2. FORECASTING THE INFLATION RATE IN POLAND AND U.S. USING DYNAMIC MODEL AVERAGING (DMA) AND GOOGLE QUERIES

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Abstract

The purpose of this paper is to apply the recently proposed Dynamic Model Averaging (DMA) to modelling the inflation rate in U.S. and Poland with the additional analysis of the usefulness of Google Trends data. One of the analysed economies is quite uniform, but the time-series available for it are quite short. The second is the developed leading economy. It is found that in the case of U.S. the DMA methodology is quite useful and produces more accurate forecasts than the alternative ones. In particular, all features of DMA (i.e., model averaging, time-varying parameters, dynamically updated weights in model averaging) improve the forecast quality. Similar analysis for Poland does not lead to such conclusions. As two types of models are considered for the U.S. (with long and short time-series) it can be suspected that the problem with applying DMA to the Polish economy comes from the length of the available time-series. Anyway, in the case of U.S. inflation the DMA produced interesting outcomes, i.e., time-varying inflation drivers could have been identified. The practical implications for Poland are that unemployment rate is the major driver of inflation. For the U.S., the drivers are change in number of new houses, money supply, stock prices, energy prices, industrial production and level of short-term interest rate, government long-term bond yield and term spread.

Keywords: CPI, data-rich models, inflation, model averaging, nowcasting, Poland, U.S.

JEL Classification: C11, C32, C53, E31

1. Introduction

Modelling inflation is an important topic in macroeconomic modelling. Various approaches have been applied to tackle this case. Generally, the conventional methods use univariate time-series approach (mostly various ARIMA-type models) or multiple equation approaches (typically VAR/VECM or structural equation modelling).

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Of course, there is also a certain amount of nonconventional approaches. One of them is to apply the Bayesian econometrics. This methodology, first of all, allows for dealing with cases when the number of explanatory variables is higher than the number of observations in the time-series. The conventional least squares method is not applicable in such a case. Secondly, the Bayesian approach is very useful in the case of model uncertainty.

In this paper, a method recently gaining attention is described. The Dynamic Model Averaging (DMA) is kind of extension of the Bayesian Model Averaging (BMA). BMA has already been extensively applied in macroeconomic forecasting, mostly to identify the drivers of the economic growth in cross-country studies.

However, the DMA has certain very important features. First, it allows for dealing with the model uncertainty. In other words, it can be applied to the situation when some models can perform well in a certain period, but in other period they should be replaced by other models. Secondly, sticking to linear regression, the coefficients can vary in time. In other words, in DMA all models which are averaged are time-varying parameters ones. Thirdly, the model averaging in DMA is done in a recursive way. The weights ascribed to each of the averaged models are also time-varying. These weights are updated with the new upcoming information from the market.

Such an approach seems to agree more with the real market situation, than the conventional approaches. Indeed, for U.S. the DMA model is shown later in this paper to produce smaller Root Mean Squared Errors (RMSE) than, for example, the rolling regression.

Finally, it is checked if extending the DMA model with Internet search queries data might improve the forecast accuracy. The analysis is based on two countries. The developed (usually used as a “benchmark” one, the U.S.) economy and the emerging one (Poland) were considered. It should also be mentioned that Poland is a very uniform country in case of the language used. Therefore, it is a desired feature for considering the Google Trends data (Koop and Onorante, 2014). Such an analysis seems to be not performed yet.

2. Literature Review

Inflation forecasting is not an easy topic. However, it is an important one (Szyszko, 2015). For example, in the Polish case Cizkowicz and Rzonca (2015) argued that inflation targeting has proved to be relatively successful and that the Polish central bank (NBP) does not need to search for an alternative to inflation targeting. In inflation modelling usually autoregressive models are used. However, depending on the criterion, the linear and non-linear approaches have both certain advantages and disadvantages. For example, Ahmadov *et al*. (2017) noticed in this context that non-linear models cannot beat the naïve forecast, but they are good at forecasting density estimations.

Sometimes non-standard methods like genetic algorithms are used (Kapetanios *et al*., 2016). In modelling inflation, also the VAR-approach is popular (Majsterek and Welfe, 2012; Sinicakova *et al*., 2011). For example, Balcilar *et al*. (2017) noticed that there was an important bi-directional relationship between inflation and the economic and political uncertainty.

Amisano and Fagan (2013) focused on different relationships between inflation and money supply depending on whether the inflation is low or high. Similarly, Canova and Ferroni (2012) studied the data from U.S. and observed that policy shocks accounted for a part of the decline in inflation volatility, but they were less effective in triggering inflation responses over time and qualitatively accounted for the rise and fall in the level of inflation. Indeed, also

Higgins *et al*. (2016), based on the data from China, observed that money supply can play a more important role in the macroeconomic forecasting than the interest rates. For the Euro area, such conclusions were formulated by Stavrev and Berger (2012).

Contrary to the above, Horvath *et al*. (2011) noticed that for the selected CEE countries it was more important to include autoregressive lags than the variable representing money supply when forecasting inflation. Ichiue *et al*. (2013) noticed the important role of wages as explanatory variable for inflation level. Valcarcel and Wohar (2013) studied the important relationship between inflation and oil price, which is one of the most important energy commodities. This variable has also been found important in the case of Polish inflation (Welfe and Majsterek, 2002).

