2009 | 01

Working Paper

Economics Department

Does forecast combination improve Norges Bank inflation forecasts?

by Hilde C. Bjørnland, Karsten Gerdrup, Anne Sofie Jore, Christie Smith and Leif Anders Thorsrud

NORGES BANK

Working papers fra Norges Bank kan bestilles over e-post:
tjenestetorget@norges-bank.no
eller ved henvendelse til:
Norges Bank, Abonnementsservice
Postboks 1179 Sentrum
0107 Oslo
Telefon 22 31 63 83, Telefaks 22 41 31 05

Fra 1999 og senere er publikasjonene tilgjengelige på www.norges-bank.no.

Working papers inneholder forskningsarbeider og utredninger som vanligvis ikke har fått sin endelige form.
Hensikten er blant annet at forfatteren kan motta kommentarer fra kolleger og andre interesserte.
Synspunkter og konklusjoner i arbeidene står for forfatternes regning.

Working papers from Norges Bank can be ordered by e-mail:
tjenestetorget@norges-bank.no
or from Norges Bank, Subscription service
P.O.Box. 1179 Sentrum
N-0107Oslo, Norway.
Tel. +47 22 31 63 83, Fax. +47 22 41 31 05

Working papers from 1999 onwards are available on www.norges-bank.no

Norges Bank's working papers present research projects and reports (not usually in their final form) and are intended inter alia to enable the author to benefit from the comments of colleagues and other interested parties.
Views and conclusions expressed in working papers are the responsibility of the authors alone.

ISSN 0801-2504 (printed) 1502-8143 (online)
ISBN 978-82-7553-482-6 (printed) 978-82-7553-483-3 (online)

Does forecast combination improve Norges Bank inflation forecasts?*

Hilde C. Bjørnland[†]
Norwegian School of Management (BI)
and
Norges Bank

Karsten Gerdrup
Norges Bank

Anne Sofie Jore
Norges Bank

Christie Smith
Norges Bank

Leif Anders Thorsrud
Norges Bank

January 19, 2009

Abstract

We develop a system that provides model-based forecasts for inflation in Norway. Forecasts are recursively evaluated from 1999 to 2008. The performance of the models over this period is then used to derive weights that are used to combine the forecasts. Our results indicate that model combination improves upon the point forecasts from individual models. Furthermore, when comparing the whole forecasting period; model combination outperforms Norges Banks own point forecast for inflation at the forecast horizon up to a year. By using a suite of models we allow for a greater range of modelling techniques and data to be used in the forecasting process.

JEL-codes: E52, E37 E47.

Keywords: Forecasting, forecast combination.

*The authors thank Gernot Doppelhofer, James Mitchell and seminar participants in Norges Bank, the Norwegian School of Economics and Business Administration (NHH) and Norwegian School of Management (BI) for valuable comments. The usual disclaimer applies. The views expressed in this paper are those of the authors and should not be attributed to Norges Bank.

†Corresponding author: Norwegian School of Management (BI). Email. hilde.c.bjornland@bi.no

1 Introduction

Policy-making entails evaluating the future trajectory of the economy, and making policy decisions to influence that trajectory in favorable directions. The forward-looking nature of these policy decisions means that macroeconomic forecasting is a critical component underlying decisions.

Developing empirical models to describe and forecast the behaviour of the economy is, however, subject to many important decisions that can have a material impact on the output – e.g. forecasts – of the models. These decisions include the choice of the data set, the transformations applied to the data, the sample period used to estimate the parameters of the model, the choice of estimation techniques, the dynamic specification of the model, and so on.

A common research strategy is to make choices to test down to a single model specification. However, the model ultimately arrived at will most likely diverge from the true but unknown process that drives the behaviour of the economy. Settling on a single model also disregards all of the other possible models that might be nearly as good as (possibly even better than) the model that was ultimately chosen. If these other models have different implications, such as different forecasts, then one may mis-characterise the central location of the forecasts and also mis-characterise the uncertainty around the forecasts. The sequential testing involved in selection can also distort inference, making it difficult to know whether variables have been correctly included or excluding from the set of regressors used to forecast the variables of interest (see for example Bancroft (1944), Bock et al. (1973) and Raftery (1995)).

In recent years it has become increasingly common to adopt an alternative research strategy, which emphasises the *combination* of models or forecasts. Rather than arrive at a single specification, one entertains a wide variety of models and then weights together the output from these models in a sensible manner. By entertaining a variety of models one can develop a better appreciation of the range of views that could be supported by formal models, and a better appreciation of which outcomes are most likely.

In this paper we evaluate the forecasts of core inflation in Norway (consumer prices excluding taxes and energy, CPIATE) obtained from a broad spectrum of models, and consider whether forecast combination improves upon the forecasts from individual models. We focus on CPIATE as it has been the key underlying inflation measure that has been used to guide Norges Bank's inflation targeting regime since 2001.[1] We then analyze, in retrospect, whether forecast combination is superior to Norges Bank's own forecasts. Although there are a number of central banks that have explicitly adopted multi-model and model/forecast combination approaches to short-term forecasting, there has been no formal evaluation of whether model/forecast combination in fact outperforms the official central bank's forecasts (with the recent exception of Adolfson et al. (2007)), once the preferred forecasts and judgment are taken into account. It turns out that forecast combination does improve upon single model forecasts. Furthermore, model combination outperforms Norges Bank's own point forecast for inflation at forecast horizons up to a year. The suite of models allows for a greater range of modelling techniques and data to be used in the forecasting process.

The rest of this paper is organized as follows. In Section 2 we discuss the motivation for the modelling/forecasting approach from a theoretical and empirical perspective. Section 3 describes how the forecasts are produced, while Section 4 presents the results and compares the model forecasts to Norges Bank's official forecasts. Section 5 concludes.

2 Model combination

Model or forecast combination has a long history, dating back at least to Bates and Granger (1969). Bates and Granger consider a situation where a decision-maker is presented with multiple forecasts and must then decide what to do. In the context of trying to forecast accurately, Bates and Granger show that, ex post, a weighted average of two unbiased forecasts will always have a variance that is less than or equal to the lowest variance of the individual forecasts. A priori, the optimal (constant) weights are not known, and so Bates and Granger (1969) consider and evaluate a variety of different schemes for deriving weights recursively. The model combination

[1] In their mandate, Norges Banks should disregard any direct effects on consumer prices resulting from changes in interest rates, taxes, excise duties and extraordinary temporary disturbances when designing monetary policy.

approach is clearly helpful in evaluating models, because weights (or probabilities) are assigned to the various models, providing a clear signal of performance. Such weights can also be used to rank the models, as we do here.

In a recent survey, Timmerman (2006) emphasizes at least three main reasons for why forecast combinations may produce better forecast on average than methods based on the ex-ante best individual forecasting model. First, forecast combination can be motivated by a simple portfolio diversification (hedging) argument. Suppose the policymaker is faced with many different forecasting models, but can not observe the information sets underlying each of the the individual forecasts. In this situation, it is not possible to pool all the relevant information sets and construct a large model that nests each of the individual forecasting models. Instead, the best way to exploit the information behind the different forecasts is to combine the forecasts. This is discussed in more detail in Huang and Lee (2008). They show that combining forecasts, often with near-equal weights, is frequently superior even when it is feasible to combine information.[2] Hendry and Clements (2002) also show why combining forecasts adds value, and can even dominate the best individual device.

A second rationale for combination, again see Timmerman (2006) and the references therein, is that there may be unknown instabilities (structural breaks) that sometimes favour one model over another. Some models may adapt to breaks quickly while others may have parameters that will only adjust slowly to the post structural breaks. By combining forecasts from different models, the decision maker may obtain forecasts that are more robust to these instabilities, than if they had chosen a single model.

Related to the above argument, a third motivation is that forecast combination may be desirable as individual forecasting models may be subject to omitted variable bias that are unknown to the model operators. If the models are subject to different biases, combining forecasts may average out the biases improving forecast accuracy; see the references in Timmerman

[2] On the other hand, Diebold and Lopez (1996) note that it is always optimal to combine information sets rather than forecasts if such combination can be done costlessly. In practice, however, it is often infeasible to combine information sets, and the combined information set may not be amenable to usual analytical techniques (for example, if the time dimension is shorter than the cross-sectional dimension).

(2006) once more. Hence, even though the combined forecast may not always be superior, model combination may be preferable as it will ensure against selecting a single bad model.

2.1 Empirical experience with model combination

Empirical experience often, though not always, supports the theoretical results that imply model combination will improve forecast performance.[3] Timmerman (2006), with suitable caveats, provides a broad characterisation of empirical results and suggests the following: i) simple combination schemes are hard to beat, and the failure of more elaborate combination schemes is often attributed to the difficulty in estimating model weights; ii) forecasts based on the model with the single-best in-sample performance often perform poorly out-of-sample; iii) shrinkage towards equal weights often improves forecast performance; yet iv) some time-variation or adaptive adjustment of the weights may improve forecast performance.

Following on from earlier papers, Makridakis and Hibon (2000) develop a forecasting competition (known as M3) to evaluate the performance of different forecasting techniques. In their summary of the M3 forecasting competition, Makridakis and Hibon (2000) draw four main conclusions. They note that: i) complex statistical models are often not superior in terms of their forecasts; ii) the relative rank of the models depends on the metric used to assess performance; iii) on average, combination is superior to individual forecasts; and iv) the accuracy of the forecast methods depends on the forecast horizon.

Specific examples and counter-examples of model performance are easy to come by. Koop and Potter (2004) find that there are appreciable gains from using model averaging of factor models to forecast quarterly US GDP and inflation, relative to using single models. Clark and McCracken (2008) argue that combining real-time point forecasts from vector autoregressions of output, prices and interest rates improves point forecast accuracy in the presence of uncertain model instabilities. Stock and Watson (2004) show that for G-7 countries, combining forecasts generally results in robust predictions of GDP growth, and sometimes improves markedly on

[3] We concentrate on examples using time series data. See for instance Fernandez et al. (2001) for application to panel data.

simple autoregressive benchmarks and dynamic factor model forecasts. Marcellino (2002) suggests that on average, across a wide variety of European economic series, a linear combination of forecasts or a combination using MSE (mean square error) weights works very well. However, he notes that linear and nonlinear models can do better for specific series, and suggests that careful forecast selection may be preferable. Kapetanios et al. (2008), in their discussion of the Bank of England's suite of forecasting models, also find that two non-linear models out-perform their combination forecasts for UK GDP growth (though their performance for inflation is less convincing).

