
FFR	0.999	1.000	1.002	1.002	1.002	1.000	0.998	0.997	0.997	0.995	0.994	0.992
REALXR	0.999	1.000	0.999	1.003	1.001	1.000	0.999	1.001	1.001	0.999	1.000	1.000

	all horizons	horz<=6	horz>6
average	0.998	0.999	0.998
median	0.999	0.999	0.998
min	0.992	0.995	0.992
max	1.003	1.003	1.001
% +- .01 of 1	1.000	1.000	1.000
%+- .005 of 1	0.882	0.990	0.775

Table 8. RMSFE ratios: direct / pseudo-iterated approach.

Panel A. RMSFE ratios: direct / pseudo-iterated approach, fixed tightness and lag length.

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	1.00	0.98	1.00	1.00	1.03	1.03	1.04	1.03	1.02	1.01	1.00	0.99
PCEPI	1.00	0.99	0.98	0.95	0.95	0.95	0.97	0.95	0.90	0.91	0.92	0.91
PCEXFEPI	1.00	0.99	0.97	0.93	0.91	0.86	0.88	0.87	0.83	0.85	0.87	0.84
PAYROLLS	1.00	0.99	0.94	0.95	0.96	0.94	0.93	0.92	0.92	0.96	0.95	0.97
WEEKLYHRS	1.00	0.88	0.82	0.82	0.83	0.84	0.84	0.85	0.85	0.87	0.85	0.86
CLAIMS	1.00	1.00	0.98	0.97	0.97	0.96	0.95	0.95	0.95	0.95	0.96	0.98
RETAILSALES	1.00	1.00	1.01	1.02	1.02	1.01	1.00	1.00	1.00	1.00	1.02	1.02
CONSCONF	1.00	1.01	1.01	1.00	0.98	0.97	0.95	0.94	0.93	0.93	0.94	0.95
STARTS	1.00	1.00	1.01	1.00	0.99	0.98	1.00	0.99	1.00	1.00	1.01	1.01
IP	1.00	0.96	0.96	0.98	1.00	0.97	0.97	0.96	0.96	0.96	0.99	0.99
CU	1.00	1.02	1.01	1.02	1.03	1.02	1.01	1.00	1.00	1.00	1.00	1.00
PMISUPDELIV	1.00	1.04	1.04	1.02	1.03	1.03	1.03	1.01	1.00	1.00	1.01	1.01
PMIORDERS	1.00	0.98	0.98	0.99	1.00	0.99	0.98	0.99	0.98	1.01	1.02	1.04
POIL	1.00	1.00	1.01	1.00	1.00	1.00	1.01	1.01	1.01	1.01	1.01	1.00
SP500	1.00	1.01	1.01	1.01	0.98	1.00	1.01	1.00	1.00	1.00	1.00	1.01
ITB10Y	1.00	1.00	1.00	1.00	0.98	0.98	0.99	1.00	1.01	1.01	1.02	1.02
FFR	1.00	1.09	1.07	1.04	1.03	1.03	1.04	1.00	0.98	0.98	0.99	1.00
REALXR	1.00	0.98	0.99	0.99	1.00	1.00	1.01	1.01	1.02	1.03	1.01	1.01

	all horizons	horz<=6	horz>6
average	0.980	0.987	0.973
median	1.000	1.000	0.998
min	0.819	0.819	0.826
max	1.085	1.085	1.045
% < 1	0.500	0.463	0.537

Panel B. RMSFE ratios: direct / pseudo-iterated approach, optimal tightness and lag length.

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	1.00	0.98	0.97	0.99	0.97	0.96	0.95	0.95	0.96	0.96	0.97	0.97
PCEPI	1.00	1.00	1.00	1.03	1.03	1.00	1.00	1.03	1.07	1.06	1.07	1.09
PCEXFEPI	1.00	1.00	1.00	1.04	1.06	1.10	1.11	1.15	1.18	1.12	1.13	1.16
PAYROLLS	1.00	1.02	1.06	1.03	1.01	1.04	1.02	1.02	1.00	0.95	0.97	0.94
WEEKLYHRS	1.00	1.05	1.11	1.11	1.09	1.12	1.13	1.13	1.14	1.16	1.19	1.17
CLAIMS	1.00	0.98	1.02	1.03	1.03	1.04	1.05	1.03	1.03	1.02	1.00	0.98
RETAILSALES	1.00	0.97	0.97	0.95	0.94	0.97	0.97	0.98	0.98	0.97	0.94	0.93
CONSCONF	1.00	0.98	0.97	0.96	0.97	0.98	0.98	0.98	0.98	0.98	0.96	0.95
STARTS	1.00	1.01	0.97	0.98	0.99	0.99	0.95	0.97	0.97	0.95	0.94	0.96
IP	1.00	1.00	1.03	1.00	0.99	1.01	1.00	1.01	1.00	0.97	0.96	0.98
CU	1.00	0.97	0.99	0.98	0.97	0.99	1.00	1.00	0.99	0.99	0.98	0.98
PMISUPDELIV	1.00	0.95	0.96	0.95	0.95	0.94	0.96	0.99	0.99	1.00	1.00	1.03
PMIORDERS	1.00	1.00	1.00	1.00	0.99	1.00	0.99	0.98	0.98	0.96	0.94	0.91
POIL	1.00	0.99	0.99	1.00	1.00	1.00	0.98	0.97	0.97	0.98	0.99	0.99
SP500	1.00	0.99	0.98	0.99	1.01	0.98	0.97	0.99	0.98	0.99	0.98	0.98
ITB10Y	1.00	1.01	1.00	0.96	0.97	0.96	0.93	0.92	0.90	0.90	0.89	0.92
FFR	1.00	0.95	0.95	0.96	0.96	0.93	0.93	0.96	0.96	0.94	0.93	0.93
REALXR	1.00	1.00	0.99	0.99	0.99	0.98	0.98	0.97	0.96	0.95	0.97	0.98

	all horizons	horz<=6	horz>6
average	0.996	0.997	0.995
median	0.987	0.999	0.978
min	0.894	0.934	0.894
max	1.193	1.117	1.193
% < 1	0.611	0.519	0.704

Table 9. RMSFE ratios: BVAR with Minnesota prior / benchmark BVAR

Panel A. Cross-shrinkage =0.5

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	0.96	0.97	0.99	1.01	1.02	1.02	1.03	1.02	1.02	1.02	1.02	1.01
PCEPI	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.03	1.03	1.02
PCEXFEPI	1.03	1.05	1.07	1.07	1.07	1.07	1.06	1.06	1.05	1.05	1.05	1.04
PAYROLLS	0.96	1.01	1.01	1.01	1.00	0.99	0.99	0.99	0.98	0.98	0.98	0.98
WEEKLYHRS	0.98	1.01	1.02	1.02	1.02	1.03	1.02	1.02	1.02	1.02	1.02	1.02
CLAIMS	0.97	0.98	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99
RETAILSALES	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CONSCONF	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
STARTS	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IP	0.97	0.99	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99
CU	0.94	0.94	0.95	0.96	0.97	0.97	0.98	0.98	0.98	0.98	0.98	0.98
PMISUPDELIV	0.96	0.96	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98
PMIORDERS	1.01	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99
POIL	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SP500	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ITB10Y	0.96	0.97	0.98	0.98	0.99	0.98	0.99	1.00	1.00	1.01	1.01	1.01
FFR	0.74	0.80	0.86	0.91	0.94	0.96	0.98	0.99	1.00	1.00	1.01	1.01
REALXR	0.98	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

	all horizons	horz<=6	horz>6
average	0.997	0.990	1.003
median	0.997	0.995	0.999
min	0.743	0.743	0.976
max	1.070	1.070	1.058
% < 1	0.588	0.657	0.519

Panel B. Cross-shrinkage =0.2

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	0.94	0.98	1.03	1.07	1.09	1.10	1.11	1.10	1.09	1.07	1.06	1.05
PCEPI	1.11	1.10	1.09	1.09	1.08	1.08	1.07	1.07	1.06	1.05	1.05	1.04
PCEXFEPI	1.09	1.13	1.14	1.15	1.14	1.14	1.13	1.12	1.11	1.10	1.09	1.08
PAYROLLS	1.01	1.12	1.11	1.09	1.05	1.02	1.01	0.98	0.97	0.96	0.95	0.95
WEEKLYHRS	0.93	0.98	1.02	1.04	1.05	1.05	1.05	1.05	1.04	1.03	1.03	1.03
CLAIMS	0.97	0.98	1.00	1.01	1.01	1.01	1.00	1.00	0.99	0.98	0.98	0.97
RETAILSALES	1.02	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CONSCONF	0.97	0.95	0.95	0.95	0.94	0.94	0.94	0.94	0.94	0.94	0.95	0.95
STARTS	0.98	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IP	0.98	1.00	1.00	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.97	0.97
CU	0.90	0.88	0.90	0.91	0.93	0.93	0.94	0.94	0.94	0.94	0.94	0.94
PMISUPDELIV	0.95	0.95	0.98	1.00	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.01
PMIORDERS	1.04	1.00	0.99	0.99	0.99	0.99	0.99	0.98	0.98	0.97	0.97	0.98
POIL	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SP500	0.98	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ITB10Y	0.97	0.98	0.99	1.00	1.01	1.01	1.02	1.04	1.05	1.06	1.07	1.07
FFR	0.59	0.69	0.79	0.86	0.92	0.96	0.99	1.02	1.04	1.05	1.06	1.06
REALXR	0.96	0.97	0.98	0.98	0.99	0.99	0.99	0.99	0.99	1.00	0.99	0.99

	all horizons	horz<=6	horz>6
average	1.002	0.995	1.009
median	0.997	0.995	0.999
min	0.594	0.594	0.937
max	1.152	1.152	1.125
% < 1	0.579	0.620	0.537

