An Embarrassment of Riches: Forecasting Using Large Panels

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Forecasting Using Large Panels

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Abstract

The increasing availability of data and potential predictor variables poses new challenges to forecasters. The task of formulating a single forecasting model that can extract all the relevant information is becoming increasingly difficult in the face of this abundance of data. The two leading approaches to addressing this ”embarrassment of riches” are philosophically distinct. One approach builds forecast models based on summaries of the predictor variables, such as principal components, and the second approach is analogous to forecast combination, where the forecasts from a multitude of possible models are averaged. Using several data sets we compare the performance of the two approaches in the guise of the diffusion index or factor models popularized by Stock and Watson and forecast combination as an application of Bayesian model averaging. We find that none of the methods is uniformly superior and that no method performs better than, or is outperformed by, a simple AR(p) process.

Keywords: Bayesian model averaging, Diffusion indexes, GDP growth rate, Inflation rate.

JEL-codes: C11, C51, C52, C53

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1 Introduction

The number of potential predictors for macroeconomic variables can easily count in the hundreds, e.g. Stock and Watson (2002b) collect some 200 predictor variables for the US economy. Paradoxically, having more information in the form of more predictor variables makes forecasting more difficult. Simply put, the task of formulating a forecasting model and extracting the relevant information from the predictors becomes more complex as the number of possible predictors increases. The increasing availability of data is thus creating new challenges for the forecaster. There are, essentially, two different approaches to address this problem. The first approach builds forecast models based on summaries of the predictor variables, such as principal components, and the second approach is analogous to forecast combination, where the forecasts from a multitude of possible models are averaged.

Each attempts to overcome the shortcomings of the traditional approach of selecting a single forecasting model based on a few predictors. Clearly, using a single model, which by necessity can only incorporate a small subset of the variables, will fail to take account of all information in the data. In addition, by being based on a single model the forecast does not take account of model uncertainty. Basing the forecast model on data summaries in the form of principal components, as in Stock and Watson (2002b), allows information from all the predictors to enter into the forecasts, but not necessarily in an optimal fashion since the summaries of the predictors are created without a reference to the predicted variable. Model averaging, on the other hand, summarizes the different possible relationships between the predicted variable and the predictor variables. With appropriately chosen weights, this should lead to more efficient extraction of information. Model averaging also has the advantage of providing robustness against misspecification, and model uncertainty can easily be accounted for if the model averaging is conducted in a Bayesian setting, i.e. the weights are the posterior probabilities of the models. In addition the models and their averages are more easily interpreted than principal components and inference on the importance of individual predictors is available.

The potential benefits of model averaging as a tool for extracting the relevant information from a large set of predictor variables come at the cost of considerable computational complexity. With 100 predictor variables one obtains more than $10^{30}$ different models just by considering the different possible combinations of the variables, and it is clearly impossible to include all of them in a model averaging exercise. Recent advances in Bayesian computing, utilized by e.g. Jacobson and Karlsson (2004), provide one way forward by identifying the subset of important models as measured by their posterior probability, i.e. the set of models which would receive a non-negligible weight in the forecast combination.

Koop and Potter (2004) apply Bayesian model averaging (BMA) to dynamic
factor models by orthogonalizing the predictors, using a transformation to principal components. Koop and Potter conclude that models containing factors do outperform autoregressive models in forecasting, but only narrowly and at short horizons. Also the gains provided by using BMA over forecasting methods based on a single model are more appreciable relative to the small forecasting gains from factor-based models.

The purpose of this paper is to evaluate the forecasting performance of the factor model approach of Stock and Watson (2002b), the Bayesian model averaging approach of Jacobson and Karlsson (2004), and the combined approach of Koop and Potter (2004). Any forecast evaluation is dependent on the choice of variable to forecast and the dataset used. To protect against this, we use three different datasets with two different frequencies, and forecast both inflation and GDP.