Indeed, Ogunc *et al*. (2013) analysed various many-variables models. They considered univariate models, decomposition-based approaches (both in frequency and time domain), the Phillips curve-based time-varying parameter model, VAR and Bayesian VAR models and dynamic factor models. They found that many-variable models usually perform better in case of the forecast quality. Secondly, they also stated that the implementation of forecast combination schemes can be highly beneficial when comparing to single model methods.

Basing on the data from the Euro area, Forni *et al*. (2003) noticed that many-variable models outperform single-variable ones. They can also outperform autoregressive single-variable-based models. However, Mandalinci (2017) noticed that the inflation forecasting performances of different models notably depend on the period and the particular country. It was stated that in the developed countries models that include stochastic volatility and time-varying parameters perform better than in the emerging countries.

For example, in the Polish case Kim (2008) found that during certain period the appreciation of the domestic currency highly influenced the level of inflation, but in other it was the wages level. This naturally leads to the consideration of time-varying parameters models. Indeed, Stock and Watson (2007) explained the importance of using time-varying parameters in inflation modelling. Tales and Zaidan (2010) found such an approach very useful in the case of developing countries.

In this context – of variable uncertainty and necessity to include structural breaks – it is natural that numerous researchers observed the usefulness of Bayesian approach and regime-switching approach in inflation forecasting (Jochmann, 2015; Kulaksizoglu, 2016). Indeed, the forecast combination approach was found highly useful by Bjornland *et al.* (2012). Finally, dealing with large number of potential inflation predictors Groen *et al.* (2013) and Wright (2009) used the Bayesian Model Averaging (BMA) for U.S. inflation modelling.

Finally, it should be mentioned that Dynamic Model Averaging (DMA) has already been applied to macroeconomic modelling. Di Filippo (2015) used this method to forecast inflation in the Euro area and the U.S. between 1980 and 2012 based on quarterly data. It was noticed that quite different variables play the major role as inflation drivers in both of these economies. Ferreira and Palma (2015) used DMA to forecast the inflation in Brazil. Koop and Korobilis (2012) successfully applied this method to the quarterly U.S. inflation.

As far as now, one may notice that two problems emerge when a model of inflation is going to be constructed: variable (model) uncertainty and possibility that the impact of the given variable on inflation changes in time (*i.e*., necessity to use time-varying parameters, deal with structural breaks, etc.). However, the third problem, quite often found in macroeconomic modelling, is that some time-series are available after a significant time delay. Recently, the information about Internet searches gained much attention from researchers. These data are believed to contain the sufficient proxy of necessary information (Choi and Varian, 2012).

In a certain sense, the ratio of searches about a certain topic in comparison to all Internet searches can play the role of a proxy of investors' attention given to this topic. These data are available as weekly or monthly frequency, and they are available without a delay. Within this context, even the whole price index was tried to be constructed on this basis (Vosen and Schmidt, 2012). Except that, inclusion of Google Trends data become quite useful in various economic modelling approaches (Bijl *et al*., 2016; Chamberlin, 2010; Hamid and Heiden, 2015; Su, 2014; Koop and Onorante, 2014).

Based on the above literature review, the following questions are interesting to be answered:

- Is there a gain from the forecast combination scheme (*i.e*., model averaging) in modelling inflation?
- Does model averaging with time-varying weights lead to more accurate forecasts than time-varying parameters model with large set of predictors (explanatory variables)?
- Which variables are the most important inflation drivers?
- Can adding the data about Internet search queries improve the forecast accuracy?
- Is there a different answer to the above questions depending on whether the developed economy (*i.e*., U.S.) or the developing one (*i.e*., Poland) is chosen?

3. Data

The already-mentioned researches usually dealt with quarterly data. Indeed, such macroeconomic data are usually easier to obtain. Secondly, in certain cases (like GDP) for monthly data only some proxies are available. However, herein, monthly data are analysed. First of all, the applied methodology allows for including many variables, which is believed to compensate the lack of some variables in the models. Secondly, the purpose is to focus on a short-term forecasting. The variables were selected on the basis of the above literature review.

For Poland, the monthly inflation rate, unemployment rate, change in real wages (to the period from the previous year), logarithmic change in government expenditures (to the period from the previous year), logarithmic change in number of new houses (to the period from the previous year), logarithmic change in money supply M2, WIBOR 3M interest rate, 10-year government bond yield, logarithmic change in WIG stock market index, logarithmic change in CRB commodity index, logarithmic change in USD to PLN and EUR to PLN, logarithmic change in steel production and logarithmic change in SP 500 stock market index were taken. Also, the term spread was taken. It was calculated as the difference between long-term and short-term interest rate (*i.e*., bond yield and WIBOR 3M). The data were obtained from Bankier.pl (2018), GUS (2017), NBP (2017), Stooq (2018) and Worldsteel (2017). If possible, deseasonalized time-series were taken.

It should be noticed that interest rates were taken at their core levels, other variables in first ordinary or logarithmic differences. However, as explained further, this was done more according to the common practice and interpretative ability. The time-series used in the DMA scheme do not need to be stationary.