Table 10. RMSFE ratios: random error variance matrix / fixed error variance matrix. Minnesota prior

Panel A. Cross-shrinkage =0.5

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	0.98	0.97	0.99	1.01	1.03	1.04	1.04	1.04	1.04	1.04	1.03	1.03
PCEPI	1.02	1.03	1.03	1.02	1.02	1.02	1.01	1.01	1.01	1.01	1.01	1.01
PCEXFEPI	1.04	1.05	1.04	1.04	1.03	1.03	1.02	1.02	1.02	1.01	1.01	1.01
PAYROLLS	1.00	1.00	1.01	1.01	1.00	1.00	1.00	0.99	0.98	0.98	0.97	0.97
WEEKLYHRS	0.99	1.00	1.01	1.02	1.02	1.03	1.03	1.03	1.03	1.02	1.02	1.02
CLAIMS	1.03	1.06	1.06	1.07	1.06	1.06	1.05	1.04	1.03	1.03	1.02	1.02
RETAILSALES	1.02	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CONSCONF	1.02	1.02	1.02	1.02	1.02	1.02	1.01	1.01	1.01	1.00	1.00	1.00
STARTS	1.01	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00
IP	1.02	1.04	1.03	1.03	1.02	1.02	1.02	1.02	1.01	1.01	1.01	1.01
CU	0.93	0.90	0.90	0.91	0.92	0.93	0.94	0.94	0.94	0.95	0.95	0.95
PMISUPDELIV	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.01	1.01	1.01	1.01	1.01
PMIORDERS	1.03	1.05	1.04	1.03	1.02	1.02	1.01	1.01	1.00	1.00	1.00	0.99
POIL	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SP500	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ITB10Y	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.01	1.00
FFR	0.94	0.96	0.98	1.00	1.01	1.02	1.02	1.02	1.03	1.03	1.03	1.03
REALXR	0.98	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

	all horizons	horz<=6	horz>6
average	1.005	1.006	1.005
median	1.005	1.005	1.005
min	0.895	0.895	0.937
max	1.066	1.066	1.049
% +- .01 of 1	0.481	0.417	0.546

Panel B. Cross-shrinkage =0.2

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	1.04	1.09	1.12	1.13	1.13	1.13	1.12	1.11	1.10	1.09	1.09	1.08
PCEPI	1.03	1.04	1.05	1.04	1.03	1.03	1.02	1.01	1.01	1.01	1.00	1.00
PCEXFEPI	1.05	1.08	1.08	1.07	1.05	1.04	1.03	1.03	1.02	1.02	1.01	1.01
PAYROLLS	1.06	1.06	1.04	1.04	1.02	1.01	1.01	0.99	0.99	0.98	0.98	0.97
WEEKLYHRS	1.10	1.13	1.13	1.11	1.09	1.08	1.06	1.05	1.04	1.03	1.03	1.02
CLAIMS	1.14	1.19	1.19	1.17	1.15	1.13	1.10	1.08	1.07	1.05	1.04	1.03
RETAILSALES	1.02	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CONSCONF	1.07	1.08	1.08	1.08	1.08	1.07	1.06	1.06	1.05	1.04	1.03	1.03
STARTS	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IP	1.07	1.08	1.06	1.04	1.03	1.02	1.01	1.01	1.01	1.01	1.00	1.01
CU	1.03	1.05	1.04	1.04	1.03	1.02	1.02	1.01	1.00	1.00	0.99	0.99
PMISUPDELIV	1.01	1.03	1.05	1.05	1.05	1.05	1.04	1.04	1.04	1.04	1.04	1.05
PMIORDERS	1.08	1.11	1.09	1.07	1.04	1.03	1.02	1.01	1.01	1.00	1.00	1.00
POIL	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SP500	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ITB10Y	1.03	1.02	1.01	1.01	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99
FFR	1.02	1.02	1.01	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00
REALXR	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

	all horizons	horz<=6	horz>6
average	1.031	1.044	1.017
median	1.014	1.032	1.003
min	0.973	0.993	0.973
max	1.194	1.194	1.123
% +- .01 of 1	0.426	0.315	0.537

Table 11. RMSFE ratios: BVAR(7 variables) /BVAR(18 variables), pseudo-iterated approach

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
BVAR(1):NW												
UR	0.97	1.07	1.18	1.27	1.32	1.34	1.34	1.32	1.29	1.26	1.23	1.19
PCEXFEPI	1.11	1.15	1.14	1.15	1.14	1.14	1.13	1.13	1.12	1.12	1.11	1.10
PAYROLLS	1.28	1.49	1.50	1.47	1.37	1.27	1.21	1.14	1.09	1.05	1.02	0.99
RETAILSALES	1.04	1.01	1.00	1.01	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99
STARTS	0.99	0.99	0.99	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
IP	1.00	1.04	1.05	1.04	1.03	1.01	0.99	0.98	0.97	0.96	0.96	0.95
FFR	0.65	0.75	0.88	0.99	1.08	1.16	1.22	1.27	1.30	1.33	1.35	1.36
BVAR(12):NW												
UR	0.97	1.04	1.11	1.17	1.20	1.23	1.23	1.23	1.22	1.22	1.21	1.20
PCEXFEPI	1.08	1.12	1.13	1.15	1.17	1.18	1.19	1.21	1.21	1.22	1.21	1.21
PAYROLLS	1.13	1.24	1.29	1.32	1.28	1.24	1.23	1.20	1.18	1.16	1.13	1.11
RETAILSALES	1.03	1.01	1.00	1.00	1.01	1.00	1.01	1.01	1.00	1.00	1.00	1.00
STARTS	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00
IP	1.04	1.06	1.05	1.04	1.04	1.04	1.04	1.03	1.03	1.02	1.01	1.00
FFR	0.68	0.71	0.78	0.84	0.88	0.91	0.94	0.96	0.97	0.99	1.01	1.02
BVAR(1):Minn												
UR	1.03	1.15	1.25	1.31	1.34	1.34	1.33	1.31	1.27	1.24	1.21	1.18
PCEXFEPI	1.08	1.10	1.08	1.09	1.08	1.08	1.08	1.08	1.07	1.07	1.07	1.07
PAYROLLS	1.28	1.46	1.47	1.44	1.35	1.26	1.21	1.14	1.10	1.06	1.03	1.01
RETAILSALES	1.03	1.01	1.00	1.01	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99
STARTS	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
IP	1.06	1.07	1.06	1.04	1.03	1.01	0.99	0.98	0.97	0.97	0.96	0.96
FFR	0.87	0.98	1.08	1.15	1.20	1.25	1.29	1.31	1.33	1.35	1.36	1.36
BVAR(12):Minn												
UR	1.04	1.15	1.21	1.25	1.26	1.27	1.26	1.25	1.23	1.22	1.21	1.19
PCEXFEPI	1.06	1.08	1.08	1.09	1.10	1.11	1.12	1.13	1.12	1.13	1.12	1.12
PAYROLLS	1.16	1.24	1.27	1.28	1.24	1.20	1.19	1.15	1.13	1.11	1.09	1.07
RETAILSALES	1.03	1.01	1.00	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00
STARTS	1.01	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00
IP	1.06	1.06	1.05	1.04	1.03	1.02	1.02	1.01	1.00	1.00	0.99	0.99
FFR	0.83	0.89	0.96	1.02	1.05	1.08	1.10	1.11	1.12	1.13	1.14	1.15