In all three cases the forecasts are based on a simple linear model,

\[ y_{t+h} = x_t \beta_h + \epsilon_{t+h}, \]

where \( x_t \), in the case of Stock and Watson, consists of the first few principal components, possibly augmented with lags of these and lagged values of \( y_t \). In the Bayesian model averaging approach of Jacobson and Karlsson, \( x_t \) is a subset of the regressor variables, possibly including lags of the predictors and \( y_t \), and the forecasts are obtained by averaging over the forecasts from the different models. In the combined approach of Koop and Potter, \( x_t \) contains a selected subset of orthogonalized regressors.

There are two features worth noting about this setup, the forecast model depends on the forecast horizon, \( h \), and the forecasts are static, i.e. there is no need to forecast \( x_t \).

The remainder of the chapter is organized as follows. Section 2 presents the forecasting approaches in large panels, Section 3 compares the different forecast methods, and Section 4 concludes.

## 2 Forecasting methods

### 2.1 Factor models

The factor based approach to forecasting with large data sets is based on the assumption that the relevant information is captured by a small number of factors common to the predictor variables. The forecasts are constructed using a two-step procedure. First, the method of principal components is used to extract factors from the predictors \( x_t \).

In the second step the factors are used to forecast the time series \( y_{t+h} \).

In particular, let \( y_{t+h} \) be a scalar series that is being forecast \( h \)-periods ahead, and let \( x_t \) be a \( N \)-dimensional multiple time series of variables serving as predictors. Now consider the forecasting equation

\[ y_{t+h} = \beta(L) f_t + \gamma y_t + \epsilon_{t+h}, \quad t = 1, \ldots, T, \]

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where \( f_t \) is a vector of \( q \) unobservable common factors and \( y_t \) is a set of \( p + 1 \) variables, such as lags of \( y_t \). Furthermore \( \beta(L) \) is a vector lag polynomial and \( \gamma = (\gamma_0, \gamma_1, \ldots, \gamma_p)' \). Suppose that the observed series \( x_t \) and \( y_{t+h} \) in (2) allow for a dynamic factor model with \( q \) common dynamic factors \( f_t \)

\[
x_{it} = \lambda_i(L)f_t + e_{it}, \quad i = 1, \ldots, N; \ t = 1, \ldots, T,
\]

(3)

where \( \lambda_i(L) \) is a lag polynomial vector, and \( e_{it} \) is an idiosyncratic disturbance. In addition, it is assumed that

\[
E(\varepsilon_{t+h}\mid f_t, y_t, x_t, f_{t-1}, y_{t-1}, x_{t-1}, \ldots) = 0.
\]

(4)

Assume that the lag polynomial vectors are of order \( s \). The dynamic factor model (2)–(3) can then be restated as

\[
y_{t+h} = B'F_t + \gamma y_t + \varepsilon_{t+h},
\]

(5)

\[
x_t = \Lambda F_t + e_t,
\]

(6)

where \( B = (\beta_0', \ldots, \beta_s')' \), \( F_t = (f_t', f_{t-1}', \ldots, f_{t-s}')' \) is a \((s+1)q \times 1\) vector, and the \( i \)-th row of \( \Lambda \) is \((\lambda_{i0}, \ldots, \lambda_{is})\).

The \((s+1)q\) factors \( F_t \) in (6) are estimated using principal components, denoted by \( \tilde{F}_t \). In the second step, after regressing \( y_{t+h} \) on a constant, \( \tilde{F}_t \), \( r \) possible lags of \( \tilde{F}_t \), \( p \) lags of \( y_t \), the general forecasting function becomes

\[
\hat{y}_{T+h\mid T} = \hat{\alpha}_h + \sum_{j=0}^{r} \hat{B}_{hj} \tilde{F}_{T-j} + \sum_{j=0}^{p} \hat{\gamma}_{hj} y_{T-j},
\]

(7)

where \( \hat{y}_{T+h\mid T} \) is the \( h \)-step ahead forecast.

