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Short run and alternative macroeconomic forecasts for Romania and strategies to improve their

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Abstract. For the same macroeconomic variables more predictions can be made, using different forecasting forecasting. The most important step is the choice of the prediction with the highest degree of accuracy, this being used in establishing the governmental policies or the monetary policy by the central bank. We made short run forecasts (January 2012-March 2012) for variables as inflation rate, unemployment rate and interest rate for Romania using techniques like: econometric modeling, exponential smoothing technique and moving average method. In order to improve the forecasts accuracy, we used two empirical strategies: making combined prognosis and building the forecasts based on historical accuracy indicators. The predictions based on exponential smoothing technique have the highest degree of acuracy, being superior to those got applying the strategies of improving the accuracy.

Keywords: forecasts, accuracy, econometric models, smoothing exponential techniques.

JEL Classification: E21, E27,C51, C53.

INTRODUCTION

There are many quantitative methods used to build forecasts, two of the most popular being the econometric models and the exponential smoothing and moving average techniques. These can be used to develop alternative predictions for the same variable. We can chose the best prediction using the accuracy indicators. Some empirical strategies could be used to improve the accuracy, their effectiveness being in relation to the particular data. Making empirical researches for USA, Bratu (2012) showed that the best strategy for the accuracy imporovement is keeping constant the historical errors. This strategy generated the best results also for Romania, but it does not exceed the performance of exponential smoothing techniques.

FORECASTS ACCURACY IN LITERATURE

Forecast accuracy is a large chapter in the literature related to the evaluation of forecasts uncertainty. There are two methods used in comparing the prediction quality : vertical methods (eg, mean squared error) and horizontal methods (such as distance in time). An exhaustive presentation of the problem taking into account all the achievements in literature is not possible, but will outline some important conclusions.

In order to evaluate the forecast performance, and also to order the predictions, statisticians have developed several measures of accuracy. Fildes R. and Steckler (2000) analyzed the problem of accuracy using statistics, indicating landmarks in the literature. For comparison between the MSE indicators of the forecasts, Granger and Newbold propose a statistic. Another statistic is presented by Diebold and Mariano in order to compare other quantitative measures of errors. Diebold and Mariano were proposed in 1995 a comparison test of two forecast's accuracy under the null hypothesis that states the lack of difference. The test proposed by them was later improved by Harvey and Ashley, who developed a new statistic based on a bootstrap inference. Later, Christoffersen and Diebold have developed a new way of measuring the accuracy that keeps the cointegration relationship between variables.

Armstrong and Fildes (1995) shows that the purpose of measuring forecast error is the provision of information about the shape of errors distribution and proposed a loss function for measuring the forecast error. Armstrong and Fildes show that it is not sufficient to use a single measure of accuracy.

Mariano R.S. (2000) presents the most significant tests of forecasts accuracy, including the changes of his test- Diebold Mariano (DM). Since the normal distribution is a poor approximation of the distribution of low volume data series, Harvey, Leybourne, and Newbold improve the properties of finite data sets, applying some corrections: the change of DM statistics in order to eliminate the bias and to make comparison not to normal distribution, but to the t-Student. Clark evaluates the power of some tests of equal forecast accuracy, such as modified versions of DM test or those of Newey and West, which are based on the Bartlett kernel and a fixed length of data series. Meese and Rogoff in their study from 1983, " The empirical exchange rate models of the seventies " compared the RMSE and the bias of exchange rate forecasts, that were based on structural models and they made a conclusion that was later used to improve macroeconomic forecasts performance. They have thus demonstrated that random walk process generates better forecasts than structural models.

In literature, there are several traditional ways of measurement, which can be ranked according to the dependence or independence of measurement scale. A complete classification is made by RJ Hyndman and AB Koehler (2005) in their reference study in the field, "Another Look at Measures of Forecast Accuracy ".

In practice, the most used measures of forecast error are:

– Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n} e_X^2 (T_0 + j, k)}$$

– Mean error (ME)

$$ME = \frac{1}{n}\sum_{j=1}^{n} e_X (T_0 + j, k)$$

The sign of indicator value provides important information: if it has a positive value, then the current value of the variable was underestimated, which means expected average values too small. A negative value of the indicator shows expected values too high on average.

– Mean absolute error (MAE)

$$MAE = \frac{1}{n}\sum_{j=1}^{n} \left| \ e_X(T_0 + j, k) \ \right|$$

Recent studies target accuracy analysis using as comparison criterion different models used in making predictions or the analysis of forecasted values for the same macroeconomic indicators registered in several countries.