Secondly, before 2005 treasury bill rate was taken as the long-term interest rate (the last observation from every month) for Poland. Afterwards, 10-year bond yield was taken. This was done due to the limited data availability. The period between Jan, 2001 and Mar, 2017 was analysed.

The steel production was taken as a proxy of industrial production and economic activity.

In the case of U.S., the corresponding variables for the same time period were obtained from the Federal Reserve Bank of St. Louis (2018). The mnemonic time-series codes are: CPIAUCSL, UNRATE, AHETPI, TLPBLCONS, HOUST, TB3MS, TWEXBMTH, INDPRO. However, for U.S. direct data of industrial production was available, trade-weighted exchange rate was taken and – instead of government expenditures – Total Public Construction Spending was taken.

Finally, for U.S. also the long time-series were taken, beginning in Jan, 1973. In this case, Total Public Construction Spending was replaced by Future Capital Expenditures (CEFNNA156MNFRBPHI) and instead of CRB commodity prices two time-series were taken: Energy commodities index and Non-energy commodity index (The World Bank, 2018).

Generally, the same data transformations were applied for the U.S. models as well as for the Polish one. In particular, rates were not transformed, changes of wages were taken, Future Capital Expenditures were not transformed, other variables were taken as logarithmic changes.

For readers' convenience, the descriptive statistics are presented in Table 1. In the case of U.S. and global indices, the statistics are based on the longest time spread used in this research.

However, as explained in the next section, certain conventional models were also estimated. For them, the data should be stationary. Fortunately, assuming 10% significance level all variables after the already described transformations can be assumed stationary according to the ADF test. The only exceptions are: unemployment rate in Poland ($p = 0.6387$), change in real wages in U.S. ($p = 0.3571$), logarithmic change in TLPBLCONS ($p = 0.4495$), bond yield in U.S. ($p = 0.1060$) and TB3MS ($p = 0.1745$).

Table 1

Descriptive Statistics

Variable	mean	standard deviation	median	min	max	skewness	kurtosis
inflation_monthly_PL	0.002	0.004	0.001	-0.005	0.012	0.258	-0.370
unemployment_rate_PL	0.139	0.036	0.130	0.076	0.207	0.322	-1.076
change_in_real_ wages_to_prev_y_ PL	0.006	0.049	0.010	-0.075	0.085	0.125	-1.025
log_change_in_gov_ex penditures_to_ prev_y_PL	0.023	0.106	0.022	-0.996	1.018	-0.290	80.817
log_change_in_new_ho uses_to_prev_y_PL	0.018	0.123	0.016	-0.765	0.862	0.180	19.304
log_change_in_M2_PL	0.007	0.011	0.008	-0.036	0.054	-0.144	1.900
WIBOR 3M	0.052	0.033	0.045	0.017	0.189	2.116	5.138
bond_yield_PL	0.058	0.027	0.055	0.020	0.169	2.193	5.829

Variable	mean	standard deviation	median	min	max	skewness	kurtosis
log_change_in_WIG	0.006	0.062	0.006	-0.275	0.188	-0.398	1.905
log_change_in_CRB	0.000	0.050	0.004	-0.253	0.129	-0.810	2.668
log_change_USD_PLN	0.000	0.041	-0.002	-0.094	0.167	0.835	1.898
log_change_EUR_PLN	0.000	0.026	-0.001	-0.073	0.091	0.658	1.081
log_change_in_steel_prod_PL	0.000	0.095	-0.011	-0.300	0.268	0.046	0.562
term_spread_PL	0.006	0.010	0.007	-0.020	0.023	-0.282	-0.747
log_change_in_Total_Public_Construction_Spending _to_prev_y_ TLPBLCONS	0.012	0.026	0.013	-0.044	0.077	0.084	-0.597
inflation_monthly_ CPIAUCSL	0.001	0.001	0.001	-0.008	0.008	0.129	3.962
unemployment_rate_UNRATE	0.064	0.016	0.060	0.038	0.108	0.650	-0.323
change_in_real_ wages_to_prev_y_ AHETPI	0.017	0.008	0.015	0.005	0.039	1.079	0.011
Future_Capital_ Expenditures_ CEFNNA156MNFRBPHI	0.489	0.079	0.479	0.292	0.763	0.309	-0.252
log_change_in_new_houses_to_prev_y_ HOUST	-0.007	0.100	0.006	-0.345	0.293	-0.516	0.907
log_change_in_M2_ M2SL	0.002	0.002	0.002	-0.002	0.012	1.183	4.820
TB3MS	0.048	0.035	0.050	0.000	0.163	0.528	0.161
bond_yield_US	0.065	0.031	0.065	0.015	0.158	0.503	-0.175
log_change_in_ SP500	0.002	0.019	0.004	-0.107	0.066	-0.714	2.725
log_change_in_ Energy_index	0.002	0.036	0.001	-0.145	0.458	3.859	50.439
log_change_in_ Non_Energy_index	0.001	0.013	0.001	-0.088	0.048	-0.559	5.494
log_change_ TWEXBMTH	0.001	0.006	0.001	-0.018	0.028	0.180	1.037
log_change_in_ INDPRO	0.001	0.003	0.001	-0.019	0.009	-1.330	6.090
term_spread_US	0.017	0.013	0.019	-0.031	0.041	-0.684	0.237