Stock and Watson (2002b) use factor models to forecast macroeconomic variables, measuring both real economic activity and prices. The factor model forecast is compared with other forecasting models, such as autoregressive forecast (AR), vector autoregressive forecast and multivariate leading indicator forecast. Stock and Watson (2002b) consider U.S. monthly series with the total number of possible predictors being 215. They find that for real variables factor models with two factors, or autoregressive factor models with two factors improve forecasting performance the most. For price indices the autoregressive factor models forecasts with one factor are preferred. In a recent paper, Boivin and Ng (2005) point out that two researchers can arrive at different forecasts using factor models, because the factors are estimated differently and/or the forecasting equations are specified differently. Boivin and Ng concentrate on the two leading methods in the literature, the dynamic method of Forni, Hallin, Lippi, and Reichlin (2005) and the static method of Stock and Watson (2002a). Boivin and Ng investigate the sensitivity of the estimates of the factors and the forecasts based on factor models to the dynamics of the factors and the specification of the
forecasting equation. Their main findings are that unconstrained modelling of the series of interest tends to give more robust forecasts when the data generating process is unknown, and that the methodology of Stock and Watson (2002a) apparently does have these properties.

2.2 Bayesian model averaging

Bayesian model averaging can be used to combine forecasts from the set of models that can be constructed using various combinations of the predictors. The averaging over many different competing models incorporates model as well as parameter uncertainty into conclusions about parameters and predictions. See Hoeting, Madigan, Raftery, and Volinsky (1999) for references and an overview of Bayesian model averaging.

Given a set \( \mathcal{M} = \{ \mathcal{M}_1, \ldots, \mathcal{M}_M \} \) of possible models, prior probabilities of the models, \( p(\mathcal{M}_i) \), prior distribution of the parameter in each model, \( p(\theta_i|\mathcal{M}_i) \) and likelihoods, \( L(y|\theta_i,\mathcal{M}_i) \) all quantities of interest for model averaging and selection can be obtained by using Bayes rule. The posterior probabilities of the models are given by

\[
p(\mathcal{M}_i|y) = \frac{m(y|\mathcal{M}_i)p(\mathcal{M}_i)}{\sum_{j=1}^{M} m(y|\mathcal{M}_j)p(\mathcal{M}_j)} = \left[ \sum_{j=1}^{M} \frac{m(y|\mathcal{M}_j)p(\mathcal{M}_j)}{m(y|\mathcal{M}_i)p(\mathcal{M}_i)} \right]^{-1},
\]

where \( m(y|\mathcal{M}_i) \) is the marginal likelihood

\[
m(y|\mathcal{M}_i) = \int L(y|\theta_i,\mathcal{M}_i) p(\theta_i|\mathcal{M}_i) \, d\theta_i,
\]

for model \( i = 1, \ldots, M \). The posterior distribution of some quantity of interest, \( \phi \), when taking account of model uncertainty, is

\[
p(\phi|y) = \sum_{j=1}^{M} p(\phi|y,\mathcal{M}_j) p(\mathcal{M}_j|y),
\]

which is an average of the posterior distribution under each of the models, weighted by their posterior model probabilities. In particular, the minimum mean squared error forecast is given by

\[
\hat{y}_{T+h|T} = E(y_{T+h}|y) = \sum_{j=1}^{M} E(y_{T+h}|y,\mathcal{M}_j) p(\mathcal{M}_j|y),
\]

where \( E(y_{T+h}|y,\mathcal{M}_j) \) is the forecast conditional on model \( \mathcal{M}_j \). This forecast is a special case of forecast combination with weights \( w_j \)

\[
\hat{y}_{T+h|T} = \sum_{j=1}^{M} \hat{y}_{T+h,j|T} w_j,
\]

where BMA provides optimal weights under the assumptions of the forecasting exercise.
2.3 The parameter prior and the posterior distributions

Consider a linear model with \( k \) regressors

\[
y_{t+h} = z_t \gamma_h + \varepsilon_{t+h},
\]

(13)

where \( \gamma_h = (\alpha_h, \beta'_h)' \), is a \( k + 1 \) parameter vector and \( z_t = (\iota, x'_t) \) is a vector of explanatory variables.