T. Teräsvirta, van Dijk D., Medeiros MC (2005) examine the accuracy of forecasts based on linear autoregressive models, autoregressive with smooth transition (STAR) and neural networks (neural network-NN) time series for 47 months of the macroeconomic variables of G7 economies. For each model is used a dynamic specification and it is showed that STAR models generate better forecasts than linear autoregressive ones. Neural networks over long horizon forecast generate better predictions than the models using an approach from private to general.

U. Heilemann and Stekler H. (2007) explain why macroeconomic forecast accuracy in the last 50 years in G7 has not improved. The first explanation refers to the critic brought to macroeconometrics models and to forecasting models, and the second one is related to the unrealistic expectations of forecast accuracy. Problems related to the forecasts bias, data quality, the forecast process, predicted indicators, the relationship between forecast accuracy and forecast horizon are analyzed.

Ruth K. (2008), using the empirical studies, obtained forecasts with a higher degree of accuracy for European macroeconomic variables by combining specific sub-groups predictions in comparison with forecasts based on a single model for the whole Union.

Gorr WL (2009) showed that the univariate method of prediction is suitable for normal conditions of forecasting while using conventional measures for accuracy, but multivariate models are recommended for predicting exceptional conditions when ROC curve is used to measure accuracy.

Dovern J. and J. Weisser (2011) used a broad set of individual forecasts to analyze four macroeconomic variables in G7 countries. Analyzing accuracy, bias and forecasts efficiency, resulted large discrepancies between countries and also in the same country for different variables. In general, the forecasts are biased and only a fraction of GDP forecasts are closer to the results registered in reality.

THE ACCURACY EVALUATION OF THE MACROECONOMIC FORECASTS BASED ON ECONOMETRIC MODELS

The variables used in models are: the inflation rate calculated starting from the harmonized index of consumer prices, unemployment rate in BIM approach and interest rate on short term. The last indicator is calculated as average of daily values of interest rates on the market. The data series for the Romanian economy are monthly ones and they are taken from Eurostat website for the period from february 1999 to december 2011. The indicators are expressed in comparable prices, the reference base being the values from january 1999.

After applying the ADF test (Augmented Dickey-Fuller test) for 1, 2 and 4 lags, we got that interest rate series is stationary, while the inflation rate (denoted rin) and the unemployment rate (denoted rsn) series have one single unit root each of them. In order to stationarize the data we differenced the series, rezulting stationary data series:

$$ri_t = rin_t - rin_{t-1}$$
$$rs_t = rsn_t - rsn_{t-1}$$

Taking into account that our objective is the achievement of one-month-ahead forecasts for January, February and March 2012, we considered necessary to update the models. We used two types of models: a VAR(2) model, an ARMA one and a model in which inflation and interest rate are explained using variables with lag. The models for each analyzed period are shown in the ***Annex 1***. We developed one-month-ahead forecasts starting from these models, then we evaluated their accuracy.

U Theil's statistic is calculated in two variants by the Australian Tresorery in order to evaluate the forecasts accuracy.

The following notations are used:

a- the registered results

p- the predicted results

t- reference time

e- the error (e=a-p)

n- number of time periods

$$U_1 = \frac{\sqrt{\sum_{t=1}^{n}(a_t - p_t)^2}}{\sqrt{\sum_{t=1}^{n} a_t^2} + \sqrt{\sum_{t=1}^{n} f_t^2}}$$

The more closer of one is U_1, the forecasts accuracy is higher.

$$U_2 = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{f_{t+1} - a_{t+1}}{a_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{a_{t+1} - a_t}{a_t}\right)^2}}$$

If U_2 =1=> there are not differences in terms of accuracy between the two forecasts to compare

If U_2 <1=> the forecast to compare has a higher degree of accuracy than the naive one

If U_2 >1=> the forecast to compare has a lower degree of accuracy than the naive one

Table 1

Indicators of inflation forecasts accuracy for January 2012- March 2012

Inflation rate	Models used to build the forecasts		
Indicators of accuracy	VAR(2)	ARMA	Models with lagged variables
RMSM	0,33866552	0,129341	0,167367
ME	-0,1997	-0,1297	-0,0910
MAE	0,2660	0,2873	0,2893
MPE	-0,0072	-0,0030	-0,0017
U1	0,004882	0,005746	0,005672
U2	0,758272	1,261447	1,176748

Source: own calculations using Excel.

All these models tend to overestimate the predicted values of the inflation rate on the forecasts horizon. The predictions of inflation based on models with lagged variables have the better accuracy, the value close to zero for U1 statistic validating this conclusion, also like other accuracy indicators with small values such as ME and MPE. How U2 statistic of Theil is more than 1 for all one-step-ahead forecasts, excepting those based on VAR(2) model, the naïve predictions are more accurate than those based on ARMA models or those with lags for inflation rate.