4. Methodology

The Dynamic Model Averaging (DMA) is described in great details in the original paper by Raftery *et al.* (2010). Briefly, the algorithm introduces the state space of models:

$$y_t = \left(x_t^{(k)}\right)^T \Theta_t^k + \varepsilon_t^{(k)} \quad , \quad \Theta_t^{(k)} = \Theta_{t-1}^{(k)} + \delta_t^{(k)} \quad ,$$

where: k = 1, …, K and Θ_t denote the regression coefficients. Index k differentiates various linear regression models, which can be created out of m potential explanatory variables. In particular, up to $K = 2^m$ such models can be constructed (including the model with the constant term only). It is assumed that $\varepsilon_t^{(k)} \sim (0, V_t^{(k)})$ and $\delta_t^{(k)} \sim (0, W_t^{(k)})$.

As $V_t^{(k)}$ is time-varying there is no need to guarantee the stationarity of the data. This variance is updated with the recursive method of moment estimation. $W_t^{(k)}$ – with a certain forgetting procedure, in which forgetting parameter λ has to be specified. In other words, with the help of the Kalman filter K time-varying parameters regressions are estimated.

The next step is the model averaging with the help of a set of two dynamically updated weights: $\pi_{t|t-1,k} = \frac{(\pi_{t-1|t-1,k})^\alpha}{\sum_{i=1}^{K}(\pi_{t-1|t-1,i})^\alpha}$ and $\pi_{t-1|t-1,k} = \frac{\pi_{t|t-1,k} f_{k,t}}{\sum_{i=1}^{K} \pi_{t|t-1,i} f_{i,t}}$, where α is the next forgetting factor, and $f_{i,t}$ denotes the predictive density of i-th model at y_t. The recursive computations are started by setting $\pi_{0|0,k} = \frac{1}{K}$, *i.e.*, non-informative priors are set for all K models. Initially, $V_0^{(k)} = 1$ was taken, which seems reasonably high enough in view of standard deviations reported in Table 1. Also, the forgetting factors α and λ have to be set. It is worth to notice that, if α = 1 = λ, then the Bayesian Model Averaging (BMA) is recovered in a computationally more efficient way.

If the forgetting factor λ = 1, it means that it is assumed that regression coefficients are fixed in time. The lower this forgetting factor is set, the more volatility in regression coefficients is assumed. The forgetting factors can also be interpreted in a way that the information from the i-th period back is given λ^i weight as compared to the information from the last period.

The final DMA forecast is given as $\sum_{i=1}^{K} \pi_{t|t-1,k}\, y_t^{(k)}$, where $y_t^{(k)}$ is the prediction from the k-th model at time t. Koop and Onorante (2014) proposed to modify the computation of weights in a way including Google Trends data.

In particular, to consider $\pi_{t|t-1,k} = \omega \frac{(\pi_{t-1|t-1,k})^\alpha}{\sum_{i=1}^{K}(\pi_{t-1|t-1,i})^\alpha} + (1-\omega)p_{t,k}$, where ω is the number between 0 and 1, and $p_{t,k} = \prod_{i \in IN} g_{i,t} \prod_{j \in OUT}(1 - g_{j,t})$, with $g_{i,t}$ denoting the Google probability of i-th variable at time t. The Google probability is defined as the Google Trends data divided by 100. (It is then a number between 0 and 1.) IN denotes variables included in k-th model and OUT – not included in k-th model. The Google search terms for the explanatory variables are reported in Table 2 (Google, 2018). They were obtained with the help of "gtrendsR" R package (Massicotte and Eddelbuettel, 2018). If for a variable a few search terms were collected, then the mean of the corresponding Google Trends data was taken.

All computations were done in an R package "fDMA" (Drachal, 2017). Several models were constructed. Monthly inflation was set as y_t above and x_t was consisting of variables presented in Table 1 and as described in the previous section. First of all, the standard DMA models were estimated for all possible combinations of forgetting factors from the grid α, λ = {1, 0.99, 0.98, …, 0.90}. For the sake of clarity and due to the limited space, the outcomes are reported only for the model with α = 0.99 = λ and the model which out of the given grid of forgetting factors minimised the Root of Mean Squared Error (RMSE).

Next, for the model minimising RMSE the Koop and Onorante (2014) modification was proposed with the grid of parameters ω = {0, 0.25, 0.50, 0.75, 1}. It should be noticed that if

$\omega = 1$, then the procedure reduces to the basic (original) DMA scheme. Moreover, Google Trends data are available since 2004. Therefore, these models were computed for the data beginning on Jan, 2004.

The DMA scheme is a model averaging scheme. However, the procedure can also work for exactly one model. Then, of course, no averaging is done. Just a time-varying parameters regression with the Kalman filter is computed. By TVP is denoted the model (with $\lambda = 0.99$) computed in such a way with explanatory variables being all ones considered for the given country.

