The Academy of Economic Studies
Doctoral School of Finance and Banking

FORECASTING INFLATION IN ROMANIA UNDER MODEL UNCERTAINTY

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Main aims of the paper:

- Forecasting inflation for the case when there is uncertainty about which model to use and when parameters within a model change over time: **DMA**
- Providing evidence on which sets of predictors are relevant for forecasting in each period;
- Analyzing the predictive power of DMA.

The advantages of the DMA methodology:

- The model relevant for forecasting can potentially change over time;
- The coefficients on the predictors can change over time;
- Many of the models under consideration are parsimonious and, if DMA attached a great deal of weight to such models, it can avoid overfitting problems;
- DMA handle the computational problems arisen from the large number of models in a simple, elegant, and sensible manner.

Literature review

- **Forecasts based on past inflation**: Atkeson and Ohanian (2001); Cecchetti et al. (2001);
- **Extensions of the Phillips curve**: Stock and Watson (2008); Canova (2007); Kamps et al. (2009);
- **Time-Varying Parameter VARs** (TVP-VARs): Cogley, Morozov and Sargent (2005); Kumar (2010);
- **Forecast combination**: Timmerman (2005); Elliot (2010);
- **Dynamic Factor Models**: Gavin and Kliesen (2008); Koop and Potter (2003);
- **Bayesian Model Averaging**: Wright (2003);
- **Dynamic Model Averaging**: Koop and Korobilis (2012); Baxa, Plasil and Vasicek (2013).

DMA - Methodological Framework

- m potential predictors for inflation => $K = 2^m$ models that are characterized by having different subsets of z_t as predictors.
- the *observation equation*: $y_t = z_t^{(k)} \theta_t^{(k)} + \varepsilon_t^{(k)}$
- where y_t denotes the measure of inflation, $z_t^{(k)}$ represents the set of predictors in model k at time t, including an intercept and past values of y_t; $\varepsilon_t^{(k)} \sim N(0, H_t^{(k)})$.
- the *state equation*: $\theta_{t+1}^{(k)} = \theta_t^{(k)} + \eta_t^{(k)}$
- where $\eta_t^{(k)} \sim N(0, Q_t^{(K)})$.

DMA - Methodological Framework

- Inference is done recursively using Kalman filter updating:

$$\theta_{t-1}|y^{t-1} \sim N\left(\hat{\theta}_{t-1}, \Sigma_{t-1|t-1}\right)$$

- the *prediction equation:* $\theta_{t-1}|\, y^{t-1} \sim N(\hat{\theta}_{t-1}, \Sigma_{t|t-1})$
- where $\Sigma_{t|t-1} = \Sigma_{t-1|t-1} + Q_t$
- Approximation: $\Sigma_{t|t-1} = \frac{1}{\lambda}\Sigma_{t-1|t-1}$
- $0 < \lambda \leq 1$ is *forgetting factor*
- λ implies that observations *j* periods in the past have weight λ^i.
- the *updating equation*: $\theta_t|y^t \sim N(\hat{\theta}_t, \Sigma_{t|t})$

DMA - Methodological Framework

- The goal for forecasting at time t is calcalating $\pi_{t|t-1,k} = \Pr(L_{t-1} = k|y^{t-1})$

- Average across *k* = 1, ..,K forecasts using $\pi_{t|t-1,k}$ as weights (DMA)

- E.g. point forecasts ($\hat{\theta}_{t-1}^{(k)}$ from Kalman filter in model *k*):

$$E(y_t|y^{t-1}) = \sum_{k=1}^{K} \pi_{t|t-1,k}\, z_t^{(k)} \hat{\theta}_{t-1}^{(k)}$$

DMA - Methodological Framework

- Some specifications for how predictors enter/leave the model at each moment in time are required.

- Raftery et al (2007) propose another *forgetting factor,* α, comparable to the forgetting factor λ, to approximate $\pi_{t|t-1,k}$

- Then use similar forgetting factor to get approximation

$$\pi_{t|t-1,k} = \frac{\pi_{t-1|t-1,k}^{\alpha}}{\sum_{l=1}^{K} \pi_{t-1|t-1,l}^{\alpha}}$$

- model updating equation:

$$\pi_{t|t} = \frac{\pi_{t|t-1,k} p_k(y_t|y^{t-1})}{\sum_{l=1}^{K} \pi_{t|t-1,l} p_l(y_t|y^{t-1})}$$

