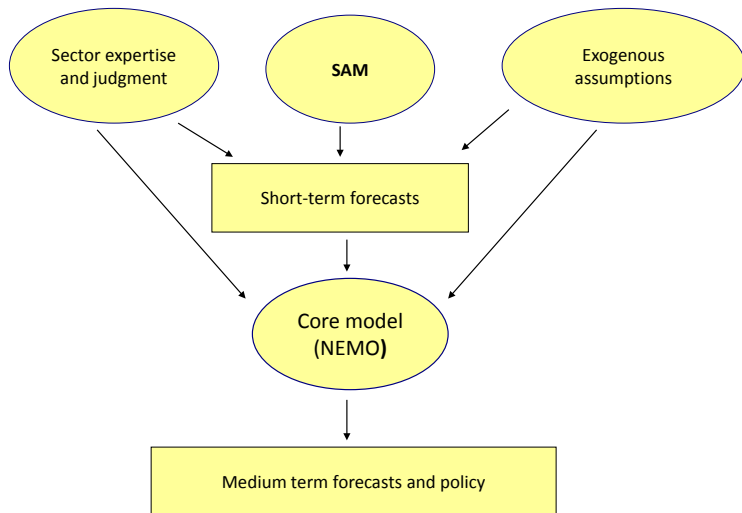


Short-term forecasting at Norges Bank

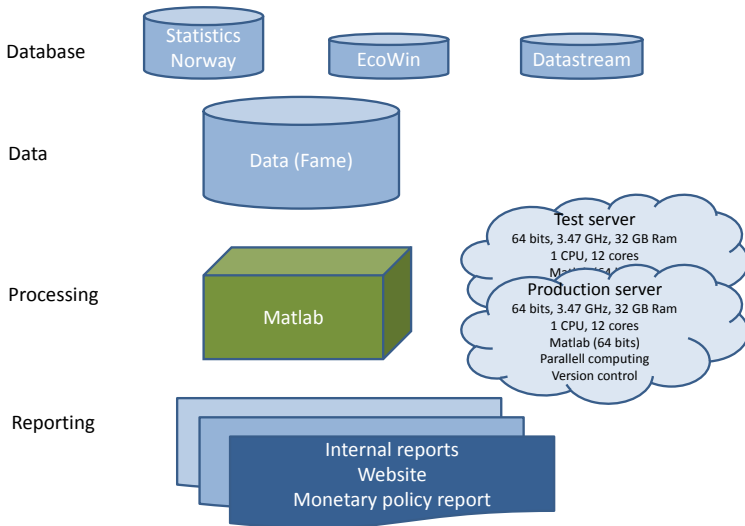
Knut Are Aastveit **Anne Sofie Jore** Francesco Ravazzolo

Cedefop experts meeting
Brussels, 18th April 2013

The forecasting and monetary policy analysis system at Norges Bank



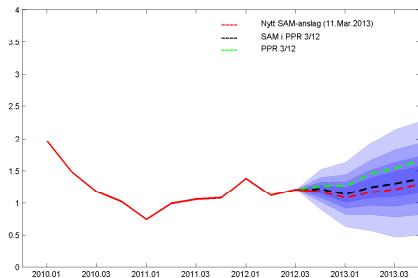
Data flow and infrastructure



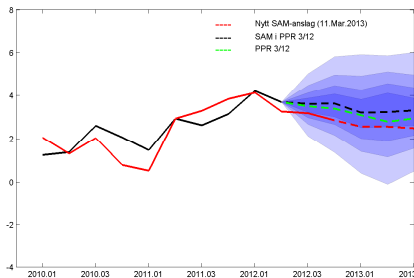
Matlab based toolbox for short-term forecasting

- Retrieve data from different sources
- Transform data
- Estimate model parameters and make recursive forecasts
 - Point forecasts
 - Density forecasts
- Evaluate out-of-sample forecasts against specified vintages of outturns
 - Rmse
 - Logarithmic score
- Construct weights
- Construct combined density forecasts
- Report results from matlab to LaTeX-based documents (fully automatized)

SAM forecasts. Four-quarter growth. Per cent



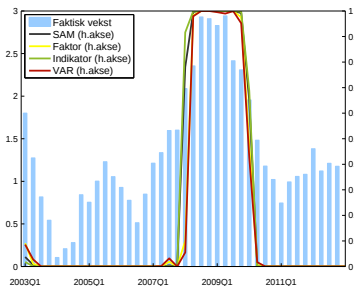
(a) Consumer prices adjusted for taxes and without energy