Table 2

Indicators of forecasts accuracy for the unemployment rate for January 2012- March 2012

Unemployment rate	Models used to build the forecasts	
Indicators of accuracy	VAR(2)	ARMA
RMSE	0,17710637	0,113871
ME	0,02	-0,05667
MAE	0,153333	0,11
MPE	0,003319	-0,00803
U1	0,013386	0,008091
U2	1,070069	0,643847

Source: own calculations using Excel.

For the unemployment rate, the VAR(2) models underestimated the predicted values. The values registered by the accuracy indicators are contradictory, because some of them show a higher accuracy for forecasts based on VAR models (ME,MPE,U1) and others for predictions using ARMA procedure (RMSE, MAE, U1). However, the unemployment rate forecasts based on ARMA models are better than those got using the naïve model.

Table 3

Indicators of forecasts accuracy for the interest rate for January 2012- March 2012

Interest rate	Models used to build the forecasts		
Indicators of accuracy	VAR(2)	ARMA	Models with lagged variables
RMSE	0,62018841	0,5067925	0,6004235
ME	-0,61167	-0,47	-0,57833
MAE	0,611667	0,47	0,578333
MPE	-0,22003	-0,17015	-0,20812
U1	1,06343829	0,87779	1,039964
U2	0,105625	0,094318	0,091728

Source: own calculations using Excel.

The best forecasts for the interest rate are generated by the ARMA models, all the accuracy measures having low values. For all the mentioned econometric values we can see a tendency of overestimating the predicted values. Only the ARMA models provided a good accuracy, the value close to zero for U1 statistic (0,877) emphasizing this conclusion, unlike VAR models or those with lags where U1 registered values greater than 1. All the forecasts based on the proposed econometric models are better than the predictions using the random walk model.

THE ACCURACY EVALUATION OF MACROECONOMIC FORECASTS BASED ON EXPONENTIAL SMOOTHING AND MOVING AVERAGE TECHNIQUES

Exponential smoothing is a technique used to make forecasts as the econometric modeling. It is a simple method that takes into account the more recent data. In other words, recent observations in the data series are given more weight in predicting than the older values. Exponential smoothing considers exponentially decreasing weights over time.

4. *Simple exponential smoothing method (M1)*

The technique can be applied for stationary data to make short run forecasts. Starting from $R_n = a + u_n$, where *a* is a constant and u_t – resid, s- seasonal frequency, the prediction for the next period is:

$$\hat{R}'_{n+1} = \alpha \times R'_n + (1-\alpha) \times \hat{R}'_n, \ n = 1,2,...,t+k \qquad (5)$$

α is a smoothing factor, with values between 0 and 1, being determined by minimizing the sum of squared prediction errors.

$$\min \frac{1}{n}\sum_{i=0}^{n-1}(R'_{n+1} - \hat{R}'_{n+1})^2 = \min \frac{1}{n}\sum_{i=0}^{n-1} e^2_{n+1} \qquad (6)$$

Each future smoothed value is calculated as a weighted average of the n past observations, resulting:

$$\hat{R}'_{n+1} = \alpha \times \sum_{i=1}^{n}(1-\alpha)^i \times \hat{R}'_{n+1-s} . \qquad (7)$$

5. *Holt-Winters Simple exponential smoothing method (M2)*

The method is recommended for data series with linear trend and without seasonal variations, the forecast being determined as:

$$R_{n+k} = a + b \times k . \qquad (8)$$

$$\begin{aligned} a_n &= \alpha \times R_n + (1-\alpha) \times (a_{n-1} + b_{n-1}) \\ b_n &= \beta \cdot (a_n - a_{n-1}) + (1-\beta) \cdot b_{n-1} \end{aligned} \qquad (9)$$

Finally, the prediction value on horizon k is:

$$\hat{R}_{n+k} = \hat{a}_n + \hat{b}_n \times k \qquad (10)$$

6. *Holt-Winters multiplicative exponential smoothing method (M3)*

This technique is used when the trend is linear and the seasonal variation follows a multiplicative model. The smoothed data series is:

$$\hat{R}'_{n+k} = (a_n + b_n \times k) \times c_{n+k} \ , \tag{11}$$

where a-intercept, b- trend, c- multiplicative seasonal factor

$$\begin{aligned} a_n &= \alpha \times \frac{R'_n}{c_{n-s}} + (1-\alpha) \times (a_{n-1} + b_{n-1}) \\ b_n &= \beta \times (a_n - a_{n-1}) + (1-\beta) \times b_{n-1} \\ c_n &= \gamma \times \frac{R'}{a_n} + (1-\gamma) \times c_{n-s} \end{aligned} \tag{12}$$

The prediction is:

$$\hat{R}'_{n+k} = (\hat{a}_n + \hat{b}_n \times k) \times \hat{c}_{n+k} \ . \tag{13}$$