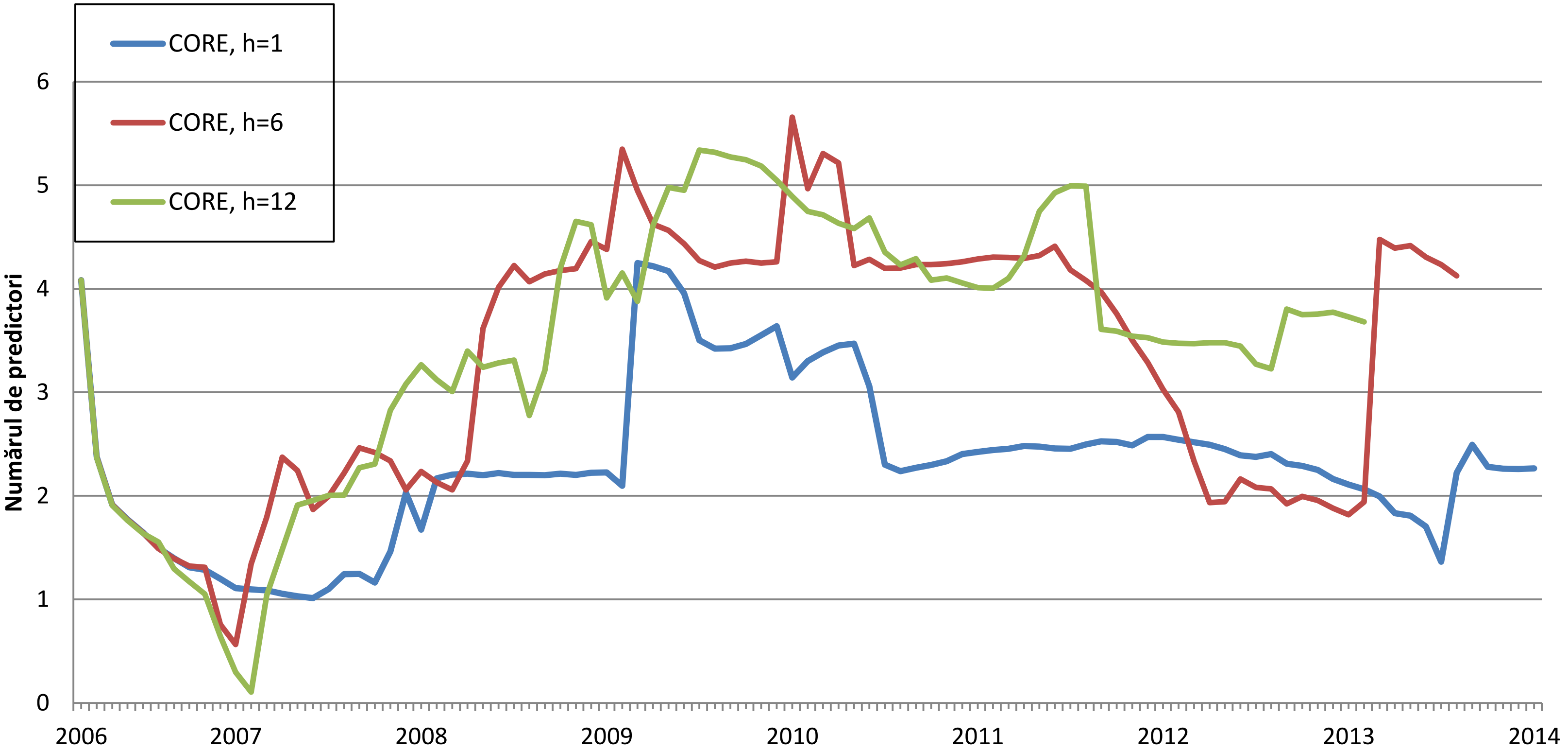
DMA application fot the case of Romania

- Monthly data;
- 2006:M1 – 2014:M2;
- 2^{10} =1024 models;
- Three forecasting horizons: h=1, h=6, h=12;
- DMA is implemented as follows:
  - All models include an intercept and two lags of inflation;
  - The forgetting factors α and λ are set at 0.99;
  - The non-informative prior over the models is set at $\pi_{0|0,k} = \frac{1}{K}$, so that, initially, all models are equally likely;
  - A very diffuse prior on the initial conditions of the states $\theta_0^{(k)} \sim N(0, 100 I_{nk})$ where n_k is the number of variables in model *k.*