Also, some variations in choosing the explanatory variables to the original DMA (and with $\alpha = 0.99 = \lambda$) were performed. DMA-1V denotes the DMA scheme over models with exactly one explanatory variable plus the constant term or with the constant term only. DMA-AR(1)-1V denotes the model with exactly two explanatory variables: first lag of monthly inflation and the one as in DMA-1V. DMA-AR denotes the DMA with explanatory variables being first, second, third, fourth and fifth lag of monthly inflation. DMA-AR(1) denotes DMA model with explanatory variables as in DMA and the first lag of inflation.

Moreover, some conventional models were estimated. AR(1)-REC denotes the recursively computed AR(1) model. AR(1)-ROLL – the rolling autoregression with the window size of 36 observations. ARIMA denotes the model proposed by Hyndman and Khandakar (2008). Finally, the naïve forecast is computed by taking the last observation as the one-ahead forecast.

The number of lags to consider above and alternative models' construction were based on the already presented literature review. For example, some previous DMA models were based on the generalized Phillips curve, *i.e.,* inflation was modelled by its lags, unemployment and other predictors. Secondly, the forgetting procedure is similar to rolling estimations with the effective window size of $\frac{1}{1-\lambda}$.

Table 2

Google Search Terms

Variable	Search terms
CPIAUCSL	inflation, price index, inflation in US, prices, prices in US, CPI, consumer price index
UNRATE	unemployment, unemployment in US, US unemployment, unemployment rate, unemployment benefits, unemployment insurance
AHETPI	wages, salary, average salary, average wage, wage growth
TLPBLCONS	public construction spending, government expenditure, government spending, investments
HOUST	new houses, construction, residential sales, residential construction
M2SL	money supply, US money supply, monetary policy, monetary policy US
TB3MS	interest rate, treasury bills
bond_yield_US	bond yield, government bonds yields
SP500 (for U.S. models)	sp500, stock markets, stock prices
CRB (for U.S. model)	commodity prices, steel price, cooper price, oil price
TWEXBMTH	exchange rate, usd

Variable	Search terms
INDPRO	industrial production, economic growth, gdp growth, Industrial Production Index
term_spread_US	term spread, interest rates
CEFNNA156MNFRBPHI	capital expenditures, government expenditure, government spending, investments
Energy_index	commodity prices, oil price, gas price, energy prices
Non_energy_index	commodity prices, steel price, cooper price, non-energy prices
inflation_monthly_PL	inflacja, stopa inflacji, indeks cen, inflacja w polsce, ceny, ceny w polsce, hicp, wskaźnik cen towarów i usług konsumpcyjnych, ceny produktów
unemployment_rate_PL	polska bezrobocie, bezrobocie, bezrobocie w polsce, stopa bezrobocia, zasiłki, polska stopa bezrobocia
change_in_real_ wages_to_prev_y_ PL	płace, wynagrodzenia, przeciętne wynagrodzenie, wzrost płac
log_change_in_gov_ expenditures_to_prev _y_PL	wydatki rządowe, wydatki budżetu państwa, budżet polski, dotacje, inwestycje
log_change_in_new_ houses_to_prev_y_PL	nowe mieszkania, budownictwo, liczba nowych mieszkań
log_change_in_M2_PL	podaż pieniądza, podaż pieniądza w polsce, polityka monetarna
WIBOR 3M	stopa procentowa, oprocentowanie
bond_yield_PL	oprocentowanie obligacji, rentowność obligacji
log_change_in_WIG	wig, giełda, akcje, ceny akcji, gpw
CRB (for Polish model)	ceny surowców, ceny surowców na świecie, ceny miedzi, ceny stali, ceny ropy, ceny energii, ceny energii elektrycznej, ceny benzyny
log_change_USD_PLN	dolar, dolar cena, usd, usd pln, kurs dolara
log_change_EUR_PLN	euro, euro cena, euro pln, kurs euro
log_change_in_steel_ prod_PL	produkcja przemysłowa, produkcja przemysłowa gus, wzrost gospodarczy, wzrost gospodarczy w polsce, gospodarka polski, wzrost pkb, wzrost pkb w polsce
term_spread_PL	struktura terminowa stóp procentowych, spread stóp procentowych, term spread, stopy procentowe
SP500 (for Polish model)	ceny akcji, giełda usa, ceny akcji na świecie

5. Results

The forecast quality measures for the estimated models are reported in Table 3. For all models, the first 36 observations were excluded, *i.e.,* treated as the “learning” period for the models.

Table 3

Forecast Quality Measures for the Estimated Models

Poland	RMSE	MAE	U.S.	RMSE	MAE	U.S. (data since 1973)	RMSE	MAE
DMA	33.88	26.89	DMA	13.05	9.15	DMA	9.55	6.69