Marcellino's two conclusions echo the theoretical perspective provided by Raftery and Zheng (2003): the long run performance of Bayesian model averaging is good, yet there may be specific instances where model selection is superior. However, the difficulty is always in knowing when such a situation occurs, and at the very least model performance needs to be reported and evaluated. Raftery and Zheng (2003) provide a number of references that show that the out-of-sample performance of Bayesian model averaging is superior to selection methods. Nevertheless, there are still advocates of model selection, see for example Campos et al. (2005).

2.2 Forecasting/combination schemes at peer central banks

A number of central banks have recently adopted multi-model and forecast/model combination approaches to short-term forecasting. For instance, the Bank of England applies combination techniques to the forecasts from the suite of models, see for example Kapetanios et al. (2005) and particularly Kapetanios et al. (2008). The suite includes linear and non-linear univariate models, vector autoregressive (VAR) models of various specifications, Bayesian VARs, factor models and time-varying coefficient models. Their results indicate individual models find it difficult to beat the forecasts from a simple benchmark autoregressive model. However, combined forecasts frequently out-perform the benchmark and exhibit similar performance to the benchmark even when beaten.

The Riksbank has also taken a multi-model approach to near-term forecasting, see Adolfson et al. (2007). The Riksbank's suite of models incorporates bivariate and multivariate VARs, Bayesian VARs, VARs that also incorporate factors (which summarise the broad comovements in a large number of data series), and indicator models (where the indicators have shorter publication lags than the variables of actual interest). The Riksbank has also explored forecast combination methods; see for example Andersson and Karlsson (2007) and Adolfson et al. (2007).

The Reserve Bank of New Zealand uses a suite of statistical models as a cross-check on the central projection provided by the forecasting and modelling teams of the Economics Department. The suite of models includes several factor models, Bayesian VARs, an average of indicator models, and a weighted combination of VAR forecasts. Together with forecasts obtained from the private sector, the suite of models is used to illustrate the uncertainty around the central projection.

The Bank of Canada is another central bank that is using multiple models for near-term forecasting. Coletti and Murchison (2002) provide a description of the multi-model approach to policy-making employed at the bank of Canada. The Bank of Canada's suite of models includes single equation and indicator models, multi-equation reduced form models and medium-sized dynamic general equilibrium models.

Although some of these central banks have adopted model combination approaches to short-term forecasting, there is no consensus with regard to whether model combination in fact outperforms the Central Banks's own projections, once model based forecasts and judgment are taken into account. This is the issue we examine below when comparing the combined model forecast to Norges Banks's own inflation forecasts.

3 Forecast comparison

Norges Bank's projections form an important basis for the conduct of monetary policy. The forecasting work involves the use of the macromodel NEMO,[4] but this model is primarily suited for medium and long-term projections. Projections for the coming few quarters are largely based

[4]See Brubakk et al. (2006) for details.

on current statistics, information from Norges Bank's regional network and forecasts obtained from a number of statistical and econometric models. The published projections are the result of an overall assessment based on both models and judgement.

The new ingredient suggested to the above forecasting framework, is the formal combination of short-term forecasts. Such a system is currently being developed in Norges Bank and is collectively referred to as SAM – the System for Averaging Models.[5] The forecasts in the SAM system are combined using univariate, horizon-specific weights. In principle it is possible to use weights derived from multivariate measures of fit (such as the log-likelihood of a model), but because not all models forecast all variables it was decided to use univariate weights for now.

To evaluate the different models developed we conduct an out-of-sample forecasting exercise by using information up to time t (but from the *final* vintage of data) to forecast variables up to four steps ahead, i.e. we wish to forecast $X_{t+1}, X_{t+2}, X_{t+3}, X_{t+4}$, where X is a vector of variables. With quarterly data, the maximum forecasting horizon is thus 1 year ahead.[6]

Here we forecast the year-on-year (yoy) inflation rate, measured by CPIATE. As mentioned above, CPIATE has been Norges bank's core/underlying inflation measure since 2001. We choose to focus on inflation as it is rarely revised, hence there is no real time issue present in the data. Below we describe the forecast exercise conducted.

3.1 Forecast combinations

All models are estimated up to 1999Q1. The models are then updated recursively to make forecasts. In particular, conditioning on information up to and including 1999Q1, the models are first used to produce forecasts for 1999Q2 to 2000Q1. The conditioning combinations information set is then extended one period forward (to 1999Q2), and forecasts are then made for 1999Q3 to 2000Q2. The conditioning information set is then extended another period, and the whole process is repeated until all available information has been used, to provide the final forecast

[5]See Bjørnland et al. (2008) for more details on Norges Bank's forecasting/nowcasting project.

[6]We choose to focus on the one-year horizon as this is the horizon for which all models can produce sensible forecasts.

(2008Q1) conditioning on currently available information.

The actual data between 1999Q2 and 2008Q1 are then used to evaluate the average performance of the h-step forecasts, $h = 1, \ldots, 4$, from the different models. We evaluate the point forecasts for each horizon, which indicate the central expected location of yoy CPIATE inflation at the four horizons. Makridakis and Hibon (2000) note that the performance of models varies by forecasting horizon. For example, a model may forecast well for a 1-step ahead horizon, but may be much worse, relative to the other models, at forecasting 4-steps ahead. The model weights conducted here have been made horizon-specific for this reason.

The period used for the out-of-sample evaluation roughly coincides with the shift towards inflation targeting in Norway. This evaluation period is neither exceptionally long nor exceptionally short. It is an open question whether using a different period would have a marked impact on the forecast performance. It is also well known that estimating model weights can be difficult, and altering the sample period will undoubtedly alter the weights that would be attached to different models. One could make a case that one should be more concerned about the recent forecasting performance, but schemes that discount data from the distant past have not generally been very successful, see Timmerman (2006).

The combination of forecasts is based on mean-squared errors to weight the models. MSE-based combination was one of the schemes first investigated in Bates and Granger (1969). It can be interpreted as a measure of the differences between the values predicted by a model and the values actually observed at a later stage. Hence, it is the amount by which a forecast differs from the true value of the quantity being forecasted. Here the weights are based on root mean squared forecast errors (RMSEs):

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_{t+h} - \hat{y}_{t+h|t})^2} \tag{1}$$

where T is the length of the series of forecasts. We investigate combinations starting with the eight models that have the lowest RMSE (approximately 10 percent of the model space)[7] and up to combinations that include all models. We also consider the simple mean of all the forecasts (that is, they have equal weight). Timmerman (2006) notes that equal weights will be appropriate when models have equal forecast error variance, but this may not be the case here.[8]

3.2 Models

To provide the forecasts, we have developed a series of models that produce sensible forecasts up to one year ahead. We do not add judgement to these individual forecasts, but wish to evaluate a relatively 'clean' technical combination of forecasts against the Norges Banks published forecasts, which do reflect additional judgement. In creating the model suite, we cast our net relatively wide. We include autoregressive integrated moving average (ARIMA) models, Vector Autoregressive (VAR) models, Bayesian estimated VAR models, error correction models, factor models and finally dynamic stochastic general equilibrium (DSGE) models. Note that within each model class, there could be several variants with different specifications. In total, we have about 80 models.

3.2.1 Autoregressive Integrated Moving Average (ARIMA) models

ARIMA models use historical variations in a single time series to provide forecasts. Generally, the form of the model is given by,

$$y_t = \alpha + \sum_{j=1}^{p} \phi_j y_{t-j} + \sum_{j=0}^{q} \theta_j \varepsilon_{t-j} \tag{2}$$

where y_t is the variable of interest and p and q are the lag order of the autoregressive (AR) and moving average (MA) terms respectively. In practice, univariate representations can often

[7]Using fewer models give very similar RMSE's, but could be interpreted as being model selection rather than model combination.

[8]We have also experimented with Bayesian (BIC) and Akaike information criteria (AIC) to compare alternative models. The BIC rewards goodness of fit, but also includes a penalty that is an increasing function of the number of estimated parameters. The AIC is related to the BIC, but penalizes free parameters less strongly than the BIC criterion. Neither the AIC or the BIC improved upon the AR(2) model, hence they are not included here.

be captured by low-order AR models. Hence, we also include simple AR models.

3.2.2 Vector AutoRegressive (VAR) models

The VAR models are based on statistical relationships between GDP, interest rates and inflation. These tri-variate models take into account that there may be co-movement between these variables. All the variables are a function of lagged values of itself and the other variables,

$$X_t = A + \sum_{j=1}^{p} B_j X_{t-j} + \nu_t \tag{3}$$

where X_t is now the vector of variables in the model. Building on Clark and McCracken (2008), we estimate a variety of models and lag combinations (based on various information criteria) and different transformations of the variables (such as double-differencing).[9] Bjørnland et al. (2008) give a list of of the alternative VAR models estimated (64 models in total), including models where we exclude one or two variables, effectively estimating bivariate and univariate (AR) models respectively.

In addition to the tri-variate VAR models reported above, we also make forecasts from a VAR model that includes monetary aggregates (VARm). That is, the VARm model predicts inflation using various measures of money and interest rates as explanatory variables.

3.2.3 Bayesian VAR (BVAR) models

Bayesian methods have proven useful in the estimation of VARs. In particular, VAR models are often overparameterized. In Bayesian analysis the econometrician has to specify prior' beliefs about the parameters. The prior' beliefs are then combined with the data in the VAR to form a posterior view of the parameters. When data samples are large the influence of the prior beliefs will diminish and the data will guide the parameter values. In small samples prior beliefs may help to guide the parameter estimates towards sensible values, assisting forecasting. For the

[9] Motivated by the difficulties structural breaks present for forecasting, Hendry (2006) suggests to difference the model twice to robustify against deterministic breaks.

BVAR models specified here we use a direct forecasting method (eg CPIATE at time $t+h$ is regressed against variables at time t).

In addition to GDP, interest rates and inflation, we also include either the exchange rate or the terms of trade as an endogenous variable, thereby allowing for open economy considerations. Furthermore, we include a series of exogenous variables, such as oil prices and a number of foreign country-specific variables. We use a normal-inverted Wishart as prior on the model parameters, see Kadiyala and Karlsson (1997). Note that the Minnesota prior will be a special case in such a framework.[10]

3.2.4 Quartely factor (FQ) models

Factor models are estimated using large data sets. Based on correlation between the different variables, the data sets are reduced to a few common factors. These factors are then used in various equations to provide forecasts of economic developments. Our factor model for predicting inflation builds on Matheson (2006) and uses a quarterly data-set. The factor model is estimated using principal components on quarterly data, including survey data.[11] We use a direct forecasting method (eg CPIATE at time $t+h$ is now regressed against *factors* from data at time t). The different factors are estimated by using subsets of data (forecasts using factors do not always improve by enlarging the data set). The indicators are ranked by correlation, and then a factor model is estimated on larger and larger subsets of the indicators most correlated with inflation.