A challenging task in BMA and model selection is the specification of the prior distribution for the parameters \( \gamma \) in the different models. The posterior model probabilities (8) depend on the prior for the model parameters. Due to the large number of models it is desirable to use priors in an automated fashion. The priors should be relatively uninformative and also robust in the sense that conclusions are qualitatively insensitive to reasonable changes in the priors. A common choice in BMA for the class of the normal linear model is the \( g \)-prior of Zellner (1986) for the regression parameters,

\[
p(\gamma | \sigma^2, \mathcal{M}) \sim N_{k+1}(0, c \sigma^2 (Z'Z)^{-1})
\]

(14)

that is, the prior mean is set to zero indicating shrinkage of the posterior towards zero and the prior variance is proportional to the data information. Improper priors can be used on the parameters that have identical interpretation across all models. In the case of a linear regression model we can use the usual uninformative prior for the variance,

\[
p(\sigma^2) \propto 1/\sigma^2.
\]

(15)

These priors lead to a proper posterior on the regression parameters, which are \( t \)-distributed with \( T \) degrees of freedom,

\[
p(\gamma | y) \sim t_{k+1}(\gamma_1, S, M, T),
\]

(16)

where

\[
\gamma_1 = \frac{c}{c+1} \hat{\gamma},
\]

(17)

is a scaled down version of the least squares estimate, and

\[
S = \frac{c}{c+1} (y - Z\gamma)'(y - Z\gamma) + \frac{1}{c+1} y'y,
\]

(18)

\[
M = \frac{c+1}{c} Z'Z.
\]

(19)

The marginal likelihood is a multivariate \( t \)-distribution

\[
m(y | \mathcal{M}) \propto (c+1)^{-(k+1)/2} S^{-T/2}.
\]

(20)

The prior (14) requires only specification of the hyperparameter \( c \). Our prior is similar to the one advocated by Fernández, Ley, and Steel (2001), the essential
difference being that they use an improper prior for both the constant term and the variance. In a rather extensive study Fernández, Ley, and Steel (2001) investigate various choices of $c$. Their recommendation is to set the hyperparameter to

\[
c = \begin{cases} 
  N^2 & \text{if } T \leq N^2, \\
  T & \text{if } T > N^2.
\end{cases}
\]  

(21)

2.3.1 The model prior and the model space

A second challenge arises with the size of the model space. All possible combinations of $N$ potential predictors result in $2^N$ models. Traversing the complete model space, calculating the posterior probabilities, BMA forecasts and the posterior inclusion probabilities of the variables is thus impractical. A convenient method to identify a set of models with non-negligible posterior model probabilities without examining the full model space, is the reversible jump Markov chain Monte Carlo algorithm, see Green (1995). The details of the algorithm are given as Algorithm 1.

This Markov chain converges to the posterior model probabilities under quite general conditions and provides one way of estimating $p(M|y)$. The estimated posterior model probabilities are (for obvious reasons) conditional on the set of models visited by the chain. To verify that the Markov chain captures most of the total posterior probability mass the method suggested by George and McCulloch (1997) can be used. This method utilizes two separate Markov chains, each starting at a random model. The secondary chain is run for a predetermined number of steps and is then used to provide a capture-recapture type estimate of the total visited probability for the primary chain.

The number of models that enter the model averaging can be further reduced by imposing restrictions on the high-dimensional model space. Being uninformative about the model space results in all models having equal probability and then unrealistically large models are included in the average. Instead, a model prior that downweights models containing a large number of predictors can be used

\[
p(M_i) \propto \delta^{k_i} (1 - \delta)^{N-k_i},
\]

(24)

where $k_i$ is number of predictors in a model $M_i$. Setting $\delta = 0.5$ is equivalent to a constant model prior

\[
p(M_i) = p_i = \frac{1}{M}, \quad i = 1, 2, \ldots, M.
\]

(25)

2.4 Bayesian model averaging with factor models

Koop and Potter (2004) use Bayesian techniques to select factors in dynamic factor models as well as BMA to average forecasts over model specifications. They consider
Algorithm 1 Reversible jump Markov chain Monte Carlo

Suppose that the Markov chain is at model $\mathcal{M}$, having parameters $\theta_{\mathcal{M}}$, where $\theta_{\mathcal{M}}$ has dimension $\text{dim}(\theta_{\mathcal{M}})$.