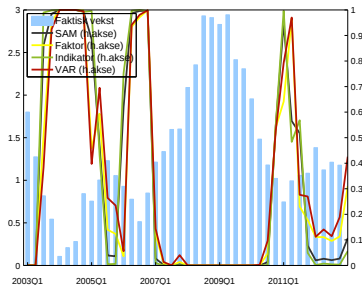
(b) Mainland GDP

Published at website after monetary policy meetings

SAM forecasts. Probabilities and growth. CPIATE



(c) Probability that four-quarter growth in CPIATE is higher than 2 per cent the next quarter, and actual growth



(d) Probability that four-quarter growth in CPIATE is lower than 1 per cent the next quarter, and actual growth

Forecasting models should forecast well!

- Evaluation criterion: Forecast well out of sample
 - Empirical in-sample fit is not sufficient
- Use real-time data to evaluate forecasting properties
 - Policy is conducted in real time
- The key to a robust forecasting system is that it hedges against uncertain instabilities, see Timmermann (2006).

The forecasting system in more detail

- Collecting data through the quarter in 57 blocks (timing and content)
- For each block:
 - Recursive exercise starting in 2000: Estimating and forecasting (real-time)
 - Save results from all models
- For each quarter we add to the collection of results
- For each forecast round we pick (automatically) the relevant results as basis for calculating the weights
- Even with density forecasts, feasible with frequent updates (less than 1 hour computation time)
- PDF reports produces automatically calling on LaTeX

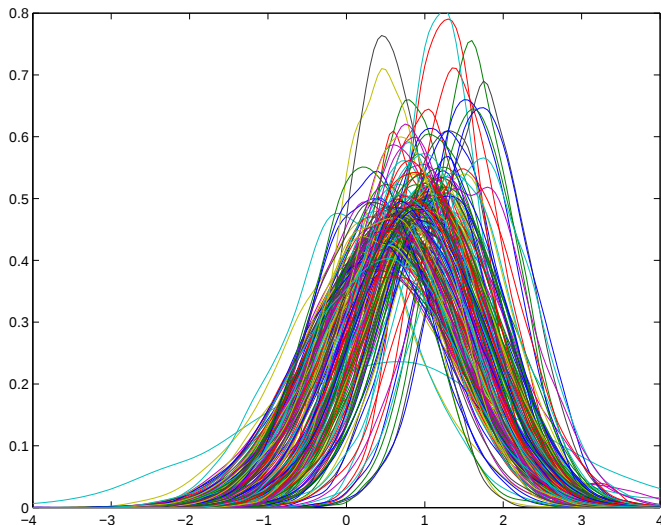
Combining predictive densities

- Policy makers are provided with forecast from different models.
 - Short-term forecasting: VARs, Leading indicator models and factor models
- There is considerable uncertainty regarding specifications
 - Lag length, data-sample, variables to include etc.
- We include a wide selection of different specifications for each model class.

Models and model classes (GDP)

Model class	Description	Number of models
VAR	ARs and VARs using GDP (and inflation and/or interest rate) Lag length: 1 – 4 Transformations: First differences, double differences, detrended Estimation period: Recursive and rolling samples of 20 and 30 obs. Combination method: Linear opinion pool and log score weights	149
LIM	Bivariate VARs with GDP and 120 different monthly surveys Lag-length: 1 Transformations: First differences Estimation Period: Recursive and rolling samples of 20 and 30 obs. Combination method: Linear opinion pool and log score weights	83
FM	Dynamic Factor Models Number of factors: 1 – 4 Estimation period: Recursive and rolling samples of 20 and 30 obs. Combination method: Linear opinion pool and log score weights	5
Combination	Combination method: Linear opinion pool and log score weights	237

Density forecast from all individual models

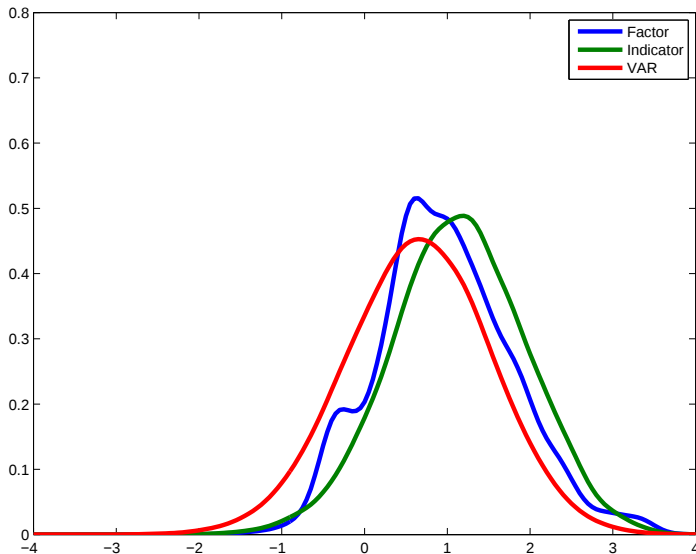


Two-stage combination approach

Step 1

- Combine density forecasts for each individual model within a model class.
 - Yields a single, combined predictive density for each model class.