7. Holt-Winters additive exponential smoothing method (M4)

This technique is used when the trend is linear and the seasonal variation follows an additive model. The smoothed data series is:

$$\hat{R}'_{n+k} = a_n + b_n \times k + c_{n+k} \tag{14}$$

a- intercept, b- trend, c- additive seasonal factor

$$\begin{aligned} a_n &= \alpha \times (R'_n - c_{n-s}) + (1-\alpha) \times (a_{n-1} + b_{n-1}) \\ b_n &= \beta \times (a_n - a_{n-1}) + (1-\beta) \times b_{n-1} \\ c_n &= \gamma \times (R'_n - a_n) + (1-\gamma) \times c_{n-s} \end{aligned} \tag{15}$$

The prediction is:

$$\hat{R}'_{n+k} = \hat{a}_n + \hat{b}_n \times k + \hat{c}_{n+k} \tag{16}$$

8. Double exponential smoothing method (M5)

This technique is recommended when the trend is linear, two recursive equations being used:

$$\begin{aligned} S_n &= \alpha \times R_n + (1-\alpha) \times S_{n-1} \\ D_n &= \alpha \times S_n + (1-\alpha) \times D_{n-1} \end{aligned} \tag{17}$$

where S and D are simple, respectively double smoothed series.

9. Moving average method (M6)

The forecast based on moving average method starts from the hypothesis of a model with constant:

$$X_t = a + \varepsilon_t \tag{14}$$

The parameter at time T is the average of the last n observations, when n is the length of the interval:

$$\hat{a}_T = \frac{\sum_{t=T-n+1}^{T} X_t}{n} \tag{15}$$

The predicted value for X variable is:

$$\hat{X}_{T+\tau} = \hat{a}_T \ , \tau = 1,2,... \tag{16}$$

In ***Annex 2*** we presented the forecasts based on exponential smoothing and moving average techniques.

All the exponential and moving average methods overestimated the inflation and unemployment rate, because of the negative values of ME indicator.

For inflation and interest rate the Holt-Winters additive exponential smoothing method generated the best predictions on a prognosis horizon of 3 months. For unemployment rate the Holt-Winters additive and multiplicative exponential smoothing method are the best to be used. The predictions based on moving average have a higher degree of accuracy than many forecasts based on exponential smoothing techniques, but these are not better than simple prognoses that use the naive model.

Analyzing the U1 indicators, we can make comparisons between the forecasting methods. For the inflation rate the VAR model generated better predictions than the exponential smoothing or moving average techniques. For the unemployment rate ARMA procedure is recommended because of the highest accuracy of forecasts. The Holt-Winters multiplicative exponential smoothing is the best choice when we predict the interest rate, because the data series has recent changes different from the old values.

Table 4

Indicators of accuracy for forecasts based on eexponential smoothing and moving average techniques

Inflation rate	M1	M2	M3	M4	M5	M6
1	2	3	4	5	6	7
RMSE	0,00055	0,2647886	0,2534423	0,266937	0,367554	0,12487594
ME	-0,5348	-0,3283	-0,3130	-0,3168	-0,4733	-0,6513
MAE	0,4938	0,2873	0,2720	0,2758	0,4323	0,6103
MPE	-0,0154	-0,0097	-0,0093	-0,0094	-0,0147	-0,0175
U1	0,0097	0,006165	0,004892	0,005636	0,008528	0,011352
U2	1,491662	0,323962	0,620037	0,386389	0,183338	1,744475
Unemployment rate	M1	M2	M3	M4	M5	M6
RMSE	0,14387495	0,1474506	0,1138713	0,1184005	0,225536	0,25942244
ME	-0,06333	-0,045	-0,01	-0,00533	-0,22	-0,02333

1	2	3	4	5	6	7
MAE	0,136667	0,138333	0,11	0,112	0,22	0,203333
MPE	-0,00863	-0,00601	-0,00113	-0,00045	-0,03104	-0,00756
U1	0,01022964	0,01047	0,008066	0,008384	0,016216	0,016389
U2	0,814291	0,835011	0,640899	0,667242	1,267296	1,296064
Interest rate	M1	M2	M3	M4	M5	M6
RMSE	2,19379428	1,2047268	1,0898012	3,500938	2,411383	1,49680771
ME	2,193333	1,143333	0,746667	3,416667	2,41	1,426667
MAE	2,193333	1,143333	0,78	3,416667	2,41	1,426667
MPE	0,790386	0,409659	0,264576	1,232735	0,868652	-0,00756
U1	0,28317872	0,179276	0,170325	0,388346	0,302792	0,204445
U2	2,780411	1,32536	0,933732	4,704357	3,071481	1,779033

Source: own calculations using Excel.

