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Abstract

The paper addresses the issue of forecasting a large set of variables using multivariate models. In particular, we propose three alternative reduced rank forecasting models and compare their predictive performance with the most promising existing alternatives, namely, factor models, large scale bayesian VARs, and multivariate boosting. Specifically, we focus on classical reduced rank regression, a two-step procedure that applies, in turn, shrinkage and reduced rank restrictions, and the reduced rank bayesian VAR of Geweke (1996). As a result, we found that using shrinkage and rank reduction in combination rather than separately improves substantially the accuracy of forecasts, both when the whole set of variables is to be forecast, and for key variables such as industrial production growth, inflation, and the federal funds rate.

Keywords: Bayesian VARs, factor models, forecasting, reduced rank.

J.E.L. Classification: C11, C13, C33, C53.

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. While some macroeconomic variables are of particular interest, e.g., GDP growth, inflation or short term interest rates, the attention is more and more focusing on a larger set of indicators, in order to obtain an overall picture of the expected evolution of the economy.

Recently there has been a boost in the developments of econometric methods for the analysis of large datasets, starting with the pioneering work of Forni et al. (2000) and Stock and Watson (2002a, 2002b). The key econometric tool in this context is the factor model, where each of a large set of variables is split into a common component, driven by a very limited number of unobservable factors, and an idiosyncratic component. From a forecasting point of view, the idea is to use the estimated factors for predicting future developments in, possibly, all the many variables under analysis. In practice, factor models have produced fairly accurate forecasts when compared with standard benchmarks, such as AR of VAR based predictions, for several countries and different macroeconomic variables, see e.g. the meta analysis in Eickmeier and Ziegler (2006).

The good performance of factor models has stimulated a search for alternative methods with further enhanced predictive power, see e.g. the overview in Stock and Watson (2006). These can be classified into methods for variable selection, such as LASSO (Tibshirani,1996, De Mol et al. 2006), or boosting (Bai and Ng 2007, Bühlmann, 2006, Lutz and Bühlmann 2006), or bagging (Breiman 1996, Buhlmann and Yu 2002, Inoue and Kilian 2004); Shrinkage estimators, such as ridge regression (De Mol et al. 2006) or Bayesian VARs in the spirit of Doan, Litterman and Sims (1984) (e.g. Banbura et al., 2007); and pooling procedures, where a large set of forecasts from alternative, possibly small scale, models are combined together, see e.g. the survey in Timmermann (2006).

Surprisingly, most existing research has used large datasets only as predictors for a small number of key macroeconomic variables, not considering the issue of forecasting all the series in the dataset itself. As a result, most of the contributions cited above are based on a single equation approach.

In this paper we focus on forecasting *all* the variables in a large dataset using *multivariate* models. In particular we propose three additional forecasting methods and evaluate their performance in forecasting a large US macroeconomic dataset, comparing them with the most promising existing alternatives, namely, large scale Bayesian VARs (BVAR), multivariate boosting (MB), and factor models (SW).

Specifically, we focus on Reduced Rank Regressions (RR), which have a long history in the time series literature but have been so far only applied in small models, see e.g. Velu et al. (1986), Reinsel (1983), Reinsel and Velu (1998), Camba-Mendez et al. (2003). RR represents a natural extension of the methods proposed so far in the large dataset literature. Actually, factor models can be obtained as a special case of Reduced Rank Regression, and the parameter dimensionality reduction needed in large scale VARs can be further enhanced by combining Bayesian priors with reduced rank restrictions.

We consider three types of RR. First, the classical RR, along the lines of Velu et al (1986). Second, a two-step procedure that applies, in turn, shrinkage and reduced rank restrictions (we label it RRP for Reduced Rank BVAR Posterior). Third, a Bayesian RR (BRR), which imposes the rank reduction on the prior as well as on the posterior mean, extending to the large scale context a proposal of Geweke (1996).

Being multivariate, the proposed reduced rank methods are well suited for medium to large datasets of the dimension typically of interest for central banks, i.e. about 50-60 variables, but cannot handle, or can handle with computational difficulty, cases in which the cross-sectional dimension is larger. For that very reason in our empirical application we use 52 US macroeconomic variables taken from the dataset provided by Stock and Watson (2005). The series have been chosen in order to represent the main categories of indicators which are relevant for central banks in understanding and forecasting developments in the macroeconomy. Basically, we have discarded from the original dataset of Stock and Watson (2005) those variables containing roughly the same information as others, such as the disaggregated sectoral data on industrial production and prices. These variables are not of particular interest to be forecasted as they are highly collinear, which may also create serious problems in estimation.

We can anticipate that RR, and in particular RRP and BRR, produce fairly good forecasts, more accurate than those of competing methods on average across several US macroeconomic variables, when measured in the terms of mean square or mean absolute forecast error (MSFE and MAFE). Moreover, they also perform well for key variables, such as industrial production growth, inflation and the short term interest rate. This is encouraging evidence that using shrinkage and rank reduction in combination improves substantially the accuracy of forecasts.

The paper is structured as follows. In Section 2 we describe in more detail the forecasting models under comparison, with a special focus on the different types of RR. In Section 3 we present some theoretical results on the consistency of the parameter estimates of VAR and reduced rank VAR models when the cross-sectional dimension tends to infinity. In Section 4 we present the results of the forecast comparison exercise. Section 5 concludes.

2 Forecasting Models

We are interested in forecasting the N-vector process $Y_t = (y_{1,t}, y_{2,t}, ..., y_{N,t})'$, where N is large, using a Np-dimensional multiple time series of predictors $X_t = (Y_{t-1}, Y_{t-2}, ...Y_{t-p})'$, observed for $t = 1, ..., T$. The baseline model is therefore a VAR(p):

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + ... + A_p Y_{t-p} + e_t, \tag{1}$$

where means have been removed. Defining $B = (A_1, A_2, ...A_p)'$ equation (1) can be compactly written as:

$$Y_t = B' X_t + e_t. \tag{2}$$

It is convenient to rewrite the VAR in (2) as a multivariate regression:

$$Y = XB + E. \tag{3}$$

In equation (3) the observations are by row, and equations by column, so $Y = (Y_1, ..., Y_T)'$ is a $T \times N$ matrix of dependent variables, $X = (X_1, ..., X_T)'$ is a $T \times M$ matrix of explanatory variables, where $M = Np$.

The matrix E is the matrix of disturbances, which are assumed to be independent and identically distributed across observations; that is, taking $E = (e_1, e_2, ..., e_T)'$, then $\varepsilon_i \sim IIDN(0, \Sigma)$. We define r as the rank of the $M \times N$ matrix of coefficients B, where of course $r \leq N$.

We focus on 6 forecasting models: reduced rank regression (RR), Bayesian VARs (BVAR), multivariate boosting (MB), Bayesian reduced rank regression (BRR), reduced rank Posterior (RRP), and factor models (SW).

SW and RR are both based on the idea of reducing dimensionality by imposing a structure which summarizes the information contained in a large set of predictors by focussing on some relevant linear combinations of them. An alternative route to obtain a more parsimonious model might be to impose exclusion restrictions on the predictors. However, excluding some variables from a regression is likely to be relatively ad hoc, unless a coherent statistical framework is adopted to do so. BVAR and MB provide a solution to this problem. Finally, BRR and RRP apply both shrinkage and rank reduction. In the latter case the reduced rank is imposed after the estimation of a BVAR has been performed. In the former case, the rank reduction is imposed on the prior as well as on the posterior mean. Each forecasting model is described in details in the following six subsections.

2.1 Reduced Rank Regression (RR)

It is often the case that estimation of VAR(p) models results in a large number of insignificant coefficients. Therefore, in order to obtain a more parsimonious model, one might impose rank reduction, i.e. to assume that $rk(B') = r < N$. This is equivalent to the parametric specification:

$$Y_t = \alpha \left(\sum_{i=1}^{p} \beta_i' Y_{t-i} \right) + e_t = \alpha \beta' X_t + e_t, \tag{4}$$

where α and $\beta = (\beta_1', ..., \beta_p')'$ are respectively a $N \times r$ and a $M \times r$ matrices. The model (4) was studied by Velu et al. (1986). Ahn and Reinsel (1988) suggested a more general specification where the rank of the coefficient matrix on each lagged vector of the explanatory variables may differ. However, this generalization creates computational problems in the large N case. Therefore, we focus on (4).

In equation (4), it is assumed that the true rank of the matrices α and β are identical and equal to r which is thus referred to as the rank of the system (4). However, note that the ranks of β_i, $i = 1, ..., p$, need not equal r; in particular, it can be $rk(\beta_i) \leq r$, $i = 1, ..., p$.

An interesting special case of the RRVAR model (4), which resembles the autoregressive index model of Reinsel (1983), results if $\beta_i = \beta_* K_i$ with $rk(\beta_*) = r$ for some (r, r) matrix K_i which need not be full rank, $i = 1, ..., p$, although $K = (K_1', ..., K_p')'$ is. Hence, $\beta = (I_p \otimes \beta_*)K$ and $\alpha\beta_i' = \alpha_i \beta_*'$, where $\alpha_i = \alpha K_i'$, in which case $\beta_*' y_{t-i}$, $i = 1, ..., p$, may be interpreted as dynamic factors for y_t.

Given the assumed system rank r, Velu et al. (1986) suggested an estimation method for the parameters α and β that may be shown to be quasi-maximum likelihood (see also Reinsel and Velu, 1998). Denote the sample second moment matrices by $S_{YY} = T^{-1}Y'Y$, $S_{YX} = T^{-1}Y'X$, $S_{YX} = S_{XY}'$, and $S_{XX} = T^{-1}X'X$. Hence, the covariance matrix of the unrestricted LS residuals, $S_{YY,X} = S_{YY} - S_{YX}S_{XX}^{-1}S_{XY}$ is the unrestricted quasi-ML estimator of the error process variance matrix. Additionally, let $\{\lambda\}_{t=1}^{T}$, $\lambda_1^2 \geq \lambda_2^2 \geq ... \geq \lambda_N^2 \geq 0$ denote the ordered squared eigenvalues of the $N \times N$ matrix $S_{YY,X}^{-1/2} S_{YX} S_{XX}^{-1} S_{XY} S_{YY,X}^{-1/2}$ with associated eigenvectors $\{v_i\}_{t=1}^{T}$ subject to the normalization $v_i'v_j = 1$ if $i = j$ and 0 otherwise, and let $\hat{V} = (v_1, v_2, ..., v_r)$. The quasi-ML estimators for α and β are given by $\hat{\alpha} = S_{YY,X}^{1/2}\hat{V}$ and $\hat{\beta} = S_{XX}^{-1}S_{XY}S_{YY,X}^{-1/2}\hat{V}$, so that $\hat{B}' = S_{YY,X}^{1/2}\hat{V}\hat{V}'S_{YY,X}^{-1/2}S_{XX}^{-1}S_{XY}$.

2.2 Bayesian VAR (BVAR)

Bayesian methods allow to impose restrictions on the data, but also to let the data speak. The exclusion restrictions are imposed as priors, so if some a-priori excluded variable turns out to be relevant in the data, the posterior estimate would contain such information. This provides a way of solving the curse of dimensionality problem without resorting to ad-hoc exclusion of some variables.

In this paper we implement a Normal-Inverted Wishart version of the so-called Minnesota prior of Doan et al. (1984) and Litterman (1986). This version of the prior was proposed by Kadiyala and Karlsson (1997) and allows both to gain substantially in terms of computational efficiency and to avoid the inconvenient assumption of fixed and diagonal residual variance matrix. The use of this prior for forecasting macroeconomic variables with large datasets has been recently advocated by Banbura et al (2007), who however focus on a smaller set of key macroeconomic variables when evaluating forecasting performance.

The Minnesota prior shrinks parameter estimates towards a random walk representation and it has proven to be robustly good in forecasting. In particular, the prior expectations and variances of $A_1, A_2, ..., A_p$ under the Minnesota prior are:

$$E[A_k^{(ij)}] = \begin{cases} 1 & for\ j = i,\ k = 1 \\ 0 & otherwise \end{cases},\ V[A_k^{(ij)}] = \begin{cases} \phi \frac{1}{k^2} & for\ j = i,\ \forall\ k \\ \phi \frac{1}{k^2} \theta \sigma_i^2 \sigma_j^{-2} & for\ j \neq i,\ \forall\ k \end{cases}, \tag{5}$$

while the residual variance matrix Σ is fixed and diagonal: $diag(\sigma_1^2, ..., \sigma_N^2)$. The hyperparameter ϕ measures the overall tightness of the prior, and we will return to it later in this subsection. The factor $1/k^2$ is the rate at which prior variance decreases with increasing lag length while the ratio σ_i^2/σ_j^2 accounts for the different scale and variability of the data. Finally, the parameter θ imposes additional shrinkage on the coefficients attached to a regressor when it is not a lag of the dependent variable in a given equation.

Kadiyala and Karlsson (1997) propose a version of this prior which allows to avoid the inconvenient assumption of a fixed and diagonal residual variance matrix and to gain substantially in terms of computational efficiency, at the cost of setting $\theta = 1$.The prior has a Normal-Inverted Wishart form:

$$\Sigma \sim iW(v_0, S_0);\ B \mid \Sigma \sim N(B_0, \Sigma \otimes \Omega_0) \tag{6}$$

where the parameters v_0, S_0, B_0, Ω_0 are such that the expectation of Σ is equal to the fixed residual covariance matrix of the Minnesota prior, and the prior expectation and variance of B is that of the Minnesota prior (with $\theta = 1$). Moreover, as we forecast after transforming variables to get stationarity, we set $E[A_1^{(ii)}] = 0$ rather than $E[A_1^{(ii)}] = 1$ to be consistent with the random walk assumption on the original variables. This provides us with the following prior expectations and variances for $A_1, A_2, ..., A_p$:

$$E[A_k^{(ij)}] = 0; \quad V[A_k^{(ij)}] = \phi \frac{1}{k^2} \sigma_i^2 \sigma_j^{-2} \tag{7}$$

The hyperparameter ϕ measures the tightness of the prior: when $\phi = 0$ the prior is imposed exactly and the data do not influence the estimates, while as $\phi \to \infty$ the prior becomes loose and the posterior estimates approach the OLS estimates. Posterior estimates can be easily obtained (via OLS) by implementing the prior in the form of dummy variable observations. For details see Kadiyala and Karlsson (1997).

2.3 Bayesian Reduced Rank Regression (BRR)

The BVAR and RR described in the previous subsections apply respectively shrinkage and rank reduction. Alternatively we could think of imposing both rank reduction and shrinkage on the VAR.