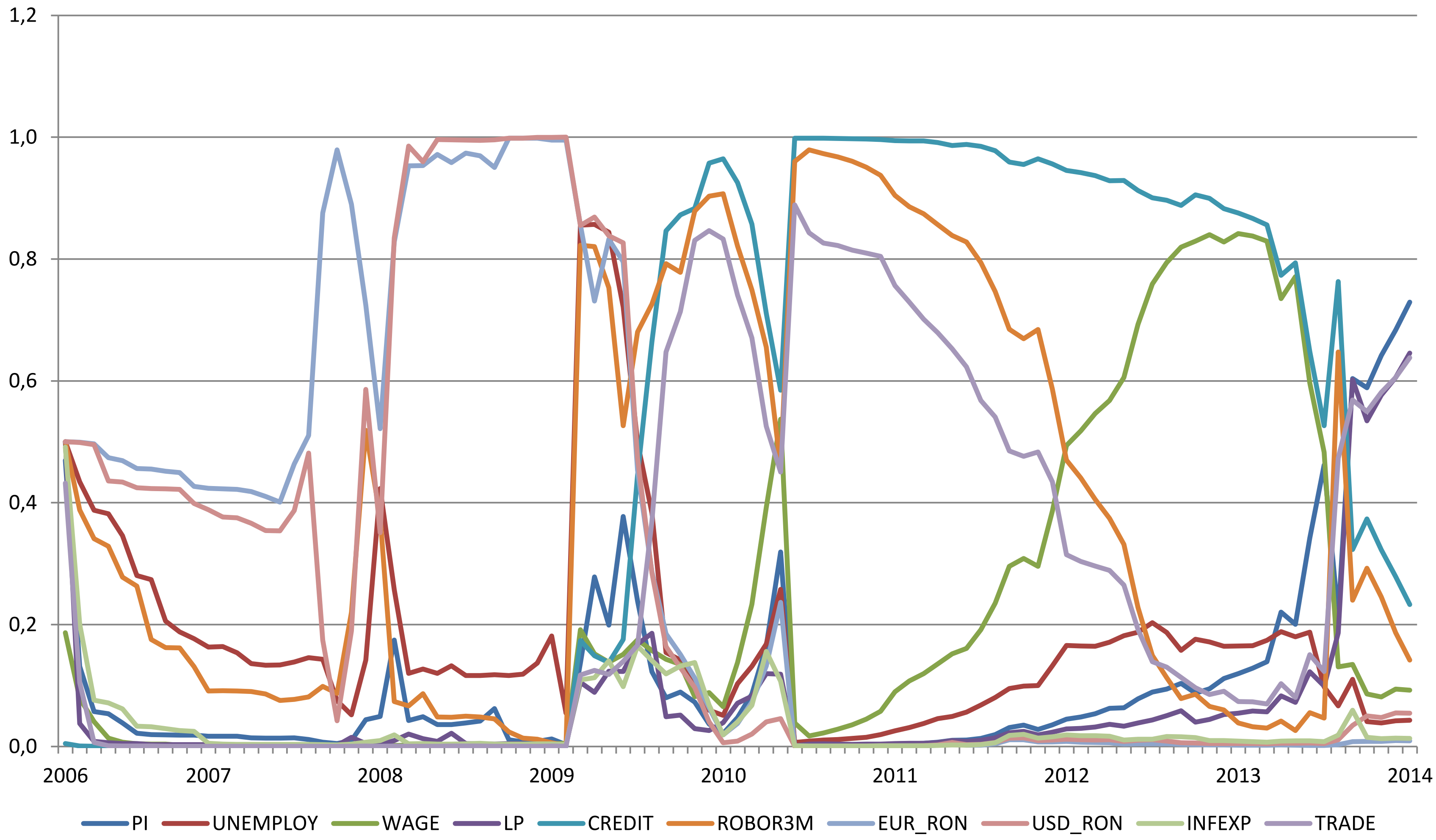
Data

- **CORE**: Adjusted CORE2 (Monthly change)
- **PI**: Industrial Production Index (Volume index, monthly evolution from the previous month, series adjusted by number of working days and seasonality);
- **UNEMPLOY**: Unemployment rate;
- **WAGE**: Monthly average net nominal wage in industry;
- **LP**: Labor productivity in Industry;
- **CREDIT**: Nongovernmental domestic credit at the end of period;
- **ROBOR3M**: Average interest rate for RON-denominated loans in the interbank market;
- **EUR_RON**: Nominal exchange rate between RON and EUR (monthly average; national currency for one unit of foreign currency);
- **USD_RON**: Nominal exchange rate between RON and USD (monthly average; national currency for one unit of foreign currency);
- **INFEXP**: European Commission measure of inflation expectations;
- **TRADE**: Trade deficit.