Poland	RMSE	MAE	U.S.	RMSE	MAE	U.S. (data since 1973)	RMSE	MAE
α = 1, λ = 0.97			α = 0.90, λ = 0.92			α = 0.90, λ = 0.97		
DMA α = 0.99 λ = 0.99	35.17	28.12	DMA α = 0.99 λ = 0.99	15.16	10.72	DMA α = 0.99 λ = 0.99	10.12	7.27
DMA ω = 0	34.88	27.84	DMA ω = 0	13.47	8.88	DMA ω = 0	13.95	9.55
DMA ω = 0.25	34.44	27.64	DMA ω = 0.25	13.42	8.78	DMA ω = 0.25	13.58	9.10
DMA ω = 0.50	34.08	27.50	DMA ω = 0.50	13.58	8.75	DMA ω = 0.50	13.36	8.67
DMA ω = 0.75	33.94	27.54	DMA ω = 0.75	14.01	8.89	DMA ω = 0.75	13.37	8.45
DMA ω = 1	34.99	28.12	DMA ω = 1	16.36	9.73	DMA ω = 1	13.59	8.45
TVP	34.36	27.55	TVP	14.78	10.21	TVP	12.29	8.72
AR(1)-REC	30.82	24.28	AR(1)-REC	12.34	8.30	AR(1)-REC	10.88	8.06
AR(1)-ROLL	30.45	23.76	AR(1)-ROLL	11.96	8.19	AR(1)-ROLL	9.61	6.78
DMA-1V	36.90	29.08	DMA-1V	15.74	11.51	DMA-1V	10.05	7.24
DMA-AR	35.74	28.18	DMA-AR	15.93	11.71	DMA-AR	15.85	11.07
DMA-AR(1)	34.69	27.56	DMA-AR(1)	15.10	10.68	DMA-AR(1)	9.71	6.98
DMA-AR(1)-1V	35.76	27.86	DMA-AR(1)-1V	15.61	11.42	DMA-AR(1)-1V	9.72	6.92
ARIMA	29.97	23.31	ARIMA	12.17	8.14	ARIMA	10.17	7.07
naive	36.79	28.16	naive	14.79	10.37	naive	11.64	8.19
All numbers are multiplied by 10^4.								

First of all, it should be noticed that in all cases DMA performed better than BMA (*i.e.*, in none of the cases the model with α = 1 = λ produced the smallest errors).

Secondly, in all three cases adding the information from Internet search queries improved the DMA scheme forecast quality. (For that, only models with ω should be compared, as the data since Jan, 2004 only are considered.)

Interestingly, when long time-series were considered for U.S., then the DMA scheme was able to beat both the naïve forecast and the ARIMA one. In this case, even the basic and most commonly used DMA with α = 0.99 = λ outperformed ARIMA and naïve forecast in case of RMSE, and was just slightly worse than ARIMA in case of MAE.

On the other hand, in case of short time-series model for the U.S. and Poland the DMA performed better only than the naïve forecast, but could not outperform the ARIMA model. It is also interesting that the suitable setting of the forgetting factors allowed to produce smaller errors than the recursive and rolling AR(1) models for the U.S. model with long time-series.

All in all, the model with the smallest RMSE for U.S. was the DMA with α = 0.90 and λ = 0.97.

Various modifications of the set of models being averaged in the DMA scheme or variables taken into the DMA scheme was not improving the forecast quality as well as changing the forgetting parameters for the initial set of variables. That has happened for both countries and length of time-series used.

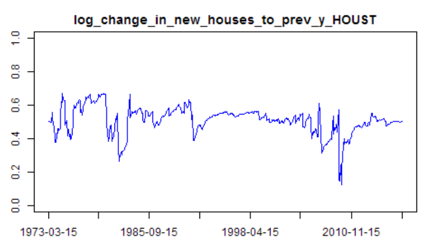
In all cases, the DMA scheme was able to outperform the TVP models, meaning that model averaging with time-varying weights improves the forecast accuracy.

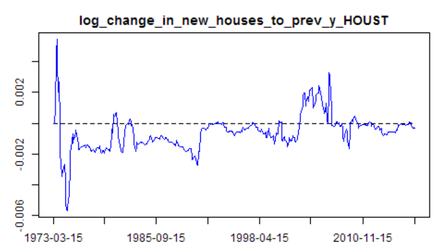
Finally, for the “best” model, *i.e.*, for Poland DMA with α = 1 and λ = 0.97, and for U.S. the one with long time-series and α = 0.90 and λ = 0.97 were analysed in the context of the “relative variable importance” (RVI). RVI is defined as the sum of $\pi_{t|t-1,i}$ for only those models which contain a given explanatory variable. The performance of RVI for the Polish model is not so interesting. Most of the time, RVI of all explanatory variables was around 0.5. Just in one period, the RVI of government expenditures variable was 0.14. The highest one, 0.84, happened for unemployment rate. In case of mean values, the smallest, 0.45, was for real wages, and the highest, 0.62, for unemployment rate.