1. Propose a jump from model $\mathcal{M}$ to a new model $\mathcal{M}'$ with probability $j(\mathcal{M}'|\mathcal{M})$.

2. Generate vector $u$ (which can have different dimension than $\theta_{\mathcal{M}'}$) from a specified proposal density $q(u|\theta_{\mathcal{M}}, \mathcal{M}, \mathcal{M}')$.

3. Set $(\theta_{\mathcal{M}'}, u') = g_{\mathcal{M}, \mathcal{M}'}(\theta_{\mathcal{M}}, u)$, where $g_{\mathcal{M}, \mathcal{M}'}$ is a specified invertible function. Hence $\text{dim}(\theta_{\mathcal{M}'}) + \text{dim}(u) = \text{dim}(\theta_{\mathcal{M}'}) + \text{dim}(u')$. Note that $g_{\mathcal{M}, \mathcal{M}'} = g_{\mathcal{M}', \mathcal{M}}^{-1}$.

4. Accept the proposed move with probability

\[
\alpha = \min\left\{1, \frac{L(y|\theta_{\mathcal{M}'}, \mathcal{M}')} p(\theta_{\mathcal{M}'}, \mathcal{M}'|\mathcal{M}) p(\mathcal{M}') j(\mathcal{M}'|\mathcal{M})}{L(y|\theta_{\mathcal{M}}, \mathcal{M}) p(\theta_{\mathcal{M}}, \mathcal{M}|\mathcal{M}) p(\mathcal{M}) j(\mathcal{M}|\mathcal{M})} \times \frac{q(u'|\theta_{\mathcal{M}'}, \mathcal{M}', \mathcal{M})}{q(u|\theta_{\mathcal{M}}, \mathcal{M}, \mathcal{M}')} \frac{\partial g_{\mathcal{M}, \mathcal{M}'}(\theta_{\mathcal{M}}, u)}{\partial (\theta_{\mathcal{M}}, u)}\right\}. \tag{22}
\]

5. Set $\mathcal{M} = \mathcal{M}'$ if the move is accepted.

If all parameters of the proposed model are generated directly from a proposal distribution, then $(\theta_{\mathcal{M}'}, u') = (u, \theta_{\mathcal{M}})$ with $\text{dim}(\theta_{\mathcal{M}}) = \text{dim}(u')$ and $\text{dim}(\theta_{\mathcal{M}'}) = \text{dim}(u)$, and the Jacobian is unity. If, in addition, the proposal $q(u|\theta_{\mathcal{M}}, \mathcal{M}, \mathcal{M}')$ is the posterior $p(\theta_{\mathcal{M}'}, y, \mathcal{M}')$ then [22] simplifies to

\[
\alpha = \min\left\{1, \frac{m(y|\mathcal{M}') p(\mathcal{M}') j(\mathcal{M}|\mathcal{M}')} {m(y|\mathcal{M}) p(\mathcal{M}) j(\mathcal{M}'|\mathcal{M})}\right\}. \tag{23}
\]

This implies that we do not need to perform steps 2 and 3 of the algorithm. Two types of model changing moves are considered:

1. Draw a variable at random and exclude it from the model if it is already in the model, otherwise add it. This step is attempted with probability $p_A$.

2. Swap a randomly selected variable in the model for a randomly selected variable outside the model. This step is attempted with probability $1 - p_A$.  

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a number of different model priors and evaluate their forecasting performance, and the in-sample and out-of-sample performance of model selection, model averaging and factor models. A common set of variables, the constant term and lags of the dependent variable, are included in each model. These are assigned flat priors and marginalized out in the same way as the constant is treated by Fernández, Ley, and Steel (2001). The basic model (13) still applies with suitably transformed dependent and explanatory variables. The priors (14) and (15) are used for the reduced model. To apply the BMA approach on the factor models, the regressors \( z_t \) are transformed to principal components using the orthogonal transformation \( W = ZE \), where \( E \) is the matrix of eigenvectors of \( Z^T Z \). The model with orthogonal regressors is then

