North American Journal of Economics and Finance 22 (2011) 61–76

Contents lists available at ScienceDirect

North American Journal of Economics and Finance

Weights and pools for a Norwegian density combination☆

Hilde C. Bjørnland[a], Karsten Gerdrup[b], Anne Sofie Jore[b], Christie Smith[c,*], Leif Anders Thorsrud[a]

[a] Norwegian School of Management (BI), 0442 Oslo, Norway
[b] Economics Department, Norges Bank, Bankplassen 2, 0151 Oslo, Norway
[c] Economics Department, Reserve Bank of New Zealand, Wellington 6011, New Zealand

ARTICLE INFO

Article history:
Received 25 March 2009
Accepted 28 September 2010

JEL classification:
C32
C52
C53
E52

Keywords:
Model combination
Evaluation
Density forecasting
KLIC

ABSTRACT

We apply a suite of models to produce quasi-real-time density forecasts of Norwegian GDP and inflation, and evaluate different combination and selection methods using the Kullback–Leibler information criterion (KLIC). We use linear and logarithmic opinion pools in conjunction with various weighting schemes, and we compare these combinations to two different selection methods. In our application, logarithmic opinion pools were better than linear opinion pools, and score-based weights were generally superior to other weighting schemes. Model selection generally yielded poor density forecasts, as evaluated by KLIC.

"My own feeling is that different combining rules are suitable for different situations, and any search for a single, all purpose, "objective" combining procedure is futile." Winkler (1986)

1. Introduction

Monetary policy-makers make policy decisions about their instruments in the context of a fundamentally uncertain world. To ensure appropriate monetary policy decisions, central bankers must

☆ The views expressed in this paper are those of the authors and should not be attributed to Norges Bank or the Reserve Bank of New Zealand.

* Corresponding author. Tel.: +64 4 471 3740; fax +64 4 473 1209.
E-mail address: Christie.Smith@rbnz.govt.nz (C. Smith).

1062-9408/$ – see front matter
doi:10.1016/j.najef.2010.09.001

provide suitable characterisations of that uncertainty. In this article we use density combination methods to characterise uncertainty and provide short term macroeconomic forecasts. In the context of a broad suite of models, we explore the performance of different density combination methods (log and linear opinion pools) and weighting schemes (weights compiled from log scores and continuous ranked probability scores). We evaluate these combinations using logarithmic scores, which can be interpreted as evaluating densities on the basis of the Kullback–Leibler information criterion.

Boiled down to its essence, our paper is a horse race to identify which combination schemes yield the best density forecasts. The imperatives of policy-making mean that forecasts are always required, irrespective of whether the forecasts are consistent with some notionally ideal model. By identifying the best forecast densities it is hoped that the losses that entail from the density misspecification will be as small as possible. The quote from Winkler (1986) above suggests that there may not be a universally 'best' combination method, a view with which we have considerable sympathy. It also implies that different combination methods should be assessed on a case-by-case basis. This paper represents one such case, and illustrates a method that can be used to discriminate between different competing densities.

Although the importance of uncertainty on decision-making has long been realised by monetary policy-makers, the vast bulk of analysis has taken refuge in a certainty equivalence framework that enables policy-makers to disregard the properties of uncertainty. If a policy-maker's loss function is quadratic and the dynamics of the economy can be adequately represented with linear equations, certainty equivalence implies it is only necessary to focus on the first moments of future outcomes, appropriately discounted, to derive optimal policy (see Simon, 1956; Theil, 1957). However, if the policy-maker's loss function is more complicated or if the world is nonlinear then it no longer suffices to focus solely on the first moments of possible outcomes entering the loss function, rather one may need to characterise *all* moments or, equivalently, the entire distribution of possible outcomes.[1] Consequently, forecasters should provide *density* forecasts rather than simply point forecasts reflecting expected values.[2]

Models should be specified and estimated taking into account the objective function of the end-user of the model, but typically the objective function is unknown. Ideally, different methods for forecasting densities would have a consistent ranking irrespective of the decision-maker's loss function; the highest ranked density forecast method would then be robust to the preferences of the ultimate end-user. However, as Diebold, Gunther, and Tay (1998) and Granger and Pesaran (2000) discuss, there is no consistent ranking over competing, misspecified density forecasts: different decision-makers with different loss functions could favour different density forecasting methods. On the other hand, if one of the density forecasting methods miraculously coincides with the true data generating process then this true density function will be preferred above all others since it enables the optimal action to be identified, which ultimately minimizes the expected loss of the policy-maker. The goal for forecasters is thus to provide density forecasts that are as close as possible to the truth, to facilitate a good approximation to the optimal action.

Policy-makers are confronted with a wide array of candidate models and hence candidate forecast densities. We use combination methods (cf. selection) to reconcile competing forecasts. Timmerman (2006) surveys combination methods and provides theoretical rationales in favour of combination – including unknown instabilities, portfolio diversification of models, and idiosyncratic biases. Empirical evidence also supports the use of combination methods, see for example Clemen (1989), Makridakis et al. (1982), Makridakis et al. (1993), Makridakis and Hibon (2000), Stock and Watson (2004), and Clark and McCracken (2010). For point forecasting, a number of these papers find that simple, equal-weighted combination methods out-perform more sophisticated 'adaptive' methods where the weights are based on past performance. However, Jore, Mitchell, and Vahey (2010) examine *density* forecasts and conclude that adaptive weights improve upon simple weights.

[1] Karagedikli and Lees (2007), Surico (2007), Cukierman and Muscatelli (2008) and Aguiar and Martins (2008) all find evidence of significant asymmetries in monetary policy preferences. Dolado, Pedrero, and Ruge-Murcia (2004) find asymmetries in the reaction function of the Volcker–Greenspan regime and infer that policy preferences are asymmetric.

[2] Timmerman (2006, sn 2.1) makes a similar point, noting that, when the loss function depends solely on forecasts, the optimal combination weights will typically depend on the entire distribution of forecast errors.