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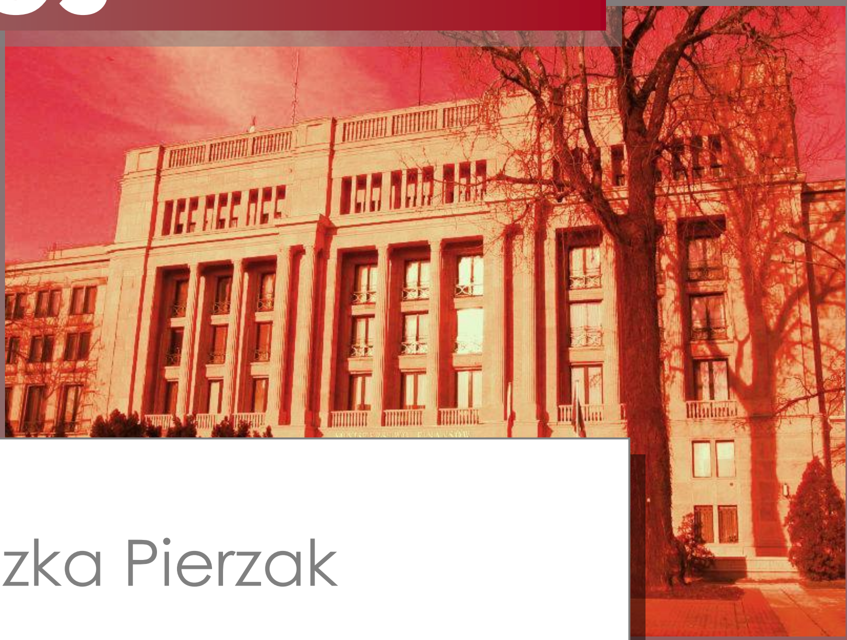

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Forecasting inflation in Poland using dynamic factor model

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Abstract

This paper investigates the use of dynamic factor model for forecasting headline and core inflation as well as food price index in Poland. Method applied in the study extend conventional approaches by using bayesian techniques to dynamic factors' estimation, way of handling "ragged edge" data structure and allowing for the model to change over time.

Forecasting results confirm that including current information extracted from data-rich environment improves inflation forecast precision and consequently DFMs perform better than the best autoregressive models. The analysis suggest also that applying dynamic model selection procedure can additionally reduce out-of-sample prediction errors.

JEL Classification: C35, C38, E31, E37
Keywords: dynamic factor model, forecasting, inflation, CPI

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Introduction

Obtaining accurate and reliable forecasts of future inflation is crucial for policymakers conducting fiscal and monetary policy, for firms making investment decisions and setting prices, as well as for employees and management negotiating wage contracts. Economists in government and business, who have to track the swings of the economy and to make forecasts that inform decision-makers in real time, monitor and examine a large number of variables from various sources. In contrast, traditional economic models cannot accommodate all important time series without the risk of running short of degrees of freedom and thus fail to forecast turning points adequately, usually due to the fact that they miss key underlying influences. Therefore, there is an increasing need of extracting information from many time series in order to mimic all economic relationships in forecasting models. Dynamic factor analysis is nowadays routinely used to meet this need.

The concept of condensing information from many predictors has long tradition in economics. First set of composite economic indicators constructed by Burns and Mitchell (1947) proved crucial in determining and explaining current and future economic situation. Since this notion was formally modelled by Sargent and Sims (1977) and Geweke (1977), the research has been continued by many economists. Finally, dynamic factor models have become standard tool applied by policymakers and economic research institutions to forecast key macroeconomic variables, such as real output and inflation.

The idea underlying factor models is that the bulk of variation of many variables can be explained by a small number of common factors, reffered to also as diffusion indexes. DFMs express observed time series as distributed lag of a small number of unobserved common factors and an indiosyncratic disturbance. They exploit the variables' comovement and efficiently reduce, in a first step, the dimension of the dataset to just a few underlying factors. In a second step, these factors are included into a rather small forecasting equation in which only a few parameters need to be estimated.