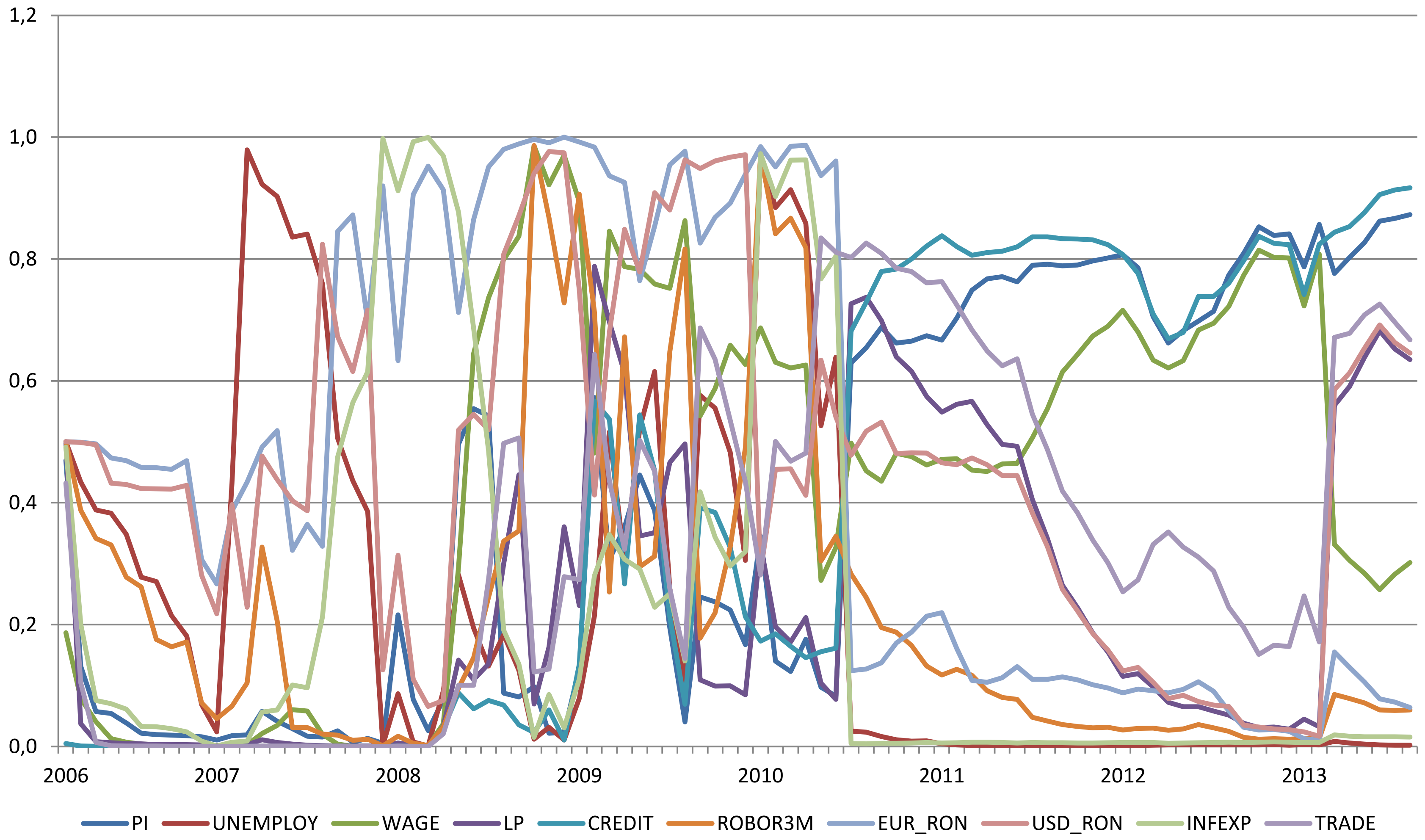
Expected number of predictors in each forecasting exercise