Step 1: Combined density forecast. Model classes.



Two-stage combination approach

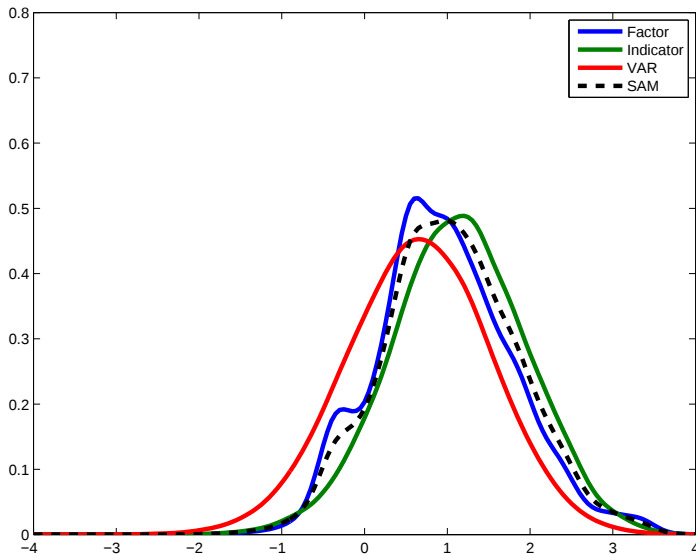
Step 1

- Combine density forecasts for each individual model within a model class.
 - Yields a single, combined predictive density for each model class.

Step 2

- Combine the predictive densities from each model class into one combined density.

Step 2: Combined density forecast.



Two-stage combination approach

Step 1

- Combine density forecasts for each individual model within a model class.
 - Yields a single, combined predictive density for each model class.

Step 2

- Combine the predictive densities from each model class into one combined density.

Advantage of this approach

- Explicitly accounts for uncertainty about model specification and instabilities within each model class.
- Implicitly gives a priori equal weight to each model class

Two-stage combination approach - an interpretation

- Some common types of models for forecasting:
 - VAR models
 - Leading Indicator models
 - Factor models
- Instead of trying to find the best specification within each type of model, we include a wide range of specifications and combine forecasts according to historical out-of-sample fit.
- The second step can be interpreted as combining forecasts from three different models

Method of aggregation

- The decision maker constructs the combined densities by a linear opinion pool method

$$p(Y_{\tau,h}) = \sum_{i=1}^N w_{i,\tau,h} g(Y_{\tau,h} \mid I_{i,\tau}), \quad \tau = \underline{\tau}, \dots, \bar{\tau},$$

where $g(Y_{\tau,h} \mid I_{i,\tau})$ are the h -step ahead forecast densities from individual model i , $i = 1, \dots, N$ of a random variable Y_{τ} , (with realization y_{τ}), conditional on the information set I_{τ} .

- $w_{i,\tau,h}$ are a set of non-negative weights that sum to unity.

Choosing the weights

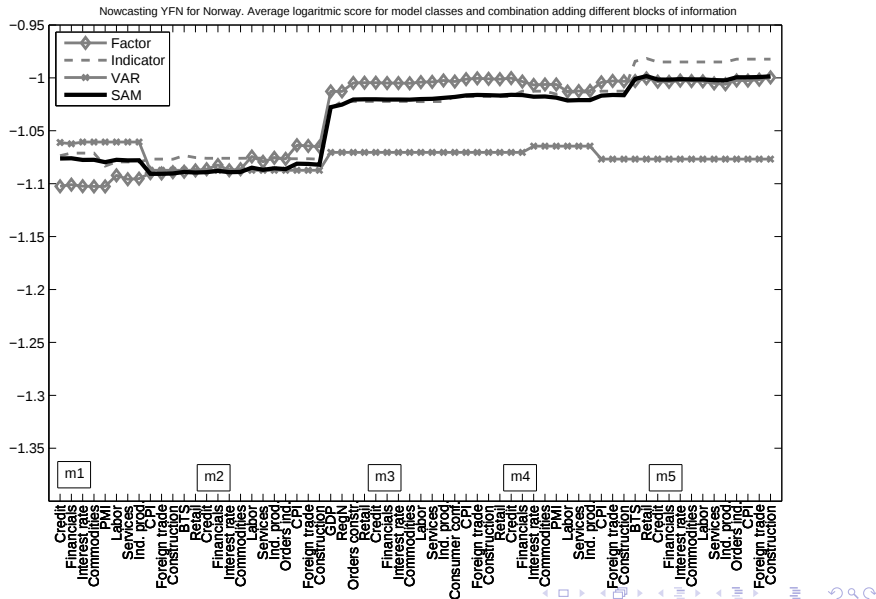
- Equal weights (Stock and Watson (2006), Clark and McCracken (2010))
- Recursive logarithmic score weights (Jore, Mitchell, Vahey (2010))

