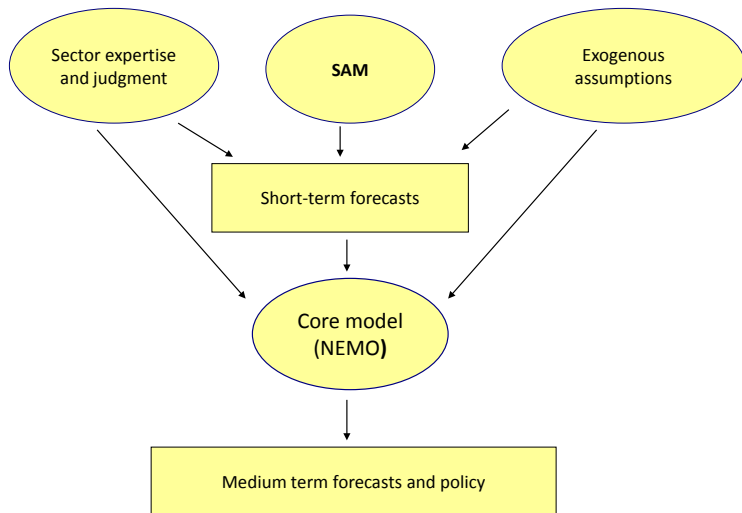


Nowcasting at Norges Bank

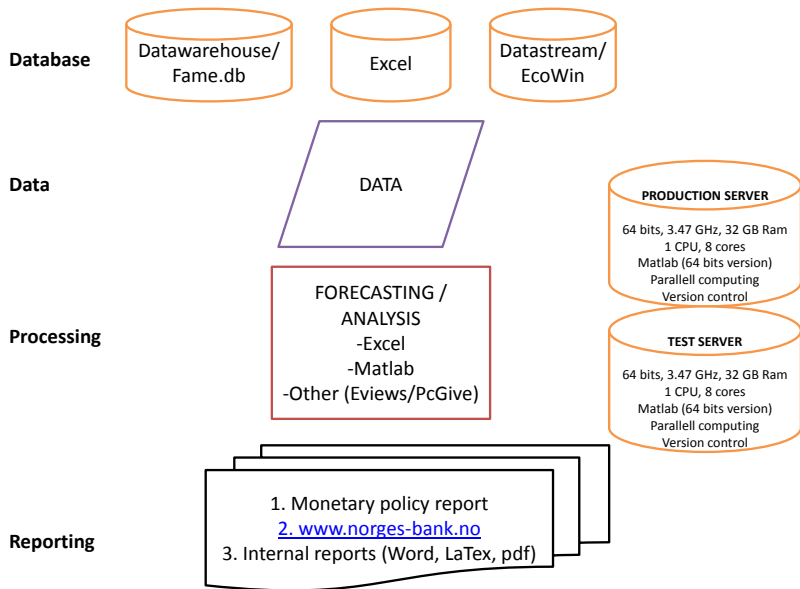
Knut Are Aastveit **Anne Sofie Jore** Francesco Ravazzolo

ProFI Nowcasting Workshop
BIRKCAM at Birkbeck College,
University of London, Thursday 17th January 2013

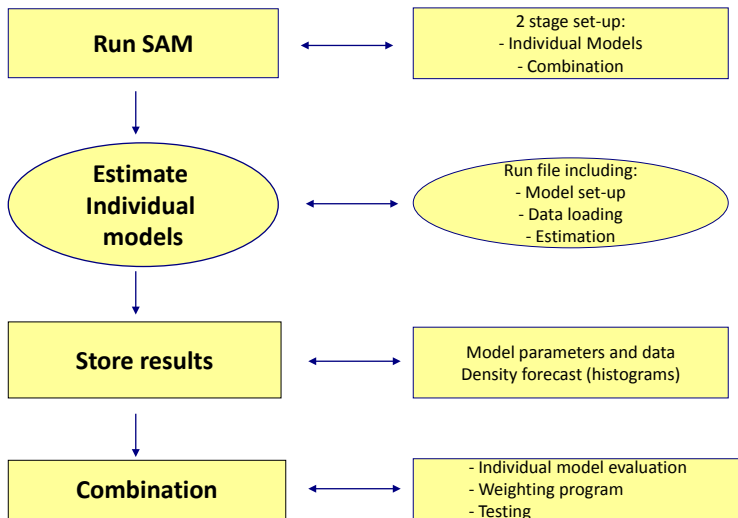
The forecasting and monetary policy analysis system at Norges Bank



Data flow and infrastructure



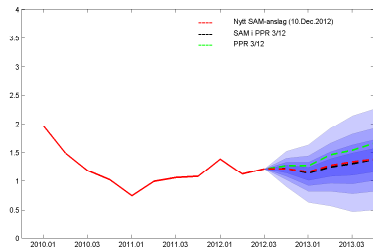
Toolbox overview



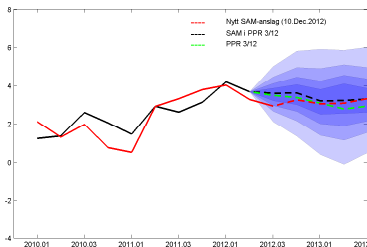
Matlab based Nowcasting Toolbox

- Retrieve data from different sources
 - Real-time data
 - Specified vintages
- 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

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
 - Results on revised data are not necessarily relevant, since policy is conducted in real time
 - Turns out complex models produce bad forecasts
- The key to a robust forecasting system is that it hedges against uncertain instabilities, see Timmermann (2006).