\[
y_{t+h} = w_t \zeta_h + \varepsilon_{t+h},
\]

with \( \zeta_h = E^{-1} \gamma_h \). The prior for the regression coefficients becomes

\[
p(\zeta | \sigma^2, M) \sim N_{k+1} \left( 0, c \sigma^2 (E^T Z^T Z E)^{-1} \right)
\]

yielding the posterior

\[
p(\zeta | y) \sim t_{k+1} (\zeta_1, S, M, T),
\]

with \( Z \) and \( \gamma \) replaced accordingly by \( W \) and \( \zeta \), respectively in the equation (17). The use of orthogonalized regressor has the practical advantage that the computational effort is reduced compared to BMA or Bayesian variable selection with non-orthogonal regressors. Since \( W^T W \) is diagonal the marginal likelihood ratio in (23) simplifies and depends only on the model variables that are unique to either model. The ratios can thus be easily precomputed for the case when the models only differ by one or two variables.

Koop and Potter (2004) focus on forecasting the growth rates of US GDP and inflation using a set of 162 predictors. They conclude that BMA forecasts improve on an AR(2) benchmark forecasts at short, but not at longer horizons and only by a small margin. These findings are attributed to the presence of structural instability and the fact that lags of the dependent variable seem to contain most of the information relevant for forecasting. Koop and Potter also investigate the forecasting performance of several model priors. They found that priors, which focus on principal components explaining 99.9% of the variance of the predictors, provide the best results, and that the non-informative prior (25) performs very poorly.

### 2.5 Median probability model

In addition we take the opportunity to apply a method proposed by Barbieri and Berger (2004). This method does not directly deal with the situation of having many predictors, but it is of some interest and is easily implemented since the posterior model probabilities are available from the BMA exercise.
Barbieri and Berger show that for selection among linear models the optimal predictive model is often the median probability model, which is defined as the model consisting of variables that have overall posterior inclusion probability of at least \( \frac{1}{2} \). The posterior inclusion probability for a variable \( i \) is given by

\[
p(x_i | y) = \sum_{j=1}^{M} I(x_i \in M_j) p(M_j | y),
\]

where \( I(x_i \in M_j) \) equals one if \( x_i \) is included in model \( M_j \) and zero otherwise. It is possible that no variable has a posterior inclusion probability exceeding \( \frac{1}{2} \). The median probability model is, however, assured to exist in two important cases, one is the problem of variable selection, when any variable can be included or excluded from the model, and the other case is when the models under consideration follow a graphical model structure, for example a sequence of nested models. Barbieri and Berger show that the median probability model will frequently coincide with the highest posterior probability model. One obvious situation is when there is a model with posterior probability higher than \( \frac{1}{2} \). Other situations include the problem of variable selection under an orthogonal design matrix, certain prior structures and known variance \( \sigma^2 \).

In Barbieri and Berger’s (2004) experience the median probability model outperforms the maximum probability model in terms of predictive performance. They suggest that the median probability model should routinely be determined and reported as a complement to the maximum probability model.

### 3 Forecast comparison

We explore the performance of the methods mentioned in the previous section on three different datasets, and compare their performance through the root mean square forecast error (RMSFE). The first dataset is the balanced U.S. monthly dataset of Stock and Watson (2002b) consisting of 146 series from 1960:01 to 1998:12. The second dataset consists of 161 quarterly U.S. time series from 1959Q1 until 2000Q1 and was used in Stock and Watson (2003) and in Koop and Potter (2004). The last dataset is a Swedish dataset comprising of 77 variables including a wide range of indicators of real and monetary aspects of the Swedish economy ranging from 1983Q1 to 2003Q4.\(^1\) We forecast the CPI or the inflation rate for all three datasets, and for the U.S. quarterly data we forecast the GDP growth rate as well. The forecasting model is

\[
y_{t+h} = \alpha_h + \mathbf{x}_t \beta_h + \epsilon_{t+h},
\]

which generalizes (7), (13) and (26) to arbitrary forecasting horizons. The choice of dependent variable as \( y_{t+h} \), instead of \( y_t \), has the great advantage that it does away

\(^1\)See the cited works for the list of the predictors for the US data and Appendix A for the list of the Swedish series and their transformation.
with the need of forecasting the predictors in $\mathbf{x}_t$ when forecasting $y_{t+h}$. The obvious disadvantage of this choice of dependent variable is that it leads to a different model for each forecast horizon.