5. STRATEGIES OF POSSIBLE IMPROVEMENT OF FORECASTS ACCURACY

Bratu (2012) states some important strategies to be used in practice in order to improve the forecasts accuracy. One of these strategies is the building of combined forecasts in different variants: predictions based on linear combinations whose coefficients are determined using the previous forecasts and predictions based on correlation matrix, the use of regression models for large data bases of predicted and effective values. On the other hand, we can apply the historical errors method, which supposes that the same value of an accuracy indicator calculated for a previous period. The combined forecasts and those based on historical errors for inflation rate and interest rate are shown in ***Annex 3***

Table 5

Indicators of combined forecasts accuracy for the inflation rate for January 2012- March 2012

Inflation rate	Combined forecasts		
Accuracy indicators	VAR(2) and ARMA	VAR(2) and models with lags	models with lags and ARMA
RMSE	0,10159396	3,3067566	3,9138178
ME	-0,6370	-2,6397	-3,6737
MAE	0,5960	2,5987	3,6327
MPE	-0,0179	-0,0882	-0,1241
U1	0,011336	0,065068	0,077034
U2	1,73899	8,699951	10,52527

Source: own calculations using Excel.

Table 6

Indicators of combined forecasts accuracy for the intrest rate for January 2012- March 2012

Interest rate	Combined forecasts		
Accuracy indicators	VAR(2) and ARMA	VAR(2) and models with lags	models with lags and ARMA
RMSE	1,09718245	1,3469944	0,8899492
ME	1,154333	1,034	0,670333
MAE	1,154333	1,112	0,683
MPE	0,417874	0,374469	0,243553
U1	0,207529	0,201624	0,141956
U2	1,819578	1,740136	1,211989

Source: own calculations using Excel.

We improved the forecasts accuracy by using combined forecasts only for the interest rate. For the inflation rate we had a lower accuracy if we combined the predictions based on econometric models.

Another strategy to build new forecasts implies to maintain constant the historical indicators of accuracy. For example, we used MPE, ME, MAE and RMSE indicators of predictions based on econometric models for November-December 2011 to build new forecasts for January-March 2012.

$$MPE = \frac{X_{t+1} - X_t}{X_t} \Rightarrow \frac{X_{t+1}}{X_t} - 1 = MPE \Rightarrow X_{t+1} = (MPE + 1) \cdot X_t$$

$$ME = X_{t+1} - X_t \Rightarrow X_{t+1} = ME + X_t$$

$$MAE1 = X_{t+1} - X_t \Rightarrow X_{t+1} = MAE1 + X_t$$
$$MAE2 = -X_{t+1} + X_t \Rightarrow X_{t+1} = -MAE2 + X_t$$
$$RMSE^2 = X_{t+1} - X_t \Rightarrow X_{t+1} = RMSE^2 + X_t$$

Table 7

Indicators of accuracy for the inflation rate and intrest rate forecasts based on historical measures of predictions for January 2012- March 2012

Indicators of forecasts accuracy for inflation rate (January 2012-March 2012)	Predictions based on MPE indicator		
	VAR(2)	ARMA	Model with lagged variables
RMSE	0,2899638	0,5390536	0,4771306
ME	-0,3031	-0,6589	-0,4611
MAE	0,4587	0,6179	0,4393

MPE	-0,0122	-0,0210	-0,0143
U1	0,008193	0,011592	0,009079
U2	1,260882	0,653022	0,295286

Indicators of forecasts accuracy for interest rate (January 2012-March 2012)	Predictions based on MPE indicator		
	VAR(2)	ARMA	Model with lagged variables
RMSE	0,77271226	0,9707928	2,0644222
ME	-0,76642	0,3871	1,010967
MAE	0,766418	0,7051	1,3503
MPE	-0,2759	0,134822	0,354858
U1	0,166805	0,159805	0,295423
U2	1,058594	0,826369	1,701469

Indicators of forecasts accuracy for inflation rate (January 2012-March 2012)	Predictions based on ME indicator		
	VAR(2)	ARMA	Model with lagged variables
RMSE	0,28665252	0,5418994	0,4804807
ME	-0,3073	-0,6607	-0,4607
MAE	0,4603	0,6197	0,4403
MPE	-0,0123	-0,0211	-0,0142
U1	0,008237	0,011617	0,009092
U2	1,267545	0,658905	0,304909

Indicators of forecasts accuracy for interest rate (January 2012-March 2012)	Predictions based on ME indicator		
	VAR(2)	ARMA	Model with lagged variables
RMSE	0,4721241	1,4637027	2,5080761
ME	-0,194	1,081	1,868333
MAE	0,485333	1,286333	2,163333
MPE	-0,07018	0,384522	0,663552
U1	0,090198	0,21625	0,324496
U2	0,61498	1,75126	2,686922