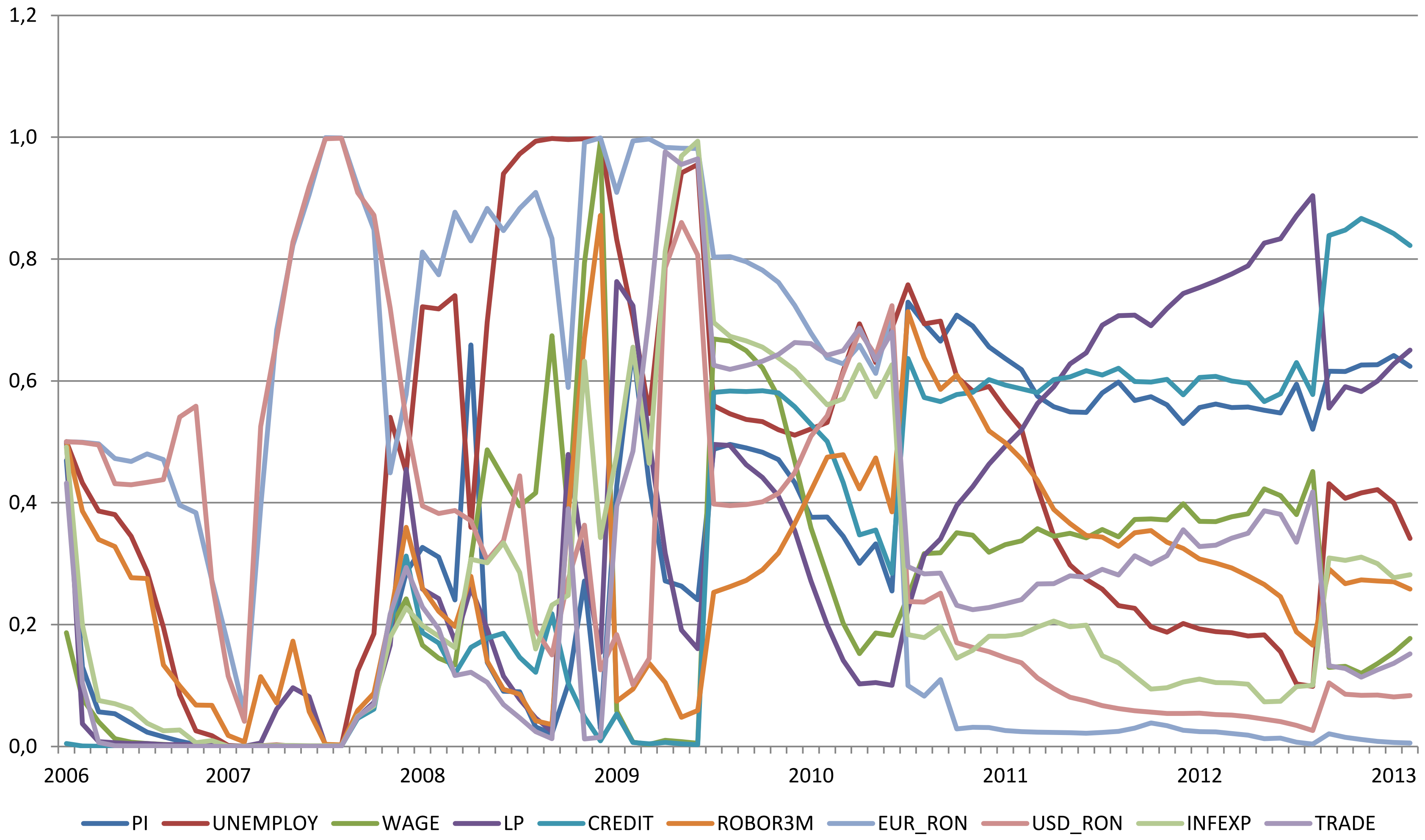
Posterior probability of inclusion of predictors, h = 1