Following Stock and Watson the dependent variable and the predictors in the U.S. datasets are transformed into stationary series. In particular, GDP is modelled as being $I(1)$ in logarithms and CPI as $I(2)$ in logarithms. This implies that $y_{t+h}$ for GDP and CPI are transformed as

$$y_{t+h} = a/h \cdot \ln \left( \frac{GDP_{t+h}}{GDP_t} \right),$$

$$y_{t+h} = a/h \cdot \ln \left( \frac{CPI_{t+h}}{CPI_t} \right) - a \ln \left( \frac{CPI_t}{CPI_{t-1}} \right),$$

where $a = 400$ for quarterly data and $a = 1200$ for monthly data.

The Swedish inflation rate is measured as the four-quarter percentage change in the consumer price index and the remaining variables in the dataset are with few exceptions 4 quarter growth rates or 4 quarter log differences. The current level of inflation is included in the set of predictor variables for inflation $h$-periods ahead. A dummy variable $d_t$, for the Swedish low inflation regime dated to start in 1992Q1, is always included in the model (30).

The forecasts are constructed for horizons $h = 6$ and $h = 12$ for the monthly data, and for horizons $h = 4$ and $h = 8$ for the quarterly data, respectively. For the U.S. monthly data we evaluate the forecast performance for the period 1989:01 until 1998:12. To investigate the possibility that some forecasts work well in some periods but poor during others, we also calculate the forecast for four 30 months sub-periods.

For the factor model forecasts we consider the following variants proposed by Stock and Watson: the forecasts denoted by FM-AR,Lag, based on equation (7), include $v$ estimated factors, $r$ lags of factors and $p$ lags of $y_t$, where all the lag lengths are determined by the Bayesian information criterion (BIC). The FM-AR forecasts contain no lags of $\hat{F}_t$, with $v$ and $p$ determined by BIC. Finally, FM forecasts contain only contemporaneous $\hat{F}_t$, with $v$ selected by BIC. Further, forecasts based on the estimated factors holding the number of factors $v$ fixed are also considered, first determining the lag length of the dependent variable, $p$, by BIC, and then setting $p = 0$. These are denoted as FM-AR,v, and FM,v, respectively.

Our implementation of BMA in dynamic factor models differs slightly from the implementation in Koop and Potter (2004). We use only contemporaneous values when forming the principal components, in particular we do not include lags of $y$. We consider forecasts based on two different sets of predictors. The BMA-FM forecasts use only the 20 first principal components as the potential predictors and the BMA-FM-AR augments the set of predictors with $p$ lags of $y_t$. The use of the 20 first principal components roughly corresponds to the 99.9% prior that Koop and Potter find to work well.
<table>
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<th>U.S. monthly dataset</th>
<th>U.S. quarterly dataset</th>
<th>Swedish quarterly dataset</th>
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<td>20</td>
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<td>5000 000</td>
<td>5000 000</td>
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<tr>
<td>Burn-in</td>
<td>50 000</td>
<td>50 000</td>
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The forecasts calculated using the Bayesian approach include forecasts based on the forecast combination from all visited models, forecasts from the 3 models with the highest posterior probabilities, denoted Top1 to Top3, and forecasts based on the median model. For the U.S. monthly data we set the model hyperparameter $\delta$ to 0.075 in the usual BMA approach. This corresponds to a prior expected model size of 11 variables. For the BMA-FM approach, $\delta = 0.5$, giving expected size of 10 variables. The value of $c$ is chosen as in (21), i.e. $c = N^2$. The Markov chain is run for 5 000 000 steps with 50 000 steps as burn-in. The parameters defining the forecast experiments are summarized in Table 1.