Bayesian analysis of reduced rank regression has been introduced by Geweke (1996). As for the reduced rank case, the $M \times N$ matrix of coefficients B is assumed to have rank r, where $r < N$. This rank reduction assumption is equivalent to the parametric specification

$$Y = X\Psi\Phi + E \tag{8}$$

with Ψ and Φ being respectively $M \times r$ and $r \times N$ matrices. To identify these matrices Geweke (1996) proposes the following normalization:

$$\Phi = [I_r \mid \Phi^*]. \tag{9}$$

Given that normalization a proper prior is:

$$\mid \Sigma \mid^{-(N+v_0+1)} \exp\left[-\frac{1}{2} tr S_0 \Sigma^{-1}\right] \exp\left[-\frac{\tau^2}{2}(tr\Phi^{*\prime}\Phi^* + tr\Psi'\Psi)\right], \tag{10}$$

namely a product of an independent Wishart distribution for Σ with v_0 degrees of freedom and matrix parameter S_0, and independent $N(0, \tau^{-2})$ shrinkage priors for each element of the coefficient matrices Φ^* and Ψ. The conditional posterior distribution of

Σ is:

$$\Sigma \mid (\Phi^*, \Psi, X, Y) \sim IW[T + v_0, S_0 + (Y - XB)'(Y - XB)]. \tag{11}$$

The conditional posterior distributions of the coefficients Φ^*,Ψ, are multivariate normals.

In particular, the conditional posterior distribution of Φ^* is:

$$vec(\Phi^*) \mid (\Psi, \Sigma, X, Y) \sim N[\Pi_\Phi * vec(\hat{\Phi}^*),\ \Pi_\Phi], \tag{12}$$

where:

$$\begin{aligned} \hat{\Phi}^* &= (\Psi' X' X \Psi)^{-1} \Psi' X' Y_1 \Sigma^{12} (\Sigma^{22})^{-1} - \Sigma^{12} (\Sigma^{22})^{-1} \\ &\quad + (\Psi' X' X \Psi)^{-1} \Psi' X' Y_2, \end{aligned} \tag{13}$$

$$\Pi_\Phi = [(\Sigma^{22})^{-1} \otimes (\Psi' X' X \Psi)^{-1} + \tau^2 I_{r(N-r)}]^{-1}, \tag{14}$$

and where $Y = [Y_1 \mid Y_2]$ is a partitioning of Y its first r and last $N - r$ columns and where Σ^{ij} denotes the partitioning of Σ^{-1} into its first r and last $N - r$ rows and columns.

The conditional posterior distribution of Ψ is:

$$vec(\Psi) \mid (\Phi, \Sigma, X, Y) \sim N[\Pi_\Psi * vec(\hat{\Psi}),\ \Pi_\Psi], \tag{15}$$

where:

$$\hat{\Psi} = \hat{B}[\Phi^+ + \Phi^0 \tilde{\Sigma}^{21} (\tilde{\Sigma}^{11})^{-1}], \tag{16}$$

$$\Pi_\Psi = [\tilde{\Sigma}^{11} \otimes X' X + \tau^2 I_{Mr}]^{-1}, \tag{17}$$

and where $\hat{B}$ is the OLS estimator, Φ^+ is the generalized inverse of Φ, Φ^0 is column-wise orthogonal to Φ^+, and where $\tilde{\Sigma}^{ij}$ denotes the partitioning of $\tilde{\Sigma}^{-1} = ([\Phi^+\ \Phi^0]' \Sigma [\Phi^+\ \Phi^0])^{-1}$ into its first r and last $N - r$ rows and columns.

Unconditional posterior distributions can be simulated by using a Gibbs sampling algorithm which draws in turn from (12), (15), and (11). See Geweke (1996) for details.

2.4 Reduced Rank BVAR Posterior (RRP)

The BRR has the shortcoming of being computationally challenging when the assumed rank is high, as the estimation of this model requires simulation involving inversion of Mr -dimensional matrices. A computationally quicker way to impose both rank reduction and shrinkage is simply to impose rank reduction on the posterior estimates of a BVAR.

The implementation of the method is straightforward. First, the system is estimated under the prior distribution described by equation (6), then a rank reduction is imposed as follows. Let $\hat{B}$ be the posterior mean of B and let $\hat{B} = U\Lambda V$ be its singular value decomposition. Collecting the largest r singular values and associated vectors in the matrices $\Lambda^* = diag(\lambda_1, \lambda_2, ..., \lambda_r)$, $U^* = (u_1, u_2, ..., u_r)$ and $V^* = (v_1, v_2, ..., v_r)$ a reduced rank approximation (of rank r) of the posterior mean is given by:

$$\hat{B}_r^* = U^* \Lambda^* V^*, \tag{18}$$

which is our RRP estimator.

2.5 Multivariate Boosting (MB)

The Minnesota prior reduces the dimensionality of the system by setting (a priori) to zero all but one coefficient in each equation. An alternative method to reach parsimony by eliminating some regressors is boosting. Theorethical results for boosting applied to multivariate models have been developed by Bühlmann (2006), while its use for macroeconomic forecasting has been recently advocated by Bai and Ng (2007) within a univariate approach.

Boosting consists in a variable selection algorithm, a stepwise regression which starts with the empty model and adds in each step the most significant covariate.

The boosting algorithm estimates $f(X_t) = E(Y_t \mid X_t)$ as a sum of $\bar{m}$ estimated learners: $\hat{f}(X_t) = \hat{f}^{(0)} + \Sigma_{m=1}^{\bar{m}} \xi \hat{g}^{(m)}$.The algorithm is based on two ingredients. The first ingredient is a loss function $L(Y_t, f(X_t))$, and a natural choice is a quadratic function (L_2 Boosting) such as the sum of squared residuals. The second ingredient is a base learner (i.e. a model to derive $\hat{g}^{(m)}$), and a natural choice is least squares regression. Let $y_{(i)},\ x_{(i)}, y_{(j)},\ x_{(j)}$ denote the i-th row vectors and j-th column vectors of $Y,\ X$. The multivariate L_2 Boosting algorithm with componentwise least squares base learner works as follows:

- Step 1. Start with the empty model $\hat{f}_j^{(0)} = \bar{Y}_j$, $j = 1, ..., N$
- Step 2. For $m = 1, ..., \bar{m}$
  - a) Compute the "current" residuals $r_{(i)} = y_{(i)} - \hat{f}_i^{(m-1)},\ i = 1, ..., T$.
  - b) Fit the base learner to $r_{(i)}$ and derive $\hat{g}^{(m)},\ i = 1, ..., T$.
    * Regress the "current" residuals $r_{(i)}$ on each regressor $x_{(j)}$, $j = 1, ..., M$, obtaining $\hat{b}_{(ij)}$

* For each regressor j and time i compute the loss function $SSR(\hat{b}_{(ij)})$
* Pick the regressor j^* and the sample point i^* which minimized the loss function and set $\hat{g}^{(m)} = \hat{b}_{(i^*j^*)} x_{i^*}$

- Step 3. Update $\hat{f}^{(m)} = \hat{f}^{(m-1)} + \xi \hat{g}^{(m)}$, where ξ is a shrinkage parameter.

The loss function used in step 2 is:

$$L(B) = \frac{1}{2} \sum_{i=1}^{T} (r'_{(i)} - x'_{(i)} B) \Gamma^{-1} (r'_{(i)} - x'_{(i)} B)' \tag{19}$$

with $\Gamma^{-1} = I$.

The base learner used in step 2 fits the linear least squares regression with one selected covariate $x_{(j)}$ and one selected pseudo-response $r'_{(i)}$ so that the loss function in (19) is reduced most:

$$\hat{s}\hat{t} = \underset{1 \le j \le M, 1 \le k \le N}{\arg\min} \{L(B); B_{jk} = \hat{\beta}_{jk}, B_{uv} = 0 \ \forall \ uv \neq jk\}$$

Thus, the learner fits one selected element of the matrix B as follows:

$$\hat{\beta}_{jk} = \frac{\sum_{v=1}^{N} r'_v x_j \Gamma^{-1}_{vk}}{x'_j x_j \Gamma^{-1}_{kk}}, \tag{20}$$

$$\hat{B}_{\hat{s}\hat{t}} = \hat{\beta}_{\hat{s}\hat{t}}, \ \hat{B}_{jk} = 0 \ \forall \ jk \neq \hat{s}\hat{t}. \tag{21}$$

Corresponding to the parameter estimate there is a function estimate $\hat{g}_\ell(\cdot)$ defined as follows: for $x = (x_1, ..., x_p)$,

$$\hat{g}_\ell(x) = \begin{cases} \hat{\beta}_{\hat{s}\hat{t}} & for\ \ell = \hat{t}, \\ 0 & otherwise, \end{cases} \quad \ell = 1, ..., N. \tag{22}$$

The algorithm terminates when the specified final iteration $\bar{m}$ is reached. Bühlmann (2006) provides a proof that this procedure is able to consistently recover sparse high-dimensional multivariate functions.

The use of the shrinkage parameter has been first suggested by Friedman (2001) and is supported by some theoretical arguments (see Efron et al 2004, and Bühlmann and Yu 2005). The boosting algorithm depend on ξ but its choice is insensitive as long as is taken to be "small" (i.e. around 0.1). On the other hand, the number of boosting iterations $\bar{m}$ is a much more crucial parameter. Indeed, $\bar{m}$ is a pivotal quantity regulating the trade-off between parsimony and fit: small values of $\bar{m}$ yield very parsimonious specifications, while as $\bar{m}$ goes to infinity the algorithm approaches to a perfect fit. Finally, in our application we slightly depart from the algorithm described by Bühlmann (2006), as we always include the first lag of the dependent variable in the model.

2.6 Factor Models (SW)

Finally, a largely used method to overcome the curse of dimensionality problem arising in forecasting with large dataset is using a factor model. In a factor model, the information contained in the predictors X_t is summarized by a set of K factors:

$$X_t = \Gamma F_t + u_t \tag{23}$$

where F_t is a K-dimensional multiple time series of factors and Γ a $N \times K$ matrix of loadings.

The forecast for y_{t+1} given the predictors can be obtained trough a two-step procedure, in which in the first step the sample data $\{X_t\}_{t=1}^T$ are used to estimate a time series of factors$\{\hat{F}_t\}_{t=1}^T$ via principal components, and then the forecasts are obtained by projecting $y_{i,t+1}$ onto $\hat{F}_t$ and $y_{i,t}$. Stock and Watson (2002a,b) develop theoretical results for this two-step procedure and show that under a set of moment and rank conditions that the MSE of the feasible forecast asymptotically approaches that of the optimal infeasible forecast for N and T approaching infinity, see Bai and Ng (2006) for additional details. To produce multistep forecasts, one can either construct forecasts directly by projecting $y_{i,t+h}$ onto the space spanned by the factors, or develop a vector time series model for $\hat{F}_t$ and use it to forecast, in turn, $\hat{F}_{t+h}$ and $y_{i,t+h}$. In this paper we use the latter strategy for comparability with the other models.

3 Consistency

This section provides some theoretical results on the parameter estimates of the infinite dimensional VAR and Reduced Rank VAR models we discussed in the previous section. We make the following assumptions

Assumption 1 *(a)* $|\lambda_{\max}(A)| < 1$ *where*

$$A = \begin{pmatrix} A_1 & ... & ... & A_p \\ I & 0 & ... & 0 \\ ... & ... & ... & ... \\ 0 & ... & I & 0 \end{pmatrix} \tag{24}$$

and $|\lambda_{\max}(.)|$ *denotes the maximum eigenvalue of a matrix in absolute value.*

(b) $c_{\max}(A) < \infty$, $r_{\max}(A) < \infty$ *where* $c_{\max}(.)$ *and* $r_{\max}()$ *denote the maximum column and row sum norm of a matrix.*

(c) e_t *is an i.i.d.* $(0, \Sigma_e)$ *sequence with finite fourth moments and* $c_{\max}(\Sigma_e) < \infty$. .

Denote the transpose of the i-th row of $(A_1, A_2, ..., A_p)$ by A^i. .We then have the following Theorem.

Theorem 1 *As* N *and* T *diverge, and under assumption 1 ,* $\left\| \hat{A}^i - A^i \right\|^2 = o_p(T^{-a})$ *for all* $i = 1, ..., N$, *and for all* $a < 1/2$, *as long as* $N = o\left((T/\ln(T))^{1/2} \right)$.

Proof. It is sufficient to prove that for each of the N equations of the VAR model,

$$\left\| \hat{A}^i - A^i \right\|^2 = o_p(T^{-a}) \text{ for all } a < 1/2. \tag{25}$$

To prove (25) we mirror the analysis of Theorems 4 and 5 of An et al. (1982). For simplicity we consider Yule-Walker estimation of $\hat{A}^i$ which is asymptotically equivalent to OLS estimation. Let γ_i^{fp} and Γ^p denote the vector of covariances between $y_{i,t}$ and $X_{p,t}^p$ and the covariance matrix of $X_{p,t}^p$, respectively and $\hat{\gamma}_i^{fp}$ and $\hat{\Gamma}^p$ their sample counterparts. Then, by (25) of An et al. (1982)

$$\Gamma^p \left(\hat{A}^i - A^i \right) = -\left(\hat{\Gamma}^p - \Gamma^p \right) \left(\hat{A}^i - A^i \right) - \left(\hat{\gamma}_i^{fp} - \gamma_i^{fp} \right) - \left(\hat{\Gamma}^p - \Gamma^p \right) A^i \tag{26}$$

Since each $y_{i,t}$ is part of a stationary VAR process by assumption 1(a), and, also taking into account assumption 1(b)-(c), it follows that $y_{i,t}$ satisfies the assumptions of Theorem 5 of An et al. (1982). Define $A^i = (A_1^i, ..., A_{Np}^i)'$and $\hat{A}^i = (\hat{A}_1^i, ..., \hat{A}_{Np}^i)'$. Then, by Theorem 5 of An et al. (1982), we have

$$\left\| \left(\hat{\Gamma}^p - \Gamma^p \right) \left(\hat{A}^i - A^i \right) \right\|^2 = o_p(1) \sum_{j=1}^{Np} \left(\hat{A}_j^i - A_j^i \right)^2 \tag{27}$$

$$\left\|\hat{\gamma}_i^{fp} - \gamma_i^{fp}\right\|^2 = o_p\left((\ln T/T)^{1/2}\right) \tag{28}$$

and

$$\left\|\left(\hat{\Gamma}^p - \Gamma^p\right) A^i\right\|^2 = o_p\left((\ln T/T)^{1/2}\right) \tag{29}$$

Hence,

$$(1 + o_p(1))\left\|\hat{A}^i - A^i\right\|^2 = o_p\left((\ln T/T)^{1/2}\right) \tag{30}$$

which implies (25) and completes the proof of the theorem. ■

Note that the above analysis straightforwardly implies that a lag order, $p = p_T$, that tends to infinity is acceptable. In this case, the above result holds as long as $Np_T = o\left((T/\ln(T))^{1/2}\right)$. Next, we consider a reduced rank approximation to the VAR model. To keep things general, we consider the case where a singular value decomposition is used to decompose $(A_1, A_2, ..., A_p)$ as $\mathcal{O}\mathcal{K}$ where $\mathcal{O}$ and $\mathcal{K}'$ are $N \times r$ and $Np \times r$ matrices respectively, for some $r < N$. The sample counterpart of this decomposition is given by $(\hat{A}_1, \hat{A}_2, ..., \hat{A}_p) = \hat{\mathcal{O}}\hat{\mathcal{K}}$. Then, we have the following Theorem.