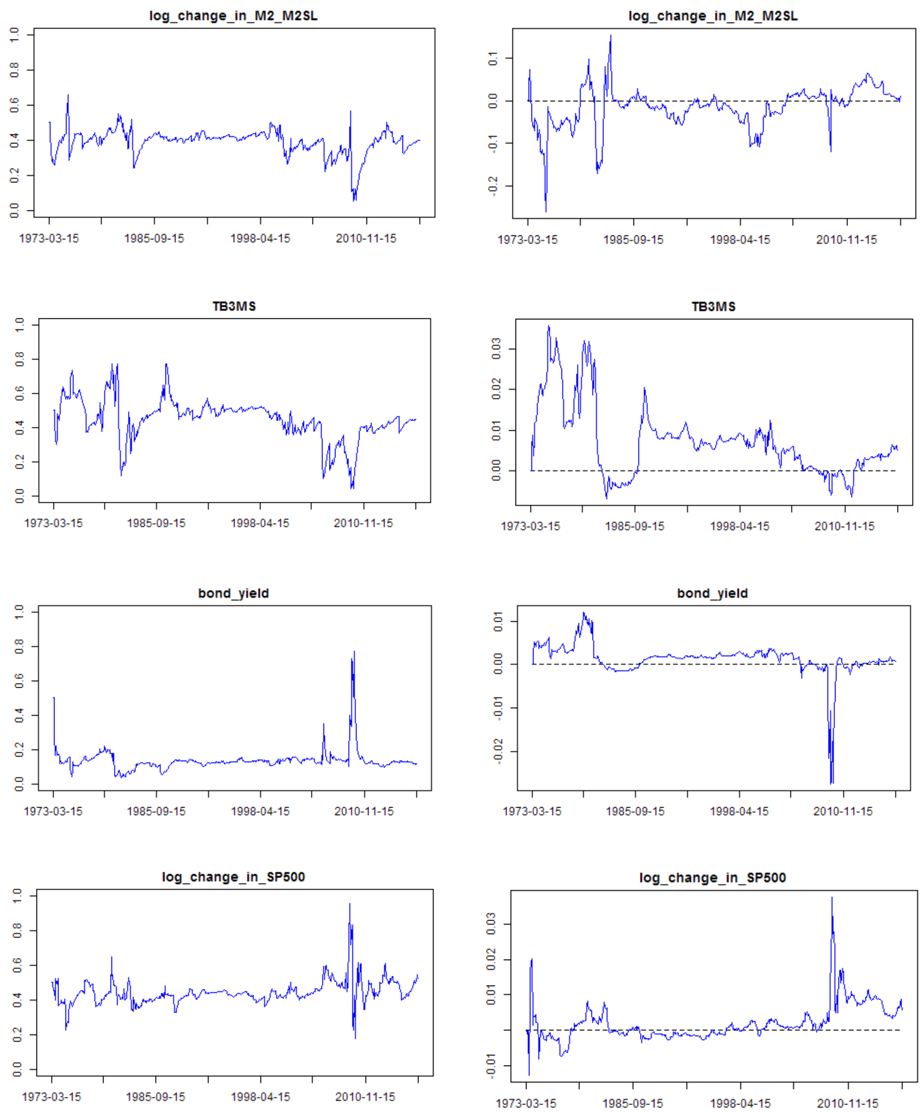
More interesting outcomes come from the U.S. model. First of all, mean RVIs and expected values of regression coefficients (weighted by $\pi_{t|t-1,i}$) were close to 0 for all the analysed period for unemployment rate, real wages, Future Capital Expenditures, Non-energy index and exchange rate. Figure 1 presents both the expected values of regression coefficients and RVIs for the other explanatory variables. It can be clearly seen that RVI varies in time. What is also interesting is that the sign of the expected regression coefficients also varies in time. For example, according to the selected DMA model around 2008 and 2009 the role in inflation forecasting of change in new houses, money supply, short-term interest rate, stock markets and energy prices dropped; but the role of bond yield, term spread and changes in industrial production increased.