3.2.5 Error correction model (EMOD)

We estimate an econometric (equilibrium correction) model of 13 (*not-seasonally adjusted*) macro variables; with specification derived from data. We use CPIATE, GDP, other domestic variables, auxiliary equations for variables such as foreign prices, interest rates, oil price. The sample period begins in 1982Q4/2001Q1 (the latter date reflecting changes in monetary policy regimes). The

[10] For more details on the BVAR model estimated here, see Ravazzolo (2008).

[11] See Aastveit and Trovik (2007) for an example of a factor model for Norwegian GDP.

missing forecasts in our evaluation period are approximated with an AR(2). EMOD produces forecasts for all variables from 2003Q4 and onwards.[12]

3.2.6 Dynamic stochastic general equilibrium (DSGE) model

The DSGE model is a New Keynesian small open economy model. A version applied to the Norwegian economy is documented in Brubakk et al. (2006). The DSGE model is estimated using Bayesian maximum likelihood on seasonal adjusted data for mainland GDP growth, consumption growth, investment growth, export growth, employment, inflation (CPIATE), imported inflation, real wage growth, the real exchange rate (I44) and the nominal interest rate. The sample period is 1987Q1–1998Q4 (extended recursively until 2008Q1). The steady-state levels are equal to recursively updated means of the variables.

4 Empirical results

In this section we describe the main results. We first look at different ways to combine the point forecasts. We then compare the individual forecasts to our preferred combined forecasts. In the end we compare the combined forecasts with Norges Bank's official forecasts, to investigate if our forecasts outperforms Norges Bank's own forecasts.

The appendix graphs the forecasts made at different points in time using some of the individual models. Based on the forecasts of all the models, we then compute the combined forecast.

Table 1 shows the RMSE for the simple benchmark AR(2) model;

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \varepsilon_t, \tag{4}$$

and then displays RMSE of the combined forecasts relative to the AR(2) model RMSEs. Hence, a value lower than one implies that the combined forecasts improve upon a simple AR(2)

[12]The model is documented in Akram (2008).

model in terms of forecast accuracy. The Table refers to *Top 8* as the weighted average of the eight models that have the lowest RMSE, *Top 16* as the weighted average of the sixteen models that have the lowest RMSE, while *All* is the weighted average of all models. Finally, *Simple mean* refers to the simple mean of all the forecasts.

Table 1: Root mean square error relative to AR benchmark

Benchmark	**1-step**	**2-steps**	**3-steps**	**4-steps**
AR(2) [Absolute RMSE]	[0.264]	[0.406]	[0.571]	[0.728]
Combined models				
Top 8	0.820	0.736	0.719	0.714
Top 16	0.861	0.786	0.766	0.758
All	0.970	0.949	0.979	0.976
Simple mean	1.021	0.977	1.001	1.007

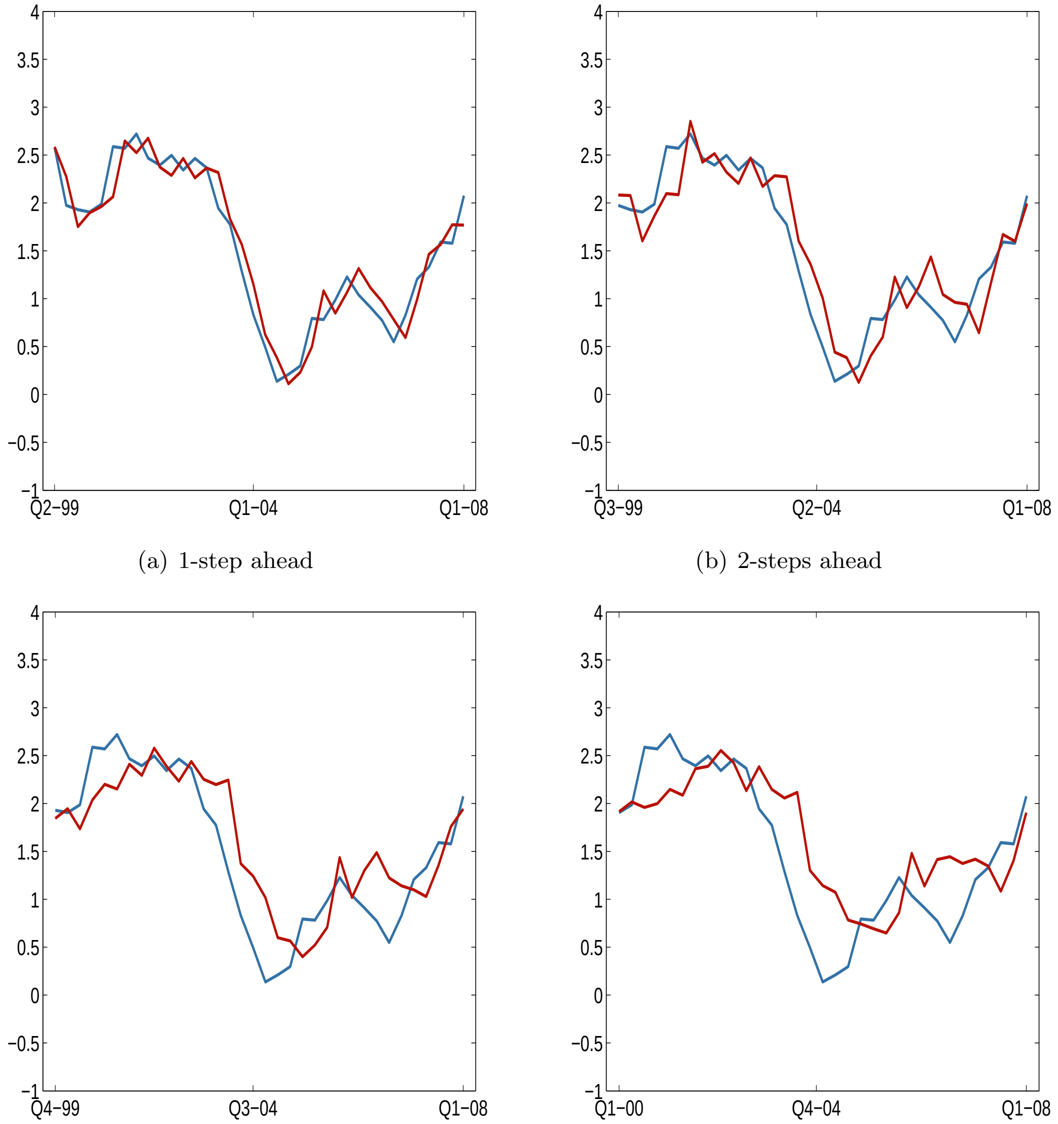
The table illustrates that combining models improve upon the forecast accuracy of the benchmark AR(2) model. With regard to finding an optimal number of models, the combination based on the smallest sample of models (top 8 models) performs the best. By including more models, the forecast accuracy deteriorates. However, using a simple mean of all the forecasts (i.e. models are not weighted by their performance), we no longer improve upon the forecast from an AR(2).

Hence, the model combination *Top 8* minimizes RMSE. In the following we therefore choose the *Top 8* model combination, and refer to this as *SAM* (system for averaging models). Figure 1 graphs the 1-4 step ahead forecast based on SAM and compares it to actual inflation. The figure graphs the inflation forecasts for various horizons against the inflation out-turns, that ideally would have been predicted.[13]

Having seen that the forecasts from SAM outperforms the forecasts from a benchmark *AR* model, we next set out to compare the performance of *SAM* to the best performing individual models. Figure 2 graphs the standard deviations for SAM forecast errors (RMSE) compared to some of the individual models at the one-to four-quarter horizon for inflation. SAM has

[13]Note that the chosen average of models referred to as SAM here, may not necessarily correspond to the weighted average referred to as SAM in current and future Norges Bank's Monetary Policy Report's, as for each forecast horizon SAM will be updated and thus depend on the available models and chosen methods of averaging.

Figure 1: *SAM-inflation forecasts at different points in time*



(a) 1-step ahead

(b) 2-steps ahead

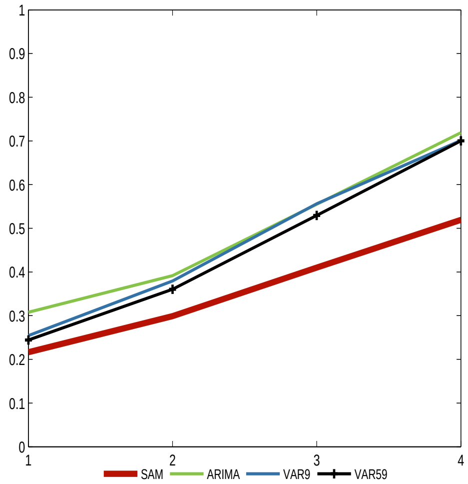
(c) 3-steps ahead

(d) 4-steps ahead

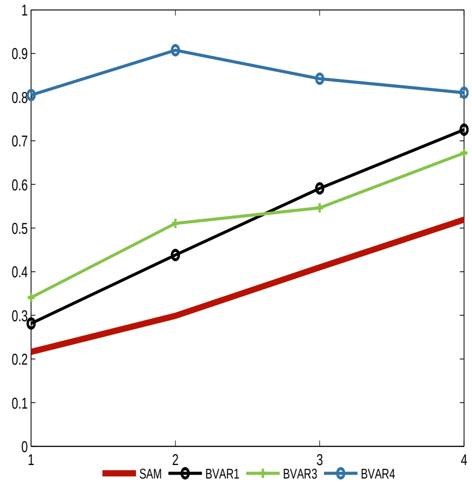
Note: The graphs compares actual inflation (CPIATE, yoy growth, blue line) with SAM forecast for inflation (red line) for the period 1999Q2-2008Q1. SAM forecasts are constructed based on the eight best performing models.

substantially lower standard deviations than the individual models for all horizons. This shows the benefit of averaging the forecasts from several models. However, Figure 2 also shows that the standard deviations of the factor model (FQ) are almost as low as those of SAM. Factor models contain a very large number of explanatory variables, and the common factors can be interpreted as an average of large amounts of information.