Theorem 2 *As N and T diverge, and under assumption 1 , each element of $\mathcal{O}$ and $\mathcal{K}'$ is $o_p(T^{-a+2b})$-consistent for $\mathcal{O}$ and $\mathcal{K}'$, for all $0 < a < 1/2$, and $0 < b < 1/4$, $2b < a$, as long as $N = o\left(T^b\right)$.*

Proof. We define formally the functions $g_{\mathcal{O}}(.)$ and $g_{\mathcal{K}}(.)$ such that

$$vec(\hat{\mathcal{K}}') = g_{\mathcal{K}}\left(vec(\hat{\mathcal{A}})\right) \tag{31}$$

and

$$vec(\hat{\mathcal{O}}') = g_{\mathcal{O}}\left(vec(\hat{\mathcal{A}})\right) \tag{32}$$

where $\hat{\mathcal{A}} = (\hat{A}_1, \hat{A}_2, ..., \hat{A}_p)$ and $\mathcal{A} = (A_1, A_2, ..., A_p)$. Therefore, $g_{\mathcal{O}}(.)$ and $g_{\mathcal{K}}(.)$ define the singular value decomposition operator. By theorems 5.6 and 5.8 of Chatelin (1983) $g_{\mathcal{O}}(.)$ and $g_{\mathcal{K}}(.)$ are bounded, continuous and differentiable and therefore admit a first order Taylor expansion. Therefore,

$$vec(\hat{\mathcal{K}}') - vec(\mathcal{K}') = \frac{\partial g'_{\mathcal{K}}}{\partial \mathcal{A}}\left(vec(\hat{\mathcal{A}}) - vec(\mathcal{A})\right)\frac{\partial g'_{\mathcal{K}}}{\partial \mathcal{A}} + o_p(T^{-a}) \tag{33}$$

and

$$vec(\hat{\mathcal{O}}') - vec(\mathcal{O}') = \frac{\partial g'_{\mathcal{O}}}{\partial \mathcal{A}}\left(vec(\hat{\mathcal{A}}) - vec(\mathcal{A})\right)\frac{\partial g'_{\mathcal{O}}}{\partial \mathcal{A}} + o_p(T^{-a}) \tag{34}$$

By theorem 1 every element of $\left(vec(\hat{\mathcal{A}}) - vec(\mathcal{A})\right)$ is $o_p(T^{-a})$. The number of columns of $\frac{\partial g'_{\mathcal{K}}}{\partial \mathcal{A}}$ and $\frac{\partial g'_{\mathcal{O}}}{\partial \mathcal{A}}$ are of the order N^2. Thus, each element of $vec(\hat{\mathcal{O}}') - vec(\mathcal{O}')$ and $vec(\hat{\mathcal{K}}') - vec(\mathcal{K}')$ is a linear combination of possibly all elements of $\left(vec(\hat{\mathcal{A}}) - vec(\mathcal{A})\right)$. It then follows that each element of $vec(\hat{\mathcal{O}}') - vec(\mathcal{O}')$ and $vec(\hat{\mathcal{K}}') - vec(\mathcal{K}')$ is $o_p(T^{-a+2b})$-consistent. ■

4 Forecasting

4.1 Data

We analyze the overall performance of the models described in the previous Section in forecasting 52 U.S. macroeconomic time series. The data are monthly observations going from 1959:1 through 2003:12, and are taken from the dataset of Stock and Watson (2005). The series have been chosen in order to represent the main categories of indicators which are relevant for central banks in understanding and forecasting developments in the macroeconomy, trying to be as parsimonious as possible given the computational bounds posed by the estimation of the competing models. In particular, some of the models at hand (RR) can not handle cases in which the time dimension is too short with respect to the cross-sectional dimension (which would be the case given the rolling scheme used for our forecasting exercise), while some others (BRR, MB) would become too computationally intensive. To solve this trade off between economic relevance and parsimony we have removed from the dataset of Stock and Watson (2005) those variables containing roughly the same information of others, such as the disaggregated sectoral data on industrial production and prices. These series contain information collinear to that of their aggregated counterparts, therefore they are both less interesting to forecast, and very likely to create problems of collinearity.

The time series under analysis represent the typical data-set of interest for central banks, and can be grouped in three broad categories: series related to the real economy, series related to money and prices, and series related to financial markets. Among the first group we have variables series on real output, income, employment, consumption, industrial production, inventories, sales. The second group comprises price indexes and several monetary aggregates. The last group comprises interest rates on Treasury bills, exchange rates, and stock indexes.

The series are transformed by taking logarithms and/or differencing so that the transformed series are approximately stationary. Forecasting is performed using the transformed data, then forecasts for the original variables are obtained integrating back.

In general, growth rates are used for real quantity variables, first differences are used for nominal interest rates, year on year growth rates for price series. For a detailed summary of the series under analysis and the used transformations see Table 1.

4.2 Forecasting exercise

The forecasting exercise is performed in pseudo real time, using a rolling estimation window of 10 years. The first estimation window is 1960:1 1969:12 (notice one year of data was used in order to compute yearly growth rates for some variables), the first forecast window is 1970:1-1970:12 and the last one 2003:1-2003:12. All variables are standardized prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly.

The BIC criterion applied to the BVAR for the 52 variables selects one lag both with the rolling samples and with the whole sample. However, this result may be driven by the high number of parameters to be estimated. To control for this we also applied the BIC to the more parsimonious reduced rank VAR, with rank set to 1, but the selected lag length does not change. To evaluate whether there is any loss from such a short dynamic specification, we also compared the results for the BVAR(1) with those from a BVAR(13), the specification adopted by Banbura et al. (2007) and we found that the gains from using a longer lag specification are minor, if any. Therefore, we have used a one lag specification for all the models.

At each point in time we grid search over the relevant dimensions of the models at hand: for the SW model we search over the number of factors K, for RR we search over the assumed rank r, for BVAR the grid is over the tightness ϕ. For the MB we search over the number of iterations $\bar{m}$ and over the rescaling parameter ξ. For models in which both shrinkage and rank reduction is used, we grid search contermporaneously on both these dimensions.[1] Then, at each point in time we optimize our forecasts by choosing the model which minimized the forecast error for each variable and forecast horizon in the previous 2 years (i.e. 24 periods).

We assess predictive accuracy in terms of Relative Mean Squared/Absolute Forecast Error (RMSFE/RMAFE) against three different benchmarks. The first benchmark is a simple autoregressive model, which turns out to be the more competitive and have been used by Stock and Watson (2002) and Bai and Ng (2007). The second benchmark is a the

[1]For SW we use $K = 1, 2, 3, 6$ factors for RR we use rank $r = 1, 2, 3, 6, 10, 25, 50, 52$, for the BVAR we use tightness $\phi = 2.0e{-}005, 0.0005, 0.002, 0.008, 0.018, 0.072, 0.2, 500$, for MB we use $\bar{m} = 2{*}52{*}1,\ 2{*}52{*}2$ iterations and $\xi = 0.05, 0.1, 0.2$. For RRP we use $\phi = 2.0e - 005, 0.0005, 0.002, 0.008, 0.018, 0.072, 0.2,$ 500 and $r = 1, 2, 3, 6, 10, 25, 50, 52$, for BRR we use $r = 1, 2, 3, 6, 10, 25, 50, 52$ and $\tau = 5, 10, 100$.

baseline Minnesota prior of Doan et al. (1984) with standard RATS hyperparameters[2], which we include in order to have a specific reference to compare the shrinkage models. Finally we use a random walk forecast (RW), which is used as benchmark by De Mol et al (2006) and Banbura et al. (2007)[3].

4.3 Results

In this section we present the results of our forecasting exercise. Results are displayed in Table 2a/b (RMSFE and RMAFE vs AR(1)), Table 3a/b (RMSFE and RMAFE vs BVAR0), Table 4a/b (RMSFE and RMAFE vs RW). Each table contains 12 panels corresponding to different forecast horizons (1 to 12). The first line of each panel in the tables reports results for the average RMSFE/RMAFE over all the 52 variables. The remaining lines display the RMSFE/RMAFE for three key macroeconomic variables, i.e. Industrial Production (IPS10), CPI Inflation (PUNEW), and the Federal Funds Rate (FYFF). The best models for each horizon are highlighted in bold. Several conclusions can be drawn by looking at the tables.

Let us first focus on the overall performance of the models, i.e. the average RMSFE and RMAFE over *all* the variables.

For very short horizons (1 and 2 step-ahead) there are no models able to beat the AR(1) benchmark. The AR(1) is overall a very competitive benchmark outperforming the BVAR0 for any horizon shorter than 8 step-ahead. On the other side, for longer horizons the BVAR0 is slightly better than the AR(1). Moreover, it is important to stress that both the AR(1) and the BVAR0 benchmark largely outperform the third one, i.e. random walk forecast.

Overall, among the six models at hand, the BRR is the best model for short horizons (up to 7-month ahead), while RRP is the best one for long horizons (8 to 12 step-ahead). In particular, at short horizons BRR produces gains in RMSFE and RMAFE up to 19% (0.81) and 11% (0.89) respect to the AR(1), and up to 19% (0.81) and 12% (0.88) respect to the BVAR0. At long horizons, RRP produces gains in RMSFE and RMAFE up to 25% (0.75) and 17% (0.83) against the AR(1), and up to 22% (0.78) and 16% (0.84) against the BVAR0. Also the BVAR and RR do a good job, but they are both systematically outperformed by RRP and BRR. SW produces the best forecasts at 1-step ahead, but its forecasting performance is quite poor for longer horizons, as well as that of MB.

[2] In particular, we use the prior in (7) with $\phi = 0.2$.

[3] More precisely Banbura et al. (2007) use the prior in (7) with $\phi = 0$, which is virtually equivalent to a random walk forecast.

Let us now focus on the prediction of three key macroeconomic variables, i.e. Industrial Production (IPS10), CPI Inflation (PUNEW), and the Federal Funds Rate (FYFF). Results for these variables are displayed in the remaining lines of Tables 2a/b and 3a/b. Importantly, for these selected variables some models beat the AR(1) also at the 1- and 2-step ahead horizon. In particular, at 1-step ahead, SW produces the best forecasts for inflation (together with MB when RMAFE is considered) and the federal funds rate, while BRR (together with MB when RMAFE is considered) produce the best forecast of industrial production. At 2-step ahead BRR is the best models for forecasting each of the three variables, with the exception of inflation when RMAFE is considered. For intermediate horizons (3- to 7- step ahead) the best model is BRR for industrial production and the federal funds rate, while RRP is the best model for inflation. For long horizons the best model is still the RRP. All the gains are systematically larger than the average, i.e. the gains obtained when forecasting all the variables.

To sum up, for very short horizons is difficult to beat an AR(1) benchmark, but SW and BRR can do so for some variables. For intermediate and long horizons the best models are respectively BRR and RRP. RR and the BVAR produce overall good results, however they are below BRR and RRP and are unable to beat the AR(1) at very short horizons. These results provide encouraging evidence that using shrinkage and rank reduction is useful, and using them *in combination* rather than separately improves substantially the accuracy of forecasts.

4.4 Robustness

To check the robustness of our results we have repeated the analysis using different subsamples and performed a small Montecarlo simulation.

Tables 5a/b and 6a/b display results obtained using the evaluation sample 1985:1 2003:12, while tables 7a/b and 8a/b display results based on the evaluation sample 1995:1 2003:12. We do not report the results (are available upon request) against the RW benchmark as it is systematically outperformed by the other two benchmarks.

For the evaluation sample 1985:1 2003:12, the emerging pattern is similar to that obtained on the whole sample, namely RRP and BRR produce on average the best forecasts, respectively for short and long horizons. The only interesting news is that in this subsample MB has the best forecast accuracy for industrial production and the federal funds rate at 1-step ahead.

Some more differences arise when using the evaluation sample, 1995:1 2003:12. Again, we have the good performance of MB at 1-step ahead, which is now accompanied by a dramatic reduction in the accuracy of the SW model, which is no more able to bear the AR(1). Moreover, the pattern for the long horizons changes slightly. In particular, while RRP remains the best models when considering all the variables and for industrial production, it is no more the best model for inflation and the federal funds rate, which are now better forecasts respectively by the BVAR and BRR.

To shed more light about the robustness of our results we have also performed a small Montecarlo experiment using bootstrapped data. We use a slight modification of the bootstrapping algorithm described Politis and Romano (1994). In particular, the bootstrapping is performed over the data once they have been differentiated to get stationarity, while a bootstrapped version of the original data is obtained by adding an initial condition and integrating out.

Results of this experiment based on 100 different bootstrapped samples are displayed in Table 9a/b. Notice that MB and BRR are missing, as both these methods are simply too computationally intensive to run such an exercise. Tables 9a/b show that at short horizons SW performs better than the remaining models, but still does not beat an AR(1) benchmark. For longer horizons RRP produces the best forecasts, followed by the BVAR and RR, which confirms that the use of *both* shrinkage *and* rank reduction produces additional gains respect to using the two methods separately.

5 Conclusions

In this paper, we have addressed the issue of forecasting a large set of variables using multivariate models. In particular, we have proposed three alternative reduced rank forecasting models and compared their predictive performance with the most promising existing alternatives, namely, factor models, large scale Bayesian VARs, and multivariate boosting.

Specifically, we focused on the classical reduced rank regression along the lines of Camba-Mendez et al. (2003), on a two-step estimation procedure that applies, in turn, shrinkage and reduced rank restrictions (RRP), and on a Bayesian VAR with rank reduction (BRR), extending to the large scale context a proposal of Geweke (1996).

As a result, we found that using shrinkage and rank reduction in combination rather than separately improves substantially the accuracy of forecasts. In particular RRP and BRR, produce fairly good forecasts, more accurate than those of competing methods on average across several US macroeconomic variables, and they also perform well for key variables, such as industrial production growth, inflation and the short term interest rate. A small Montecarlo simulation confirmed these findings.