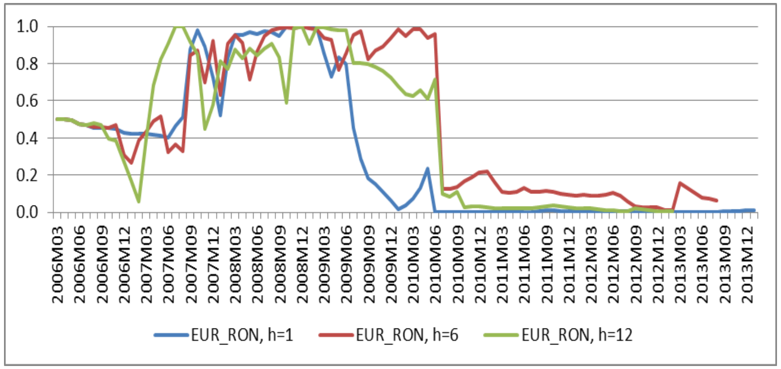


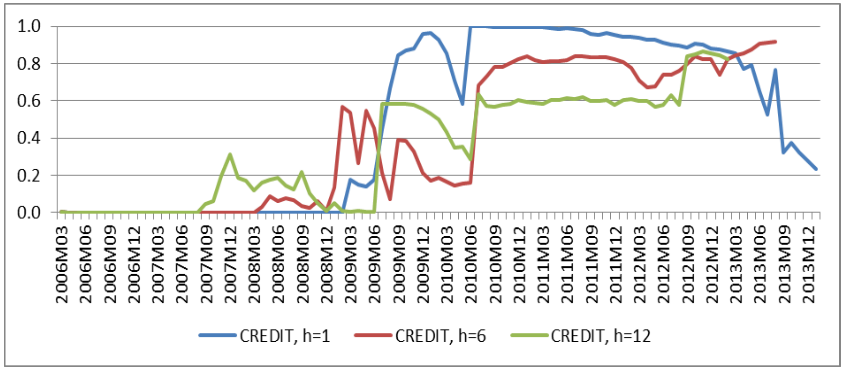
Posterior probability of inclusion of predictors, h = 6

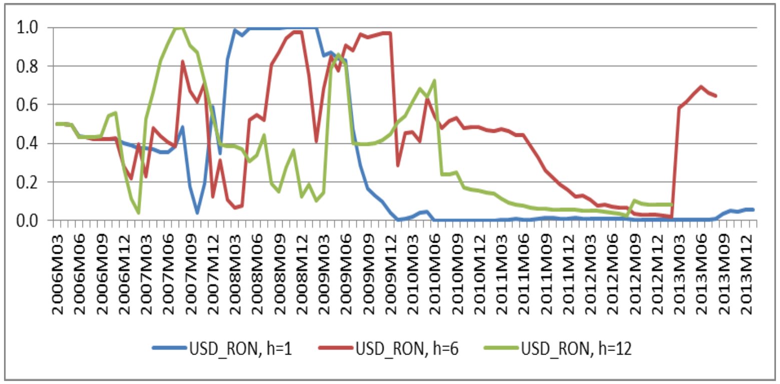


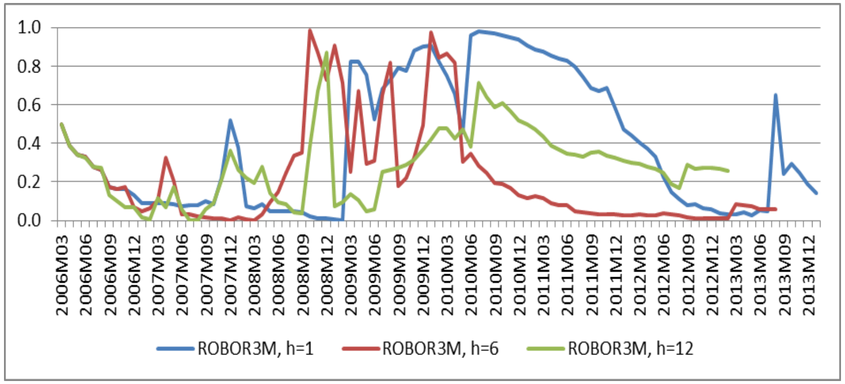
Posterior probability of inclusion of predictors, h = 12