Practical implementation of DFM-based forecasting requires many modeling decisions, notably concerning variables to be included in a dataset, factor estimation method and the specification of a forecasting equation. Existing literature provides limited guidance on these choices. The purpose of this paper is to assess predictive performance of a dynamic factor model for consumer price index in Poland and its frequently analyzed components: core inflation (inflation net of food and energy prices) as well as food price index and fuels price index.

1 Data

1.1 Variables selection

There is a natural tendency for researchers to use in dynamic factor models as much data as possible, which stems from the belief that it provides the opportunity to exploit a reach base of information and ensures some robustness against the structural instability that plagues low-dimensional forecasting. Moreover, basic statistical principles suggest that more data improve statistical efficiency of factors.

However, these opportunities bring also substantial challenges. Simulations and empirical example considered by Boivin and Ng (2005) prove that increasing number of variables beyond a certain point is not desirable. The asymptotic theory under which the method of extracting factors is based assumes that the cross-correlation in the errors is small, and that the variability of the common component is relatively large. Expanding dataset by variables hightly correlated with initially chosen series increases the possibility of residual cross-correlation without offering any information gain for the common components. Results achieved by Boivin and Ng show that sample size alone does not determine the properties of the estimates and the quality of the data must be taken into account in factor extracting process. Therefore, selection of the variables is a sensitive issue in DFMs.

The literature (Stock, Watson 2003) does suggest that economic theory in many cases has empirically proven to be bad guidance in proposing relevant predictors of inflation, and the variables with the clearest theoretical justification for use as indicators often have scant empirical predictive content. Moreover, finding an indicator that predicts well in one period is no guarantee that it will predict well in later periods. Even the most common econometric method of identifying a potentially useful predictor relying on in-sample significance tests such as Granger causality tests provide little assurance that the identified relation is potent and stable. On the other hand, simple methods for combining the information in the various indicators seem to circumvent the worst of these instability problems and allow for surpassing predictions based on the past behaviour of inflation. Conclusions concerning the predictive performance of leading indicators for Polish inflation presented by Szafrański are consistent with specified hereinabove.

In the study, 198 macroeconomic time series commonly used for forecasting inflation were initially considered. However, CPI was forecasted finally using only 62 among them, core inflation - 48, food - 36 and fuels - 59 variables. Selection procedure aimed at eliminating high correlations between variables used in the model. Ultimatelly chosen series are also directly interrelated with forecasted individual price indexes (each price index is forecasted with its individual dataset).

1.2 Data transformation

The data available on a daily and weekly basis were aggregated to monthly observations, which were formed as averages of the higher frequency values. All variables which display a clear pattern of seasonality were seasonally adjusted using the TRAMO-SEATS procedure with concurrent revision strategy. The series were also transformed to be stationary by taking first or second differences, logarithms, or first or second differences of logarithms, following standard practice. In the final step, they were standarized to have zero mean and unit standard deviation.

2 Estimation of factors

2.1 Estimation procedure

The DFM implies that the variance (or the spectral density in frequency domain) of X_t can be written as the sum of two parts, one arising from the factors and the other arising from the idiosyncratic disturbance. Factor estimation methods vary from principal component analysis (PCA) to full likelihood-based approaches. Bayesian techniques are believed to have advantage over traditional methods of a probably more efficient one-step estimation of the factors through the Kalman filter algorithm. Therefore, Bayes methods might offer substantial computational gains. However, this comes at a huge computational cost which makes the application of this model prohibitive in the recursive forecasting setting. Moreover, to date not enough is known to say whether this approach provides an improvement over PCA-type methods. For the purpose of this analysis factors are treated as unobserved latent variables and estimated in a state-space model framework. The vector of factors is assumed to follow a VAR process with ϵ_t^f being i.i.d. $N(0, \sigma^f)$ and is estimated using Bayesian methods founded on the algorithm proposed by Koop and Korobilis (2009).

$$X_{it} = \lambda_{0i} + \lambda_i F_t + \epsilon_{it} \tag{1}$$

$$F_t = \beta_1 F_{t-1} + ... + \beta_p F_{t-l} + \epsilon_t^f \tag{2}$$

The method largely follows Carter and Kohn's (1994) Gibbs-sampling algorithm for estimation of the state space models. The posterior distribution is approximated by a Gibbs sampling algorithm. All priors and initial values required to initiate the Gibbs sampling are found using principal components.