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Table 1: Data Description

Code	Series	Transformation
IPS10	INDUSTRIAL PRODUCTION INDEX - TOTAL INDEX	Monthly Growth Rate
PUNEW	CPI-U: ALL ITEMS (8First Difference-84=No Transf.00,SA)	change in Yearly Growth Rate
a0m052	Personal income (AR, bil. chain First Difference000 $)	Monthly Growth Rate
A0M051	Personal income less transfer payments (AR, bil. chain First Difference000 $)	Monthly Growth Rate
A0M224_R	Real Consumption (AC) A0mFirst DifferenceFirst Difference4/gmdc	Monthly Growth Rate
A0M057	Manufacturing and trade sales (mil. Chain No Transf.996 $)	Monthly Growth Rate
A0M059	Sales of retail stores (mil. Chain First Difference000 $)	Monthly Growth Rate
PMP	NAPM PRODUCTION INDEX (PERCENT)	No Transf.
A0m082	Capacity Utilization (Mfg)	First Difference
LHEL	INDEX OF HELP-WANTED ADVERTISING IN NEWSPAPERS (No Transf.967=No Transf.00;SA)	First Difference
LHELX	EMPLOYMENT: RATIO; HELP-WANTED ADS:NO. UNEMPLOYED CLF	First Difference
LHEM	CIVILIAN LABOR FORCE: EMPLOYED, TOTAL (THOUS.,SA)	Monthly Growth Rate
LHUR	UNEMPLOYMENT RATE: ALL WORKERS, No Transf.6 YEARS & OVER (%,SA)	First Difference
CES002	EMPLOYEES ON NONFARM PAYROLLS - TOTAL PRIVATE	Monthly Growth Rate
A0M048	Employee hours in nonag. establishments (AR, bil. hours)	Monthly Growth Rate
PMI	PURCHASING MANAGERS' INDEX (SA)	No Transf.
PMNO	NAPM NEW ORDERS INDEX (PERCENT)	No Transf.
PMDEL	NAPM VENDOR DELIVERIES INDEX (PERCENT)	No Transf.
PMNV	NAPM INVENTORIES INDEX (PERCENT)	No Transf.
FM1	MONEY STOCK: MNo Transf.(CURR,TRAV.CKS,DEM DEP,OTHER CK'ABLE DEP)(BIL$,SA)	change in Yearly Growth Rate
FM2	MONEY STOCK:MFirst Difference(MNo Transf.+O'NITE RPS,EURO$,G/P&B/D MMMFS&SAV&SM	change in Yearly Growth Rate
FM3	MONEY STOCK: M3(MFirst Difference+LG TIME DEP,TERM RP'S&INST ONLY MMMFS)(BIL$,SA	change in Yearly Growth Rate
FM2DQ	MONEY SUPPLY - MFirst Difference IN No Transf.996 DOLLARS (BCI)	Monthly Growth Rate
FMFBA	MONETARY BASE, ADJ FOR RESERVE REQUIREMENT CHANGES(MIL$,SA)	change in Yearly Growth Rate
FMRRA	DEPOSITORY INST RESERVES:TOTAL,ADJ FOR RESERVE REQ CHGS(MIL$,SA)	change in Yearly Growth Rate
FMRNBA	DEPOSITORY INST RESERVES:NONBORROWED,ADJ RES REQ CHGS(MIL$,SA)	change in Yearly Growth Rate
FCLNQ	COMMERCIAL & INDUSTRIAL LOANS OUSTANDING IN No Transf.996 DOLLARS (BCI)	change in Yearly Growth Rate
FCLBMC	WKLY RP LG COM'L BANKS:NET CHANGE COM'L & INDUS LOANS(BIL$,SAAR)	No Transf.
CCINRV	CONSUMER CREDIT OUTSTANDING - NONREVOLVING(GNo Transf.9)	change in Yearly Growth Rate
A0M095	Ratio, consumer installment credit to personal income (pct.)	First Difference
FSPCOM	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (No Transf.94No Transf.-43=No Transf.0)	Monthly Growth Rate
FSPIN	S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS (No Transf.94No Transf.-43=No Transf.0)	Monthly Growth Rate
FSDXP	S&P'S COMPOSITE COMMON STOCK: DIVIDEND YIELD (% PER ANNUM)	First Difference
FSPXE	S&P'S COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO (%,NSA)	Monthly Growth Rate
FYFF	INTEREST RATE: FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM,NSA)	First Difference
CP90	Cmmercial Paper Rate (AC)	First Difference
FYGM3	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,3-MO.(% PER ANN,NSA)	First Difference
FYGM6	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,6-MO.(% PER ANN,NSA)	First Difference
FYGT1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,No Transf.-YR.(% PER ANN,NSA)	First Difference
FYGT5	INTEREST RATE: U.S.TREASURY CONST MATURITIES,Monthly Growth Rate-YR.(% PER ANN,	First Difference
FYGT10	INTEREST RATE: U.S.TREASURY CONST MATURITIES,No Transf.0-YR.(% PER ANN,NSA)	First Difference
FYAAAC	BOND YIELD: MOODY'S AAA CORPORATE (% PER ANNUM)	First Difference
FYBAAC	BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM)	First Difference
EXRUS	UNITED STATES;EFFECTIVE EXCHANGE RATE(MERM)(INDEX NO.)	Monthly Growth Rate
EXRSW	FOREIGN EXCHANGE RATE: SWITZERLAND (SWISS FRANC PER U.S.$)	Monthly Growth Rate
EXRJAN	FOREIGN EXCHANGE RATE: JAPAN (YEN PER U.S.$)	Monthly Growth Rate
EXRUK	FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND)	Monthly Growth Rate
EXRCAN	FOREIGN EXCHANGE RATE: CANADA (CANADIAN $ PER U.S.$)	Monthly Growth Rate
PWFSA	PRODUCER PRICE INDEX: FINISHED GOODS (8First Difference=No Transf.00,SA)	change in Yearly Growth Rate
PWFCSA	PRODUCER PRICE INDEX:FINISHED CONSUMER GOODS (8First Difference=No Transf.00,SA)	change in Yearly Growth Rate
PWIMSA	PRODUCER PRICE INDEX:INTERMED MAT.SUPPLIES & COMPONENTS(8First Difference=No T	change in Yearly Growth Rate
PWCMSA	PRODUCER PRICE INDEX:CRUDE MATERIALS (8First Difference=No Transf.00,SA)	change in Yearly Growth Rate

Table 2a: RMSFEs against AR(1)

	RR	SW	BVAR	MB	RRP	BRR
Hor:1						
Avg.RMSFE	1.40	**1.07**	1.28	1.45	1.30	1.20
IPS10	1.31	1.10	1.09	0.98	1.13	**0.90**
PUNEW	1.19	**0.94**	1.26	1.00	1.25	1.15
FYFF	1.11	**0.94**	1.01	1.02	1.03	0.98
Hor:2						
Avg.RMSFE	1.21	1.05	1.11	1.26	1.14	**1.02**
IPS10	1.11	1.06	0.92	1.02	0.92	**0.77**
PUNEW	0.96	**0.86**	1.01	0.99	0.95	0.94
FYFF	1.01	0.94	0.98	1.01	0.98	**0.91**
Hor:3						
Avg.RMSFE	1.12	1.06	1.02	1.14	1.04	**0.93**
IPS10	1.07	1.06	0.87	1.03	0.87	**0.72**
PUNEW	0.83	0.84	0.84	0.97	**0.80**	**0.80**
FYFF	0.99	0.96	0.96	1.01	0.93	**0.88**
Hor:4						
Avg.RMSFE	1.05	1.09	0.96	1.08	0.97	**0.89**
IPS10	1.01	1.06	0.81	1.03	0.79	**0.69**
PUNEW	0.75	0.86	0.76	0.97	**0.72**	0.74
FYFF	1.03	0.98	0.96	1.00	0.92	**0.88**
Hor:5						
Avg.RMSFE	1.00	1.11	0.92	1.05	0.91	**0.85**
IPS10	0.96	1.08	0.78	1.01	0.74	**0.68**
PUNEW	0.71	0.84	0.71	0.97	**0.67**	0.70
FYFF	1.05	1.01	0.96	0.99	0.90	**0.85**
Hor:6						
Avg.RMSFE	0.95	1.14	0.87	1.03	0.86	**0.83**
IPS10	0.93	1.10	0.75	1.01	0.71	**0.67**
PUNEW	0.68	0.83	0.67	0.97	**0.63**	0.67
FYFF	1.03	1.04	0.91	0.98	0.86	**0.81**

	RR	SW	BVAR	MB	RRP	BRR
Hor:7						
Avg.RMSFE	0.92	1.17	0.84	1.02	0.82	**0.81**
IPS10	0.89	1.12	0.73	1.01	0.70	**0.66**
PUNEW	0.66	0.84	0.64	0.98	**0.61**	0.64
FYFF	1.01	1.07	0.89	0.98	0.83	**0.80**
Hor:8						
Avg.RMSFE	0.88	1.20	0.82	1.01	**0.79**	0.81
IPS10	0.85	1.13	0.71	1.01	**0.67**	**0.67**
PUNEW	0.63	0.83	0.62	0.98	**0.59**	0.62
FYFF	0.95	1.07	0.86	0.99	**0.80**	0.80
Hor:9						
Avg.RMSFE	0.87	1.22	0.81	1.01	**0.78**	0.80
IPS10	0.83	1.13	0.70	1.01	**0.66**	0.68
PUNEW	0.61	0.82	0.61	0.99	**0.58**	0.61
FYFF	0.91	1.07	0.82	0.99	**0.77**	0.79
Hor:10						
Avg.RMSFE	0.85	1.24	0.79	1.00	**0.76**	0.80
IPS10	0.79	1.13	0.68	1.01	**0.64**	0.68
PUNEW	0.61	0.82	0.62	0.99	**0.58**	0.60
FYFF	0.90	1.08	0.80	0.99	**0.75**	0.78
Hor:11						
Avg.RMSFE	0.84	1.27	0.79	1.00	**0.75**	0.80
IPS10	0.78	1.13	0.68	1.01	**0.63**	0.68
PUNEW	0.60	0.83	0.62	0.99	**0.58**	0.60
FYFF	0.90	1.09	0.81	0.99	**0.75**	0.78
Hor:12						
Avg.RMSFE	0.85	1.31	0.80	0.99	**0.77**	0.81
IPS10	0.78	1.15	0.68	1.01	**0.64**	0.69
PUNEW	0.61	0.87	0.63	0.98	**0.61**	**0.61**
FYFF	0.92	1.11	0.83	0.99	**0.76**	0.80

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1960:1 1969:12 and the first forecast window is 1970:1 1970:12, while the last estimation window is 1984:1 1993:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 2b: RMAFEs against AR(1)

	RR	SW	BVAR	MB	RRP	BRR		RR	SW	BVAR	MB	RRP	BRR
Hor:1							**Hor:7**						
Avg.RMAFE	1.20	**1.04**	1.14	1.14	1.15	1.09	Avg.RMAFE	0.95	1.06	0.90	1.01	0.89	**0.89**
IPS10	1.16	1.04	1.05	**0.99**	1.05	**0.99**	IPS10	0.99	1.08	0.89	1.01	0.86	**0.83**
PUNEW	1.12	**1.00**	1.08	**1.00**	1.09	1.06	PUNEW	0.81	0.93	0.78	0.99	**0.76**	0.78
FYFF	1.17	**1.00**	1.06	1.03	1.09	1.06	FYFF	0.92	0.95	0.90	0.99	0.86	**0.85**
Hor:2							**Hor:8**						
Avg.RMAFE	1.11	1.02	1.06	1.09	1.07	**1.01**	Avg.RMAFE	0.93	1.07	0.89	1.01	**0.87**	0.88
IPS10	1.09	1.01	0.97	0.99	0.97	**0.89**	IPS10	0.96	1.07	0.86	1.01	0.83	**0.81**
PUNEW	0.97	0.94	0.97	0.98	0.94	**0.93**	PUNEW	0.80	0.92	0.78	0.99	**0.76**	0.78
FYFF	1.07	0.99	0.99	1.03	1.01	**0.96**	FYFF	0.92	0.97	0.89	1.00	**0.86**	**0.86**
Hor:3							**Hor:9**						
Avg.RMAFE	1.06	1.03	1.01	1.06	1.02	**0.96**	Avg.RMAFE	0.92	1.08	0.88	1.00	**0.85**	0.88
IPS10	1.10	1.04	0.97	1.01	0.97	**0.89**	IPS10	0.93	1.07	0.84	1.01	**0.81**	**0.81**
PUNEW	0.92	0.93	0.90	0.98	0.87	**0.87**	PUNEW	0.80	0.92	0.77	1.00	**0.75**	0.77
FYFF	1.02	0.95	0.97	1.03	0.96	**0.92**	FYFF	0.92	0.96	0.88	1.01	**0.84**	0.85
Hor:4							**Hor:10**						
Avg.RMAFE	1.03	1.03	0.98	1.04	0.98	**0.94**	Avg.RMAFE	0.90	1.08	0.86	1.00	**0.83**	0.87
IPS10	1.07	1.05	0.96	1.01	0.94	**0.87**	IPS10	0.90	1.07	0.81	1.01	**0.79**	0.80
PUNEW	0.87	0.95	0.88	0.98	**0.84**	0.85	PUNEW	0.80	0.92	0.78	1.00	**0.75**	0.77
FYFF	1.00	0.93	0.95	1.02	0.92	**0.89**	FYFF	0.91	0.96	0.87	1.01	**0.82**	0.84
Hor:5							**Hor:11**						
Avg.RMAFE	1.00	1.04	0.95	1.03	0.95	**0.92**	Avg.RMAFE	0.90	1.10	0.86	1.00	**0.83**	0.87
IPS10	1.04	1.06	0.94	1.01	0.90	**0.86**	IPS10	0.89	1.06	0.81	1.01	**0.78**	0.81
PUNEW	0.85	0.93	0.84	0.99	**0.81**	0.83	PUNEW	0.79	0.94	0.78	0.99	**0.75**	0.77
FYFF	0.99	0.95	0.94	1.01	0.90	**0.88**	FYFF	0.92	0.96	0.87	1.01	**0.82**	0.84
Hor:6							**Hor:12**						
Avg.RMAFE	0.97	1.05	0.92	1.02	0.91	**0.90**	Avg.RMAFE	0.91	1.12	0.87	1.00	**0.85**	0.88
IPS10	1.03	1.07	0.91	1.01	0.88	**0.84**	IPS10	0.87	1.06	0.81	1.01	**0.78**	0.80
PUNEW	0.83	0.93	0.80	0.98	**0.78**	0.80	PUNEW	0.80	0.97	0.79	0.99	**0.77**	0.78
FYFF	0.95	0.94	0.92	1.00	0.88	**0.86**	FYFF	0.92	0.97	0.88	1.01	**0.84**	0.85