EUR_RON, h=1
EUR_RON, h=6
EUR_RON, h=12


CREDIT, h=1
CREDIT, h=6
CREDIT, h=12


USD_RON, h=1
USD_RON, h=6
USD_RON, h=12

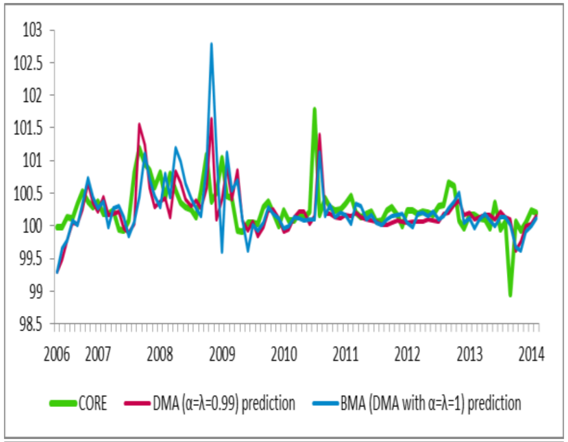

ROBOR3M, h=1
ROBOR3M, h=6
ROBOR3M, h=12

Forecasting Performance

- DMA vs. Bayesian Model Averaging (BMA) and Dynamic Model Selection(DMS)
  - Dynamic Model Selection involves selecting the single model with the highest value for $\Pr(L_t = k|y^{t-1})$ and using this to forecast.
  - Standard Bayesian model averaging (BMA) addresses the static situation where the correct model *k* and its parameter *θ(k)* are taken to be fixed but unknown. When α = λ = 1, there is no forgetting and the solution for the static situation can be viewed as a special case of DMA.
- Results for the following forecasting exercises:
  - Forecasting using DMA with α = λ = 0.99;
  - Forecasting using DMS with α = λ = 0.99;
  - Forecasting using DMA with α = λ = 0.95;
  - Forecasting using DMS with α = λ = 0.95;
  - Forecasting using BMA as a special case of DMA (α = λ = 1).

	h = 1		h = 6		h = 12	
	MAFE	MSFE	MAFE	MSFE	MAFE	MSFE
DMA (α=λ=0.99)	0.2599	0.1502	0.3090	0.2039	0.2778	0.1859
DMS (α=λ=0.99)	0.2243	0.1098	0.2521	0.1277	0.2329	0.1475
DMA (α=λ=0.95)	0.2613	0.1624	0.2759	0.1754	0.2786	0.1829
DMS (α=λ=0.95)	0.2005	0.0969	0.1879	0.0808	0.2168	0.1430
BMA (DMA with α=λ=1)	0.2930	0.2178	0.3094	0.2191	0.3023	0.1996

For all three forecasting horizons, DMA and DMS lead to better results.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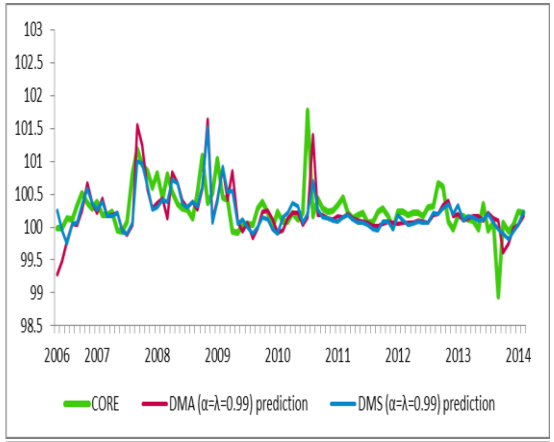
CORE
DMA (α=λ=0.99) prediction
BMA (DMA with α=λ=1) prediction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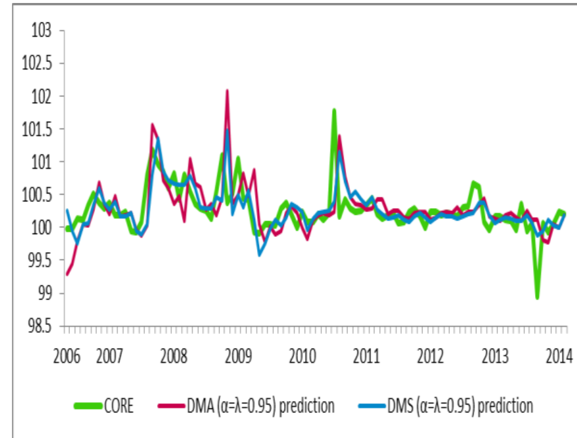
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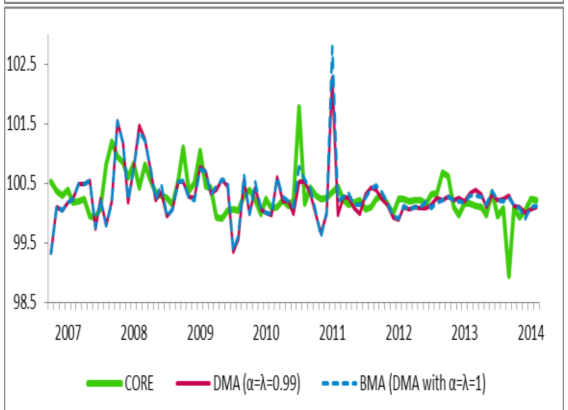
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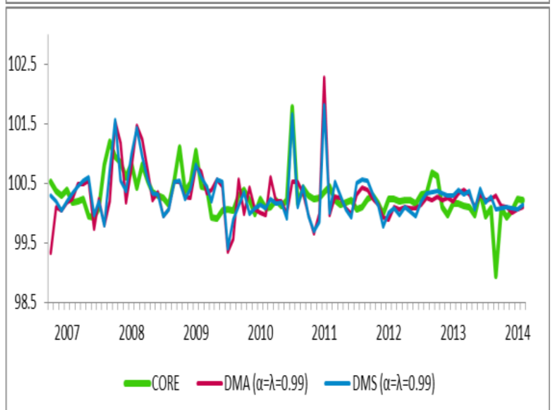
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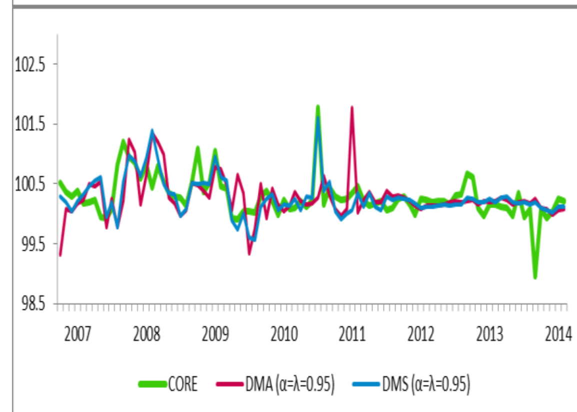
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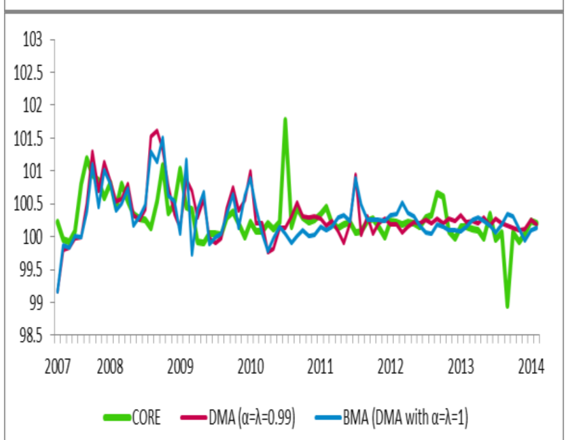
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BMA (DMA with α=λ=1)