2.2 Handling "ragged edge" data structure

Taking into account real-time data released in a non-synchronous manner and with varying publication lags implies that one must use econometric approaches that allow to deal with an unbalanced panel at the end of the sample (i.e. at the forecast origin), which is commonly referred to as a "ragged edge" structure.

Dealing with ragged edge drawbacks directed some researchers towards replacing missing observations with their extrapolations. The other group of economists, in contrast, reorganise the structure of the data placing each viariable in a database at the time of its publication (connecting the data with this date) instead of combining it with the month it concerns. Incorporating the first approach often generates additional problems in state space models and involves forecasting considerable part of the variables before forecasting inflation. The second may help taking into account delays in impact of some variables on inflation, but this "influence delay" and the data publication lag do not necessarily overlap.

In this analysis abovementioned problem was solved by estimating factors using data available for particular period, which means that real time factors (at current time $t = t_n$) are estimated using only available information (mainly commodity price indices, interest rates, exchange rates, business climate indicators), while previous periods' factors (from $t = t_0$ to $t = t_{n-1}$) are calculated on the basis of all timeseries in a database used for forecasting particular price index.

2.3 Determining the number of factors

There are various statistical approaches in determining the number of factors in the DFM. For example, it is common to order factors estimated throug PCA according to the size of their eigenvalues and consider models where all of the first k factors are included. However, there are no widely accepted norms as to what percentage of explained variance may be deemend satisfactory. The second, recommended for the dynamic factors, method of identifying the number of factors is based on information criteria's indicators, e.g. proposed by Bai and Ng (2006) and Hallin and Liska (2007). In this paper IC were calculated according to the following formula:

$$IC(k)_l = log\left[\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(X_{it} - \lambda_i F_t\right)^2\right] + kp(n,T), 0 \leqslant k \leqslant k_{max} \qquad (3)$$

where $n = 1, ..., N$ stands for the number of variables, $t = 1, ..., T$ represents time, $l = 1, ..., L$ denotes maximum lag of factors in equation (2) and $p(n, T)$ is a penalty function for overfitting the model represented by the equation (1).

Abovementioned criteria are helpful in identifing the number of dynamic factors which maximizes the amount of information extracted from the explanatory variables, but they do not provide suggestions concerning their explanatory power for the dependent variable. Therefore, while forecasting using models defined by the first k factors exclusively, the researcher risks including irrelevant factors and missing important ones. Moreover, the optimal number of factors k^* representing information from the database may not be optimal (usually is too high) from the point of view of the forecaster aiming at identifying model which delivers maximum amount of information about the dependent variable and provides the best out-of-sample forecasts.

Thus, estimated for the purpose of this analysis number of factors, for given N and T, is the smallest number for which the criterion reaches its minimum within a range predefined by the researcher:

$$k^* = argmin_{0 \leqslant k \leqslant k_{max}} IC_l(k), \tag{4}$$

where $l = 1, 2$ and k_{max} is an upper bound of k determined on the basis of information criteria and forecast errors calculated for the dynamic factor model (5).

Hereinbelow graphs show how information criteria change as number of factors rises for datasets describing consumer price index, core inflation, food price index and fuels price index. Eventually, in the models used for foracasting CPI and core inflation 3 factors were included, and in the case of food and fuel price indexes - 2 factors.