Table 12. RMSFE ratios: BVAR(7 variables) /BVAR(18 variables), direct approach

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
BVAR(1):NW												
UR	0.97	1.06	1.12	1.20	1.25	1.28	1.28	1.29	1.29	1.28	1.26	1.23
PCEXFEPI	1.11	1.14	1.09	1.10	1.09	1.07	1.06	1.07	1.06	1.05	1.03	1.03
PAYROLLS	1.28	1.24	1.28	1.28	1.22	1.18	1.14	1.10	1.09	1.03	0.99	0.98
RETAILSALES	1.04	1.01	1.00	0.99	0.98	0.99	0.99	0.99	0.99	1.00	0.98	0.98
STARTS	0.99	1.01	0.99	1.00	1.00	1.01	1.00	1.00	0.99	0.99	0.99	0.99
IP	1.00	1.06	1.06	1.04	1.03	1.03	1.02	1.00	1.02	1.01	0.97	0.97
FFR	0.65	0.77	0.93	1.03	1.07	1.07	1.05	1.05	1.05	1.05	1.06	1.07
BVAR(12):NW												
UR	0.97	1.02	1.08	1.16	1.21	1.25	1.26	1.27	1.27	1.26	1.24	1.22
PCEXFEPI	1.08	1.11	1.08	1.09	1.07	1.05	1.05	1.06	1.04	1.03	1.01	1.01
PAYROLLS	1.13	1.17	1.22	1.23	1.19	1.15	1.13	1.10	1.08	1.02	0.99	0.97
RETAILSALES	1.03	1.00	1.00	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.98	0.98
STARTS	1.00	1.00	0.99	1.00	1.00	1.00	0.99	0.99	0.98	0.98	0.98	0.99
IP	1.04	1.06	1.06	1.04	1.03	1.03	1.02	1.02	1.02	1.01	0.98	0.97
FFR	0.68	0.72	0.80	0.85	0.87	0.87	0.87	0.88	0.89	0.91	0.92	0.93
BVAR(1):Minn												
UR	1.03	1.15	1.20	1.22	1.22	1.22	1.21	1.20	1.20	1.18	1.17	1.15
PCEXFEPI	1.08	1.09	1.06	1.07	1.06	1.05	1.05	1.05	1.05	1.04	1.03	1.03
PAYROLLS	1.28	1.20	1.16	1.12	1.08	1.05	1.03	1.01	1.00	0.97	0.96	0.96
RETAILSALES	1.03	1.01	1.00	1.00	0.99	0.99	1.00	1.00	1.00	1.00	0.99	0.99
STARTS	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	1.00
IP	1.06	1.07	1.05	1.02	1.01	1.01	1.00	0.99	0.99	0.99	0.98	0.99
FFR	0.87	1.09	1.21	1.23	1.21	1.18	1.16	1.15	1.14	1.14	1.13	1.12
BVAR(12):Minn												
UR	1.04	1.13	1.19	1.22	1.23	1.23	1.22	1.21	1.20	1.19	1.17	1.16
PCEXFEPI	1.06	1.07	1.05	1.06	1.06	1.05	1.05	1.05	1.05	1.04	1.03	1.04
PAYROLLS	1.16	1.14	1.13	1.11	1.07	1.05	1.03	1.01	1.00	0.97	0.96	0.96
RETAILSALES	1.03	1.01	1.00	0.99	0.99	0.99	1.00	1.00	1.00	1.00	0.99	0.99
STARTS	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	1.00
IP	1.06	1.06	1.05	1.03	1.01	1.01	1.00	1.00	1.00	1.00	0.99	0.99
FFR	0.83	0.97	1.08	1.13	1.12	1.11	1.10	1.10	1.10	1.10	1.09	1.08

Table 13. RMSFE ratios: BVAR in levels / benchmark BVAR(12), pseudo-iterated approach

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UR	0.96	0.96	0.98	0.99	1.00	1.00	0.98	0.97	0.96	0.96	0.96	0.96
PCEPI	1.04	1.05	1.06	1.06	1.05	1.05	1.04	1.03	1.03	1.02	1.00	0.99
PCEXFEPI	0.95	0.94	0.94	0.93	0.90	0.90	0.89	0.88	0.86	0.86	0.84	0.82
PAYROLLS	0.98	1.03	1.03	1.03	1.03	1.01	0.98	0.99	0.98	0.99	0.98	0.99
WEEKLYHRS	0.98	0.96	0.98	0.99	1.01	1.02	1.01	1.01	1.01	1.01	1.01	1.02
CLAIMS	1.04	1.06	1.07	1.10	1.12	1.13	1.13	1.14	1.15	1.15	1.16	1.17
RETAILSALES	1.03	1.03	1.02	1.00	1.02	1.01	1.01	1.02	1.01	1.00	1.00	1.00
CONSCONF	1.03	1.05	1.07	1.08	1.11	1.13	1.15	1.17	1.18	1.19	1.20	1.20
STARTS	1.03	1.03	1.03	1.02	1.02	1.02	1.02	1.02	1.01	1.01	1.02	1.02
IP	1.01	1.04	1.04	1.05	1.05	1.04	1.03	1.04	1.04	1.05	1.04	1.04
CU	1.02	1.04	1.06	1.06	1.06	1.06	1.04	1.03	1.03	1.02	1.01	1.00
PMISUPDELIV	1.09	1.20	1.35	1.45	1.51	1.58	1.64	1.70	1.76	1.84	1.91	1.99
PMIORDERS	1.07	1.10	1.12	1.13	1.14	1.16	1.16	1.18	1.19	1.20	1.20	1.21
POIL	1.01	1.02	1.01	1.02	1.05	1.04	1.03	1.03	1.04	1.04	1.02	1.02
SP500	1.02	1.03	1.04	1.04	1.04	1.05	1.03	1.02	1.03	1.03	1.02	1.03
ITB10Y	1.07	1.13	1.20	1.25	1.30	1.34	1.37	1.40	1.43	1.47	1.51	1.55
FFR	1.07	1.19	1.34	1.47	1.56	1.61	1.64	1.64	1.64	1.64	1.64	1.65
REALXR	1.00	0.99	1.00	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00

	all horizons	horz<=6	horz>6
average	1.105	1.077	1.133
median	1.031	1.038	1.025
min	0.822	0.897	0.822
max	1.987	1.611	1.987
% < 1	0.236	0.213	0.259

Table 14: Mean errors of the benchmark BVAR (12 lags)

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
Mean errors												
UR	-0.03	-0.04	-0.04	-0.04	-0.03	-0.03	-0.02	0.00	0.01	0.03	0.05	0.06
PCEPI	-0.29	-0.41	-0.43	-0.47	-0.49	-0.55	-0.61	-0.66	-0.69	-0.73	-0.76	-0.79
PCEXFEPI	-0.33	-0.48	-0.54	-0.59	-0.63	-0.66	-0.70	-0.74	-0.77	-0.81	-0.84	-0.87
PAYROLLS	-0.09	-0.17	-0.28	-0.39	-0.48	-0.55	-0.61	-0.67	-0.73	-0.78	-0.82	-0.86
WEEKLYHRS	0.04	0.05	0.05	0.04	0.04	0.03	0.03	0.02	0.01	0.01	0.01	0.00
CLAIMS	2.20	4.56	6.96	8.90	10.68	12.37	14.01	15.42	16.53	17.64	18.76	19.84
RETAILSALES	-1.18	-1.01	-1.05	-1.12	-1.21	-1.51	-1.51	-1.47	-1.51	-1.76	-1.60	-1.55
CONSCONF	-0.36	-0.82	-1.37	-1.78	-2.11	-2.42	-2.72	-2.99	-3.23	-3.46	-3.74	-4.02
STARTS	-0.97	-0.73	-0.61	-0.57	-0.54	-0.48	-0.48	-0.44	-0.44	-0.37	-0.33	-0.30
IP	-0.24	-0.61	-0.96	-1.11	-1.23	-1.31	-1.35	-1.39	-1.39	-1.38	-1.42	-1.48
CU	-0.05	-0.11	-0.19	-0.28	-0.38	-0.47	-0.57	-0.67	-0.76	-0.86	-0.95	-1.05
PMISUPDELIV	0.26	0.33	0.31	0.26	0.21	0.14	0.05	-0.05	-0.14	-0.20	-0.27	-0.32
PMIORDERS	-0.40	-0.82	-1.22	-1.57	-1.81	-2.01	-2.16	-2.25	-2.32	-2.38	-2.44	-2.47
POIL	0.13	0.26	0.39	0.33	0.31	0.17	0.20	0.22	0.08	0.07	0.04	0.04
SP500	-0.28	-0.27	-0.22	-0.18	-0.14	-0.10	-0.07	-0.03	-0.02	-0.02	-0.03	-0.03
ITB10Y	0.00	-0.01	-0.03	-0.04	-0.05	-0.07	-0.08	-0.10	-0.11	-0.13	-0.14	-0.16
FFR	0.13	0.20	0.21	0.19	0.17	0.14	0.12	0.10	0.08	0.06	0.03	0.00
REALXR	0.29	0.29	0.30	0.30	0.31	0.30	0.29	0.29	0.31	0.31	0.31	0.30
P-values of tests of mean errors=0 (HAC s.e.)												
UR	0.00	0.01	0.09	0.26	0.47	0.68	0.85	0.99	0.91	0.84	0.78	0.73
PCEPI	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03
PCEXFEPI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PAYROLLS	0.20	0.04	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02
WEEKLYHRS	0.01	0.04	0.14	0.30	0.46	0.61	0.74	0.82	0.89	0.93	0.96	0.98
CLAIMS	0.03	0.02	0.02	0.04	0.07	0.08	0.10	0.11	0.13	0.14	0.14	0.15
RETAILSALES	0.16	0.14	0.12	0.10	0.08	0.04	0.04	0.05	0.04	0.02	0.03	0.03
CONSCONF	0.36	0.31	0.28	0.30	0.33	0.35	0.37	0.39	0.41	0.42	0.43	0.43
STARTS	0.01	0.03	0.07	0.08	0.09	0.14	0.15	0.20	0.22	0.32	0.40	0.46
IP	0.54	0.12	0.05	0.06	0.07	0.08	0.10	0.10	0.11	0.12	0.12	0.12
CU	0.08	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
PMISUPDELIV	0.02	0.09	0.25	0.46	0.63	0.79	0.94	0.94	0.83	0.76	0.68	0.62
PMIORDERS	0.04	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01
POIL	0.81	0.69	0.57	0.60	0.62	0.78	0.74	0.71	0.88	0.89	0.93	0.93
SP500	0.23	0.34	0.46	0.56	0.66	0.75	0.82	0.93	0.95	0.96	0.92	0.94
ITB10Y	0.87	0.72	0.60	0.56	0.54	0.51	0.46	0.42	0.38	0.35	0.31	0.27
FFR	0.00	0.00	0.01	0.08	0.22	0.38	0.54	0.66	0.76	0.84	0.92	0.99
REALXR	0.00	0.03	0.03	0.02	0.02	0.02	0.03	0.03	0.02	0.02	0.02	0.02

Table 15: Description of other country dataset and transformations

Code	Series	Transformation
UNRATE	unemployment rate	*none*
EMPLOY	total employment	$1200 \ln (y_t/y_{t-1})$
IP	industrial production	$1200 \ln (y_t/y_{t-1})$
CPI	CPI inflation	$1200 \ln (y_t/y_{t-1})$
OIL	Spot commodity price - crude oil	$100 \ln (y_t/y_{t-1})$
XRATE	real exchange rate vs. major currencies	$100 \ln (y_t/y_{t-1})$
STOCKPRICE	stock price index[4]	$100 \ln (y_t/y_{t-1})$
POLRATE	official policy rate[5]	*none*
BONDRATE	10-year government bond yield	*none*

The used Stock Price Index is TSE-300 for Canada, SPF-250 for France, and FTSE-100 for UK. The used policy rate is Overnight target rate for Canada, Banque de France Official Lending Rate and ECB policy rate for France, and Bank of England official bank rate for UK. Data are taken from the Forecasting Analysis and Modeling Environment Database, OECD, Conference board, BIS, ECB, and Bank of England.