The results from the different approaches are compared to a benchmark, an AR process with the lag length determined by BIC. In addition we calculate forecasts based on the random walk, i.e. when the forecast of $y_{t+h}$ equals the current value of the dependent variable.

### 3.1 Results

The results for the transformed U.S. CPI series are reported in Tables 2 and 3. Tables 4-7 show the results for the U.S. quarterly data, and the results for the Swedish inflation rate can be found in Tables 8-9. The first data column in the tables represents results based on the whole forecasting period and the remaining columns contain results for
the sub-periods. The values reported in the tables are the relative RMSFEs

\[
\frac{\text{RMSFE}(\hat{y}_{T+h|T})}{\text{RMSFE}(\hat{y}^\text{AR}_{T+h|T})}.
\]

(33)

In general, there is no method that consistently outperforms other methods across all periods, datasets or forecasting horizons. There are, however, some patterns in the results that merit further investigation.

It is important to include lags of the dependent variable when forecasting inflation. Only then is it possible to outperform an AR(\(p\)) process. This conclusion is supported in as much as 2/3 of the different periods. Koop and Potter (2004) find that an AR(2) process outperforms factor-based models for longer forecasting horizons. The better predictive performance of an AR(2) can, according to Koop and Potter, probably be explained by the fact that the relevant predictive information is included in the lags of the dependent variable.

One possible exception to this is the US GDP forecasts, where the predictive performance of the FM forecasts is unaffected by allowing for lags of the dependent variable. The GDP forecasts from the sub-periods and the whole period also indicate that it is not clear what the number of included factors should be. The best performing model contains different number of factors across the sub-periods. Also, choosing the number of factors included in a model in advance often performs better than using BIC for their determination.

Forecast combination using BMA regularly outperforms the forecasts from models selected by the posterior model probabilities.

The results differ substantially between the Swedish dataset, where the BMA-based methods perform poorly, and the two US datasets. Overall BMA-FM does better than the FM forecasts for the US datasets. Allowing for lags of the dependent variable in BMA-FM-AR improves the forecasts somewhat, but the FM-AR forecasts show a larger improvement.

On the issue of selecting predictors from the original variables, or data summaries such as principal components, the evidence is mixed. The BMA forecasts do better for the monthly data and the BMA-FM forecasts better for the quarterly data.

Comparing the median model with the highest posterior probability model fails to prove its superiority for forecasting. The median model produces smaller RMSFE than Top1 model only in 47% of all cases.

4 Conclusions

This paper compares methods for extracting information relevant for forecasting from a large number of predictors. Factor based models, the Bayesian model averaging
approach and the combination of the two are evaluated on US and Swedish data at both monthly and quarterly frequencies. We find that none of the methods is uniformly superior and that no method performs better than, or is outperformed by, a simple AR($p$) process.

A possible disadvantage of all the methods considered here is that they are based on linear models that forecast $h$-steps ahead directly. It is quite possible that these simple models fail to capture all the information contained in the data. In future research, more complicated, and thus more realistic functions, will be considered. This could improve forecast accuracy, but comes at the cost of increased computational complexity as the result.
Table 2 RMSFE relative to an AR($p$) for monthly U.S. CPI, 6 months ahead forecast.

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Table 3 RMSFE relative to an AR($p$) for monthly U.S. CPI, 12 months ahead forecast.

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Table 4 RMSFE relative to an AR($p$) for quarterly U.S. CPI, 4 quarters ahead forecast.

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References


## Appendix A  Data

The transformation codes for the time series are

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<td>2</td>
<td>4 quarters log difference $(\ln y_t - \ln y_{t-4})$</td>
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<td>4 quarters growth rate $(y_t - y_{t-4})$</td>
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<tr>
<td>4</td>
<td>4 quarters percentage change $\left(\frac{y_t - y_{t-4}}{y_{t-4}}\right)$</td>
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### Table A.1 Financial variables

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<td>3. REPO</td>
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### Table A.2 Exchange rates

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### Table A.3 Money supply

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### Table A.4 Labor costs

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<td>19. WageMM</td>
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<td>20. HLCInd</td>
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### Table A.5 Population

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### Table A.6 Labor market variables

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