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1960:1 1969:12 and the first forecast window is 1970:1 1970:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 3a: RMSFEs against BVAR0

	RR	SW	BVAR	MB	RRP	BRR
Hor:1						
Avg.RMSFE	1.04	**0.80**	0.95	1.08	0.97	0.90
IPS10	1.12	0.94	0.93	0.84	0.96	**0.76**
PUNEW	0.82	**0.65**	0.87	0.69	0.87	0.79
FYFF	1.05	**0.90**	0.96	0.97	0.98	0.93
Hor:2						
Avg.RMSFE	1.00	0.87	0.92	1.04	0.94	**0.84**
IPS10	1.03	0.99	0.86	0.95	0.85	**0.72**
PUNEW	0.79	**0.71**	0.83	0.81	0.78	0.77
FYFF	1.05	0.98	1.01	1.04	1.01	**0.94**
Hor:3						
Avg.RMSFE	0.98	0.93	0.90	1.00	0.92	**0.82**
IPS10	1.04	1.03	0.84	1.00	0.84	**0.70**
PUNEW	0.79	0.79	0.79	0.92	**0.75**	**0.75**
FYFF	1.02	0.99	0.99	1.04	0.96	**0.91**
Hor:4						
Avg.RMSFE	0.96	0.99	0.87	0.99	0.88	**0.81**
IPS10	1.04	1.10	0.84	1.06	0.81	**0.72**
PUNEW	0.76	0.87	0.77	0.99	**0.73**	0.75
FYFF	0.99	0.95	0.93	0.97	0.89	**0.85**
Hor:5						
Avg.RMSFE	0.94	1.05	0.87	1.00	0.86	**0.81**
IPS10	1.03	1.16	0.84	1.09	0.79	**0.73**
PUNEW	0.78	0.93	0.78	1.07	**0.73**	0.76
FYFF	0.98	0.94	0.89	0.92	0.84	**0.80**
Hor:6						
Avg.RMSFE	0.92	1.11	0.85	1.01	0.84	**0.81**
IPS10	1.05	1.24	0.84	1.13	0.80	**0.75**
PUNEW	0.77	0.95	0.76	1.11	**0.72**	0.77
FYFF	0.96	0.97	0.85	0.91	0.80	**0.75**

	RR	SW	BVAR	MB	RRP	BRR
Hor:7						
Avg.RMSFE	0.91	1.16	0.84	1.01	0.82	**0.81**
IPS10	1.04	1.31	0.86	1.18	0.81	**0.77**
PUNEW	0.78	1.00	0.76	1.16	**0.73**	0.77
FYFF	0.94	1.00	0.83	0.92	0.77	**0.74**
Hor:8						
Avg.RMSFE	0.89	1.21	0.83	1.02	**0.80**	0.81
IPS10	1.03	1.36	0.86	1.22	**0.81**	**0.81**
PUNEW	0.77	1.02	0.76	1.21	**0.73**	0.77
FYFF	0.90	1.01	0.81	0.94	**0.76**	0.75
Hor:9						
Avg.RMSFE	0.88	1.25	0.82	1.02	**0.79**	0.82
IPS10	1.02	1.40	0.87	1.26	**0.82**	0.84
PUNEW	0.78	1.05	0.78	1.26	**0.74**	0.77
FYFF	0.87	1.02	0.78	0.94	**0.73**	0.75
Hor:10						
Avg.RMSFE	0.88	1.29	0.82	1.04	**0.78**	0.82
IPS10	1.02	1.45	0.88	1.31	**0.82**	0.87
PUNEW	0.79	1.06	0.80	1.28	**0.75**	0.78
FYFF	0.87	1.04	0.77	0.95	**0.72**	0.75
Hor:11						
Avg.RMSFE	0.88	1.33	0.83	1.04	**0.79**	0.84
IPS10	1.03	1.50	0.90	1.34	**0.84**	0.90
PUNEW	0.79	1.10	0.82	1.30	**0.77**	0.79
FYFF	0.86	1.05	0.78	0.95	**0.72**	0.75
Hor:12						
Avg.RMSFE	0.89	1.38	0.84	1.04	**0.81**	0.85
IPS10	1.04	1.53	0.91	1.35	**0.85**	0.93
PUNEW	0.80	1.15	0.83	1.29	**0.80**	**0.80**
FYFF	0.87	1.05	0.79	0.94	**0.71**	0.75

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1960:1 1969:12 and the first forecast window is 1970:1 1970:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 3b: RMAFEs against BVAR0

	RR	SW	BVAR	MB	RRP	BRR
Hor:1						
Avg.RMAFE	0.99	**0.86**	0.94	0.94	0.96	0.90
IPS10	1.03	0.92	0.92	**0.88**	0.93	**0.88**
PUNEW	0.94	**0.84**	0.90	**0.84**	0.92	0.89
FYFF	0.98	**0.84**	0.89	0.86	0.91	0.88
Hor:2						
Avg.RMAFE	0.98	0.90	0.93	0.96	0.95	**0.89**
IPS10	1.02	0.94	0.90	0.92	0.90	**0.83**
PUNEW	0.90	0.87	0.89	0.91	0.87	**0.86**
FYFF	1.00	0.92	0.93	0.96	0.94	**0.89**
Hor:3						
Avg.RMAFE	0.97	0.94	0.92	0.97	0.93	**0.88**
IPS10	1.02	0.96	0.90	0.94	0.89	**0.83**
PUNEW	0.89	0.90	0.87	0.94	0.83	**0.83**
FYFF	0.99	0.92	0.94	0.99	0.93	**0.89**
Hor:4						
Avg.RMAFE	0.96	0.97	0.92	0.97	0.92	**0.88**
IPS10	1.00	0.98	0.90	0.95	0.88	**0.82**
PUNEW	0.86	0.94	0.86	0.97	**0.83**	0.84
FYFF	0.99	0.92	0.94	1.00	0.91	**0.87**
Hor:5						
Avg.RMAFE	0.95	0.99	0.91	0.98	0.90	**0.88**
IPS10	1.01	1.03	0.91	0.98	0.87	**0.83**
PUNEW	0.87	0.95	0.86	1.00	**0.82**	0.85
FYFF	0.97	0.93	0.93	0.99	0.88	**0.86**
Hor:6						
Avg.RMAFE	0.94	1.02	0.90	1.00	0.89	**0.88**
IPS10	1.01	1.05	0.89	1.00	0.86	**0.83**
PUNEW	0.87	0.97	0.84	1.03	**0.82**	0.84
FYFF	0.95	0.94	0.92	1.00	0.88	**0.86**
Hor:7						
Avg.RMAFE	0.93	1.05	0.89	1.00	0.88	**0.88**
IPS10	0.99	1.08	0.89	1.01	0.86	**0.83**
PUNEW	0.88	1.00	0.84	1.06	**0.81**	0.84
FYFF	0.93	0.97	0.91	1.01	0.87	**0.86**
Hor:8						
Avg.RMAFE	0.92	1.06	0.88	1.00	**0.86**	0.88
IPS10	0.99	1.11	0.89	1.05	0.86	**0.84**
PUNEW	0.87	1.00	0.84	1.08	**0.82**	0.84
FYFF	0.92	0.97	0.89	1.00	**0.86**	**0.86**
Hor:9						
Avg.RMAFE	0.92	1.08	0.88	1.00	**0.85**	0.88
IPS10	0.99	1.13	0.89	1.07	**0.86**	**0.86**
PUNEW	0.87	1.01	0.84	1.09	**0.82**	0.85
FYFF	0.91	0.95	0.87	1.00	**0.84**	0.85
Hor:10						
Avg.RMAFE	0.91	1.09	0.87	1.01	**0.84**	0.88
IPS10	0.99	1.18	0.90	1.12	**0.87**	0.88
PUNEW	0.87	1.01	0.85	1.09	**0.81**	0.84
FYFF	0.90	0.95	0.85	1.00	**0.81**	0.83
Hor:11						
Avg.RMAFE	0.91	1.11	0.87	1.01	**0.84**	0.89
IPS10	1.00	1.20	0.92	1.14	**0.89**	0.91
PUNEW	0.87	1.03	0.86	1.09	**0.83**	0.85
FYFF	0.91	0.95	0.86	1.00	**0.81**	0.83
Hor:12						
Avg.RMAFE	0.92	1.13	0.89	1.01	**0.86**	0.89
IPS10	1.01	1.22	0.94	1.16	**0.91**	0.93
PUNEW	0.87	1.05	0.86	1.08	**0.84**	0.85
FYFF	0.91	0.95	0.87	0.99	**0.82**	0.84

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1960:1 1969:12 and the first forecast window is 1970:1 1970:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 4a: RMSFEs against RW

	RR	SW	BVAR	MB	RRP	BRR
Hor:1						
Avg.RMSFE	1.03	**0.79**	0.94	1.18	0.96	0.91
IPS10	0.99	0.83	0.82	0.74	0.85	**0.68**
PUNEW	0.79	**0.63**	0.84	0.66	0.83	0.76
FYFF	1.04	**0.89**	0.95	0.96	0.97	0.92
Hor:2						
Avg.RMSFE	0.73	0.62	0.67	0.87	0.68	0.63
IPS10	0.73	0.70	0.61	0.67	0.60	**0.51**
PUNEW	0.56	0.50	0.58	0.57	0.55	**0.54**
FYFF	0.83	**0.78**	0.81	0.82	0.80	0.75
Hor:3						
Avg.RMSFE	0.59	0.54	0.53	0.67	0.54	**0.50**
IPS10	0.64	0.63	0.52	0.62	0.52	**0.43**
PUNEW	0.42	0.42	0.42	0.49	**0.40**	**0.40**
FYFF	0.72	0.69	0.69	0.73	0.67	**0.63**
Hor:4						
Avg.RMSFE	0.49	0.48	0.44	0.56	0.45	**0.42**
IPS10	0.55	0.58	0.44	0.56	0.43	**0.38**
PUNEW	0.34	0.39	0.35	0.45	**0.33**	0.34
FYFF	0.64	0.61	0.60	0.63	0.58	**0.55**
Hor:5						
Avg.RMSFE	0.42	0.45	0.38	0.48	0.38	**0.36**
IPS10	0.47	0.53	0.38	0.49	0.36	**0.33**
PUNEW	0.30	0.36	0.30	0.41	**0.28**	0.30
FYFF	0.56	0.53	0.51	0.52	0.48	**0.45**
Hor:6						
Avg.RMSFE	0.36	0.42	0.33	0.43	0.33	**0.32**
IPS10	0.42	0.49	0.34	0.45	0.32	**0.30**
PUNEW	0.27	0.33	0.26	0.38	**0.25**	0.27
FYFF	0.47	0.47	0.41	0.44	0.39	**0.37**

	RR	SW	BVAR	MB	RRP	BRR
Hor:7						
Avg.RMSFE	0.32	0.39	0.30	0.38	0.29	**0.29**
IPS10	0.36	0.46	0.30	0.42	0.29	**0.27**
PUNEW	0.25	0.31	0.24	0.37	**0.23**	0.24
FYFF	0.40	0.42	0.35	0.39	0.33	**0.32**
Hor:8						
Avg.RMSFE	0.29	0.38	0.27	0.35	**0.26**	0.27
IPS10	0.33	0.44	0.28	0.39	**0.26**	**0.26**
PUNEW	0.22	0.29	0.22	0.35	**0.21**	0.22
FYFF	0.34	0.38	0.30	0.35	**0.28**	0.28
Hor:9						
Avg.RMSFE	0.27	0.36	0.25	0.33	**0.24**	0.25
IPS10	0.30	0.41	0.26	0.37	**0.24**	0.25
PUNEW	0.21	0.29	0.21	0.34	**0.20**	0.21
FYFF	0.29	0.35	0.26	0.32	**0.25**	0.25
Hor:10						
Avg.RMSFE	0.25	0.35	0.23	0.31	**0.22**	0.24
IPS10	0.28	0.40	0.24	0.36	**0.22**	0.24
PUNEW	0.21	0.28	0.21	0.33	**0.20**	0.20
FYFF	0.27	0.33	0.24	0.30	**0.23**	0.24
Hor:11						
Avg.RMSFE	0.23	0.34	0.22	0.29	**0.21**	0.22
IPS10	0.26	0.38	0.23	0.34	**0.21**	0.23
PUNEW	0.20	0.28	0.21	0.33	**0.19**	0.20
FYFF	0.26	0.31	0.23	0.28	**0.21**	0.22
Hor:12						
Avg.RMSFE	0.22	0.33	0.21	0.27	**0.21**	0.22
IPS10	0.25	0.36	0.22	0.32	**0.20**	0.22
PUNEW	0.19	0.27	0.19	0.30	**0.18**	**0.18**
FYFF	0.25	0.30	0.23	0.27	**0.21**	0.22

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1960:1 1969:12 and the first forecast window is 1970:1 1970:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 4b: RMAFEs against RW