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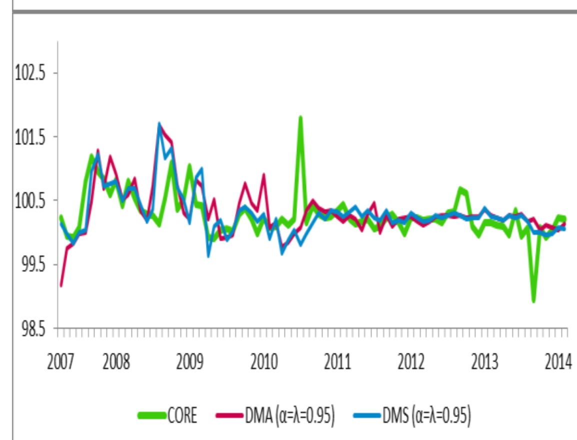
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2007 2008 2009 2010 2011 2012 2013 2014
CORE
DMA (α=λ=0.95)
DMS (α=λ=0.95)

Conclusions and further improvements

- For the case of Romania, DMA has the tendency to favor the models that include a small number of predictors;
- The results offer clear evidence that the forecasting models are changing over time;
- DMA allows for both gradual and abrupt changes in the role of a predictor;
- Each of the variables considered in this paper becomes important at a certain moment in time, for each of the three forecasting horizons;
- Inflation does respond to economic activity, but the explanatory potential of different measures of economic activity varies across time and no measure of economic activity clearly dominates over the whole sample;
- DMA leads to forecasting improvements over the BMA approach;
- In most cases, DMS forecasts a bit better than DMA since it can select an entirely new model as opposed to adjusting the weights on all the models.

Conclusions and further improvements

- **Possible drawbacks**:
  - Monthly data were used instead of the more usual quarterly data;
  - The Industrial Production is not a very good proxy for output, since its weight in GDP is about 30%;
  - The evolutions over time of the posterior probabilities for each variable considered illustrate an important benefit of DMA that it will pick up good predictors automatically but they might or might not be associated with an economic background.
- **Topics for future improvements**:
  - One future direction would be to analyze the time-varying coefficients of selected measures of economic activity.
  - Other external variables could be added to the potential set of predictors.

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Thank you!