$$w_{i,\tau,h} = \frac{\exp \left[\sum_{\underline{\tau}}^{\tau-h} \ln g(y_{\tau,h} \mid l_{i,\tau}) \right]}{\sum_{i=1}^N \exp \left[\sum_{\underline{\tau}}^{\tau-h} \ln g(y_{\tau,h} \mid l_{i,\tau}) \right]}, \quad \tau = \underline{\tau}, \dots, \bar{\tau}$$

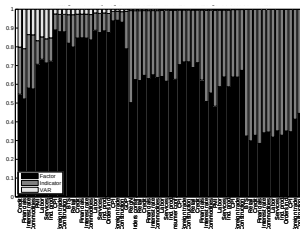
Evaluating forecasts - GDP and CPI

- Density fit through the quarter (nowcasting)
- How the weights evolve through the quarter for horizons up to 4 steps ahead
- Compare different weighting schemes

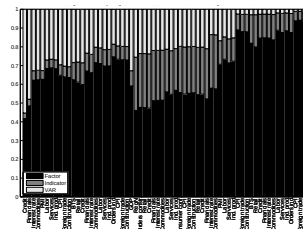
Evaluating nowcast - GDP



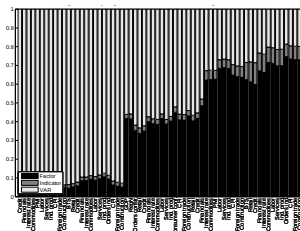
Weights evolving through the quarter - GDP