	RR	SW	BVAR	MB	RRP	BRR
Hor:1						
Avg.RMAFE	1.01	**0.87**	0.95	0.98	0.97	0.92
IPS10	1.01	0.90	0.91	**0.86**	0.91	**0.86**
PUNEW	0.94	**0.84**	0.90	**0.84**	0.92	0.89
FYFF	1.08	**0.92**	0.97	0.94	1.00	0.97
Hor:2						
Avg.RMAFE	0.83	0.77	0.80	0.84	0.81	0.76
IPS10	0.87	0.80	0.77	0.79	0.77	**0.71**
PUNEW	0.76	0.74	0.76	0.77	0.74	**0.73**
FYFF	0.95	**0.87**	0.87	0.91	0.89	0.85
Hor:3						
Avg.RMAFE	0.75	0.72	0.71	0.77	0.72	**0.68**
IPS10	0.81	0.76	0.71	0.74	0.71	**0.65**
PUNEW	0.66	0.67	0.65	0.70	**0.62**	**0.62**
FYFF	0.84	0.78	0.80	0.85	0.79	**0.76**
Hor:4						
Avg.RMAFE	0.68	0.68	0.65	0.71	0.65	**0.63**
IPS10	0.74	0.73	0.67	0.70	0.65	**0.61**
PUNEW	0.60	0.66	0.60	0.68	**0.58**	0.59
FYFF	0.78	0.72	0.74	0.79	0.71	**0.69**
Hor:5						
Avg.RMAFE	0.63	0.65	0.60	0.67	0.60	**0.59**
IPS10	0.69	0.70	0.62	0.67	0.60	**0.57**
PUNEW	0.57	0.62	0.56	0.66	**0.54**	0.55
FYFF	0.72	0.69	0.69	0.73	0.66	**0.64**
Hor:6						
Avg.RMAFE	0.59	0.63	0.56	0.63	0.56	**0.55**
IPS10	0.66	0.69	0.58	0.65	0.56	**0.54**
PUNEW	0.53	0.60	0.52	0.64	**0.50**	0.52
FYFF	0.66	0.65	0.64	0.69	0.61	**0.60**
Hor:7						
Avg.RMAFE	0.55	0.62	0.53	0.60	0.52	**0.52**
IPS10	0.61	0.67	0.55	0.63	0.53	**0.51**
PUNEW	0.51	0.58	0.49	0.62	**0.47**	0.49
FYFF	0.60	0.63	0.59	0.65	0.56	**0.56**
Hor:8						
Avg.RMAFE	0.53	0.60	0.50	0.58	**0.49**	0.50
IPS10	0.58	0.65	0.52	0.62	**0.51**	**0.50**
PUNEW	0.49	0.56	0.47	0.60	**0.46**	0.47
FYFF	0.57	0.60	0.56	0.62	**0.53**	0.53
Hor:9						
Avg.RMAFE	0.50	0.59	0.48	0.56	**0.47**	0.48
IPS10	0.56	0.64	0.50	0.61	**0.49**	0.49
PUNEW	0.48	0.55	0.46	0.60	**0.45**	0.47
FYFF	0.55	0.58	0.53	0.60	**0.50**	0.51
Hor:10						
Avg.RMAFE	0.49	0.58	0.46	0.55	**0.45**	0.47
IPS10	0.54	0.64	0.49	0.60	**0.47**	0.48
PUNEW	0.47	0.55	0.46	0.59	**0.44**	0.46
FYFF	0.53	0.56	0.51	0.59	**0.48**	0.49
Hor:11						
Avg.RMAFE	0.47	0.57	0.45	0.53	**0.44**	0.46
IPS10	0.52	0.62	0.48	0.59	**0.46**	0.47
PUNEW	0.46	0.55	0.45	0.58	**0.44**	0.45
FYFF	0.53	0.55	0.50	0.58	**0.47**	0.48
Hor:12						
Avg.RMAFE	0.46	0.56	0.44	0.51	**0.43**	0.45
IPS10	0.51	0.61	0.47	0.58	**0.45**	0.47
PUNEW	0.44	0.53	0.44	0.55	**0.43**	**0.43**
FYFF	0.52	0.54	0.50	0.57	**0.47**	0.48

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1960:1 1969:12 and the first forecast window is 1970:1 1970:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 5a: RMSFEs against AR(1), Evaluation sample 1985:2003

	RR	SW	BVAR	MB	RRP	BRR
Hor:1						
Avg.RMSFE	1.43	**1.04**	1.29	1.28	1.36	1.17
IPS10	1.09	1.03	1.17	**0.83**	1.23	1.00
PUNEW	1.24	**0.95**	0.97	1.03	1.12	0.98
FYFF	1.68	1.26	1.40	**0.97**	1.38	1.02
Hor:2						
Avg.RMSFE	1.27	1.04	1.16	1.17	1.21	**1.02**
IPS10	1.03	1.03	0.91	0.87	0.96	**0.85**
PUNEW	1.13	**0.94**	1.03	1.03	1.03	0.97
FYFF	1.29	1.16	1.12	1.02	1.03	**0.76**
Hor:3						
Avg.RMSFE	1.17	1.08	1.07	1.10	1.09	**0.95**
IPS10	1.00	1.06	0.91	0.92	0.92	**0.84**
PUNEW	1.11	1.03	0.97	1.03	0.94	**0.88**
FYFF	1.05	1.03	0.94	1.04	0.82	**0.64**
Hor:4						
Avg.RMSFE	1.10	1.11	1.01	1.06	1.01	**0.91**
IPS10	1.00	1.11	0.86	0.94	**0.82**	0.84
PUNEW	1.06	1.11	0.90	1.01	0.86	**0.83**
FYFF	0.96	0.96	0.81	1.05	0.71	**0.62**
Hor:5						
Avg.RMSFE	1.05	1.16	0.96	1.04	0.95	**0.88**
IPS10	1.01	1.11	0.86	0.96	**0.77**	0.85
PUNEW	1.05	1.17	0.88	1.00	0.82	**0.81**
FYFF	0.90	0.94	0.73	1.05	0.67	**0.63**
Hor:6						
Avg.RMSFE	1.01	1.21	0.93	1.02	0.91	**0.87**
IPS10	1.05	1.14	0.85	0.97	**0.77**	0.86
PUNEW	1.04	1.23	0.84	0.99	0.80	**0.78**
FYFF	0.84	0.92	0.69	1.05	0.65	**0.63**

	RR	SW	BVAR	MB	RRP	BRR
Hor:7						
Avg.RMSFE	0.99	1.24	0.90	1.01	0.88	**0.86**
IPS10	1.06	1.15	0.88	0.97	**0.79**	0.87
PUNEW	1.05	1.29	0.81	1.01	0.78	**0.76**
FYFF	0.81	0.91	0.66	1.04	0.63	**0.63**
Hor:8						
Avg.RMSFE	0.97	1.29	0.89	1.01	**0.86**	**0.86**
IPS10	1.03	1.14	0.89	0.98	**0.78**	0.87
PUNEW	1.04	1.34	0.80	1.02	0.78	**0.76**
FYFF	0.80	0.90	0.66	1.04	**0.62**	0.63
Hor:9						
Avg.RMSFE	0.96	1.34	0.89	1.00	**0.85**	0.86
IPS10	1.02	1.15	0.89	0.98	**0.79**	0.87
PUNEW	1.03	1.38	0.79	1.02	0.77	**0.76**
FYFF	0.79	0.88	0.66	1.03	**0.62**	0.63
Hor:10						
Avg.RMSFE	0.95	1.37	0.87	1.00	**0.84**	0.85
IPS10	1.03	1.15	0.90	0.98	**0.80**	0.89
PUNEW	1.06	1.47	0.80	1.02	**0.76**	0.77
FYFF	0.78	0.88	0.66	1.03	**0.63**	0.65
Hor:11						
Avg.RMSFE	0.95	1.43	0.87	1.00	**0.83**	0.86
IPS10	1.04	1.14	0.91	0.98	**0.82**	0.89
PUNEW	1.08	1.57	0.82	1.02	**0.78**	0.79
FYFF	0.78	0.87	0.66	1.02	**0.64**	0.66
Hor:12						
Avg.RMSFE	0.96	1.48	0.88	0.99	**0.85**	0.87
IPS10	1.04	1.14	0.92	0.99	**0.83**	0.91
PUNEW	1.08	1.70	0.82	0.99	**0.78**	0.79
FYFF	0.77	0.87	0.67	1.02	**0.65**	0.69

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1974:1 1984:12 and the first forecast window is 1985:1 1985:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 5b: RMAFEs against AR(1), Evaluation sample 1985:2003

	RR	SW	BVAR	MB	RRP	BRR
Hor:1						
Avg.RMAFE	1.19	**1.01**	1.13	1.11	1.17	1.08
IPS10	1.05	0.97	1.02	**0.92**	1.04	1.00
PUNEW	1.14	0.97	**0.97**	0.99	1.08	1.01
FYFF	1.25	1.04	1.15	**0.99**	1.17	1.02
Hor:2						
Avg.RMAFE	1.12	**1.01**	1.07	1.07	1.09	1.01
IPS10	1.02	0.97	**0.90**	0.94	0.92	0.90
PUNEW	1.05	0.97	0.98	0.97	0.98	**0.96**
FYFF	1.16	1.01	1.01	1.02	1.03	**0.85**
Hor:3						
Avg.RMAFE	1.07	1.02	1.02	1.05	1.03	**0.97**
IPS10	1.02	0.99	**0.90**	0.97	0.93	0.91
PUNEW	1.05	1.02	0.95	0.97	0.93	**0.91**
FYFF	1.05	0.96	0.94	1.03	0.93	**0.81**
Hor:4						
Avg.RMAFE	1.04	1.03	0.99	1.04	0.99	**0.95**
IPS10	1.01	1.01	0.89	0.98	**0.88**	0.90
PUNEW	1.02	1.09	0.94	1.00	0.91	**0.90**
FYFF	1.00	0.91	0.88	1.01	0.86	**0.78**
Hor:5						
Avg.RMAFE	1.02	1.06	0.97	1.02	0.97	**0.94**
IPS10	1.00	1.01	0.90	0.98	**0.87**	0.91
PUNEW	1.00	1.08	0.92	0.99	0.90	**0.89**
FYFF	0.97	0.93	0.84	1.01	0.82	**0.78**
Hor:6						
Avg.RMAFE	1.00	1.08	0.95	1.01	0.94	**0.93**
IPS10	1.04	1.06	0.91	0.99	**0.87**	0.92
PUNEW	0.98	1.10	0.88	0.98	0.88	**0.85**
FYFF	0.94	0.91	0.83	1.01	0.82	**0.78**

	RR	SW	BVAR	MB	RRP	BRR
Hor:7						
Avg.RMAFE	0.99	1.09	0.94	1.01	**0.92**	**0.92**
IPS10	1.05	1.06	0.93	0.99	**0.88**	0.92
PUNEW	0.99	1.12	0.86	0.99	0.86	**0.85**
FYFF	0.92	0.90	0.83	1.01	0.81	**0.79**
Hor:8						
Avg.RMAFE	0.98	1.11	0.93	1.01	**0.91**	0.92
IPS10	1.02	1.06	0.93	0.99	**0.88**	0.91
PUNEW	0.99	1.15	0.87	1.00	0.87	**0.87**
FYFF	0.92	0.91	0.83	1.01	0.81	**0.80**
Hor:9						
Avg.RMAFE	0.97	1.12	0.92	1.00	**0.89**	0.92
IPS10	1.03	1.07	0.93	0.99	**0.88**	0.91
PUNEW	1.00	1.16	0.87	1.00	**0.86**	0.87
FYFF	0.91	0.90	0.82	1.00	0.80	**0.79**
Hor:10						
Avg.RMAFE	0.96	1.14	0.91	1.00	**0.88**	0.91
IPS10	1.02	1.06	0.92	0.99	**0.88**	0.90
PUNEW	1.01	1.17	0.87	1.00	**0.85**	0.86
FYFF	0.90	0.90	0.82	1.01	0.80	**0.79**
Hor:11						
Avg.RMAFE	0.96	1.16	0.91	1.00	**0.88**	0.91
IPS10	1.03	1.04	0.92	0.99	**0.89**	0.91
PUNEW	1.00	1.20	0.86	1.00	**0.85**	0.87
FYFF	0.90	0.90	0.82	1.00	0.80	**0.79**
Hor:12						
Avg.RMAFE	0.97	1.18	0.92	1.00	**0.90**	0.92
IPS10	1.01	1.03	0.91	0.99	**0.89**	0.91
PUNEW	1.01	1.25	0.87	1.00	**0.86**	0.88
FYFF	0.90	0.91	0.83	1.00	0.82	**0.81**

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1974:1 1984:12 and the first forecast window is 1985:1 1985:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 6a: RMSFEs against BVAR0, Evaluation sample 1985:2003

	RR	SW	BVAR	MB	RRP	BRR
Hor:1						
Avg.RMSFE	0.99	**0.72**	0.89	0.88	0.94	0.81
IPS10	0.83	0.78	0.89	**0.63**	0.93	0.76
PUNEW	0.97	**0.74**	0.76	0.81	0.88	0.77
FYFF	0.80	0.60	0.66	**0.46**	0.65	0.48
Hor:2						
Avg.RMSFE	0.97	0.80	0.89	0.89	0.92	**0.78**
IPS10	0.96	0.95	0.84	0.81	0.89	**0.79**
PUNEW	0.87	**0.72**	0.79	0.79	0.79	0.74
FYFF	0.86	0.78	0.75	0.68	0.69	**0.51**
Hor:3						
Avg.RMSFE	0.96	0.88	0.87	0.90	0.89	**0.77**
IPS10	0.93	1.00	0.85	0.86	0.86	**0.78**
PUNEW	0.86	0.80	0.75	0.80	0.73	**0.68**
FYFF	0.99	0.97	0.89	0.99	0.78	**0.60**
Hor:4						
Avg.RMSFE	0.95	0.95	0.86	0.91	0.86	**0.78**
IPS10	0.93	1.04	0.80	0.88	**0.76**	0.78
PUNEW	0.84	0.88	0.71	0.80	0.68	**0.66**
FYFF	1.09	1.09	0.92	1.19	0.81	**0.71**
Hor:5						
Avg.RMSFE	0.93	1.03	0.85	0.92	0.84	**0.78**
IPS10	0.95	1.04	0.81	0.90	**0.73**	0.79
PUNEW	0.81	0.90	0.67	0.77	0.63	**0.62**
FYFF	1.04	1.08	0.85	1.21	0.77	**0.73**
Hor:6						
Avg.RMSFE	0.91	1.09	0.84	0.92	0.82	**0.78**
IPS10	0.98	1.07	0.80	0.90	**0.72**	0.81
PUNEW	0.79	0.94	0.64	0.76	0.61	**0.59**
FYFF	0.98	1.07	0.81	1.22	0.75	**0.73**

	RR	SW	BVAR	MB	RRP	BRR
Hor:7						
Avg.RMSFE	0.90	1.13	0.82	0.92	0.80	**0.78**
IPS10	0.98	1.07	0.82	0.90	**0.73**	0.81
PUNEW	0.79	0.98	0.61	0.76	0.59	**0.57**
FYFF	0.99	1.11	0.81	1.27	0.76	**0.77**
Hor:8						
Avg.RMSFE	0.89	1.18	0.81	0.92	**0.78**	**0.78**
IPS10	0.98	1.09	0.85	0.93	**0.74**	0.83
PUNEW	0.79	1.02	0.61	0.77	0.59	**0.58**
FYFF	1.00	1.12	0.82	1.29	**0.77**	0.79
Hor:9						
Avg.RMSFE	0.88	1.22	0.81	0.92	**0.78**	**0.78**
IPS10	0.98	1.10	0.85	0.94	**0.76**	0.84
PUNEW	0.79	1.06	0.61	0.78	0.59	**0.58**
FYFF	0.96	1.08	0.80	1.26	**0.75**	0.77
Hor:10						
Avg.RMSFE	0.87	1.26	0.80	0.92	**0.77**	0.78
IPS10	0.99	1.11	0.87	0.95	**0.77**	0.85
PUNEW	0.80	1.11	0.61	0.77	**0.58**	0.58
FYFF	0.94	1.06	0.80	1.24	**0.76**	0.78
Hor:11						
Avg.RMSFE	0.87	1.32	0.80	0.92	**0.77**	0.79
IPS10	1.00	1.09	0.88	0.95	**0.78**	0.86
PUNEW	0.81	1.18	0.61	0.76	**0.58**	0.59
FYFF	0.94	1.06	0.81	1.24	**0.78**	0.80
Hor:12						
Avg.RMSFE	0.88	1.36	0.81	0.91	**0.78**	0.80
IPS10	0.99	1.09	0.87	0.94	**0.79**	0.86
PUNEW	0.81	1.28	0.62	0.74	**0.59**	0.59
FYFF	0.93	1.04	0.81	1.22	**0.78**	0.82