Indicators of forecasts accuracy for inflation rate (January 2012-March 2012)	Predictions based on MAE1 indicator		
	VAR(2)	ARMA	Model with lagged variables
RMSE	0,36882878	0,3754717	0,3055738
ME	-0,1723	-0,4533	-0,3497
MAE	0,3253	0,4197	0,3293
MPE	-0,0077	-0,0140	-0,0105
U1	0,005841	0,008927	0,00685
U2	0,909527	0,185023	0,208883

Indicators of forecasts accuracy for interest rate (January 2012-March 2012)	Predictions based on MAE1 indicator		
	VAR(2)	ARMA	Model with lagged variables

RMSE	1,08753544	1,8986048	0,500999
ME	1,603333	-0,51	-0,48667
MAE	1,923333	1,603333	0,486667
MPE	0,587224	-0,17312	-0,17485
U1	0,309909	0,335344	0,098837
U2	3,304297	1,920489	0,564121

Indicators of forecasts accuracy for inflation rate (January 2012-March 2012)	Predictions based on MAE2 indicator		
	VAR(2)	ARMA	Model with lagged variables
RMSE	0,30188077	0,3754717	0,4704714
ME	-0,8210	-0,5400	-0,6437
MAE	0,7800	0,4990	0,6027
MPE	-0,0205	-0,0170	-0,0205
U1	0,013949	0,009276	0,011355
U2	2,139033	0,427269	0,639328

Indicators of forecasts accuracy for interest rate (January 2012-March 2012)	Predictions based on MAE2 indicator		
	VAR(2)	ARMA	Model with lagged variables
RMSE	2,88835593	0,8654286	0,1888562
ME	2,75	0,063333	0,006667
MAE	2,75	0,75	0,16
MPE	0,989958	0,01777	0,003102
U1	0,331438	0,150283	0,033935
U2	3,395113	1,002042	0,270369

Indicators of forecasts accuracy for inflation rate (January 2012-March 2012)	Predictions based on RMSE indicator		
	VAR(2)	ARMA	Model with lagged variables
RMSE	0,21652084	0,3004148	0,2924571
ME	-0,3353	-0,4247	-0,4188
MAE	0,4100	0,3837	0,3778
MPE	-0,0119	-0,0130	-0,0128
U1	0,007785	0,008238	0,008064
U2	1,204588	0,265303	0,265379

Indicators of forecasts accuracy for interest rate (January 2012-March 2012)	Predictions based on RMSE indicator		
	VAR(2)	ARMA	Model with lagged variables
RMSE	3,11373457	2,6078793	0,3393762
ME	3,471219	1,98069	0,330105
MAE	3,471219	1,98069	0,330105
MPE	1,253772	0,707623	0,119029
U1	0,390858	0,33276	0,057669
U2	4,776603	2,36759	0,417691

Source: own calculations using Excel.

The inflation predictions on short run (January 2012-March 2012) based on historical accuracy indicators like MAE1 have the highest degree of accuracy. In this case, VAR(2) models determined the best forecasts for the following indicators: MAE, ME, MPE, U1. All the predictions based on MAE1 are superior, in terms of accuracy, to those based on the naïve model. For the rest of historical accuracy indicators, the forecasts using VAR models are inferior to those built using the naïve model, unlike ARMA models and models with lag.

The best predictions of the interest rate based on historical accuracy indicators are those that use the RMSE for models with lags. Good results appear when MAE1 is used for VAR models and MAE2 for models with lagged variables.

The accuracy for inflation forecasts based on historical errors is superior to those evaluated when the simple models are used, but the exponential smoothing techniques provide better results.

6. CONCLUSION

The chose of the best forecast from many alternative ones for the same variable, but elaborated using different methods is a rational step that is preceded before the establishment of governemental or monetary policies or before any decisional process based on the previous knowledge of some macroeconomic variables.

For data series of the Romanian economy, for short run forecasts on 3 months (January 2012-March 2012), the econometric models generated predictions with a rather good degree of accuracy, but these could be improved for the interest rate by combining the forecasts based on these econometric models. The prognoses for inflation and interest rate are closer of real values when the forecasts are based on an historical indicator of accuracy, more often the MAE and the RMSE corresponding to the previous two months from the forecast origin. However, the exponential smoothing methods determined the best predictions in terms of accuracy, because these techniques take into account only the recent values in the data series used tu build forecasts

ANNEX 1

Econometric models used to build one-step-ahead forecasts on horizon January 2012- March 2012