Table Appendix

Table A3. RMSFE ratios: optimal tightness / fixed tightness.

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	1.00	1.00	0.98	0.98	1.00	1.00	1.00	1.00	1.01	1.02	1.01
employ	1.00	0.99	1.00	1.00	1.01	1.00	1.00	1.01	1.01	1.01	1.01	1.01
ip	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
cpi	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.99
oil	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
xrate	1.00	1.00	1.00	1.00	1.00	1.01	1.01	1.00	1.00	1.00	1.00	1.01
stockprice	1.00	1.01	1.01	1.01	1.01	1.01	1.00	1.01	1.01	1.00	1.00	1.00
polrate	0.98	0.99	1.00	0.99	1.00	1.00	1.00	0.99	0.99	0.98	0.98	0.98
bondrate	0.97	0.93	0.95	0.94	0.93	0.94	0.94	0.93	0.94	0.94	0.93	0.94

	all horizons	horz<=6	horz>6
average	0.99	0.99	0.99
median	1.00	1.00	1.00
min	0.93	0.93	0.93
max	1.02	1.01	1.02
% < 1	0.36	0.41	0.31

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	1.00	0.93	0.95	0.92	0.93	0.94	0.92	0.93	0.94	0.92	0.93
employ	0.97	0.97	0.96	0.96	0.95	0.94	0.94	0.95	0.96	0.96	0.97	0.97
ip	0.99	1.00	1.01	1.00	1.00	1.00	1.00	1.01	1.01	1.01	1.01	1.01
cpi	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
oil	1.01	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.01
xrate	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.03	1.01	1.01	1.01	1.01
stockprice	1.00	1.00	1.00	1.00	0.99	1.00	0.99	0.99	1.00	1.00	1.00	1.00
polrate	0.84	0.85	0.86	0.89	0.91	0.93	0.96	0.97	0.98	0.98	0.99	0.99
bondrate	0.96	0.97	0.98	0.97	0.97	0.96	0.97	0.97	0.97	0.97	0.97	0.98

	all horizons	horz<=6	horz>6
average	0.98	0.98	0.98
median	1.00	1.00	1.00
min	0.84	0.84	0.92
max	1.03	1.01	1.03
% < 1	0.54	0.52	0.56

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
employ	1.01	1.01	1.01	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99
ip	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
cpi	1.00	1.01	1.01	1.01	1.01	1.00	1.00	1.00	1.00	0.99	0.98	0.98
oil	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
xrate	1.01	1.01	1.02	1.02	1.02	1.03	1.02	1.03	1.02	1.02	1.02	1.02
stockprice	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
polrate	1.03	0.98	0.96	0.95	0.94	0.93	0.92	0.92	0.91	0.92	0.91	0.92
bondrate	0.93	0.90	0.88	0.88	0.88	0.87	0.87	0.87	0.87	0.87	0.87	0.88

	all horizons	horz<=6	horz>6
average	0.98	0.99	0.98
median	1.00	1.00	1.00
min	0.87	0.87	0.87
max	1.03	1.03	1.03
% < 1	0.39	0.26	0.52

Table A4. RMSFE ratios: BVAR(12) / BVAR(1)

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	0.95	0.93	0.89	0.89	0.90	0.91	0.92	0.94	0.96	0.99	1.00	1.00
employ	0.96	0.93	0.96	0.98	1.00	1.01	1.02	1.03	1.03	1.04	1.04	1.04
ip	0.98	0.97	0.98	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.00	1.00
cpi	0.97	0.97	0.97	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.97	0.98
oil	1.01	1.01	1.01	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00
xrate	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.01
stockprice	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
polrate	1.00	0.99	0.99	0.98	0.97	0.96	0.95	0.95	0.95	0.96	0.96	0.95
bondrate	1.06	1.02	1.02	1.02	1.00	0.99	0.99	0.98	0.98	0.98	0.97	0.96

	all horizons	horz<=6	horz>6
average	0.99	0.99	0.99
median	1.00	1.00	1.00
min	0.89	0.89	0.92
max	1.06	1.06	1.04
% < 1	0.45	0.46	0.44

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	1.00	0.87	0.95	0.92	0.93	0.91	0.92	0.91	0.92	0.92	0.91
employ	0.99	0.98	0.96	0.97	0.96	0.96	0.97	0.97	0.99	0.99	1.01	1.01
ip	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
cpi	1.00	1.01	1.00	1.00	1.00	0.99	0.99	1.00	1.00	1.00	1.00	1.01
oil	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
xrate	1.01	1.03	1.03	1.03	1.01	1.03	1.01	1.03	1.01	1.01	1.01	1.01
stockprice	1.00	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
polrate	1.03	1.02	1.01	1.02	1.03	1.04	1.04	1.03	1.04	1.04	1.04	1.04
bondrate	1.00	1.00	1.02	1.02	1.03	1.02	1.03	1.04	1.05	1.06	1.07	1.08

	all horizons	horz<=6	horz>6
average	1.00	1.00	1.00
median	1.00	1.00	1.00
min	0.87	0.87	0.91
max	1.08	1.04	1.08
% < 1	0.44	0.39	0.50

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	0.89	0.87	0.82	0.82	0.79	0.80	0.80	0.80	0.82	0.82	0.84	0.85
employ	0.91	0.94	0.93	0.95	0.97	0.97	0.99	1.00	0.99	1.01	1.01	1.01
ip	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
cpi	0.99	0.98	0.98	0.99	0.99	0.99	1.00	1.01	1.02	1.02	1.02	1.02
oil	1.00	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.01
xrate	1.01	1.01	1.01	1.01	1.01	1.00	1.00	1.00	0.99	1.00	1.00	1.01
stockprice	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
polrate	0.97	0.98	0.99	1.00	1.00	1.02	1.02	1.03	1.04	1.06	1.06	1.07
bondrate	1.03	1.00	0.98	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.97	0.96

	all horizons	horz<=6	horz>6
average	0.98	0.97	0.98
median	1.00	1.00	1.00
min	0.79	0.79	0.80
max	1.07	1.03	1.07
% < 1	0.48	0.56	0.41

Table A5. RMSFE ratios: optimal lag length / fixed lag length

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	0.97	0.94	0.93	0.94	0.97	0.97	0.97	0.97	1.00	1.00	1.00
employ	0.96	0.94	0.97	0.99	1.00	1.00	1.01	1.01	1.01	1.01	1.01	1.00
ip	0.98	0.97	0.97	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
cpi	0.99	0.99	0.99	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	1.00
oil	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
xrate	1.01	1.01	1.00	1.00	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.01
stockprice	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
polrate	0.98	0.97	0.98	0.97	0.97	0.97	0.97	0.96	0.97	0.97	0.97	0.97
bondrate	1.00	0.98	0.98	0.97	0.97	0.96	0.96	0.96	0.96	0.96	0.95	0.96

	all horizons	horz<=6	horz>6
average	0.99	0.99	0.99
median	1.00	0.99	1.00
min	0.93	0.93	0.95
max	1.01	1.01	1.01
% < 1	0.53	0.61	0.44

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.20	1.00	0.93	0.95	0.96	0.96	0.94	0.95	0.95	0.96	0.94	0.95
employ	1.00	0.99	0.98	0.98	0.98	0.98	0.98	0.98	0.99	0.99	0.99	0.99
ip	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
cpi	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.99	0.99	0.99
oil	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
xrate	1.00	1.01	1.01	1.01	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00
stockprice	1.00	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
polrate	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00
bondrate	1.00	1.00	1.00	0.98	1.00	0.99	0.99	0.99	1.00	1.00	1.00	1.00

	all horizons	horz<=6	horz>6
average	1.00	1.00	0.99
median	1.00	1.00	1.00
min	0.93	0.93	0.94
max	1.20	1.20	1.01
% < 1	0.39	0.31	0.46

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	1.00	0.95	0.93	0.94	0.93	0.93	0.94	0.95	0.95	0.96	0.96
employ	0.94	0.97	0.97	0.97	0.97	0.97	0.97	0.98	0.98	0.98	0.98	0.99
ip	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
cpi	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00	1.00
oil	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
xrate	0.99	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
stockprice	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
polrate	0.94	0.96	0.97	0.98	0.98	0.99	0.99	1.00	1.01	1.02	1.02	1.03
bondrate	1.00	0.98	0.97	0.97	0.98	0.97	0.97	0.97	0.98	0.98	0.98	0.98

	all horizons	horz<=6	horz>6
average	0.99	0.99	0.99
median	1.00	1.00	1.00
min	0.93	0.93	0.93
max	1.03	1.01	1.03
% < 1	0.49	0.52	0.46

Table A6. RMSFE ratios: optimal tightness and lag length / fixed tightness and lag length