3 Forecasting

Forecasts for h months are obtained on the basis of a model, which has the following general structure:

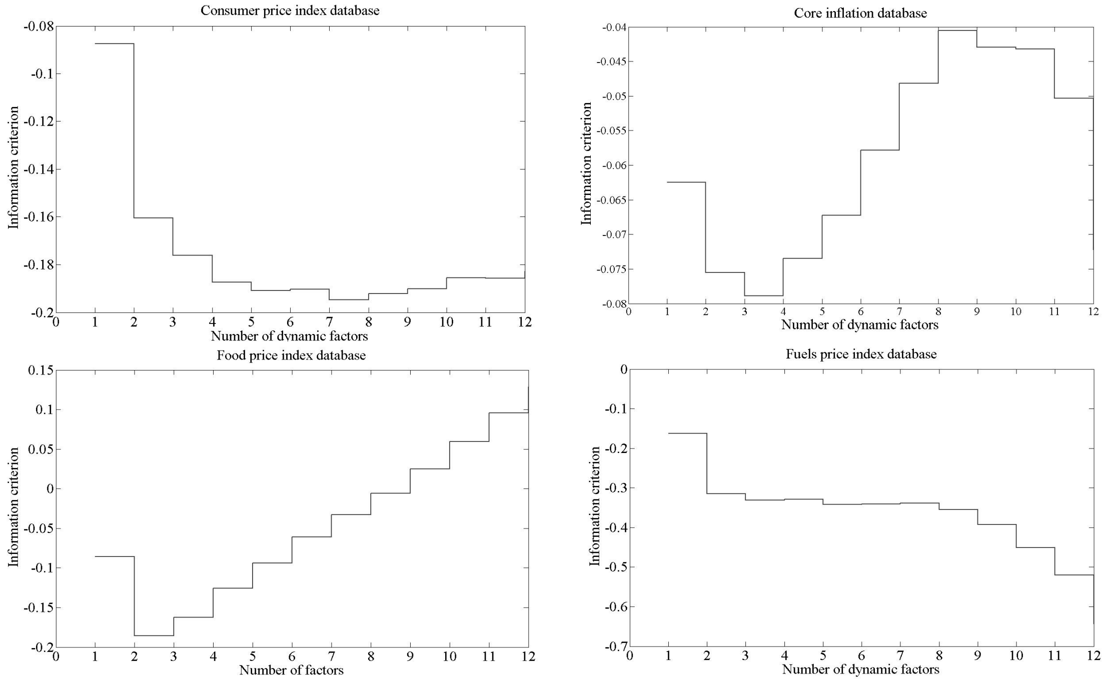
$$y_{t+1} = \alpha_p^k \sum_{p=0}^{P} \sum_{k=1}^{k^*} F_{t+1-p}^i + \gamma_q \sum_{q=1}^{Q} y_{t+1-q} + c_0 \tag{5}$$

where y_{t+1} is the one month ahead forecast of a difference of the logarithms of seasonally adjusted price index with a constant base, F_{t+1-p}^k stands for factor k lagged by p months, y_{t+1-q} is the autoregressive component of lag q. P, Q are the maximum lags of factors and autoregressive components, k^* is the optimal number of factors.

3.1 Model selection procedure

The standard approach in the relevant literature is to choose a single model and present empirical results based on this model. This approach provides stability

Figure 1: Information criteria for different number of factors



and comparability of results, but also is a source of some potential problems connected with the fact that if single model is selected, statistical evidence from other plausible models is ignored. As a result, model selected at time t, either on the basis of evaluation of historical adjustment to data or its predictive performance in the past, may not provide the best forecast for time $t + h$.

If k^* is the number of factors and models are defined only by the inclusion or exclusion of each factor, then 2^{k^*} possible models exist. Considering p possible lags of each factor significantly increases this number together with computational complexity and time necessary to obtain outcomes. These have motivated imposing restrictions on a number of factors' lags and their possible combinations in the model.

Eventually, basing on a preliminary results in which many variants of models were verified,[1] for the purpose of this analysis it was assumed that maximum lag of factor is $p = 6$ and each factor may occur in the model only once. It is reasonable to assume also that the first factor should appear in each model, since

[1]Initially models with maximum number of factors and their lags ammounting to 5 with their all possible combinations were tested, but almost no gain was achieved in the predictive performance by choosing among so many models. What is more, it increased the risk of promoting the one with relatively worse forecasting properties than model rejected because of slightly higher selection criteria.

the selection of variables ensures relatively strong representation of price category in the variable sets and justifies its interpretation as the "driving force" behind price processes in the economy.