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1974:1 1984:12 and the first forecast window is 1985:1 1985:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 6b: RMAFEs against BVAR0, Evaluation sample 1985:2003

	RR	SW	BVAR	MB	RRP	BRR		RR	SW	BVAR	MB	RRP	BRR
Hor:1							**Hor:7**						
Avg.RMAFE	0.97	**0.83**	0.92	0.90	0.95	0.88	Avg.RMAFE	0.94	1.04	0.89	0.96	**0.87**	**0.87**
IPS10	0.93	0.86	0.90	**0.81**	0.92	0.89	IPS10	0.98	1.00	0.87	0.92	**0.82**	0.86
PUNEW	0.98	0.83	**0.83**	0.85	0.93	0.87	PUNEW	0.88	0.99	0.76	0.88	0.76	**0.75**
FYFF	0.87	0.72	0.80	**0.68**	0.81	0.71	FYFF	0.96	0.94	0.86	1.05	0.84	**0.82**
Hor:2							**Hor:8**						
Avg.RMAFE	0.97	**0.88**	0.93	0.93	0.95	0.88	Avg.RMAFE	0.93	1.05	0.88	0.95	**0.86**	0.87
IPS10	1.01	0.95	**0.88**	0.92	0.91	0.89	IPS10	0.98	1.01	0.88	0.94	**0.83**	0.87
PUNEW	0.93	0.87	0.87	0.86	0.87	**0.86**	PUNEW	0.87	1.01	0.77	0.88	0.77	**0.76**
FYFF	0.95	0.83	0.83	0.84	0.84	**0.70**	FYFF	0.97	0.95	0.87	1.06	0.84	**0.83**
Hor:3							**Hor:9**						
Avg.RMAFE	0.97	0.92	0.92	0.95	0.93	**0.87**	Avg.RMAFE	0.92	1.06	0.87	0.95	**0.84**	0.87
IPS10	1.01	0.98	**0.89**	0.96	0.92	0.90	IPS10	0.98	1.02	0.88	0.94	**0.84**	0.86
PUNEW	0.93	0.90	0.85	0.86	0.82	**0.80**	PUNEW	0.87	1.02	0.76	0.88	**0.75**	0.76
FYFF	1.00	0.91	0.90	0.98	0.88	**0.77**	FYFF	0.95	0.94	0.86	1.05	0.84	**0.82**
Hor:4							**Hor:10**						
Avg.RMAFE	0.96	0.95	0.91	0.95	0.91	**0.88**	Avg.RMAFE	0.91	1.08	0.86	0.95	**0.83**	0.87
IPS10	0.98	0.99	0.87	0.96	**0.85**	0.87	IPS10	0.98	1.02	0.89	0.96	**0.85**	0.87
PUNEW	0.90	0.96	0.83	0.88	0.81	**0.79**	PUNEW	0.88	1.02	0.76	0.88	**0.74**	0.75
FYFF	1.03	0.94	0.90	1.05	0.88	**0.80**	FYFF	0.93	0.94	0.85	1.05	0.83	**0.82**
Hor:5							**Hor:11**						
Avg.RMAFE	0.95	0.99	0.91	0.95	0.90	**0.87**	Avg.RMAFE	0.92	1.10	0.86	0.95	**0.84**	0.87
IPS10	0.99	1.00	0.89	0.97	**0.86**	0.90	IPS10	0.99	1.01	0.89	0.96	**0.86**	0.88
PUNEW	0.88	0.95	0.81	0.87	0.79	**0.78**	PUNEW	0.87	1.05	0.76	0.87	**0.75**	0.76
FYFF	0.99	0.95	0.85	1.03	0.83	**0.79**	FYFF	0.93	0.93	0.85	1.04	0.83	**0.82**
Hor:6							**Hor:12**						
Avg.RMAFE	0.94	1.01	0.89	0.95	0.89	**0.87**	Avg.RMAFE	0.92	1.12	0.88	0.95	**0.85**	0.88
IPS10	0.99	1.01	0.87	0.94	**0.83**	0.87	IPS10	0.99	1.01	0.90	0.98	**0.87**	0.89
PUNEW	0.87	0.97	0.78	0.87	0.78	**0.76**	PUNEW	0.88	1.09	0.76	0.87	**0.75**	0.77
FYFF	0.96	0.93	0.85	1.03	0.83	**0.80**	FYFF	0.92	0.93	0.85	1.03	0.84	**0.84**

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1974:1 1984:12 and the first forecast window is 1985:1 1985:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 7a: RMSFEs against AR(1), Evaluation sample 1995:2003

	RR	SW	BVAR	MB	RRP	BRR
Hor:1						
Avg.RMSFE	1.46	**1.15**	1.26	1.19	1.37	**1.15**
IPS10	1.37	1.21	1.25	**0.87**	1.42	1.05
PUNEW	1.17	1.04	0.92	**0.91**	1.10	0.93
FYFF	1.30	2.07	**0.70**	1.11	0.90	0.76
Hor:2						
Avg.RMSFE	1.23	1.17	1.11	1.11	1.19	**1.00**
IPS10	1.15	1.20	0.91	0.88	1.02	**0.83**
PUNEW	1.06	0.96	1.04	0.94	1.11	**0.94**
FYFF	1.13	1.80	0.66	1.13	0.69	**0.56**
Hor:3						
Avg.RMSFE	1.11	1.18	1.02	1.07	1.07	**0.92**
IPS10	0.98	1.20	0.85	0.91	0.84	**0.80**
PUNEW	0.90	1.05	0.87	0.96	0.92	**0.77**
FYFF	0.91	1.54	0.49	1.11	0.50	**0.40**
Hor:4						
Avg.RMSFE	1.05	1.20	0.96	1.05	0.97	**0.88**
IPS10	0.90	1.21	0.74	0.93	**0.71**	0.78
PUNEW	0.85	1.11	0.76	0.96	0.79	**0.73**
FYFF	0.81	1.40	0.47	1.09	0.47	**0.39**
Hor:5						
Avg.RMSFE	0.99	1.24	0.92	1.03	0.92	**0.86**
IPS10	0.85	1.22	0.74	0.95	**0.63**	0.77
PUNEW	0.84	1.08	0.78	0.97	0.81	**0.77**
FYFF	0.81	1.32	0.50	1.08	0.49	**0.42**
Hor:6						
Avg.RMSFE	0.95	1.28	0.89	1.02	0.89	**0.85**
IPS10	0.88	1.23	0.74	0.96	**0.63**	0.79
PUNEW	0.78	1.09	0.75	0.98	0.80	**0.73**
FYFF	0.80	1.28	0.53	1.07	0.51	**0.45**

	RR	SW	BVAR	MB	RRP	BRR
Hor:7						
Avg.RMSFE	0.94	1.31	0.87	1.01	0.87	**0.85**
IPS10	0.90	1.24	0.78	0.97	**0.66**	0.82
PUNEW	0.72	1.15	0.67	0.98	0.74	**0.67**
FYFF	0.81	1.26	0.55	1.06	0.53	**0.48**
Hor:8						
Avg.RMSFE	0.92	1.34	0.87	1.00	**0.85**	**0.85**
IPS10	0.89	1.23	0.80	0.97	**0.68**	0.83
PUNEW	0.72	1.15	0.68	0.98	0.76	**0.69**
FYFF	0.82	1.24	0.58	1.05	0.56	**0.51**
Hor:9						
Avg.RMSFE	0.92	1.37	0.88	1.00	**0.85**	**0.85**
IPS10	0.90	1.22	0.82	0.98	**0.70**	0.83
PUNEW	0.74	1.11	0.73	0.98	0.80	**0.72**
FYFF	0.83	1.22	0.61	1.04	0.59	**0.54**
Hor:10						
Avg.RMSFE	0.91	1.39	0.87	0.99	**0.84**	0.86
IPS10	0.91	1.21	0.84	0.98	**0.71**	0.85
PUNEW	0.78	1.15	0.73	0.99	0.80	**0.73**
FYFF	0.83	1.19	0.64	1.03	0.62	**0.58**
Hor:11						
Avg.RMSFE	0.92	1.41	0.88	0.99	**0.85**	0.87
IPS10	0.93	1.20	0.85	0.98	**0.74**	0.87
PUNEW	0.81	1.15	0.73	1.00	0.80	**0.76**
FYFF	0.83	1.16	0.66	1.02	0.64	**0.61**
Hor:12						
Avg.RMSFE	0.93	1.45	0.89	0.99	**0.87**	0.88
IPS10	0.94	1.20	0.87	0.98	**0.76**	0.88
PUNEW	0.83	1.16	**0.75**	0.99	0.82	0.78
FYFF	0.84	1.15	0.68	1.01	0.67	**0.65**

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1984:1 1994:12 and the first forecast window is 1995:1 1995:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 7b: RMAFEs against AR(1), Evaluation sample 1995:2003

	RR	SW	BVAR	MB	RRP	BRR
Hor:1						
Avg.RMAFE	1.20	**1.06**	1.12	1.08	1.17	1.08
IPS10	1.15	1.03	1.06	**0.93**	1.14	1.02
PUNEW	1.10	1.02	0.96	**0.95**	1.07	0.97
FYFF	1.34	1.31	**0.97**	1.08	1.09	1.02
Hor:2						
Avg.RMAFE	1.10	1.06	1.05	1.05	1.09	**1.00**
IPS10	1.12	1.03	0.96	0.94	1.03	**0.91**
PUNEW	1.01	0.98	1.03	**0.97**	1.05	0.98
FYFF	1.17	1.28	0.88	1.10	0.93	**0.80**
Hor:3						
Avg.RMAFE	1.05	1.06	1.00	1.04	1.02	**0.95**
IPS10	1.03	0.98	0.93	0.95	0.94	**0.89**
PUNEW	0.93	1.00	0.89	0.97	0.89	**0.85**
FYFF	1.00	1.11	0.73	1.07	0.76	**0.65**
Hor:4						
Avg.RMAFE	1.01	1.08	0.97	1.02	0.97	**0.93**
IPS10	0.95	1.00	0.86	0.97	**0.85**	0.87
PUNEW	0.89	1.06	**0.84**	0.97	0.86	**0.84**
FYFF	0.92	1.05	0.71	1.04	0.71	**0.62**
Hor:5						
Avg.RMAFE	0.99	1.09	0.96	1.01	0.96	**0.92**
IPS10	0.91	1.01	0.85	0.97	**0.80**	0.87
PUNEW	**0.89**	1.03	0.90	0.99	0.91	0.90
FYFF	0.91	1.05	0.73	1.03	0.71	**0.65**
Hor:6						
Avg.RMAFE	0.97	1.10	0.94	1.01	0.93	**0.91**
IPS10	0.93	1.03	0.83	0.98	**0.78**	0.85
PUNEW	**0.82**	1.02	0.84	0.98	0.87	0.84
FYFF	0.91	1.05	0.77	1.02	0.75	**0.66**
Hor:7						
Avg.RMAFE	0.96	1.11	0.93	1.00	0.92	**0.91**
IPS10	0.95	1.05	0.87	0.98	**0.82**	0.88
PUNEW	0.81	1.02	0.80	0.98	0.84	**0.80**
FYFF	0.92	1.05	0.78	1.02	0.76	**0.69**
Hor:8						
Avg.RMAFE	0.95	1.11	0.92	1.00	**0.91**	0.92
IPS10	0.94	1.05	0.88	0.98	**0.82**	0.87
PUNEW	0.82	1.02	**0.82**	0.99	0.86	0.83
FYFF	0.94	1.05	0.80	1.01	0.78	**0.71**
Hor:9						
Avg.RMAFE	0.95	1.13	0.92	1.00	**0.89**	0.92
IPS10	0.94	1.03	0.88	0.99	**0.83**	0.85
PUNEW	0.85	1.00	**0.84**	0.99	0.87	0.86
FYFF	0.94	1.05	0.81	1.00	0.80	**0.73**
Hor:10						
Avg.RMAFE	0.94	1.13	0.91	1.00	**0.88**	0.91
IPS10	0.93	1.03	0.87	0.99	**0.82**	0.86
PUNEW	0.85	1.00	**0.84**	0.99	0.86	0.85
FYFF	0.94	1.05	0.82	1.00	0.81	**0.75**
Hor:11						
Avg.RMAFE	0.95	1.14	0.92	1.00	**0.89**	0.92
IPS10	0.94	1.03	0.87	0.99	**0.82**	0.86
PUNEW	0.85	1.00	**0.82**	0.99	0.85	0.86
FYFF	0.96	1.06	0.84	1.00	0.82	**0.78**
Hor:12						
Avg.RMAFE	0.96	1.16	0.93	1.00	**0.91**	0.93
IPS10	0.94	1.02	0.88	0.99	**0.84**	0.86
PUNEW	0.85	1.01	**0.83**	1.00	0.86	0.87
FYFF	0.98	1.06	0.87	1.00	0.85	**0.82**

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1984:1 1994:12 and the first forecast window is 1995:1 1995:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 8a: RMSFEs against BVAR0, Evaluation sample 1995:2003

	RR	SW	BVAR	MB	RRP	BRR
Hor:1						
Avg.RMSFE	1.02	**0.80**	0.88	0.83	0.95	**0.80**
IPS10	0.95	0.84	0.87	**0.60**	0.99	0.73
PUNEW	1.07	0.95	0.85	**0.84**	1.01	0.85
FYFF	1.22	1.96	**0.66**	1.05	0.84	0.72
Hor:2						
Avg.RMSFE	0.96	0.91	0.87	0.87	0.94	**0.78**
IPS10	1.19	1.25	0.94	0.91	1.06	**0.86**
PUNEW	0.88	0.80	0.87	0.79	0.93	**0.78**
FYFF	1.21	1.95	0.71	1.22	0.75	**0.60**
Hor:3						
Avg.RMSFE	0.97	1.03	0.89	0.93	0.94	**0.80**
IPS10	1.15	1.42	1.00	1.07	0.99	**0.94**
PUNEW	0.84	0.97	0.80	0.89	0.85	**0.71**
FYFF	1.29	2.17	0.68	1.57	0.70	**0.56**
Hor:4						
Avg.RMSFE	0.97	1.12	0.89	0.97	0.90	**0.82**
IPS10	1.15	1.54	0.94	1.19	**0.90**	0.99
PUNEW	0.85	1.11	0.76	0.97	0.80	**0.73**
FYFF	1.29	2.23	0.75	1.75	0.75	**0.62**
Hor:5						
Avg.RMSFE	0.94	1.18	0.88	0.98	0.88	**0.82**
IPS10	1.12	1.61	0.97	1.25	**0.83**	1.02
PUNEW	0.86	1.11	0.80	1.00	0.84	**0.79**
FYFF	1.22	2.01	0.76	1.64	0.74	**0.64**
Hor:6						
Avg.RMSFE	0.92	1.24	0.86	0.98	0.86	**0.82**
IPS10	1.17	1.63	0.98	1.27	**0.84**	1.05
PUNEW	0.87	1.21	0.84	1.09	0.89	**0.82**
FYFF	1.17	1.88	0.78	1.58	0.76	**0.66**