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	0.93	0.92	0.91	0.90	0.91	0.92	0.94	0.96	0.99	0.99	0.99
employ	0.96	0.93	0.96	0.98	1.00	1.00	1.01	1.02	1.02	1.02	1.02	1.01
ip	0.98	0.96	0.96	0.99	1.00	1.00	1.00	1.01	1.01	1.00	1.00	1.00
cpi	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.99
oil	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
xrate	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.00	1.00	1.00	1.01
stockprice	1.00	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
polrate	0.96	0.99	1.00	0.98	0.97	0.97	0.95	0.94	0.95	0.95	0.95	0.95
bondrate	1.00	0.98	0.96	0.95	0.95	0.95	0.94	0.93	0.94	0.93	0.93	0.92

	all horizons	horz<=6	horz>6
average	0.98	0.98	0.98
median	1.00	0.99	1.00
min	0.90	0.90	0.92
max	1.02	1.01	1.02
% < 1	0.52	0.57	0.46

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	0.90	0.87	0.89	0.88	0.89	0.91	0.89	0.91	0.90	0.91	0.91
employ	0.99	0.99	0.98	0.98	0.96	0.96	0.97	0.97	0.97	0.98	0.99	0.99
ip	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.01
cpi	1.01	1.01	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.98
oil	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
xrate	1.03	1.04	1.04	1.03	1.01	1.03	1.01	1.03	1.01	1.01	1.01	1.01
stockprice	1.01	1.03	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
polrate	0.89	0.93	0.93	0.97	0.97	0.99	0.99	1.00	1.01	1.02	1.01	1.01
bondrate	0.96	0.97	1.00	0.98	0.99	0.99	0.99	0.98	0.99	0.99	0.99	1.00

	all horizons	horz<=6	horz>6
average	0.99	0.98	0.99
median	1.00	1.00	1.00
min	0.87	0.87	0.89
max	1.04	1.04	1.03
% < 1	0.48	0.48	0.48

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	0.93	0.91	0.93	0.91	0.90	0.93	0.92	0.93	0.94	0.94	0.94
employ	0.94	0.99	0.98	0.98	0.98	0.98	0.97	0.98	0.98	0.98	0.98	0.98
ip	1.03	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
cpi	1.02	1.01	1.01	1.01	1.01	1.00	1.01	1.01	1.01	1.01	1.00	1.00
oil	1.00	1.00	1.01	1.00	1.00	1.01	1.01	1.00	1.00	1.00	1.00	1.00
xrate	1.01	1.02	1.01	0.99	1.00	1.00	1.01	1.01	1.01	1.01	1.01	1.01
stockprice	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
polrate	0.91	0.98	1.01	1.02	1.03	1.04	1.06	1.07	1.08	1.09	1.10	1.11
bondrate	0.93	0.94	0.92	0.92	0.91	0.91	0.91	0.92	0.92	0.92	0.92	0.93

	all horizons	horz<=6	horz>6
average	0.99	0.98	0.99
median	1.00	1.00	1.00
min	0.90	0.90	0.91
max	1.11	1.04	1.11
% < 1	0.44	0.41	0.48

Table A7. RMSFE ratios: iterated (simulation) / pseudo-iterated (no simulation) approach, benchmark BVAR

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.000	1.002	1.000	0.999	0.999	0.999	0.999	0.999	1.000	0.999	1.000	1.000
EMPLOY	1.001	1.000	1.000	1.000	0.999	1.000	1.000	0.998	0.999	0.999	0.999	1.001
IP	1.001	0.999	0.999	1.000	1.002	1.001	0.998	1.000	1.000	1.000	1.000	0.999
CPI	0.999	0.999	1.000	0.999	1.000	0.999	0.999	1.000	1.000	0.999	0.999	0.998
OIL	1.001	1.000	1.000	1.001	1.000	1.000	1.001	1.001	1.000	0.999	0.999	1.001
XRATE	1.001	0.999	1.000	1.000	1.001	0.999	0.999	1.000	0.999	1.001	1.001	1.001
STOCKPRICE	0.999	0.999	1.001	0.999	1.000	1.000	1.001	1.000	1.000	0.999	1.001	1.001
POLRATE	0.999	0.999	0.999	0.999	0.999	0.998	0.999	0.998	0.998	0.998	0.997	0.997
BONDRATE	0.999	1.001	0.999	0.999	0.998	0.996	0.996	0.996	0.996	0.996	0.995	0.995

	all horizons	horz<=6	horz>6
average	0.999	1.000	0.999
median	0.999	1.000	0.999
min	0.995	0.996	0.995
max	1.002	1.002	1.001
% < 1	0.519	0.481	0.556
% +- .01 of 1	1.000	1.000	1.000
% +- .005 of 1	0.981	1.000	0.963

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.002	1.000	0.999	0.999	0.999	0.997	0.997	0.996	0.996	0.995	0.995	0.995
EMPLOY	1.001	1.000	1.000	0.998	0.998	0.996	0.997	0.996	0.996	0.996	0.996	0.997
IP	1.000	1.000	1.001	1.000	1.002	1.000	1.000	0.999	1.000	0.999	1.000	1.001
CPI	1.000	0.999	1.000	1.000	1.000	0.999	1.001	1.001	1.001	1.000	1.001	1.000
OIL	0.999	0.999	1.000	1.002	1.000	1.000	1.001	1.002	1.000	1.000	0.999	1.000
XRATE	1.001	1.002	0.999	0.998	1.001	1.001	1.001	0.999	1.000	0.999	1.001	0.998
STOCKPRICE	1.000	0.998	1.001	1.000	1.000	1.000	1.002	1.001	1.001	1.000	1.002	1.002
POLRATE	1.001	0.998	0.996	0.997	0.997	0.998	0.999	0.999	1.000	1.000	1.001	1.001
BONDRATE	1.000	1.000	1.000	1.000	1.000	0.999	0.999	0.999	0.998	0.998	0.998	0.998

	all horizons	horz<=6	horz>6
average	0.999	1.000	0.999
median	1.000	1.000	1.000
min	0.995	0.996	0.995
max	1.002	1.002	1.002
% < 1	0.426	0.370	0.481
% +- .01 of 1	1.000	1.000	1.000
% +- .005 of 1	0.972	1.000	0.944

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.000	1.000	1.001	1.001	1.002
EMPLOY	1.000	1.000	1.000	1.001	1.000	0.998	1.000	0.999	1.000	0.999	1.000	1.000
IP	1.001	0.998	1.001	0.999	1.000	0.999	1.000	1.001	0.999	0.999	0.999	0.999
CPI	1.001	1.001	1.000	1.001	0.999	1.000	1.001	1.000	0.999	1.000	0.998	0.997
OIL	1.000	1.001	1.000	1.000	1.000	1.000	1.002	1.001	1.000	1.001	1.001	1.000
XRATE	0.998	1.000	1.000	0.998	1.001	1.002	1.003	1.000	1.002	1.002	1.002	1.000
STOCKPRICE	0.999	0.999	1.000	1.000	1.000	0.999	1.001	0.998	1.001	1.000	1.002	1.001
POLRATE	0.999	1.000	0.999	0.997	0.996	0.994	0.992	0.992	0.991	0.991	0.990	0.990
BONDRATE	1.001	1.000	0.998	0.996	0.994	0.992	0.990	0.989	0.988	0.986	0.985	0.984

	all horizons	horz<=6	horz>6
average	0.999	0.999	0.998
median	1.000	1.000	1.000
min	0.984	0.992	0.984
max	1.003	1.002	1.003
% < 1	0.380	0.352	0.407
% +- .01 of 1	0.926	1.000	0.852
% +- .005 of 1	0.861	0.944	0.778

Table A8.1. RMSFE ratios: direct / pseudo-iterated approach, fixed tightness and lag length.

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	0.97	0.97	0.93	0.94	0.97	0.95	0.99	1.00	1.04	1.05	1.05
employ	1.00	0.95	0.97	0.98	1.02	1.01	1.00	1.03	1.01	1.05	1.01	1.08
ip	1.00	0.98	0.96	1.01	1.01	1.00	1.01	1.00	1.00	1.00	0.99	1.01
cpi	1.00	0.99	0.99	0.99	1.00	1.02	1.00	0.99	0.99	0.98	0.97	0.95
oil	1.00	1.00	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.02	1.01	1.01
xrate	1.00	1.01	1.01	1.00	1.01	1.00	1.00	1.00	1.01	1.01	1.00	1.01
stockprice	1.00	1.00	1.00	1.00	1.01	1.01	1.01	1.00	1.00	1.00	1.01	1.01
polrate	1.00	1.01	1.02	1.02	1.03	1.03	1.05	1.04	1.05	1.06	1.06	1.07
bondrate	1.00	1.00	1.00	1.00	0.97	0.99	1.00	0.98	0.98	0.98	0.98	0.99

	all horizons	horz<=6	horz>6
average	1.00	1.00	1.01
median	1.00	1.00	1.01
min	0.93	0.93	0.95
max	1.08	1.03	1.08
% < 1	0.29	0.30	0.28