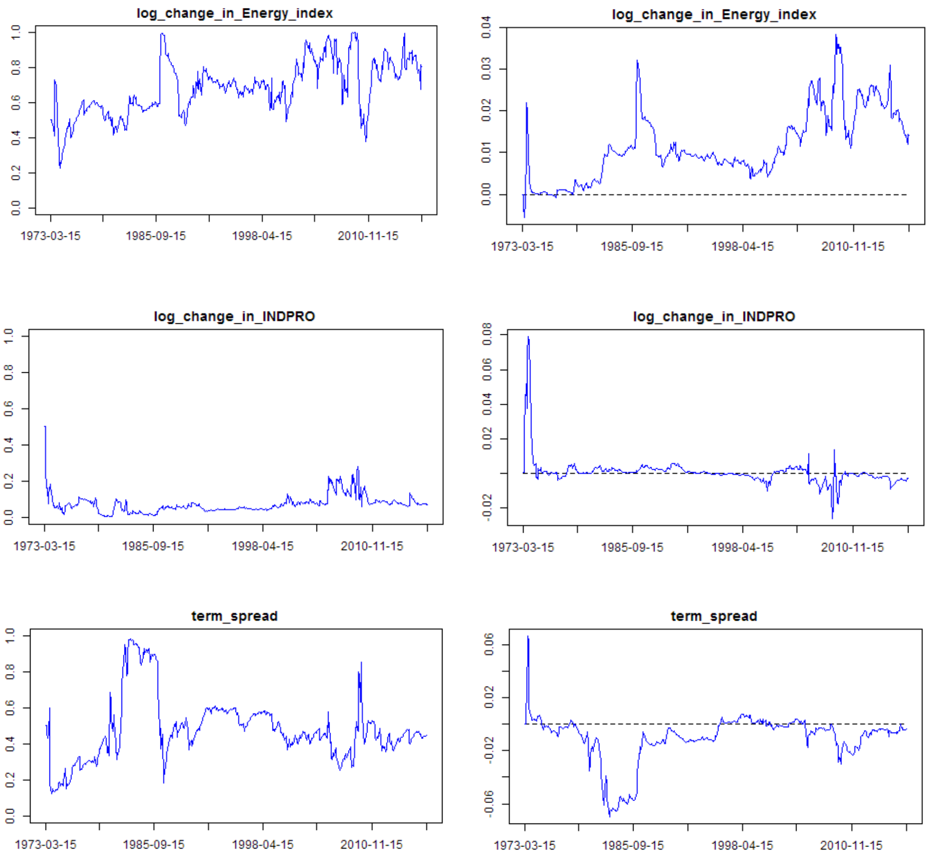
Figure 1

RVIs (Left) and Expected Regression Coefficients (Right) for U.S. DMA Model with α = 0.90 and λ = 0.97






log_change_in_M2_M2SL
log_change_in_M2_M2SL
TB3MS
TB3MS
bond_yield
bond_yield
log_change_in_SP500
log_change_in_SP500
1973-03-15
1985-09-15
1998-04-15
2010-11-15



It was also checked with the Diebold-Mariano (Diebold and Mariano, 1995) test whether the outcomes in Table 3 are statistically significant. The p-values of the test are reported in Table 4. The forecasts fro2m the estimated models were compared with the forecasts produced by ARIMA and NAÏVE models. The null hypothesis was that both forecasts have the same accuracy, and the alternative one – that the estimated model produced more accurate forecast than ARIMA model (or NAÏVE).

Table 4

P-values from the Diebold-Mariano Tests

	Poland		U.S.		U.S. (data since 1973)	
Poland	ARIMA	NAIVE	ARIMA	NAIVE	ARIMA	NAIVE
DMA α and λ as in Table 3	0.9952	0.1263	0.9021	0.0606	0.1380	**0.0000**
DMA α = 0.99 = λ	0.9996	0.2658	0.9986	0.5921	0.5548	**0.0024**
DMA ω = 0	0.9986	0.1711	0.9946	0.4970	1.0000	0.8499

	Poland		U.S.		U.S. (data since 1973)	
DMA ω = 0.25	0.7882	**0.0003**	0.6142	**0.0128**	0.9997	**0.0204**
DMA ω = 0.50	0.6156	**0.0005**	0.2538	**0.0018**	**0.0233**	**0.0000**
DMA ω = 0.75	0.9999	0.3257	0.9999	0.7391	1.0000	1.0000
DMA ω = 1	0.9984	0.2784	0.9558	0.4710	0.9593	0.5768
TVP	0.9970	0.2247	0.9451	0.4597	0.9253	0.4970
AR(1)-REC	0.9947	0.1850	0.9338	0.4970	0.8850	0.4495
AR(1)-ROLL	0.9928	0.1721	0.9313	0.5745	0.8664	0.4539
DMA-1V	0.9919	0.3002	0.9616	0.8561	0.8710	0.4995
DMA-AR	0.9991	0.2055	0.9985	0.5794	0.1413	**0.0000**
DMA-AR(1)	1.0000	0.5156	0.9999	0.7306	0.4727	**0.0003**
DMA-AR(1)-1V	0.9998	0.3454	0.9998	0.7044	0.1064	**0.0000**

One may notice that in the case of Poland or the short time-series for U.S. none of the model was able to significantly produce more accurate forecasts than the ARIMA model. However, when long time-series were taken for U.S., assuming 5% significance level, DMA with ω = 0.50 produced significantly more accurate forecasts than the ARIMA model. Indeed, DMA with ω = 0.50 and DMA with ω = 0.25 produced significantly more accurate forecasts than NAÏVE method for Poland and U.S. (with both short and long time-series). Additionally, for long time-series for U.S. some other DMA type models produced also significantly more accurate forecasts than NAÏVE method. These results state that it is hard to beat the traditional methods in forecasting, but implementing Google Trends data leads to much improvement in a sense of forecast accuracy. Also, the length of time-series matters.

6. Conclusions

The outcomes for Poland indicated that unemployment rate is the most important variable out of the selected ones in forecasting inflation. However, the DMA scheme did not produce any outstanding outcomes in this case. It can be suspected that this is because DMA requires rather longer time-series to produce interesting outcomes. On the other hand, for the U.S. model with time-series beginning in Jan., 1973, the DMA scheme produced more accurate forecasts (according to RMSE and MAE) than the alternative methods.

For U.S., DMA identified change in number of new houses, money supply, stock prices, energy prices, industrial production and level of short-term interest rate, government long-term bond yield and term spread as the most important inflation explanatory variables for one-ahead forecasting. Time-varying patterns both in sign and size of regression coefficients were also found.

Moreover, in both countries it was found that adding the information from Internet search queries improves the forecast accuracy. Also, the general DMA scheme improves the forecast accuracy as compared to the alternative methods. In particular, this can be linked to features of DMA like the model averaging and incorporation of time-varying weights.

The importance of time-series length and, therefore, appropriate “learning time period” was found. The models for U.S. beginning in Jan., 1973, performed much better than models with time-series beginning in Jan., 2001.

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