Reference period for the data series	VAR(2)
February 1999-December 2011	RI = - 0.2303012991*RI(-1) + 0.01690524458*RI(-2) + 0.7635057172*RS(-1) - 4.045179635*RS(-2) + 0.009459812909*RD(-1) + 0.01372850021*RD(-2) + 0.1784371173 RS = 0.0001183673666*RI(-1) + 0.000913245091*RI(-2) + 0.004531655955*RS(-1) + 0.1733869236*RS(-2) - 6.370296664e-06*RD(-1) + 8.205158788e-05*RD(-2) - 0.0001483905251 RD = 0.2043938188*RI(-1) + 0.1955891697*RI(-2) + 5.707574422*RS(-1) + 4.649473166*RS(-2) + 0.0200642759*RD(-1) + 0.04027759109*RD(-2) + 0.09565218477

February 1999-January 2012	RI = - 0.304515527*RI(-1) - 0.06631998407*RI(-2) - 1.040458918*RS(-1) - 7.026360125*RS(-2) + 0.7778407167*RD(-1) - 0.404246351*RD(-2) + 0.145112499 RS = - 2.344516219e-05*RI(-1) + 0.0007916728915*RI(-2) + 0.0005940877651*RS(-1) + 0.1695243629*RS(-2) - 0.00133333556*RD(-1) + 0.002036539678*RD(-2) - 0.0002191616153 RD = 0.03229810895*RI(-1) + 0.01229693648*RI(-2) + 1.27352077*RS(-1) - 0.09728647967*RS(-2) + 0.7345485482*RD(-1) + 0.1123912626*RD(-2) + 0.01381123609
February 1999-February 2012	RI = - 0.3043419246*RI(-1) - 0.06624258531*RI(-2) - 0.9649453802*RS(-1) - 7.028635591*RS(-2) + 0.7784642521*RD(-1) - 0.4044845337*RD(-2) + 0.1448847522 RS = - 4.411419007e-05*RI(-1) + 0.0007824578299*RI(-2) - 0.008396519856*RS(-1) + 0.1697952788*RS(-2) - 0.001407573395*RD(-1) + 0.002064897598*RD(-2) - 0.0001920461849 RD = 0.03257643527*RI(-1) + 0.01242102525*RI(-2) + 1.394587069*RS(-1) - 0.1009345956*RS(-2) + 0.7355482248*RD(-1) + 0.1120093987*RD(-2) + 0.01344610339

Reference period for the data series	ARMA
February 1999-December 2011	$ri_t = 0{,}436 \cdot ri_{t-2} + \varepsilon_{1t}$ $rs_t = 0{,}178 \cdot rs_{t-2} + \varepsilon_{2t}$ $rd_t = 0{,}128 + 0{,}814 \cdot rd_{t-2} + \varepsilon_t$
February 1999-January 2012	$ri_t = 0{,}153 - 0{,}217 \cdot ri_{t-1} + \varepsilon_t$ $rs_t = 0{,}761 \cdot rs_{t-1} - 0{,}715 \cdot \varepsilon_{t-1} + \varepsilon_t$ $rd_t = 0{,}121 + 0{,}914 \cdot rd_{t-1} + \varepsilon_t$
February 1999- February 2012	$ri_t = 0{,}153 - 0{,}217 \cdot ri_{t-1} + \varepsilon_t$ $rs_t = 0{,}761 \cdot rs_{t-1} - 0{,}715 \cdot \varepsilon_{t-1} + \varepsilon_t$ $rd_t = 0{,}121 + 0{,}914 \cdot rd_{t-1} + \varepsilon_t$

Reference period for the data series	Model with lagged variables
February 1999-December 2011	$ri_t = 0{,}1106 + 0{,}226 \cdot rd_{t-1} + \varepsilon_{1t}$ $rd_t = 0{,}055 + 0{,}23 \cdot ri_t + 0{,}303 \cdot ri_{t-1} + 0{,}235 \cdot ri_{t-2} + \varepsilon_{2t}$
February 1999-January 2012	$rd_t = 0{,}095 + 0{,}249 \cdot ri_{t-2} + 0{,}257 \cdot ri_{t-1} + \varepsilon_t$ $ri_t = 0{,}110 + 0{,}226 \cdot rd_{t-1} + \varepsilon_t$
February 1999- February 2012	$rd_t = 0{,}094 + 0{,}251 \cdot ri_{t-2} + 0{,}258 \cdot ri_{t-1} + \varepsilon_t$ $ri_t = 0{,}11 + 0{,}226 \cdot rd_{t-1} + \varepsilon_t$

Source: own computations using EViews.