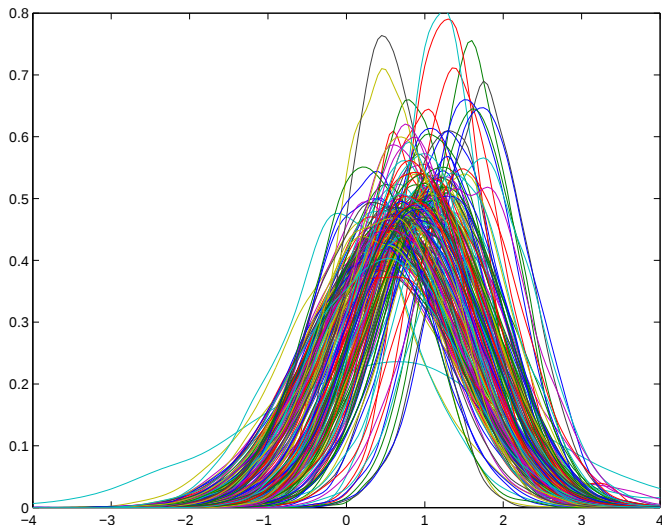
Combining predictive densities

- 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

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 nowcast from all individual models

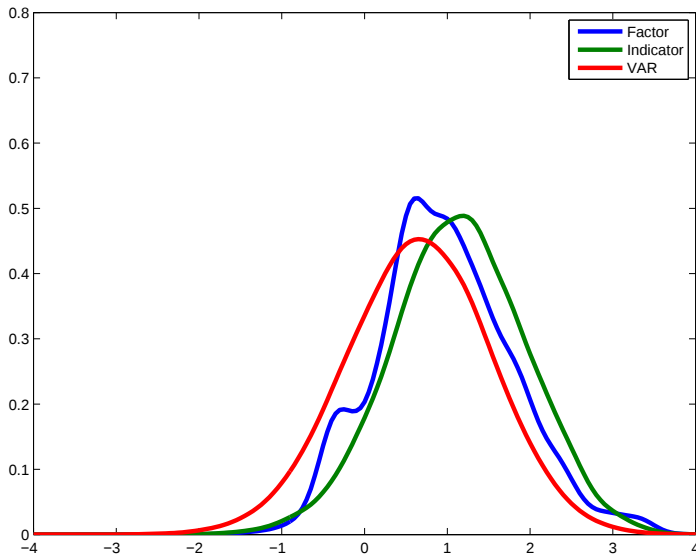


Two-stage combination approach

Step 1

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

Step 1: Combined density nowcast. Model classes.



Two-stage combination approach

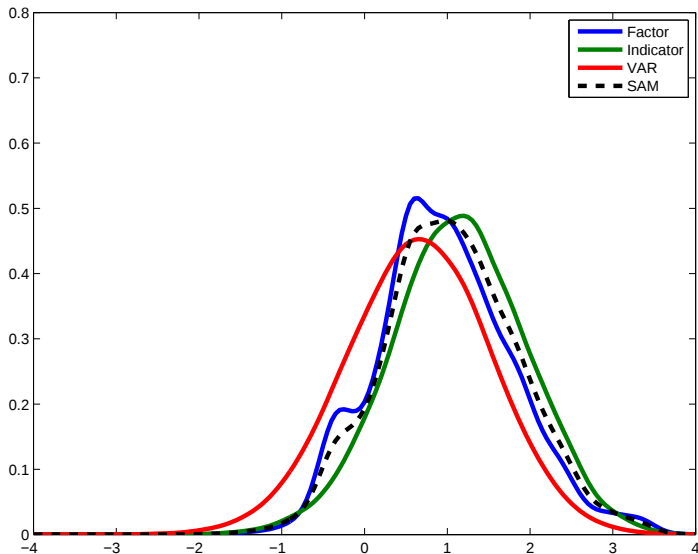
Step 1

- Combine density nowcasts 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 nowcast.



Two-stage combination approach

Step 1

- Combine density nowcasts 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.
- Forecast combination is not influenced by the number of models within each model class.

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))

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

Plans for the future

- Revising the model set
- More generalized loss function
 - Investigating structural breaks
 - Turning points
- Extend the set of forecasted variables

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/)