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	1.00	1.00	1.05	1.04	1.07	1.09	1.08	1.07	1.06	1.04	1.03
employ	1.00	1.01	1.01	1.01	0.99	0.99	0.98	1.00	1.01	1.02	1.03	1.04
ip	1.00	1.01	1.00	1.01	1.00	1.00	1.01	1.00	1.00	0.98	0.99	0.99
cpi	1.00	1.01	1.01	1.01	1.01	0.96	1.01	1.03	1.03	1.05	1.05	1.00
oil	1.00	1.01	1.01	1.00	1.00	1.00	1.01	1.00	0.99	1.01	1.01	1.00
xrate	1.00	1.03	1.04	1.03	1.00	1.03	1.01	1.03	1.00	1.00	1.01	1.03
stockprice	1.00	1.02	1.02	1.01	1.00	1.00	1.00	1.00	0.99	0.99	0.99	1.00
polrate	1.00	1.07	1.00	1.01	1.04	1.02	1.01	1.02	1.05	1.08	1.12	1.15
bondrate	1.00	1.03	1.06	1.07	1.10	1.11	1.12	1.14	1.17	1.21	1.23	1.25

	all horizons	horz<=6	horz>6
average	1.03	1.02	1.04
median	1.01	1.01	1.01
min	0.96	0.96	0.98
max	1.25	1.11	1.25
% < 1	0.17	0.13	0.20

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	1.00	1.00	0.96	0.97	0.98	0.98	0.96	0.98	0.97	0.97	0.97
employ	1.00	1.01	1.04	1.03	1.05	1.03	1.03	1.04	1.04	1.04	1.04	1.05
ip	1.00	1.02	1.01	1.00	1.01	1.02	1.00	1.01	1.02	1.01	1.00	1.00
cpi	1.00	1.00	0.99	1.00	1.02	0.98	1.02	1.04	1.04	1.03	1.05	0.84
oil	1.00	1.00	1.01	1.01	1.00	0.99	1.00	1.00	1.01	1.01	1.01	1.01
xrate	1.00	0.99	0.99	0.98	0.98	0.99	1.00	1.00	0.99	1.00	1.01	1.02
stockprice	1.00	1.01	1.02	1.01	1.00	1.01	1.00	1.01	1.02	1.01	1.00	1.02
polrate	1.00	1.11	1.15	1.17	1.19	1.22	1.24	1.26	1.27	1.27	1.26	1.26
bondrate	1.00	1.10	1.14	1.15	1.15	1.15	1.14	1.12	1.11	1.10	1.09	1.08

	all horizons	horz<=6	horz>6
average	1.04	1.03	1.05
median	1.01	1.00	1.01
min	0.84	0.96	0.84
max	1.27	1.22	1.27
% < 1	0.20	0.24	0.17

Table A8.2. RMSFE ratios: direct vs pseudo-iterated approach, optimal tightness and lag length

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	1.00	0.97	0.93	0.96	0.94	0.93	0.94	0.95	0.96	1.00	1.02
employ	1.00	1.00	0.98	1.00	1.02	0.99	0.99	1.01	1.02	1.05	1.06	1.11
ip	1.00	0.99	1.01	1.03	1.01	1.02	1.02	1.02	1.03	1.02	1.03	1.05
cpi	1.00	0.99	0.99	1.00	1.00	1.02	1.01	0.99	0.99	0.95	0.94	0.95
oil	1.00	1.01	1.00	1.01	1.02	1.02	1.02	1.02	1.02	1.02	1.00	1.00
xrate	1.00	1.00	0.99	0.99	1.00	1.00	1.00	1.01	1.01	1.01	1.01	1.01
stockprice	1.00	1.01	1.02	1.01	1.02	1.02	1.01	1.00	1.01	1.01	1.02	1.03
polrate	1.00	1.03	1.03	1.04	1.05	1.04	1.05	1.05	1.05	1.05	1.05	1.07
bondrate	1.00	1.02	1.02	1.03	1.03	1.03	1.04	1.02	1.01	1.01	1.01	1.02

	all horizons	horz<=6	horz>6
average	1.01	1.01	1.01
median	1.01	1.00	1.01
min	0.93	0.93	0.93
max	1.11	1.05	1.11
% < 1	0.19	0.20	0.19

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	1.00	1.00	1.06	1.10	1.12	1.10	1.12	1.10	1.12	1.10	1.08
employ	1.00	1.00	0.99	1.00	1.00	1.00	1.01	1.03	1.05	1.05	1.06	1.07
ip	1.00	1.00	1.00	1.01	1.00	1.01	1.01	1.00	0.99	0.99	0.99	0.99
cpi	1.00	1.01	1.04	1.00	0.97	0.96	1.03	1.04	1.05	1.04	1.02	1.02
oil	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.00	1.02	1.02	1.01
xrate	1.00	1.01	1.04	1.04	1.03	1.04	1.04	1.01	1.01	1.03	1.04	1.04
stockprice	1.00	1.02	1.01	1.01	1.01	1.02	1.01	1.02	1.01	1.01	1.01	1.01
polrate	1.00	1.07	1.07	1.13	1.16	1.11	1.08	1.04	1.02	1.01	1.04	1.06
bondrate	1.00	1.03	1.02	1.05	1.06	1.06	1.07	1.08	1.10	1.13	1.15	1.15

	all horizons	horz<=6	horz>6
average	1.03	1.02	1.04
median	1.02	1.01	1.03
min	0.96	0.96	0.99
max	1.16	1.16	1.15
% < 1	0.08	0.07	0.09

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
unrate	1.00	1.00	1.00	0.96	1.00	1.03	1.00	1.00	1.02	1.00	1.00	1.00
employ	1.00	1.01	1.01	1.01	1.01	1.01	1.04	1.06	1.07	1.09	1.09	1.08
ip	1.00	1.01	1.02	1.03	1.04	1.02	1.01	1.06	1.06	1.05	1.02	1.00
cpi	1.00	1.01	1.00	1.02	0.99	0.98	1.03	1.03	1.03	0.93	0.88	0.83
oil	1.00	1.02	1.01	1.00	0.99	1.00	1.01	1.01	1.02	1.02	1.02	1.02
xrate	1.00	0.99	1.00	1.02	1.03	1.03	1.02	1.02	1.00	1.01	1.02	1.04
stockprice	1.00	1.05	1.02	1.02	1.02	1.03	1.02	1.04	1.06	1.05	1.04	1.05
polrate	1.00	1.05	1.04	1.04	1.04	1.05	1.06	1.08	1.08	1.07	1.05	1.03
bondrate	1.00	1.02	1.07	1.08	1.11	1.12	1.13	1.12	1.13	1.12	1.12	1.11

	all horizons	horz<=6	horz>6
average	1.03	1.02	1.04
median	1.02	1.01	1.03
min	0.83	0.96	0.83
max	1.13	1.12	1.13
% < 1	0.09	0.11	0.07

Table A9.1. RMSFE ratios: BVAR with Minnesota prior / benchmark BVAR, cross shrinkage=0.5

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.00	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99
EMPLOY	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IP	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CPI	1.01	1.01	1.01	1.01	1.01	1.00	1.01	1.01	1.01	1.01	1.01	1.00
OIL	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
XRATE	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
STOCKPRIC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
POLRATE	0.97	0.98	0.99	1.00	1.00	1.01	1.01	1.02	1.02	1.02	1.02	1.02
BONDRATE	0.97	0.98	0.99	0.99	1.00	1.00	1.01	1.01	1.02	1.02	1.02	1.02

	all horizons	horz<=6	horz>6
average	1.00	1.00	1.00
median	1.00	1.00	1.00
min	0.97	0.97	0.99
max	1.02	1.01	1.02
% < 1	0.53	0.56	0.50

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.07	1.11	1.13	1.15	1.15	1.16	1.15	1.15	1.14	1.14	1.13	1.12
EMPLOY	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
IP	1.03	1.01	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CPI	1.01	0.98	0.98	0.98	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
OIL	0.98	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
XRATE	0.95	0.95	0.95	0.96	0.97	0.97	0.98	0.98	0.98	0.98	0.98	0.98
STOCKPRIC	1.00	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
POLRATE	0.68	0.73	0.78	0.82	0.86	0.89	0.92	0.94	0.95	0.97	0.98	0.98
BONDRATE	1.00	1.01	1.01	1.01	1.01	1.01	1.00	1.00	1.00	1.00	0.99	0.99

	all horizons	horz<=6	horz>6
average	1.00	0.98	1.01
median	1.00	1.00	1.00
min	0.68	0.68	0.92
max	1.16	1.16	1.15
% < 1	0.64	0.65	0.63

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	0.99	1.00	0.99	0.98	0.97	0.97	0.97	0.96	0.96	0.96	0.96	0.96
EMPLOY	1.02	1.03	1.02	1.01	1.00	0.99	0.98	0.98	0.98	0.98	0.98	0.98
IP	0.98	0.99	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CPI	0.99	0.99	0.99	1.00	1.01	1.01	1.01	1.00	0.99	0.99	0.99	0.99
OIL	1.00	1.00	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00
XRATE	0.97	0.96	0.97	0.97	0.97	0.98	0.99	0.99	0.99	0.99	0.99	0.99
STOCKPRIC	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
POLRATE	0.92	0.95	0.97	0.98	0.99	0.99	0.99	0.99	0.98	0.98	0.98	0.98
BONDRATE	0.94	0.94	0.93	0.92	0.92	0.91	0.91	0.90	0.90	0.91	0.91	0.91

	all horizons	horz<=6	horz>6
average	0.98	0.98	0.98
median	0.99	0.99	0.99
min	0.90	0.91	0.90
max	1.03	1.03	1.01
% < 1	0.84	0.83	0.85

Table A9.2. RMSFE ratios: BVAR with Minnesota prior / benchmark BVAR, cross shrinkage=0.2