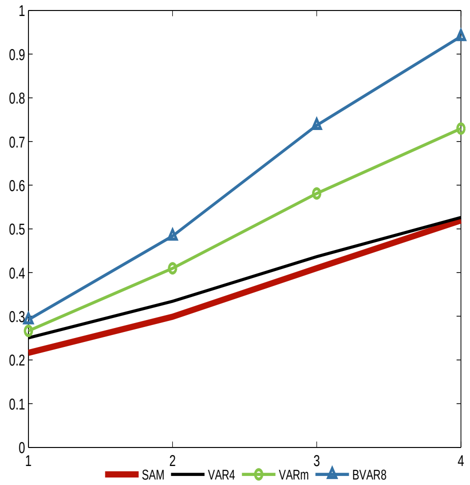
Figure 2: *RMSE for inflation*



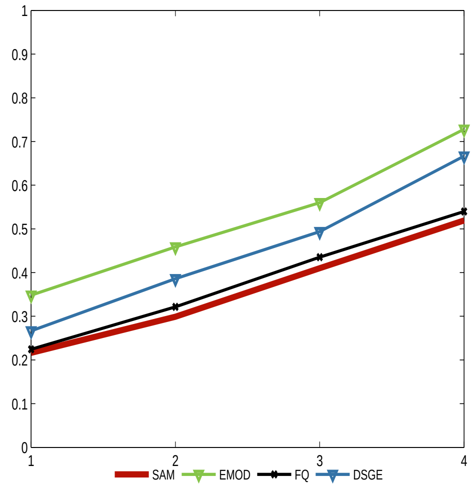
(a) RMSE



(b) RMSE



(c) RMSE



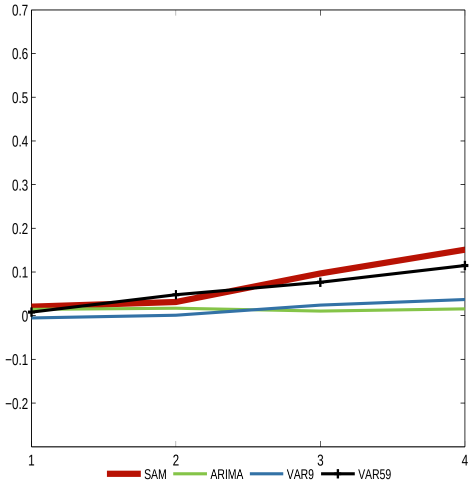
(d) RMSE

Note: Root mean square forecast error (RMSE) for SAM forecast (red line) is present in each panel. The horizontal axis give the different forecast horizons.

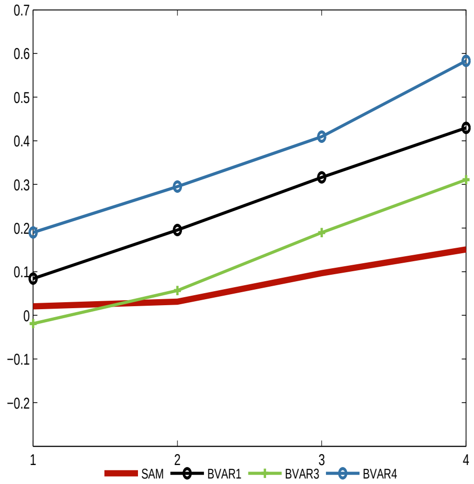
Finally, Figure 3 graphs the bias (mean forecast error) for inflation for all four horizons. Most models, including SAM, have a slightly positive bias, indicating that they have, on average, over-predicted inflation somewhat during the evaluation period. Only the factor model shows a small tendency for under-predicting inflation.

Figure 4 illustrates the performance of the 8 best forecasting models over time for CPIATE.

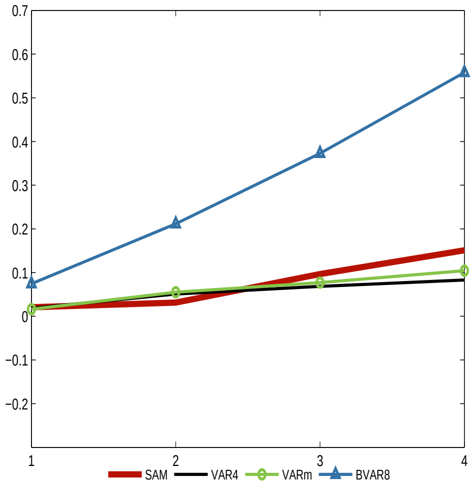
Figure 3: *Bias for inflation*



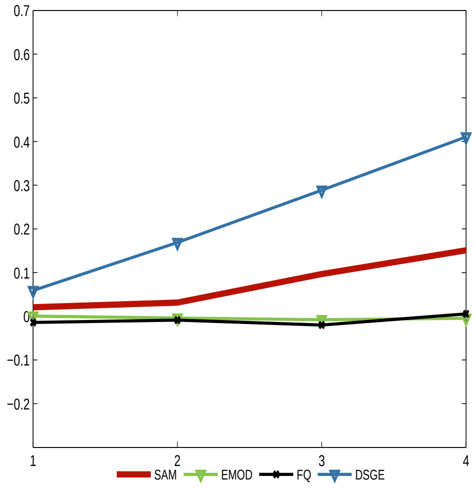
(a) Bias



(b) Bias



(c) Bias

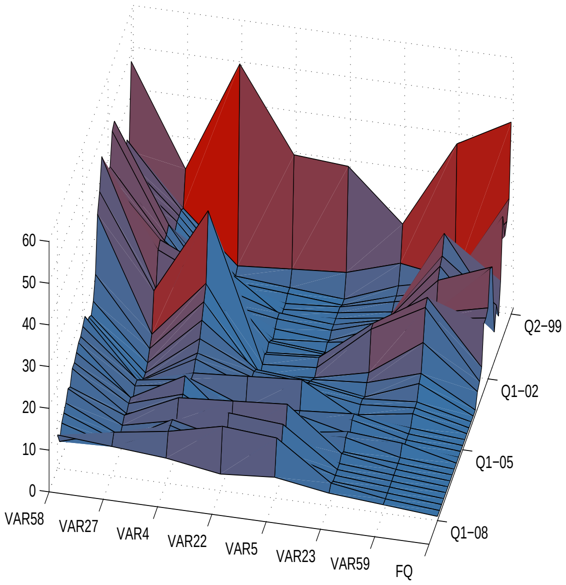


(d) Bias

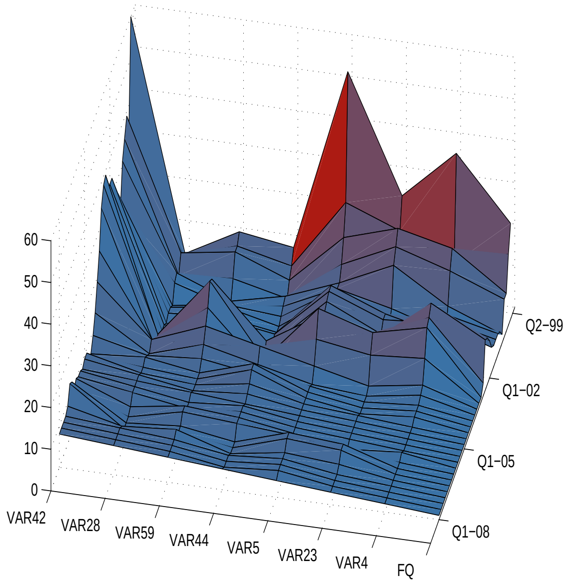
Note: Bias is the average forecast failure at each horizon. Bias for SAM forecast (red line) is present in each panel. The horizontal axis give the different forecast horizons.

The graph is 3-dimensional and should be read as follows. Along the horizontal axis we display the name of the eight best forecasting models, with the model ranked best (number one) placed to the far right. Moving left we find the name of the model that is ranked as number two etc. The ranking is based on the average of the whole forecasting period; 1999-2008. Moving back into the graph, we investigate how these eight models have performed in the past. That is, we

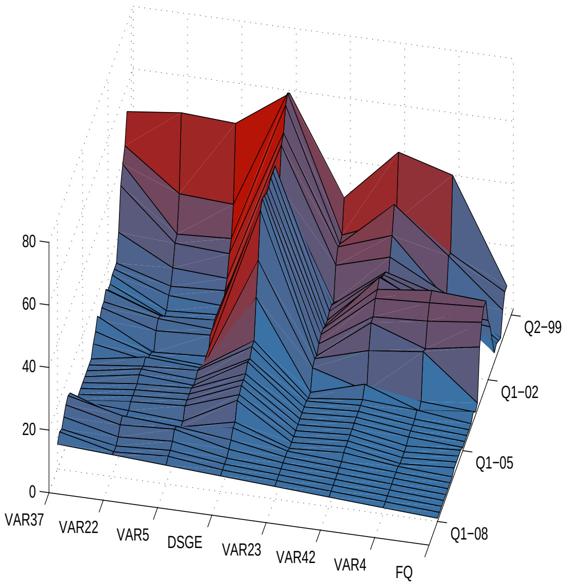
Figure 4: *Rank of 8 best models predicting inflation*



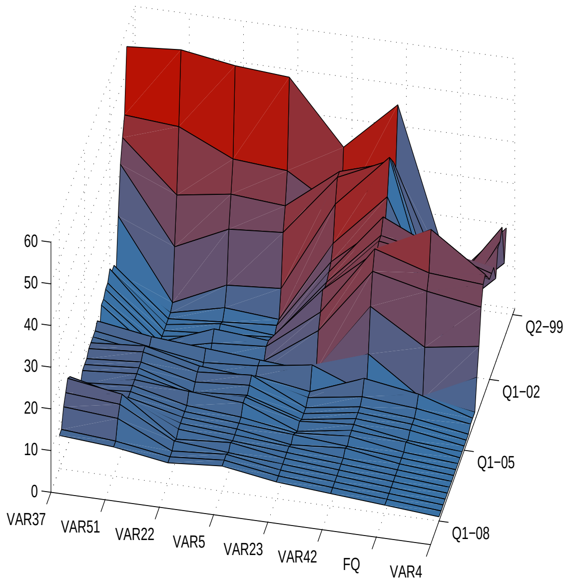
(a) 1-step ahead



(b) 2-steps ahead



(c) 3-steps ahead



(d) 4-steps ahead

Note: The graphs compares the rank of the 8 best models over time.

ask to what extent the models that are ranked from one to eight would be ranked similarly had the forecasting period ended in, say, 2001 instead of 2008. If one observes a flat (visualized as blue) landscape, the models have been ranked among the best models at all time. A mountain (visualized as red), on the other hand, indicates that the models have been ranked worse earlier in the period (that is, they are ranked with a higher number, as can be seen along the vertical axis). Overall, most of the top eight models have been ranked among the best over the whole sample (mostly flat landscape). However, some models, like the DSGE model, have only been among the top eight performing models the last three years.

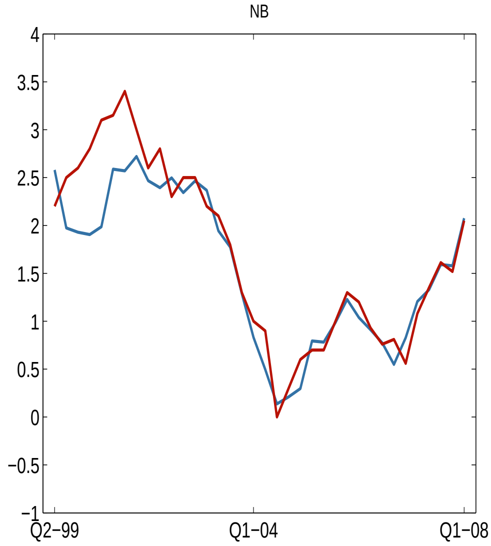
4.1 Do combined forecasts outperforms Norges Bank's official forecasts?