ANNEX 2

One-step-ahead forecasts based on econometric models and the techniques of exponential smoothing or moving average techniques

One-month-ahead forecasts based on VAR(2) models

	January	February	March
Inflation rate (ri) (1999=100)	29,06 %	29,12 %	29, 17 %
Interest rate (rd)	2,156 %	2,163 %	2,176 %
Unemployment rate (rs)	7,002 %	7,1 %	7,15 %

Inflation rate (%)	VAR	ARMA	Model with lags	Effective values
November	29,12783 %	28,55084 %	28,83468 %	28,71 %
December	29,18881 %	28,68428 %	28,95068 %	28,78 %

Interest rate (%)	VAR	ARMA	Model with lags	Effective values
November	2,055 %	3,896 %	5,59 %	5,47 %
December	2,138 %	4,58 %	6,5 %	4,97 %

One-month-ahead forecasts based on ARMA models

	January	February	March
Inflation rate (ri) (1999=100)	28,83 %	29,027 %	29,7047 %
Interest rate (rd)	2,626 %	2,148 %	2,146 %
Unemployment rate (rs)	7,053 %	7,18 %	6,7872 %

One-month-ahead forecasts of inflation and interest rate based on inflation rate from the previous period

	January	February	March
Inflation rate (ri) (1999=100)	29,02 %	29,016%	29,641 %
Interest rate (rd)	2,085 %	2,42%	2,09 %

One-month-ahead forecasts based on the techniques of exponential smoothing or moving average techniques

Inflation rate (%)	M1	M2	M3	M4	M5	M6 (n=10)
January 2012	28.78155	28.888	28.712	28.856	28.795	28.616
February 2012	28.78155	28.988	29.136	29.0486	28.843	28.652
March 2012	28.78155	29.088	29.162	29.094	28.891	28.727

Unemployment rate	M1	M2	M3	M4	M5	M6 (n=10)
January 2012	0.07	0.070	0.0710	0.0709	0.0695	0.0727
February 2012	0.07	0.07025	0.0702	0.07034	0.0684	0.073
March 2012	0.07	0.0703	0.0704	0.0705	0.0674	0.0655

Interest rate	M1	M2	M3	M4	M5	M6 (n=10)
January 2012	0.0497	0.0444	0.0466	0.0532	0.0514	0.043
February 2012	0.0497	0.0392	0.0324	0.0714	0.0519	0.0422
March 2012	0.0497	0.034	0.0267	0.0612	0.0523	0.0409

Source: own calculations using Excel.

ANNEX 3

Combined forecasts and predictions based on historical accuracy indicators for inflation and interest rate

Combined forecasts

Inflation rate (%)	Combined forecasts VAR(2) and ARMA	Combined forecasts VAR(2) and models with lags	Combined forecasts models with lags and ARMA	Effective values
January 2012	28,690	28,519	24,783	28,899
February 2012	28,688	23,340	23,494	29,525
March 2012	28,660	28,171	28,651	29,402

Interest rate (%)	Combined forecasts VAR(2) and ARMA	Combined forecasts VAR(2) and models with lags	Combined forecasts models with lags and ARMA	Effective values
January 2012	4,144	4,087	3,448	2,83
February 2012	2,876	2,663	2,761	2,78
March 2012	4,773	4,682	4,132	2,72

Historical indicator of accuracy	Monthly inflation forecasts (January 2012- March 2012) based on accuracy indicators of predictions made two months ago		
January 2012	VAR	ARMA	Model with lags
MPE	29,19383	28,65237	28,92783
ME	29,19	28,65	28,93
MAE1	29,19	28,91	28,93
MAE2	28,37	28,65	28,63
RMSE	29,07248	28,86416	28,85691
February 2012			
MPE	29,06457	28,69778	28,92559
ME	29,06	28,70	28,93
MAE1	29,06	28,78	28,95
MAE2	28,50	28,78	28,61
RMSE	28,87652	28,78696	28,80189
March 2012			
MPE	28,78129	28,62225	28,71235
ME	28,777	28,617	28,707
MAE1	29,182	28,899	29,02
MAE2	28,616	28,899	28,778
RMSE	28,99397	29,02389	29,03383

Historical indicator of accuracy	Monthly interest forecasts (January 2012- March 2012) based on accuracy indicators of predictions made two months ago		
January 2012	VAR	ARMA	Model with lags
MPE	2,204045	4,468382	6,371962
ME	2,35	4,49	6,30
MAE1	5,18	5,47	5,59
MAE2	5,76	5,47	5,35
RMSE	5,31122	6,784788	6,64765
February 2012			
MPE	1,686706	2,616964	2,893104
ME	0,00	2,44	4,36
MAE1	1,75	2,74	3,97
MAE2	3,91	2,92	1,69
RMSE	7,06725	2,926858	4,277963
March 2012			
MPE	2,140454	2,363802	2,234081
ME	2,18	2,41	2,28
MAE1	2,75	2,99	2,59
MAE2	2,81	2,57	2,97
RMSE	3,197483	3,00052	3,122313

Source: own calculations using Excel.

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