3.1.1 Selection criteria

Literature provides two main methods of a selection of the best forecast over a wide range of projections from different models. First approach is based on the choice of a single model using information criteria, forecast errors or predictive likelihoods. The second consists in combining forecasts from many possible models and averaging them, usually assigning weights to models according to above mentioned criretia, i.e. forecast errors, information criteria or predictive likelihood. Specific case of model averaging is a dynamic model selection (DMS), which puts zero weight on all models other than the best one, thus shrinking the contribution of all models except one towards zero (Koop and Korobilis, 2009). In this paper forecast errors obtained in the DMS procedure were compared with forecast errors from a single model with constant set of factors. Three selection criteria (AIC, BIC, weighted average of BIC and forecast errors) and two model revision strategies (selection of a model each month or once in a year) were applied. Forecast errors for all considered selection methods are gathered in the Appendix. All forecasts were made on the basis of the data available on the 5th day of each month.

3.2 Empirical results

The results of the evaluation procedure (performed for inflation forecasts in the year 2012) show that dynamic factor models on average provided consumer price index forecasts comparable to the best performing autoregressive models. However, forecast errors of the best DFMs were lower than errors obtained from the benchmark model (AR). Gain from using dynamic factor models was higher while forecasting main inflation components than aggregate consumer price index. Dynamic factor models' relatively good performance in forecasting core inflation and food price index was not only limited to certain special sub-models. Even randomly chosen DFM was almost always better than the autoregressive model for abovementioned inflation subindexes. Unfortunately these conclusions do not concern fuel price index for which both dynamic factor models and autoregressive models do not provide satisfactory forecasts. The difficulties in forecasting fuel prices probably stem from the fact that fuel market is not fully competitive. Fluctuations in fuel prices are determined mainly by the supply side factors (e.g. decisions of organizations of oil exporters and suppliers dominating the domestic martket) which are not captured by the available data.

Table 1: Forecast errors

CPI						
Rolling estimation sample	Horizon			% of AR model error		
MODEL	1M	3M	6M	1M	3M	6M
DFM selected each month	0.180	0.442	0.929	79%	79%	97%
DFM constant over the year	0.175	0.491	1.010	77%	88%	106%
AR	0.228	0.557	0.957	100%	100%	100%
Core inflation						
Recursive estimation sample	Horizon			% of AR model error		
MODEL	1M	3M	6M	1M	3M	6M
DFM selected each month	0.236	0.274	0.254	82%	88%	69%
DFM constant over the year	0.243	0.264	0.277	85%	85%	75%
AR	0.287	0.310	0.367	100%	100%	100%
Food price index						
Rolling estimation sample	Horizon			% of AR model error		
MODEL	1M	3M	6M	1M	3M	6M
DFM selected each month	0.336	0.533	0.785	73%	71%	87%
DFM constant over the year	0.330	0.467	0.711	72%	63%	79%
AR	0.458	0.747	0.899	100%	100%	100%

For the purpose of forecast evaluation the DFM was estimated in two ways. The first method consisted in recursive estimation with the first sub-sample spanning from January 2001 to December 2011. The time span of the sub-sample was then expanded by one month ahead in each step of recursion. This approach appeared to be effective in forecasting core inflation. The second approach was based on rolling estimation sample including 24 recent months. This estimation strategy allowed to reduce forecast errors of more volatile and prone to cyclical changes in world commodities' prices: CPI and food price index.

The implementation of DFM allowed to increase forecast accuracy on average by 23% over the benchmark autoregressive model in nowcasting and by 12% in case of three-month forecasts in 2012. Intuitive guess that including recent information extracted from large dataset can improve its explanatory and forecasting features has found its measurable confirmation. However, longer horizon forecast of headline inflation was less precise.

Gain from using dynamic factor models was higher while forecasting underlying than headline inflation. For all verified horizons it offered minimal error associated with forecst with one-month error smaller by 15%, three-month errors lower by 15% and six-month errors - by 25%.

Benefits from implementation of DFMs in forecasting food price index were even bigger. Exploiting rich data sets including agricultural and food prices enabled dynamic factor models to outperform benchmark models by 28% considering one-month forecast errors, 37% - three-month forecast errors and 21% - six-month forecast errors.