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.01	1.01	1.01	1.00	0.99	0.99	0.98	0.98	0.97	0.97	0.97	0.97
EMPLOY	1.00	1.00	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.98	0.98	0.98
IP	1.03	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
CPI	1.04	1.03	1.03	1.03	1.03	1.03	1.03	1.03	1.03	1.02	1.02	1.02
OIL	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
XRATE	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
STOCKPRIC	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
POLRATE	0.98	1.00	1.02	1.03	1.04	1.05	1.06	1.07	1.08	1.08	1.08	1.08
BONDRATE	0.94	0.94	0.95	0.96	0.98	0.99	1.01	1.02	1.03	1.03	1.04	1.05

	all horizons	horz<=6	horz>6
average	1.00	1.00	1.01
median	1.00	1.00	1.00
min	0.94	0.94	0.97
max	1.08	1.05	1.08
% < 1	0.67	0.67	0.67

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.18	1.20	1.22	1.21	1.21	1.20	1.19	1.18	1.17	1.15	1.14	1.14
EMPLOY	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.01
IP	1.02	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99
CPI	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.01	1.01	1.01	1.01
OIL	0.98	0.99	1.00	1.00	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00
XRATE	0.95	0.97	0.98	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99
STOCKPRIC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
POLRATE	0.70	0.77	0.83	0.88	0.92	0.95	0.98	0.99	1.01	1.02	1.03	1.04
BONDRATE	1.00	1.01	1.00	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01

	all horizons	horz<=6	horz>6
average	1.01	1.00	1.02
median	1.00	1.00	1.00
min	0.70	0.70	0.98
max	1.22	1.22	1.19
% < 1	0.55	0.61	0.48

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.06	1.09	1.09	1.08	1.08	1.08	1.08	1.08	1.08	1.07	1.07	1.07
EMPLOY	1.00	1.01	1.00	1.00	0.99	0.99	0.98	0.98	0.98	0.98	0.98	0.98
IP	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CPI	0.99	0.98	0.99	1.00	1.01	1.02	1.03	1.02	1.02	1.03	1.03	1.03
OIL	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
XRATE	0.97	0.97	0.97	0.97	0.97	0.97	0.98	0.98	0.98	0.99	0.99	0.99
STOCKPRIC	1.00	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
POLRATE	0.92	0.95	0.97	0.98	0.99	1.00	1.00	1.00	1.01	1.01	1.01	1.01
BONDRATE	0.96	0.96	0.96	0.95	0.95	0.96	0.96	0.96	0.96	0.96	0.96	0.96

	all horizons	horz<=6	horz>6
average	1.00	1.00	1.00
median	1.00	1.00	1.00
min	0.92	0.92	0.96
max	1.09	1.09	1.08
% < 1	0.60	0.72	0.48

Table A10.1: RMSFE ratios: random error variance matrix / fixed error variance matrix, Minnesota prior with cross shrinkage=0.5

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.00
EMPLOY	1.02	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IP	1.02	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CPI	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.01	1.00	1.00
OIL	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
XRATE	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
STOCKPRIC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
POLRATE	0.99	1.00	1.00	1.00	1.01	1.01	1.01	1.02	1.02	1.02	1.02	1.03
BONDRATE	1.01	1.01	1.01	1.01	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02

	all horizons	horz<=6	horz>6
average	1.00	1.00	1.01
median	1.00	1.00	1.00
min	0.99	0.99	1.00
max	1.03	1.02	1.03
% < 1	0.25	0.24	0.26

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00	1.00
EMPLOY	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.00
IP	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CPI	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
OIL	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
XRATE	1.00	1.01	1.00	1.00	1.01	1.01	1.00	1.00	1.00	1.00	1.01	1.00
STOCKPRIC	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.99	0.99	0.99	0.99	0.99
POLRATE	0.95	0.96	0.97	0.98	0.99	0.99	1.00	1.00	1.00	1.01	1.01	1.01
BONDRATE	1.00	1.01	1.01	1.01	1.01	1.02	1.02	1.02	1.02	1.02	1.02	1.02

	all horizons	horz<=6	horz>6
average	1.00	1.00	1.00
median	1.00	1.00	1.00
min	0.95	0.95	0.99
max	1.02	1.02	1.02
% < 1	0.29	0.31	0.26

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.00	1.00
EMPLOY	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.99	0.99
IP	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CPI	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
OIL	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
XRATE	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
STOCKPRIC	1.01	1.01	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00
POLRATE	0.97	0.97	0.98	0.98	0.98	0.98	0.99	0.99	1.00	1.00	1.00	1.01
BONDRATE	1.00	1.00	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01

	all horizons	horz<=6	horz>6
average	1.00	1.00	1.00
median	1.00	1.00	1.00
min	0.97	0.97	0.99
max	1.01	1.01	1.01
% < 1	0.32	0.31	0.33

Table A10.2: RMSFE ratios: random error variance matrix / fixed error variance matrix, Minnesota prior with cross shrinkage=0.2

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
EMPLOY	1.03	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IP	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CPI	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00	1.00
OIL	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
XRATE	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
STOCKPRIC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
POLRATE	1.00	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.02	1.02	1.02	1.02
BONDRATE	1.02	1.03	1.03	1.04	1.04	1.05	1.06	1.06	1.06	1.06	1.06	1.06

	all horizons	horz<=6	horz>6
average	1.01	1.01	1.01
median	1.00	1.00	1.00
min	1.00	1.00	1.00
max	1.06	1.05	1.06
% < 1	0.28	0.24	0.31

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
EMPLOY	1.02	1.02	1.02	1.03	1.03	1.03	1.03	1.02	1.02	1.02	1.02	1.02
IP	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CPI	1.00	1.00	1.00	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01
OIL	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
XRATE	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
STOCKPRIC	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
POLRATE	1.08	1.08	1.08	1.07	1.07	1.06	1.06	1.06	1.06	1.06	1.06	1.06
BONDRATE	1.02	1.03	1.03	1.04	1.04	1.04	1.04	1.05	1.05	1.05	1.05	1.05

	all horizons	horz<=6	horz>6
average	1.01	1.01	1.01
median	1.00	1.00	1.00
min	0.99	0.99	0.99
max	1.08	1.08	1.06
% < 1	0.28	0.26	0.30

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
EMPLOY	0.98	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IP	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CPI	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
OIL	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
XRATE	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
STOCKPRIC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
POLRATE	0.97	0.97	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.97
BONDRATE	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01

	all horizons	horz<=6	horz>6
average	1.00	0.99	1.00
median	1.00	1.00	1.00
min	0.96	0.96	0.96
max	1.01	1.01	1.01
% < 1	0.54	0.50	0.57

Table A13. RMSFE ratios: benchmark BVAR in levels / BVAR(12), pseudo-iterated approach

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.04	1.05	1.06	1.05	1.05	1.05	1.05	1.06	1.07	1.08	1.09	1.11
EMPLOY	0.96	0.96	0.95	0.94	0.94	0.92	0.92	0.92	0.91	0.91	0.91	0.90
IP	1.02	1.01	1.01	1.00	0.99	0.98	0.98	0.97	0.96	0.97	0.96	0.97
CPI	0.98	0.97	0.97	0.97	0.97	0.96	0.96	0.96	0.95	0.95	0.94	0.94
OIL	1.01	1.01	1.01	1.01	1.02	1.02	1.02	1.02	1.02	1.02	1.01	1.01
XRATE	1.02	1.01	1.01	1.01	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.00
STOCKPRIC	1.01	1.01	1.02	1.02	1.02	1.02	1.02	1.02	1.01	1.00	1.00	1.00
POLRATE	1.13	1.20	1.26	1.33	1.39	1.46	1.52	1.56	1.58	1.59	1.59	1.59
BONDRATE	1.10	1.13	1.16	1.19	1.21	1.25	1.29	1.31	1.32	1.33	1.34	1.36

	all horizons	horz<=6	horz>6
average	1.07	1.05	1.09
median	1.01	1.01	1.01
min	0.90	0.92	0.90
max	1.59	1.46	1.59
% < 1	0.32	0.28	0.37

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.12	1.14	1.15	1.17	1.18	1.19	1.19	1.20	1.20	1.20	1.19	1.19
EMPLOY	1.29	1.12	1.05	1.05	1.04	1.04	1.04	1.03	1.02	1.00	0.99	0.97
IP	1.05	1.03	1.01	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.98
CPI	1.02	1.00	1.01	1.00	1.00	1.02	1.03	1.02	1.03	1.04	1.05	1.06
OIL	1.01	1.01	1.01	1.01	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00
XRATE	1.01	1.00	1.01	1.02	1.01	1.00	0.99	0.98	0.97	0.96	0.97	0.97
STOCKPRIC	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00
POLRATE	0.88	0.91	0.95	0.98	1.01	1.04	1.07	1.11	1.14	1.18	1.21	1.25
BONDRATE	1.08	1.11	1.14	1.17	1.19	1.21	1.22	1.23	1.24	1.25	1.26	1.26

	all horizons	horz<=6	horz>6
average	1.06	1.05	1.07
median	1.01	1.01	1.01
min	0.88	0.88	0.96
max	1.29	1.29	1.26
% < 1	0.29	0.19	0.39