Below we compare the official Norges Bank (NB) projections for inflation with the SAM projections. The NB projections are collected from various monetary policy reports (MPRs) and are graphed in Figure 5. Note that for the period 1999-2000, Norges Bank's forecasts are for CPI and not CPIATE. This may give Norges Bank a disadvantage if CPI tracks systematically above or below CPIATE in this period. In the following we therefore compare the forecasts starting in 2001, when Norges Bank began publishing forecasts for CPIATE. The period 2001-2008 is also of interest because this is the official inflation targeting period.

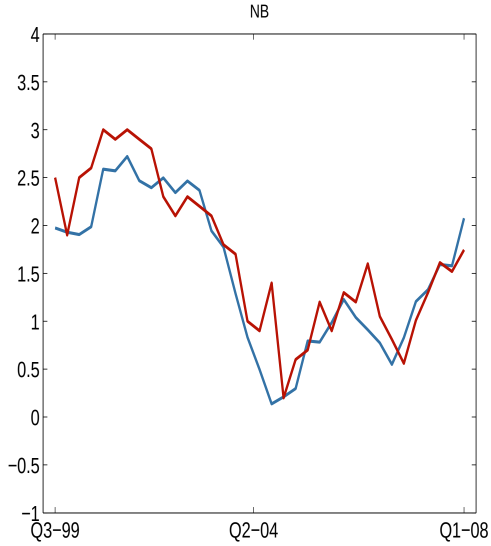
Note that Norges Bank's one step ahead forecast is made in the same quarter that it is forecasting, implying that they will have observed 1 or 2 months of CPIATE when making the one-step ahead forecasts. This gives Norges Bank an advantage in the forecast competition. On the other hand, Norges Bank also has a disadvantage as they publish forecasts only three times a year. Overall the net benefit may therefore be small. This is summarized below:

- The forecasts for Q1 are taken from MPR1 (published at the end of March), when CPI is known for January and February, giving Norges Bank two months information **advantage** relative to SAM (in the period 2001 to 2004, the monetary policy reports are published before CPI is known for February, giving Norges Bank only one month information advantage).
- The forecasts for Q2 are taken from MPR2 (published at the end of June), when CPI is known for April and May, giving Norges Bank two months information **advantage** relatively to SAM.
- Regarding the forecast for Q3, Norges Bank does not publish any forecast in the third

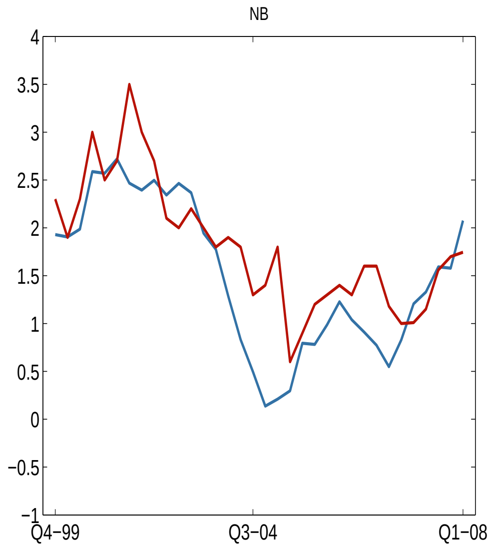
Figure 5: *Norges Bank's inflation forecasts at different points in time*



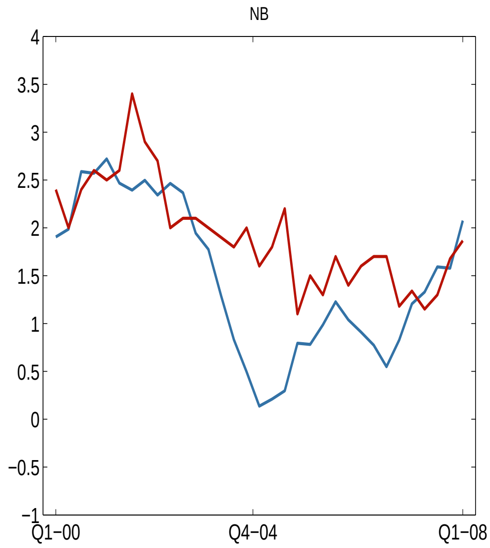
(a) 1-step ahead



(b) 2-steps ahead



(c) 3-steps ahead



(d) 4-steps ahead

Note: The graphs compares actual inflation (CPIATE, yoy growth, blue line) with Norges Bank's forecast for inflation (red line) for the period 1999Q2-2008Q1.

quarter. Most of the forecasts for Q3 are therefore taken from MPR2 (published at the end of June), giving Norges Bank one month information **disadvantage** relative to SAM (since June figures for CPI were yet not known).

- The forecasts for Q4 are taken from MPR3 (published at the end of October), when no information for Q4 is known. Hence, in Q4, Norges Bank has no advantage over SAM.

This gives Norges Bank an advantage over SAM in two of the quarters (Q1 and Q2) and a disadvantage in one quarter (Q3). For Q4, the information content is about the same.

Table 2 compares RMSE for Norges Bank's projections with SAM's projections. The results emphasize that for the period 2001Q1-2008Q1, Norges Bank outperforms SAM (marginally) at horizon 1. For horizons 2-4, on the other hand, SAM's forecasts outperforms Norges Bank's forecast. The gain from using SAM also increases with the horizons and illustrates the usefulness in averaging short term forecasts.

Table 2: RMSE for inflation: Comparing Norges Bank and SAM

Model		**1-step**	**2-steps**	**3-steps**	**4-steps**
2001Q1-2008Q1					
	SAM	0.21	0.30	0.42	0.53
	NB	0.18	0.36	0.59	0.78

Is the improvement in forecast accuracy reported above statistically significant? To examine this hypothesis, we use the Diebold and Mariano (1995) and West (1996) (DMW henceforth) test statistics. The DMW test statistics measure statistical differences in the forecasting performance of two competing models and can be computed as follows:

$$DMW = \frac{d}{\sqrt{\frac{2\pi \hat{f}(0)}{T}}} \tag{5}$$

where d is the mean of the difference in squared forecast errors between the two models that is compared, and $\hat{f}(0)$ is an estimator of its spectral density at frequency zero. Here we use the standard Newey-West robust estimator of the long run variance of d. Note, however, that Ashley (2003) has argued that more than 100 observations are necessary to establish significant differences in predictive accuracy across models. Hence, with fewer observations, our results should be taken with some caution.[14]

[14]Note also that the the DMW statistics may provide non-normal critical values for asymptotic inference if the

In Table 3 we first present the DMW test statistics for the forecasts to be equally accurate as the benchmark AR forecast, with corresponding p-values. Failure to reject the null hypothesis implies that forecasts do not improve the AR model significantly. We then finally compare the SAM and NB forecasts, to investigate if SAM performs significantly better than the official Norges Bank's forecasts.

Table 3: Diebold-Mariano-West test. P-values in parenthesis

Horizon	**SAM vs AR(2)**	**NB vs AR(2)**	**SAM vs NB**
2001-2008			
1-step	-1.782 (0.037)	-1.785 (0.037)	1.149 (0.875)
2-step	-2.925 (0.002)	-0.279 (0.389)	-0.745 (0.228)
3-step	-3.093 (0.001)	0.274 (0.608)	-1.752 (0.040)
4-step	-3.023 (0.001)	-0.441 (0.330)	-2.129 (0.017)

Comparing the forecasts with the simple benchmark AR model, we find, consistent with the results suggested above, that SAM performs significantly better than the benchmark AR model at all horizons.[15] Norges Bank's forecasts, however, perform significantly better than the benchmark AR model only at the 1-step horizon. Finally, when comparing SAM to Norges Bank's official forecasts, SAM performs significantly better than Norges Bank at the 3- and 4-step horizons. For the 1- and 2-step horizons, the forecasts are not significantly different.

4.2 Where can monetary policymakers add value?

Having compared Norges Bank's official forecasts to SAM's forecasts, we finally analyze in more detail where monetary policymakers can add value to the forecast process (analyzed in retrospect). In so doing, we follow Romer and Romer (2008) and test whether policymakers have useful information in the area of forecasting by estimating a regression of the form:

$$X_t = \alpha + \beta_1 S_t + \beta_2 P_t + \varepsilon_t, \tag{6}$$

two models being compared are nested. However, we believe this to be less of a problem here.

[15] The results may be even sharper than indicated, as Clark and West (2006) have suggested that by reducing the noise inherent in the less parsimonious models we have in SAM, the RMSE from these models will be reduced relatively to the parsimonious AR(2) benchmark model.

where X is the realized value of inflation, S is the SAM forecast and P is the policymaker forecast (published in Norges Bank's official reports). Our main interest is if β_2 is positive: Conditional on the SAM forecast, does inflation turn out higher when the policymaker forecast is higher? The results are given in Table 4 where we again focus on the recent inflation targeting period 2001-2008. The table reports OLS estimates, with t-values in parenthesis [16]

Table 4: Where does Norges Bank's forecast add value?

Horizon	**Constant**	β_1	β_2	R^2
2001-2008				
1-step	-0.02 (-0.33)	0.34 (4.01)	0.64 (5.23)	0.96
2-step	-0.10 (-0.83)	0.64 (4.02)	0.36 (2.12)	0.89
3-step	-0.32 (-1.53)	0.78 (4.10)	0.30 (1.55)	0.76
4-step	-0.41 (-1.21)	0.87 (3.87)	0.22 (0.91)	0.61

The positive coefficient on β_2 suggests that policymakers in Norges Bank add some value to the SAM forecasts.[17] However, only at the 1-step ahead horizon, do the policymakers have more useful information than the SAM forecast. The OLS estimate suggests that someone having access to both the SAM and the policymaker forecast should put a weight of 0.64 on the policymakers forecast and a weight of 0.34 on the SAM forecast the first quarter.

For forecasts further out, however, the weights are reversed. In particular, at the 2-step ahead horizon one should put a weight of 0.64 on the SAM forecast and 0.36 on the policymakers forecast. For horizon 3 and 4 the weights on the policymaker forecasts are no longer significant. That is, if one has access to both SAM and policymakers forecasts, one should put a weight of close to 1 on the SAM forecasts and a weight of zero on the policymaker forecast.