Forecast precision of DFMs was changing over time and no model significantly outperformed the others. This suggests that implementation of a dynamic model selection should provide some additional forecast benefits over traditional approach in treatment of model evolution. A message provided by the forecast errors is that allowing for the model to change each month can in fact offer some additional improvements.

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Appendix A. CPI forecast errors

Criterion - weighted average of BIC and 3-month forecast error						
Recursive estimation sample	Horizon			% of AR model error		
MODEL	1M	3M	6M	1M	3M	6M
DFM on average the best over the year	0.169	0.225	0.365	84%	86%	71%
DFM selected each month	0.196	0.261	0.448	97%	100%	83%
DFM constant over the year	0.223	0.264	0.517	110%	101%	100%
AR	0.202	0.260	0.516	100%	100%	100%

Criterion - AIC						
Recursive estimation sample	Horizon			% of AR model error		
MODEL	1M	3M	6M	1M	3M	6M
DFM on average the best over the year	0.187	0.238	0.463	87%	71%	88%
DFM selected each month	0.225	0.282	0.555	104%	84%	105%
DFM constant over the year	0.208	0.272	0.526	96%	81%	100%
AR	0.216	0.337	0.526	100%	100%	100%

Criterion - BIC						
Recursive estimation sample	Horizon			% of AR model error		
MODEL	1M	3M	6M	1M	3M	6M
DFM on average the best over the year	0.197	0.238	0.480	91%	71%	91%
DFM selected each month	0.226	0.283	0.548	105%	84%	104%
DFM constant over the year	0.223	0.278	0.512	103%	83%	97%
AR	0.216	0.337	0.526	100%	100%	100%

Appendix B. Core inflation forecast errors

Criterion - weighted average of BIC and 3-month forecast error						
Recursive estimation sample	Horizon			% of AR model error		
MODEL	1M	3M	6M	1M	3M	6M
DFM on average the best over the year	0.179	0.192	0.237	62%	62%	65%
DFM selected each month	0.236	0.274	0.254	82%	88%	69%
DFM constant over the year	0.243	0.264	0.277	85%	85%	75%
AR	0.287	0.310	0.367	100%	100%	100%

Criterion - AIC						
Recursive estimation sample	Horizon			% of AR model error		
MODEL	1M	3M	6M	1M	3M	6M
DFM on average the best over the year	0.220	0.487	0.308	77%	157%	84%
DFM selected each month	0.238	0.417	0.279	83%	134%	76%
DFM constant over the year	0.257	0.310	0.283	90%	100%	77%
AR	0.288	0.310	0.367	100%	100%	100%

Criterion - BIC						
Recursive estimation sample	Horizon			% of AR model error		
MODEL	1M	3M	6M	1M	3M	6M
DFM on average the best over the year	0.220	0.387	0.308	77%	139%	84%
DFM selected each month	0.240	0.399	0.279	84%	114%	76%
DFM constant over the year	0.243	0.288	0.283	85%	82%	77%
AR	0.288	0.350	0.367	100%	100%	100%

Appendix C. Food price index forecast errors

Criterion - weighted average of BIC and 3M forecast error						
Rolling estimation sample (24 months)	Horizon			% of AR model error		
MODEL	1M	3M	6M	1M	3M	6M
DFM on average the best over the year	0.173	0.300	0.394	74%	79%	72%
DFM selected each month	0.190	0.421	0.944	81%	111%	172%
DFM constant over the year	0.210	0.436	1.029	90%	113%	187%
AR	0.234	0.378	0.550	100%	100%	100%

Appendix D. Fuel price index forecast errors

Criterion - weighted average of BIC and 3M forecast error						
Rolling estimation sample (24 months)	Horizon			% of AR model error		
MODEL	1M	3M	6M	1M	3M	6M
DFM on average the best over the year	2.279	3.638	4.479	92%	72%	59%
DFM selected each month	2.368	6.261	11.182	96%	124%	148%
DFM constant over the year	3.207	7.652	12.422	130%	152%	164%
AR	2.472	5.048	7,564	100%	100%	100%