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	1.00	0.99	0.98	0.97	0.96	0.96	0.96	0.96	0.97	0.97	0.97	0.97
EMPLOY	0.99	0.99	0.98	0.99	0.99	0.98	0.97	0.97	0.97	0.98	0.99	1.00
IP	1.01	1.01	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00	1.00
CPI	1.02	1.02	1.01	1.01	0.99	0.97	0.96	0.97	0.98	0.98	0.97	0.96
OIL	1.02	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99
XRATE	1.03	1.02	1.04	1.03	1.02	1.02	1.01	1.01	1.01	1.01	1.02	1.01
STOCKPRIC	1.11	1.10	1.09	1.07	1.06	1.05	1.04	1.04	1.03	1.03	1.03	1.02
POLRATE	1.19	1.24	1.28	1.31	1.32	1.31	1.30	1.30	1.29	1.28	1.27	1.27
BONDRATE	1.07	1.11	1.12	1.11	1.09	1.07	1.05	1.03	1.01	1.00	0.98	0.97

	all horizons	horz<=6	horz>6
average	1.04	1.05	1.03
median	1.01	1.01	1.00
min	0.96	0.96	0.96
max	1.32	1.32	1.30
% < 1	0.46	0.33	0.59

Table A14.1: Mean errors of the benchmark BVAR (12 lags)

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	0.02	0.05	0.09	0.12	0.16	0.19	0.23	0.27	0.31	0.35	0.38	0.42
EMPLOY	-0.85	-0.95	-1.15	-1.25	-1.31	-1.38	-1.43	-1.49	-1.49	-1.51	-1.52	-1.49
IP	-2.84	-3.02	-3.31	-3.66	-3.75	-3.83	-3.79	-3.76	-3.68	-3.49	-3.43	-3.33
CPI	-0.89	-1.06	-1.25	-1.34	-1.49	-1.57	-1.65	-1.75	-1.81	-1.87	-1.96	-2.05
OIL	-0.72	-0.78	-0.83	-0.81	-0.82	-0.82	-0.83	-0.86	-0.87	-0.91	-0.92	-0.92
XRATE	0.15	0.19	0.19	0.21	0.21	0.21	0.21	0.21	0.21	0.20	0.21	0.21
STOCKPRICE	-0.47	-0.55	-0.49	-0.43	-0.37	-0.34	-0.30	-0.24	-0.28	-0.24	-0.19	-0.17
POLRATE	0.06	0.06	0.03	-0.03	-0.10	-0.18	-0.27	-0.37	-0.46	-0.56	-0.67	-0.77
BONDRATE	-0.03	-0.08	-0.13	-0.18	-0.23	-0.29	-0.35	-0.41	-0.47	-0.53	-0.59	-0.65

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	0.00	0.00	0.01	0.01	0.02	0.02	0.03	0.04	0.05	0.06	0.08	0.09
EMPLOY	-0.10	-0.18	-0.25	-0.30	-0.34	-0.38	-0.41	-0.44	-0.47	-0.49	-0.51	-0.52
IP	-1.95	-1.62	-1.86	-2.02	-2.06	-2.24	-2.28	-2.31	-2.37	-2.35	-2.39	-2.27
CPI	0.10	0.04	0.05	0.02	0.02	0.00	-0.01	-0.05	-0.06	-0.07	-0.10	-0.12
OIL	-0.60	-0.62	-0.54	-0.55	-0.53	-0.51	-0.52	-0.52	-0.56	-0.56	-0.55	-0.59
XRATE	-0.08	-0.10	-0.11	-0.10	-0.09	-0.08	-0.07	-0.07	-0.06	-0.06	-0.05	-0.06
STOCKPRICE	-0.38	-0.52	-0.51	-0.49	-0.49	-0.48	-0.44	-0.40	-0.39	-0.36	-0.34	-0.36
POLRATE	0.03	0.04	0.04	0.03	0.00	-0.03	-0.07	-0.11	-0.16	-0.20	-0.25	-0.30
BONDRATE	-0.04	-0.07	-0.09	-0.12	-0.15	-0.19	-0.22	-0.26	-0.30	-0.34	-0.38	-0.42

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	0.01	0.03	0.05	0.07	0.09	0.12	0.14	0.17	0.20	0.23	0.26	0.30
EMPLOY	-0.10	-0.19	-0.27	-0.32	-0.38	-0.43	-0.48	-0.52	-0.57	-0.60	-0.62	-0.63
IP	-0.94	-1.09	-1.09	-1.29	-1.38	-1.44	-1.44	-1.42	-1.43	-1.40	-1.25	-1.15
CPI	0.00	-0.15	-0.32	-0.48	-0.66	-0.81	-0.93	-1.04	-1.13	-1.26	-1.36	-1.45
OIL	-0.21	-0.27	-0.24	-0.33	-0.43	-0.54	-0.56	-0.59	-0.65	-0.63	-0.63	-0.64
XRATE	0.01	0.02	0.02	-0.03	-0.07	-0.12	-0.14	-0.15	-0.18	-0.18	-0.20	-0.23
STOCKPRICE	0.13	0.20	0.23	0.27	0.27	0.27	0.20	0.17	0.17	0.12	0.11	0.13
POLRATE	-0.04	-0.11	-0.19	-0.28	-0.38	-0.47	-0.56	-0.66	-0.77	-0.87	-0.98	-1.08
BONDRATE	-0.11	-0.21	-0.30	-0.40	-0.49	-0.57	-0.66	-0.74	-0.82	-0.89	-0.96	-1.03

Table A14.2: Pvalues of tests of mean errors= (HAC s.e.)

Canada

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	0.05	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
EMPLOY	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CPI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OIL	0.14	0.20	0.19	0.19	0.16	0.15	0.13	0.11	0.08	0.05	0.04	0.03
XRATE	0.07	0.05	0.07	0.05	0.04	0.04	0.04	0.04	0.05	0.05	0.04	0.04
STOCKPRICE	0.09	0.07	0.12	0.16	0.23	0.25	0.31	0.39	0.31	0.38	0.46	0.51
POLRATE	0.02	0.31	0.76	0.77	0.43	0.23	0.12	0.06	0.04	0.02	0.01	0.01
BONDRATE	0.08	0.05	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

France

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	0.97	0.81	0.73	0.66	0.60	0.55	0.51	0.47	0.44	0.41	0.38	0.36
EMPLOY	0.01	0.01	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.09	0.10	0.11
IP	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CPI	0.54	0.82	0.82	0.93	0.95	0.99	0.99	0.88	0.86	0.84	0.79	0.75
OIL	0.28	0.34	0.43	0.40	0.40	0.41	0.39	0.37	0.32	0.30	0.29	0.24
XRATE	0.06	0.04	0.04	0.08	0.14	0.21	0.25	0.28	0.32	0.39	0.40	0.37
STOCKPRICE	0.16	0.14	0.18	0.22	0.23	0.25	0.31	0.36	0.38	0.41	0.44	0.42
POLRATE	0.14	0.44	0.64	0.82	0.99	0.87	0.74	0.62	0.52	0.44	0.37	0.32
BONDRATE	0.01	0.03	0.06	0.06	0.07	0.06	0.06	0.05	0.04	0.04	0.03	0.03

United Kingdom

	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
UNRATE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00
EMPLOY	0.21	0.04	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
IP	0.16	0.05	0.05	0.03	0.03	0.02	0.03	0.03	0.03	0.03	0.05	0.06
CPI	1.00	0.68	0.33	0.13	0.04	0.01	0.01	0.01	0.01	0.01	0.01	0.01
OIL	0.72	0.70	0.74	0.63	0.51	0.39	0.37	0.34	0.27	0.26	0.25	0.23
XRATE	0.89	0.87	0.91	0.86	0.64	0.43	0.32	0.27	0.19	0.17	0.12	0.07
STOCKPRICE	0.62	0.47	0.40	0.33	0.33	0.35	0.48	0.56	0.56	0.71	0.73	0.69
POLRATE	0.06	0.03	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01
BONDRATE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Figures

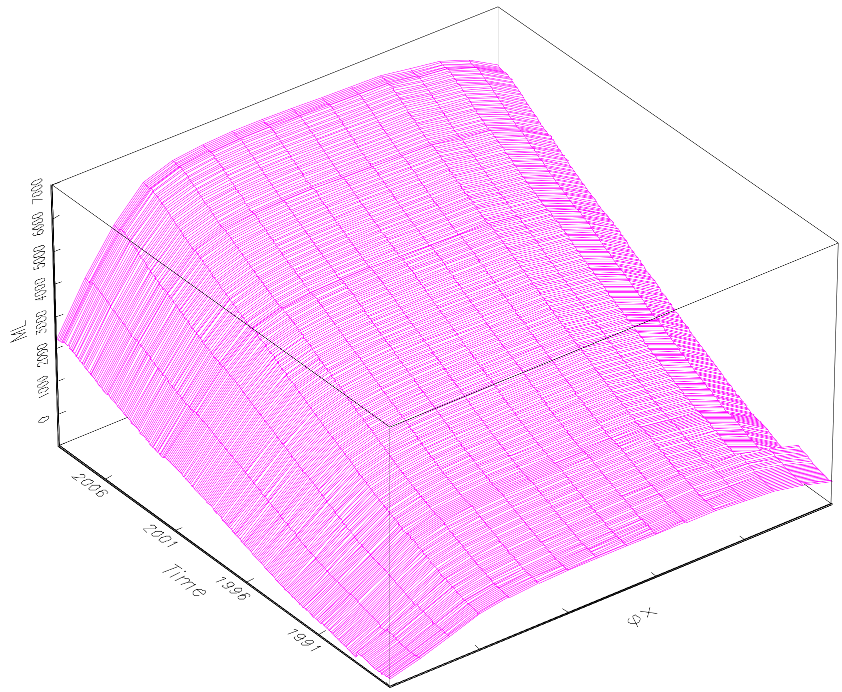

Figure 1: Data density over time, for different values of the hyperparameter θ.