How do our results compare with those of Romer and Romer (2008)? By comparing the projections for inflation from the Federal Open Market Committee (FOMC) in the US to the staff forecasts (Green book), they find β_2 to be negative and insignificant. According to Romer and Romer (2008), this implies that the FOMC do not contribute any useful information relative

[16] We also tried estimating (6) using weighted least squares (WLS) (using Newey-West standard errors with three lags), to correct for any possible evidence of serial correlation. The results remained robust.

[17] Note that in the period we are examining, Norges Bank did not have access to the actual SAM forecasts we have constructed here. However, many of the individual models present in SAM have been available to the policymakers in some form or the other in this period.

to the staff forecast at all.[18] Although our results are in line with their general findings, by focusing on different forecasting horizons, we have modified their conclusion a bit. In particular, while Norges Bank's official forecasts did not contribute any value added relative to SAM (staff) forecasts when predicting inflation one year ahead, policymakers had useful information at the immediate forecast horizon. However, whether this is due to good judgment or to good models used for the immediate forecast horizon, is not clear.

5 Concluding remarks

Combination methods have gained grounds in the forecast literature. There is by now a body of empirical evidence suggesting that forecast combinations produce better forecasts on average than alternative forecasts from a single model. This paper has added further evidence to this conclusion. By developing a System for Averaging Models (*SAM*), we have shown that there are clear advantages to averaging forecasts from several individual models when predicting inflation in Norway in the short term (up to a year). Furthermore, the combined forecast clearly outperforms Norges Bank's own forecasts, even more so at longer horizons.

References

Aastveit, K. A. and T. G. Trovik (2007). Nowcasting Norwegian GDP: The role of asset prices in a small open economy. Working Paper 2007/9, Norges Bank.

Adolfson, M., M. K. Andersson, J. Lindé, M. Villani, and A. Vredin (2007). Bayesian forecast combination for VAR models. *International Journal of Central Banking 3*, 111–144.

Akram, F. (2008). An econometric model of mainland Norway: EMod. Mimeo, April, Norges Bank.

[18] Although this may technically be the case, another interpretation could just be that the Policymaker's forecast are negatively correlated with the staff forecast.

Andersson, M. and S. Karlsson (2007). Bayesian forecast combination for VAR models. Sveriges Riksbank Working Paper 216.

Ashley, R. (2003). Statistically significant forecasting improvements: How much out-of-sample data is likely necessary? *International Journal of Forecasting 13*, 229–239.

Bancroft, T. (1944). On biases in estimation due to the use of preliminary tests of significance. *The Annals of Mathematical Statistics 15*(2), 190–204.

Bates, J. M. and C. W. J. Granger (1969). The combination of forecasts. *Operational Research Quarterly 20*(4), 451–468.

Bjørnland, H. C., A. S. Jore, C. Smith, and L. A. Thorsrud (2008). Improving and evaluating short term forecasts at the Norges Bank. Staff memo 2008/4, Norges Bank.

Bock, M. E., T. A. Yancey, and G. G. Judge (1973). The statistical consequences of preliminary test estimators in regression. *Journal of the American Statistical Association 68*(341), 109–116.

Brubakk, L., T. A. Husebø, J. Maih, K. Olsen, and M. Østnor (2006). Finding NEMO: Documentation of the norwegian economy model. Staff memo 2006/6, Norges Bank.

Campos, J., N. R. Ericsson, and D. F. Hendry (Eds.) (2005). *General-to-Specific Modelling*. Cheltenham: Edward Elgar.

Clark, T. E. and M. W. McCracken (2008). Averaging forecasts from VARs with uncertain instabilities. *Journal of Applied Econometrics*. (Forthcoming).

Coletti, D. and S. Murchison (2002). Models in policy-making. *Bank of Canada Review*, 19–26.

Diebold, F. X. and J. Lopez (1996). Forecast evaluation and combination. In G. Maddala and C. Rao (Eds.), *Statistical Methods in Finance, Handbook of Statistics*, Volume 14, pp. 241–268. Amsterdam: Elsevier.

Diebold, F. X. and R. S. Mariano (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics 13*, 134–144.

Fernandez, C., E. Ley, and M. F. J. Steel (2001, September-October). Model uncertainty in cross-country growth regressions. *Journal of Applied Econometrics 16*(5), 563–76.

Hendry, D. F. (2006). Robustifying forecasts from equilibrium-correction systems. *Journal of Econometrics 135*(1-2), 399–426.

Hendry, D. F. and M. P. Clements (2002). Pooling of forecasts. *Econometrics Journal 5*, 1–26.

Huang, H. and T.-H. Lee (2008). To combine forecasts or to combine information? Mimeo, University of California Riverside.

Kadiyala, K. R. and S. Karlsson (1997). Numerical methods for estimation and inference in Bayesian VAR-models. *Journal of Applied Econometrics 12*(2), 99–132.

Kapetanios, G., V. Labhard, and S. Price (2005). Forecasting using Bayesian and information theoretic averaging: An application to UK inflation. Technical Report 268, Bank of England.

Kapetanios, G., V. Labhard, and S. Price (2008). Forecast combination and the Bank of England's suite of statistical forecasting models. *Economic Modelling 25*, 772–792.

Koop, G. and S. Potter (2004). Forecasting in dynamic factor models using Bayesian model averaging. *Econometrics Journal 7*(2), 550–65.

Makridakis, S. and M. Hibon (2000). The M3 competition: Results, conclusions, and implications. *International Journal of Forecasting 16*, 451–476.

Marcellino, M. (2002). Forecast pooling for short time series of macroeconomic variables. Working Papers 212, IGIER (Innocenzo Gasparini Institute for Economic Research), Bocconi University.

Matheson, T. (2006). Factor model forecasts for New Zealand. *International Journal of Central Banking 2*, 169–237.

Raftery, A. E. (1995). Bayesian model selection in social research. In P. V. Marsden (Ed.), *Sociological Methodology 1995*. Oxford: Basil Blackwell.

Raftery, A. E. and Y. Zheng (2003, December). Frequentist model average estimators: Discussion: Performance of Bayesian model averaging. *Journal of the American Statistical Association 98*(464), 931–38.

Ravazzolo, F. (2008). Unrestricted Bayesian VAR to forecast quarterly Norwegian macroeconomic series. Mimeo, Norges Bank.

Romer, C. D. and D. H. Romer (2008). The FOMC versus the staff: Where can monetary policymakers add value? *American Economic Review: Papers and Proceedings 98*(2), 230–35.

Stock, J. H. and M. W. Watson (2004). Combination forecasts of output growth in a seven-country data set. *Journal of Forecasting 23*, 405–430.

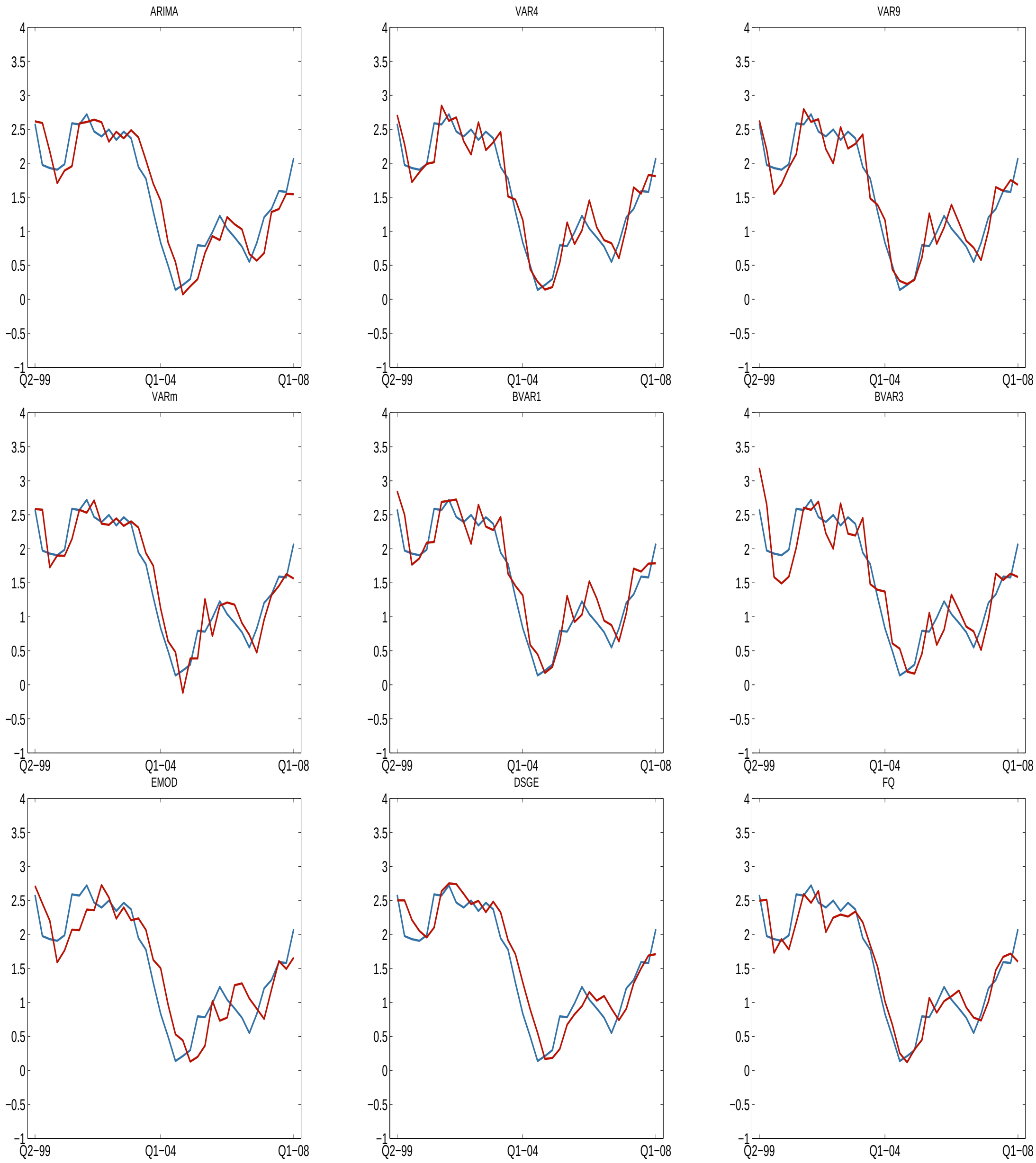
Timmerman, A. (2006). Forecast combinations. In G. Elliott, C. W. J. Granger, and A. Timmerman (Eds.), *Handbook of Economic Forecasting*, Volume 1. Amsterdam: Elsevier.

West, K. D. (1996). Asymptotic inference about predictive ability. *Econometrica 64*, 1067–1084.