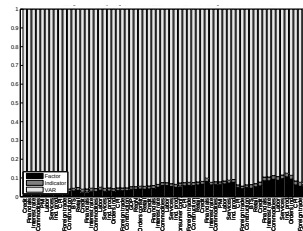
(e) Nowcast



(f) Next quarter

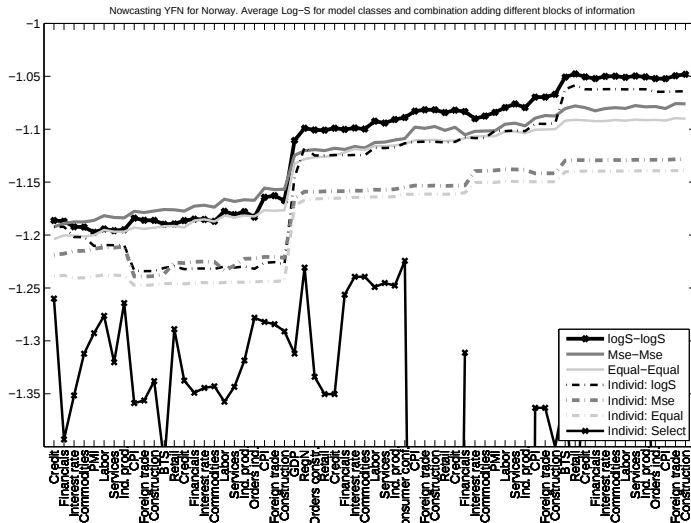


(g) Two quarters

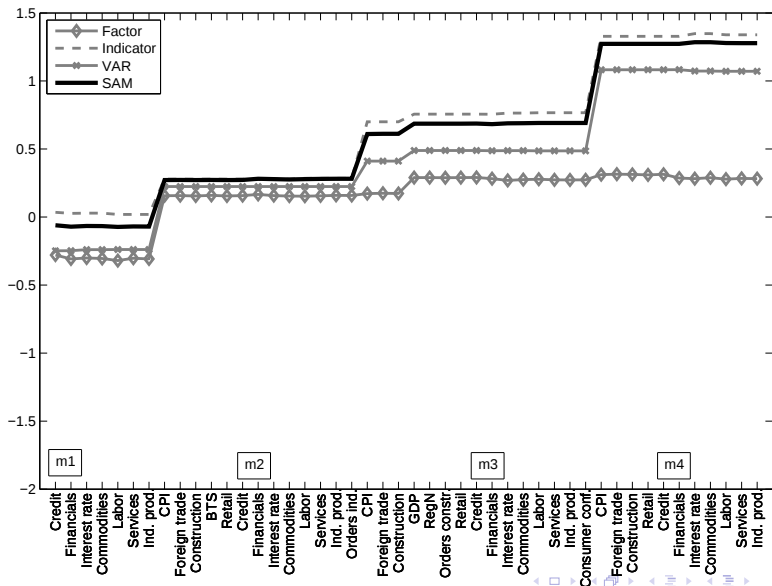


(h) Three quarters

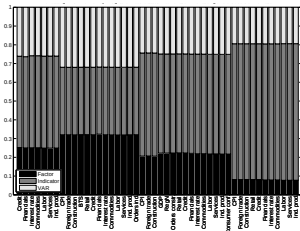
Comparing weighting schemes - GDP (nowcasting)



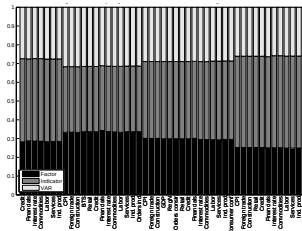
Evaluating nowcast - CPIATE



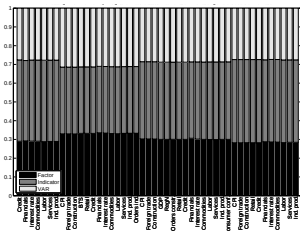
Weights evolving through the quarter - CPIATE



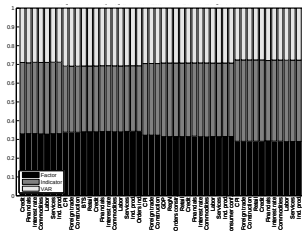
(j) Nowcast



(k) Next quarter

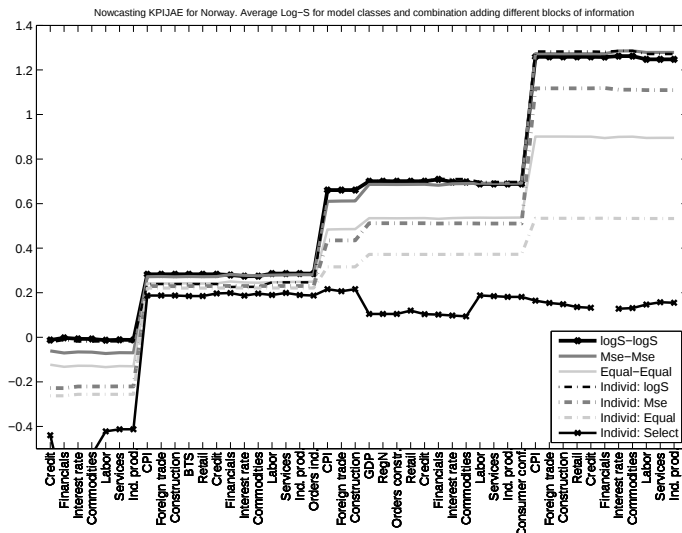


(l) Two quarters



(m) Three quarters

Comparing weighting schemes - CPIATE (nowcasting)



Summary - short term forecasting system at Norges Bank

- Short-term forecasting system using a large amount of information, (almost) fully automatized
- Reporting detailed results automatically
- Main tools: MatLab and LaTeX

Summary - short term forecasting system at Norges Bank

- Advantages

- Explicitly accounts for uncertainty about model specifications and instabilities
- Implicitly gives a priori equal weight to each model class
- General approach, can be extended to other types of models and longer horizons

- Disadvantages

- Can not (by itself) tell stories based on relationships from economic theory

Documentation at Norges Bank web site:

- Aastveit, K. A., K. Gerdrup, A.S. Jore and L.A Thorsrud, "Nowcasting GDP in real-time: A density combination approach", Norges Bank Working Paper 2011/11
- ...and more..

[http://www.norges-bank.no/en/price-stability/
models-for-monetary-policy-analysis-and-forecasting/sam/](http://www.norges-bank.no/en/price-stability/models-for-monetary-policy-analysis-and-forecasting/sam/)