	RR	SW	BVAR	MB	RRP	BRR
Hor:7						
Avg.RMSFE	0.92	1.28	0.86	0.99	0.85	**0.83**
IPS10	1.12	1.55	0.97	1.21	**0.83**	1.03
PUNEW	0.88	1.40	0.82	1.19	0.90	**0.82**
FYFF	1.17	1.83	0.79	1.55	0.77	**0.70**
Hor:8						
Avg.RMSFE	0.90	1.32	0.85	0.99	**0.84**	**0.84**
IPS10	1.13	1.55	1.01	1.23	**0.86**	1.05
PUNEW	0.89	1.42	0.84	1.21	0.93	**0.85**
FYFF	1.17	1.78	0.83	1.51	0.80	**0.73**
Hor:9						
Avg.RMSFE	0.90	1.34	0.85	0.97	**0.83**	**0.83**
IPS10	1.11	1.52	1.01	1.21	**0.86**	1.04
PUNEW	0.88	1.33	0.87	1.17	0.96	**0.86**
FYFF	1.17	1.71	0.86	1.46	0.83	**0.76**
Hor:10						
Avg.RMSFE	0.89	1.37	0.85	0.98	**0.83**	0.84
IPS10	1.09	1.46	1.01	1.18	**0.86**	1.03
PUNEW	0.92	1.35	0.87	1.17	0.94	**0.86**
FYFF	1.14	1.64	0.88	1.42	0.85	**0.80**
Hor:11						
Avg.RMSFE	0.90	1.38	0.86	0.97	**0.83**	0.85
IPS10	1.11	1.43	1.02	1.17	**0.88**	1.03
PUNEW	0.94	1.34	0.85	1.16	0.93	**0.88**
FYFF	1.13	1.58	0.89	1.38	0.87	**0.83**
Hor:12						
Avg.RMSFE	0.90	1.40	0.87	0.96	**0.84**	0.85
IPS10	1.09	1.38	1.01	1.14	**0.88**	1.02
PUNEW	0.95	1.34	**0.86**	1.15	0.95	0.90
FYFF	1.11	1.51	0.90	1.34	0.88	**0.86**

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1984:1 1994:12 and the first forecast window is 1995:1 1995:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 8b: RMAFEs against BVAR0 Evaluation sample 1995:2003

	RR	SW	BVAR	MB	RRP	BRR		RR	SW	BVAR	MB	RRP	BRR
Hor:1							**Hor:7**						
Avg.RMAFE	0.99	**0.88**	0.93	0.89	0.97	0.89	Avg.RMAFE	0.95	1.09	0.92	0.99	0.91	**0.90**
IPS10	0.96	0.86	0.88	**0.77**	0.94	0.85	IPS10	1.06	1.18	0.98	1.10	**0.91**	0.99
PUNEW	1.04	0.97	0.91	**0.90**	1.02	0.92	PUNEW	0.90	1.14	0.90	1.10	0.93	**0.89**
FYFF	1.09	1.06	**0.78**	0.88	0.88	0.82	FYFF	1.02	1.16	0.86	1.13	0.84	**0.77**
Hor:2							**Hor:8**						
Avg.RMAFE	0.98	0.94	0.93	0.93	0.97	**0.88**	Avg.RMAFE	0.95	1.10	0.92	1.00	**0.90**	0.91
IPS10	1.10	1.01	0.94	0.92	1.00	**0.89**	IPS10	1.08	1.20	1.01	1.13	**0.95**	0.99
PUNEW	0.93	0.91	0.95	**0.89**	0.96	0.90	PUNEW	0.91	1.12	**0.90**	1.09	0.95	0.91
FYFF	1.08	1.17	0.81	1.01	0.86	**0.73**	FYFF	1.03	1.15	0.88	1.11	0.86	**0.79**
Hor:3							**Hor:9**						
Avg.RMAFE	0.99	0.99	0.94	0.97	0.96	**0.89**	Avg.RMAFE	0.94	1.12	0.91	0.99	**0.89**	0.91
IPS10	1.10	1.05	0.99	1.01	1.01	**0.95**	IPS10	1.08	1.19	1.01	1.13	**0.95**	0.98
PUNEW	0.94	1.02	0.90	0.98	0.90	**0.86**	PUNEW	0.92	1.08	**0.90**	1.07	0.94	0.92
FYFF	1.09	1.21	0.80	1.16	0.83	**0.70**	FYFF	1.04	1.16	0.90	1.11	0.88	**0.81**
Hor:4							**Hor:10**						
Avg.RMAFE	0.98	1.04	0.94	0.99	0.94	**0.90**	Avg.RMAFE	0.94	1.13	0.91	1.00	**0.88**	0.91
IPS10	1.07	1.13	0.97	1.09	**0.96**	0.98	IPS10	1.07	1.20	1.01	1.14	**0.95**	0.99
PUNEW	0.91	1.10	**0.87**	1.00	0.89	**0.86**	PUNEW	0.93	1.08	**0.91**	1.07	0.93	0.92
FYFF	1.10	1.26	0.86	1.25	0.86	**0.74**	FYFF	1.02	1.14	0.90	1.09	0.89	**0.82**
Hor:5							**Hor:11**						
Avg.RMAFE	0.97	1.05	0.93	0.98	0.93	**0.90**	Avg.RMAFE	0.94	1.13	0.91	0.99	**0.88**	0.92
IPS10	1.08	1.21	1.01	1.16	**0.95**	1.03	IPS10	1.09	1.19	1.01	1.15	**0.96**	1.00
PUNEW	**0.88**	1.03	0.90	0.98	0.91	0.89	PUNEW	0.93	1.10	**0.90**	1.09	0.93	0.94
FYFF	1.04	1.21	0.84	1.18	0.81	**0.74**	FYFF	1.01	1.12	0.89	1.06	0.88	**0.83**
Hor:6							**Hor:12**						
Avg.RMAFE	0.95	1.08	0.92	0.99	0.91	**0.90**	Avg.RMAFE	0.94	1.14	0.92	0.98	**0.90**	0.92
IPS10	1.11	1.23	1.00	1.17	**0.93**	1.02	IPS10	1.09	1.18	1.01	1.14	**0.97**	1.00
PUNEW	**0.87**	1.08	0.89	1.04	0.92	0.89	PUNEW	0.93	1.10	**0.90**	1.08	0.94	0.94
FYFF	1.01	1.17	0.85	1.13	0.83	**0.74**	FYFF	1.00	1.10	0.89	1.03	0.88	**0.85**

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior, BRR is Bayesian Reduced Rank Regression. The forecasting exercise is performed using a rolling window of 10 years, so the first estimation window is 1984:1 1994:12 and the first forecast window is 1995:1 1995:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 9a: Montecarlo Simulation, RMSFE

	RR	SW	BVAR	RRP		RR	SW	BVAR	RRP
Hor:1					**Hor:7**				
Avg.RMSFE	1.23	**1.04**	1.19	1.25	Avg.RMSFE	1.04	1.17	1.02	**0.95**
IPS10	1.26	**1.07**	1.20	1.24	IPS10	1.03	1.06	1.02	**0.90**
PUNEW	1.28	**1.06**	1.20	1.23	PUNEW	1.03	1.07	1.00	**0.85**
FYFF	1.11	**1.02**	1.07	1.07	FYFF	1.03	1.06	1.01	**0.96**
Hor:2					**Hor:8**				
Avg.RMSFE	1.16	**1.08**	1.14	1.16	Avg.RMSFE	1.03	1.18	1.01	**0.93**
IPS10	1.17	**1.08**	1.13	1.12	IPS10	1.02	1.05	1.01	**0.89**
PUNEW	1.17	**1.07**	1.13	1.08	PUNEW	1.01	1.07	0.99	**0.83**
FYFF	1.07	1.02	1.04	**1.01**	FYFF	1.02	1.07	1.00	**0.95**
Hor:3					**Hor:9**				
Avg.RMSFE	1.13	1.10	1.11	**1.09**	Avg.RMSFE	1.03	1.20	1.00	**0.92**
IPS10	1.13	1.08	1.10	**1.05**	IPS10	1.01	1.05	1.00	**0.88**
PUNEW	1.12	1.07	1.09	**1.00**	PUNEW	1.00	1.07	0.98	**0.83**
FYFF	1.06	1.03	1.03	**0.99**	FYFF	1.01	1.07	0.99	**0.92**
Hor:4					**Hor:10**				
Avg.RMSFE	1.10	1.12	1.08	**1.05**	Avg.RMSFE	1.02	1.21	1.00	**0.91**
IPS10	1.09	1.07	1.07	**0.99**	IPS10	1.00	1.05	0.99	**0.86**
PUNEW	1.09	1.08	1.06	**0.94**	PUNEW	1.00	1.07	0.97	**0.82**
FYFF	1.05	1.04	1.03	**0.99**	FYFF	1.00	1.08	0.99	**0.90**
Hor:5					**Hor:11**				
Avg.RMSFE	1.08	1.14	1.06	**1.01**	Avg.RMSFE	1.03	1.22	0.99	**0.90**
IPS10	1.07	1.06	1.05	**0.95**	IPS10	0.99	1.05	0.99	**0.86**
PUNEW	1.06	1.07	1.03	**0.90**	PUNEW	0.99	1.07	0.97	**0.82**
FYFF	1.04	1.05	1.02	**0.99**	FYFF	1.00	1.08	0.98	**0.89**
Hor:6					**Hor:12**				
Avg.RMSFE	1.06	1.15	1.04	**0.97**	Avg.RMSFE	1.04	1.23	0.99	**0.91**
IPS10	1.05	1.06	1.03	**0.92**	IPS10	0.99	1.05	0.99	**0.86**
PUNEW	1.04	1.07	1.01	**0.87**	PUNEW	0.99	1.07	0.97	**0.83**
FYFF	1.03	1.05	1.02	**0.97**	FYFF	1.00	1.09	0.98	**0.90**

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior. The forecasting exercise is performed using bootstrapped data on a rolling window of 10 years, so the first estimation window is 1984:1 1994:12 and the first forecast window is 1995:1 1995:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

Table 9b: Montecarlo Simulation , RMAFE

	RR	SW	BVAR	RRP		RR	SW	BVAR	RRP
Hor:1					**Hor:7**				
Avg.RMAFE	1.13	**1.03**	1.10	1.14	Avg.RMAFE	1.01	1.08	1.00	**0.96**
IPS10	1.14	**1.04**	1.10	1.12	IPS10	1.01	1.03	1.00	**0.95**
PUNEW	1.14	**1.04**	1.10	1.13	PUNEW	1.01	1.04	0.99	**0.91**
FYFF	1.13	**1.04**	1.08	1.10	FYFF	1.01	1.04	0.99	**0.96**
Hor:2					**Hor:8**				
Avg.RMAFE	1.09	**1.05**	1.07	1.09	Avg.RMAFE	1.01	1.08	0.99	**0.95**
IPS10	1.10	**1.05**	1.07	1.08	IPS10	1.00	1.03	0.99	**0.94**
PUNEW	1.08	**1.04**	1.06	**1.04**	PUNEW	1.00	1.04	0.98	**0.90**
FYFF	1.08	**1.04**	1.05	**1.04**	FYFF	1.00	1.04	0.99	**0.94**
Hor:3					**Hor:9**				
Avg.RMAFE	1.07	1.06	1.05	**1.05**	Avg.RMAFE	1.00	1.09	0.99	**0.94**
IPS10	1.08	1.05	1.05	**1.05**	IPS10	0.99	1.02	0.98	**0.92**
PUNEW	1.06	1.05	1.04	**1.00**	PUNEW	0.99	1.04	0.97	**0.89**
FYFF	1.06	1.04	1.03	**1.01**	FYFF	1.00	1.04	0.98	**0.93**
Hor:4					**Hor:10**				
Avg.RMAFE	1.05	1.07	1.04	**1.02**	Avg.RMAFE	0.99	1.09	0.98	**0.93**
IPS10	1.05	1.04	1.04	**1.02**	IPS10	0.99	1.02	0.97	**0.91**
PUNEW	1.05	1.05	1.02	**0.97**	PUNEW	0.99	1.04	0.96	**0.89**
FYFF	1.04	1.04	1.02	**1.00**	FYFF	0.99	1.04	0.97	**0.92**
Hor:5					**Hor:11**				
Avg.RMAFE	1.04	1.07	1.02	**1.00**	Avg.RMAFE	0.99	1.09	0.97	**0.92**
IPS10	1.04	1.04	1.02	**0.99**	IPS10	0.98	1.02	0.97	**0.90**
PUNEW	1.03	1.05	1.01	**0.94**	PUNEW	0.98	1.04	0.96	**0.89**
FYFF	1.03	1.04	1.01	**0.99**	FYFF	0.99	1.04	0.97	**0.91**
Hor:6					**Hor:12**				
Avg.RMAFE	1.02	1.08	1.01	**0.98**	Avg.RMAFE	0.99	1.10	0.98	**0.93**
IPS10	1.02	1.03	1.00	**0.97**	IPS10	0.98	1.02	0.97	**0.90**
PUNEW	1.02	1.04	1.00	**0.92**	PUNEW	0.99	1.04	0.96	**0.90**
FYFF	1.02	1.04	1.00	**0.97**	FYFF	0.99	1.04	0.97	**0.91**

RR is the Reduced Rank Regression, SW is the Factor Model, BVAR is a Bayesian VAR with Minnesota-type prior, MB is Multivariate Boosting, RRP is Reduced Rank Posterior. The forecasting exercise is performed using bootstrapped data on a rolling window of 10 years, so the first estimation window is 1984:1 1994:12 and the first forecast window is 1995:1 1995:12, while the last estimation window is 1992:1 2002:12 and the last forecast window is 2003:1 2003:12. All variables are standardised prior to estimation, and then mean and variance are re-attributed to the forecasts accordingly. Best models are in bold.

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