6 Appendix

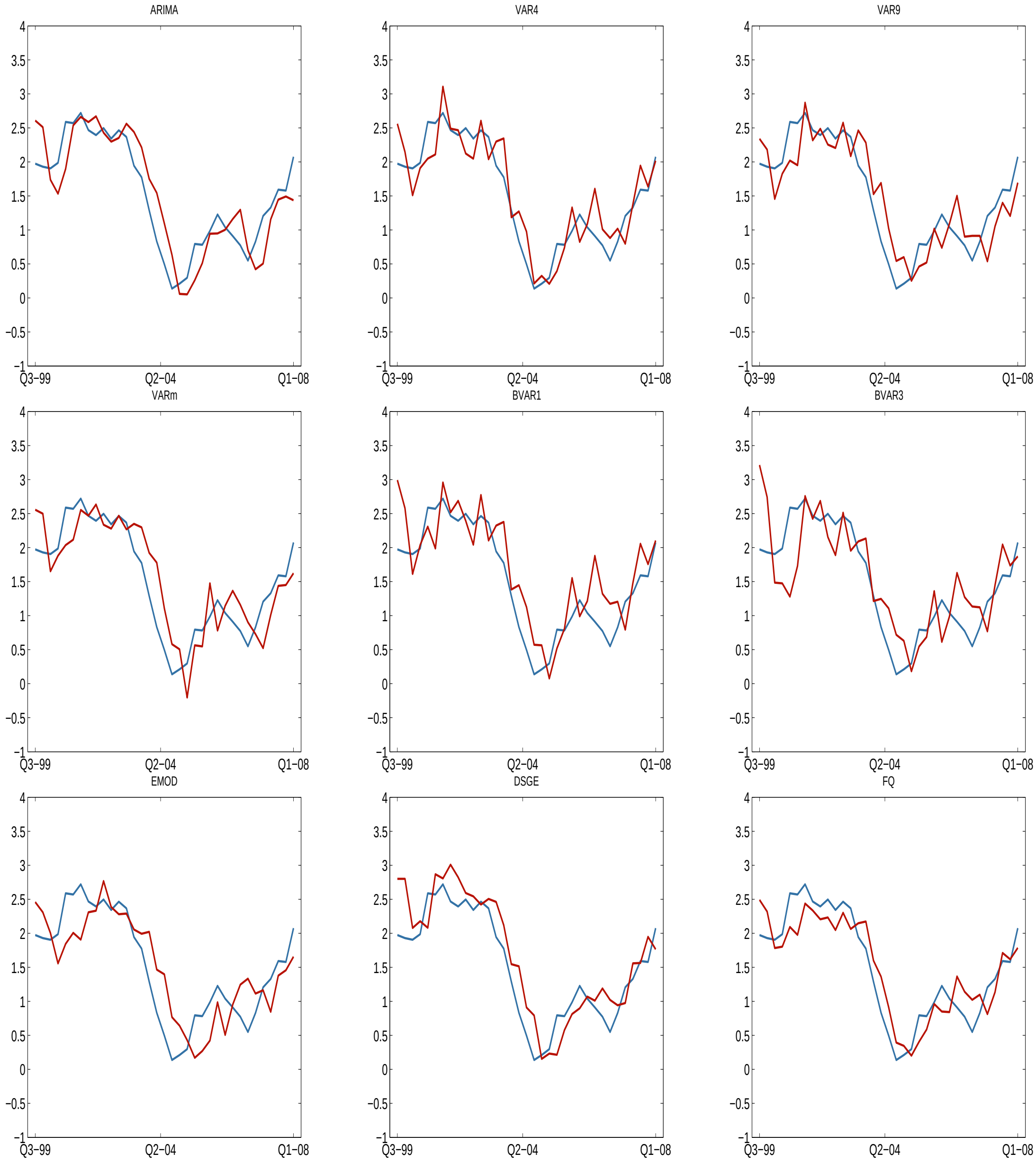
Below we depict the forecasts made at different points in time. In particular, Figures 6-9 show what the forecasts for inflation would have been one to four quarters ahead in the period 1999Q2 - 2008Q1 for some selected models.

Figure 6: *Actual inflation vs. forecast (1999Q1-2008Q1). 1-step ahead*



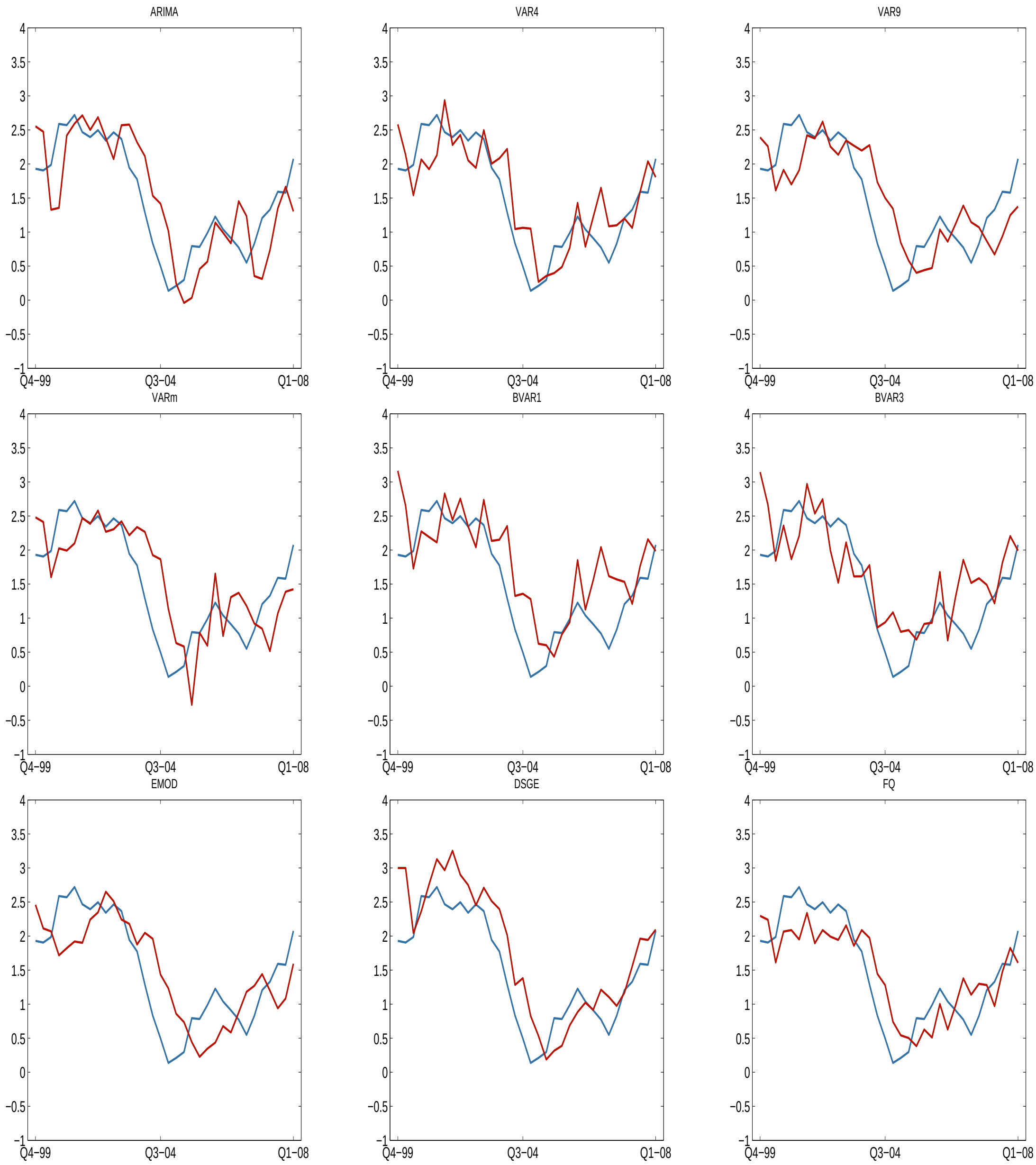
Note: Inflation (CPIATE, yoy growth). Actual (blue) and forecast (red). NB refers to Norges Bank's official forecast collected from various monetary policy reports.

Figure 7: *Actual inflation vs. forecast (1999Q2-2008Q1). 2-steps ahead*



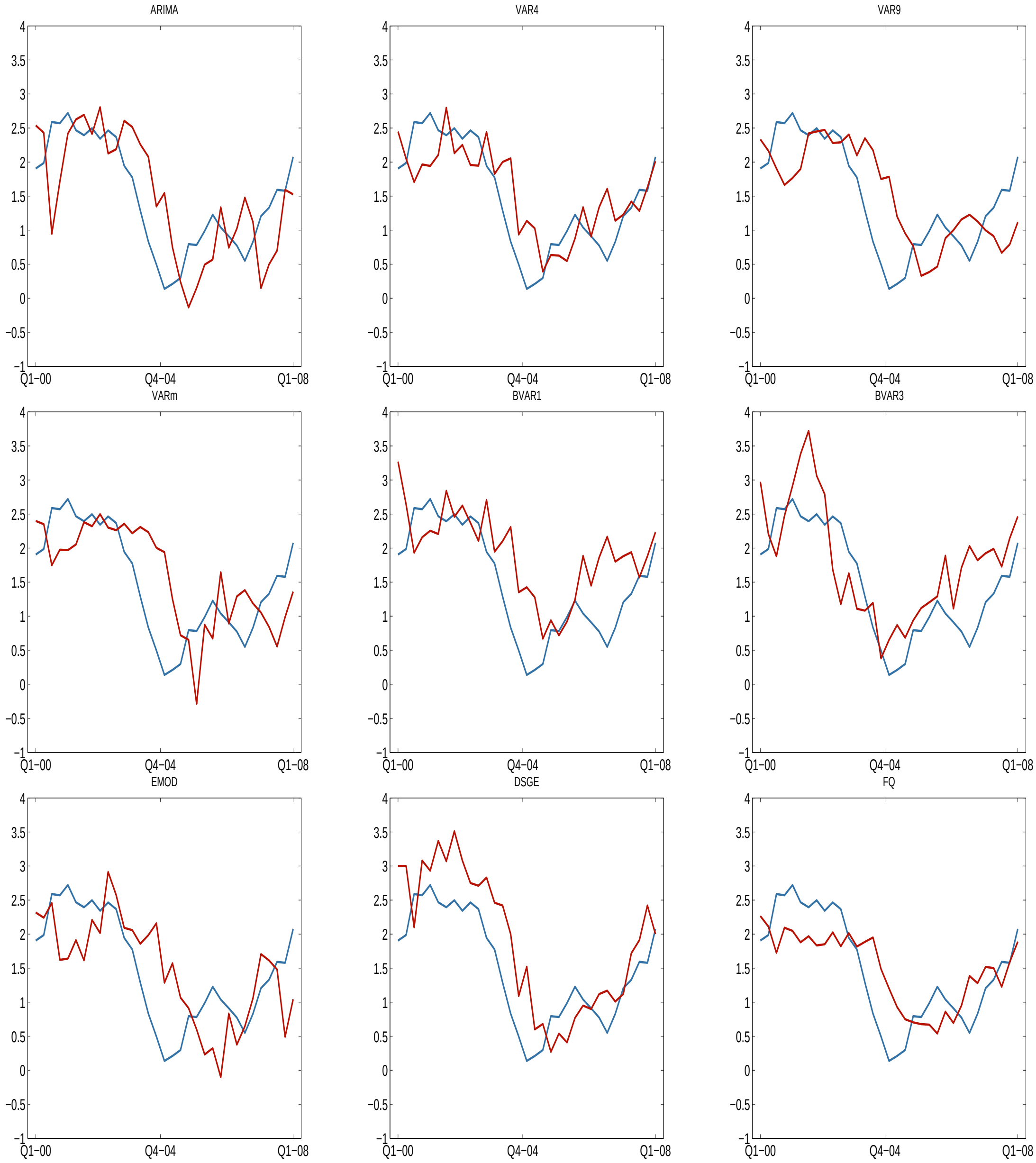
Note: Inflation (CPIATE, yoy growth). Actual (blue) and forecast (red). NB refers to Norges Bank's official forecast collected from various monetary policy reports.

Figure 8: *Actual inflation vs. forecast (1999Q2-2008Q1). 3-steps ahead*



Note: Inflation (CPIATE, yoy growth). NB refers to Norges Bank's official forecast collected from various monetary policy reports.

Figure 9: *Actual inflation vs. forecast (1999Q2-2008Q1). 4-steps ahead*



Note: Inflation (CPIATE, yoy growth). Actual (blue) and forecast (red). NB refers to Norges Bank's official forecast collected from various monetary policy reports.

WORKING PAPERS (ANO) FROM NORGES BANK 2006-2009

Working Papers were previously issued as Arbeidsnotater from Norges Bank, see Norges Bank's website http://www.norges-bank.no

2006/1 Gunnar Bårdsen, Kjersti-Gro Lindquist and Dimitrios P. Tsomocos
Evaluation of macroeconomic models for financial stability analysis
Financial Markets Department, 45 p

2006/2 Hilde C. Bjørnland, Leif Brubakk and Anne Sofie Jore
Forecasting inflation with an uncertain output gap Economics Department, 37 p

2006/3 Ragna Alstadheim and Dale Henderson
Price-level determinacy, lower bounds on the nominal interest rate, and liquidity traps
Research Department, 34 p

2006/4 Tommy Sveen and Lutz Weinke
Firm-specific capital and welfare Research Department, 34 p

2006/5 Jan F. Qvigstad
When does an interest rate path „look good"? Criteria for an appropriate future interest rate path Norges Bank Monetary Policy, 20 p

2006/6 Tommy Sveen and Lutz Weinke
Firm-specific capital, nominal rigidities, and the Taylor principle Research Department, 23 p

2006/7 Q. Farooq Akram and Øyvind Eitrheim
Flexible inflation targeting and financial stability: Is it enough to stabilise inflation and output? Research Department, 29 p

2006/8 Q. Farooq Akram, Gunnar Bårdsen and Kjersti-Gro Lindquist
Pursuing financial stability under an inflation-targeting regime Research Department, 29 p

2006/9 Yuliya Demyanyk, Charlotte Ostergaard and Bent E. Sørensen
U.S. banking deregulation, small businesses, and interstate insurance of personal income
Research Department, 57 p

2006/10 Q. Farooq Akram, Yakov Ben-Haim and Øyvind Eitrheim
Managing uncertainty through robust-satisficing monetary policy Research Department, 33 p

2006/11 Gisle James Natvik:
Government spending and the Taylor pinciple Research Department, 41 p

2006/12 Kjell Bjørn Nordal:
Banks' optimal implementation strategies for a risk sensitive regulatory capital rule: a real options and signalling approach Research Department, 36 p

2006/13 Q. Farooq Akram and Ragnar Nymoen
Model selection for monetary policy analysis – importance of empirical validity
Research Department, 37 p

2007/1 Steinar Holden and Fredrik Wulfsberg
Are real wages rigid downwards? Research Department, 44 p

2007/2 Dagfinn Rime, Lucio Sarno and Elvira Sojli
Exchange rate forecasting, order flow and macroeconomic information
Research Department, 43 p

2007/3 Lorán Chollete, Randi Næs and Johannes A. Skjeltorp
What captures liquidity risk? A comparison of trade and order based liquidity factors
Research Department, 45 p

2007/4 Moshe Kim, Eirik Gaard Kristiansen and Bent Vale
Life-cycle patterns of interest rate markups in small firm finance Research Department, 42 p

2007/5 Francesco Furlanetto and Martin Seneca
Rule-of-thumb consumers, productivity and hours Research Department, 41 p

2007/6 Yakov Ben-Haim, Q. Farooq Akram and Øyvind Eitrheim
Monetary policy under uncertainty: Min-max vs robust-satisficing strategies
Research Department, 28 p

2007/7 Carl Andreas Claussen and Øistein Røisland
Aggregating judgments on dependent variables: an (im)possibility result
Research Department, 17 p

2007/8 Randi Næs, Johannes Skjeltorp og Bernt Arne Ødegaard
Hvilke faktorer driver kursutviklingen på Oslo Børs? Forskningsavdelingen, 68 s

2007/9 Knut Are Astveit and Tørres G. Trovik
Nowcasting Norwegian GDP: The role of asset prices in a small open economy
Research Department, 29 p

2007/10 Hilde C. Bjørnland, Kai Leitemo and Junior Maih
Estimating the natural rates in a simple new Keynesian framework
Economics Department, 33 p

2007/11 Randi Næs and Bernt Arne Ødegaard
Liquidity and asset pricing: Evidence on the role of investor holding period
Research Department, 31 p

2007/12 Ida Wolden Bache
Assessing estimates of the exchange rate pass-through Research Department, 60 p

2007/13 Q. Farooq Akram
What horizon for targeting inflation? Research Department, 45 p

2007/14 Q. Farooq Akram, Yakov Ben-Haim and Øyvind Eitrheim
Robust-satisficing monetary policy under parameter uncertainty Research Depatrment, 33 p

2007/15 Ida Wolden Bache and Bjørn E. Naug
Estimating New Keynesian import price models Research Department, 40 p

2008/1 Anne Sofie Jore, James Mitchell and Shaun P. Vahey
Combining forecast densities from VARs with uncertain instabilities
Economics Department, 26 p

2008/2 Henrik Andersen
Failure prediction of Norwegian banks: A logit approach Financial Markets Department, 49 p

2008/3 Lorán Chollete, Randi Næs and Johannes A. Skjeltorp
The risk components of liquidity Research Department, 28 p

2008/4 Hilde C. Bjørnland and Kai Leitemo
Identifying the interdependence between US monetary policy and the stock market
Economics Department, 28 p

2008/5 Christian Kascha and Karel Mertens
Business cycle analysis and VARMA models Research Department, 40 p

2008/6 Alan S. Blinder
On the design of Monetary policy committees Norges Bank Monetary Policy, 22 p

2008/7 Francesco Furlanetto
Does monetary policy react to asset prices? Some international evidence
Research Department, 44 p

2008/8 Christian Huurman, Francesco Ravazzolo and Chen Zhou
The power of weather. Some empirical evidence on predicting day-ahead power prices through weather forecasts Research Department, 28 p

2008/9 Randi Næs, Johannes A. Skjeltorp and Bernt Arne Ødegaard
Liquidity at the Oslo Stock Exchange Research Department, 49 p

2008/10 Francesco Furlanetto and Martin Seneca
Fiscal shocks and real rigidities Research Department, 41 p

2008/11 Randi Næs, Johannes A. Skjeltorp and Bernt Arne Ødegaard
Liquidity and the business cycle Research Department, 45 p

2008/12 Q. Farooq Akram
Commodity prices, interest rates and the dollar Research Department, 33 p

2008/13 Henrik Andersen, Sigbjørn Atle Berg and Eilev S. Jansen
The dynamics of operating income in the Norwegian banking sector
Financial Markets Department, 27 p

2008/14 Lars Fredrik Øksendal
Monetary policy under the gold standard – examining the case of Norway, 1893-1914
Norges Bank's bicentenary project, 103 p

2008/15 Hilde C. Bjørnland and Jørn I. Halvorsen
How does monetary policy respond to exchange rate movements? New international evidence
Research Department, 45 p

2008/16 Hilde C. Bjørnland
Oil price shocks and stock market booms in an oil exporting country
Research Department, 37 p

2008/17 Özer Karagedikli, Troy Matheson, Christie Smith and Shaun Vahey
RBCs and DSGEs: The computational approach to business cycle theory and evidence
Research Department, 36 p

2008/18 Ida Wolden Bache and Kai Leitemo
The price puzzle: Mixing the temporary and permanent monetary policy shocks
Monetary Policy Department, 12 p

2008/19 Q. Farooq Akram, Dagfinn Rime and Lucio Sarno
Does the law of one price hold in international financial markets? Research Department, 43 p

2008/20 Amund Holmsen, Jan F. Qvigstad, Øistein Røisland and Kristin Solberg-Johansen
Communicating monetary policy intentions: The case of Norges Bank
Monetary Policy Department, 33 p

2008/21 Pelin Ilbas
Revealing the preferences of the US Federal Reserve Research Department, 52 p

2008/22 Christian Kascha and Francesco Ravazzolo
Combining inflation density forecasts Research Department, 39 p

2008/23 Knut Are Aastveit and Tørres G. Trovik
Estimating the output gap in real time: A factor model approach Research Department, 42 p

2008/24 Hilde C. Bjørnland and Dag Henning Jacobsen
The role of house prices in the monetary policy transmission mechanism in the U.S.
Research Department, 25 p

2008/25 Geir H. Bjønnes, Carol L. Oster and Dagfinn Rime
Asymmetric information in the interbank foreign exchange market Research Department, 31 p

2009/1 Hilde C. Bjørnland, Karsten Gerdrup, Anne Sofie Jore, Christie Smith and Leif Anders Thorsrud
Does forecast combination improve Norges Bank inflation forecasts?
Economics Department, 35 p

Hilde C. Bjørnland, Karsten Gerdrup, Anne Sofie Jore, Christie Smith and Leif Anders Thorsrud:
Does forecast combination improve Norges Bank inflation forecasts?

Working Paper 2009/1

KEYWORDS:
Forecasting
Forecast combination