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SHORT ARTICLE

Econometric Models or Smoothing Exponential Techniques to Predict Macroeconomic Indicators in Romania

*Mihaela Bratu**

Abstract: Inflation rate, unemployment rate and interest rate are some of the most important indicators used at macroeconomic level. These variables present an important interest for the central banks that establish the monetary policy (inflation target), but also for the government interested in public policies. Macroeconometric modeling offers the advantage of using more models to describe the evolution of a single variable and also the advantage of predicting it. But it is important to choose the forecast with the higher degree of accuracy. Calculating some indicators of accuracy we may know the best forecast that will be used to establish the macroeconomic policies. For the interest rate and unemployment rate in Romania VAR(2) models generated more accurate forecasts than ARMA models or models with lags. For the inflation rate the model with lag, which is consistent with Granger causality, determined the most accurate forecasts. The predictions based on all these models are better than those got using smoothing exponential techniques.

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

JEL Classification: E21, E27,C51, C53

Introduction

In establishing the monetary policy, the deciders must take into account the possible future evolution of some important macroeconomic variables as inflation rate, unemployment rate or interest rate. This fact implies the knowledge of the predictions of these indicators. In econometrics we can build forecasts starting from a valid model. The real problem appears when we have some alternative models and we must choose the one with the higher degree of accuracy.

In this article, we modeled the three selected variables and we made predictions for them. Using indicators of accuracy we demonstrated that simple econometric

* Mihaela Bratu is at Faculty of Cybernetics, Statistics and Economic Informatics, Bucharest, Romania.

models generated better forecasts in Romania than the smoothing exponential techniques.

Literature Review

To assess the forecast accuracy, as well as their ordering, statisticians have developed several measures of accuracy. For comparisons between the MSE indicators of forecasts, Granger and Newbold proposed a statistic. Another statistic is presented by Diebold and Mariano (1995) for comparison of other quantitative measures of errors. Diebold and Mariano test proposed in 1995 a test to compare the accuracy of two forecasts under the null hypothesis that assumes no differences in accuracy. The test proposed by them was later improved by Ashley and Harvey, who developed a new statistic based on a bootstrap inference. Subsequently, Diebold and Christoffersen have developed a new way of measuring the accuracy while preserving the cointegrating relation between variables.

Armstrong and Fildes (1995) showed that the purpose of measuring an error of prediction is to provide information about the distribution of errors form and they proposed to assess the prediction error using a loss function. They showed that it is not sufficient to use a single measure of accuracy.

Since the normal distribution is a poor approximation of the distribution of a low-volume data series, Harvey, Leybourne, and Newbold improved the properties of small length data series, applying some corrections: the change of DM statistics to eliminate the bias and the comparison of this statistics not with normal distribution, but with the T-Student one. Clark evaluated the power of equality forecast accuracy tests , such as modified versions of the DM test or those used by or Newey and West, based on Bartlett core and a determined length of data series.

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 Hyndman and Koehler (2005) in their reference study in the field, "Another Look at Measures of Forecast Accuracy":

- Scale-dependent measures

The most used measures of scale dependent accuracy are:
→ Mean-Square Error (MSE) = average (e_t^2)
→ Root Mean Square Error (RMSE) = $\sqrt{MSE}$
→ Mean Absolute Error (MAE) = average ($|e_t|$)
→ Median Absolute Error (MdAE) = median ($|e_t|$)

RMSE and MSE are commonly used in statistical modeling, although they are affected by outliers more than other measures.

- Scale-independent errors:

→ *Measures based on percentage errors*

The percentage error is given by: $p_t = \frac{e_t}{X_t} \cdot 100$

The most common measures based on percentage errors are:

* Mean Absolute Percentage Error (MAPE) = average ($|p_t|$)
* Median Absolute Percentage Error (MdAPE) = median ($|p_t|$)
* Root Mean Square Percentage Error (RMSPE) = geometric mean (p_t^2)
* Root Median Square Percentage Error (RMdSPE) = median (p_t^2)

When X_t takes the value 0, the percentage error becomes infinite or it is not defined and the measure distribution is highly skewed, which is a major disadvantage. Makridakis introduced symmetrical measures in order to avoid another disadvantage of MAPE and MdAPE, for example, too large penalizing made to positive errors in comparison with the negative ones.

* Mean Absolute Percentage Error (sMAPE) = average ($\frac{|X_t - F_t|}{X_t + F} \cdot 200$)

* Symmetric Median Absolute Percentage Error (sMdAPE) = median ($\frac{|X_t - F_t|}{X_t + F} \cdot 200$), where F_t - forecast of X_t.

→ *Measures based on relative errors*

It is considered that $r_t = \frac{e_t}{e_t^*}$, where e_t^* is the forecast error for the reference model.

* Mean Relative Absolute Error (MRAE) = average ($|r_t|$)
* Median Relative Absolute Error (MdRAE) = median ($|r_t|$)
* Geometric Mean Relative Absolute Error (GMRAE) = geometric mean ($|r_t|$)

A major disadvantage is the too low value for the error of benchmark forecast.

→ *Relative measures*

Forexample,therelativeRMSEiscalculated: $rel\_RMSE = \frac{RMSE}{RMSE_b}$, *where* $RMSE_b$ is the RMSE of "benchmark model"

Relative measures can be defined for MFA MdAE, MAPE. When the benchmark model is a random walk, it is used rel_RMSE, which is actually Theil's U statistic. Random walk or naive model is used the most, but it may be replaced with naive2 method, in which the forecasts are based on the latest seasonally adjusted values according Makridakis, Wheelwright and Hyndman.

• Free-scale error metrics (resulted from dividing each error at average error)

Hyndman and Koehler (2005) introduce in this class of errors “Mean Absolute Scaled Error” (MASE) in order to compare the accuracy of forecasts of more time series.

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)

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

These measures of accuracy have some disadvantages. For example, RMSE is affected by outliers. Armstrong and Collopy (2000) stress that these measures are not independent of the unit of measurement, unless if they are expressed as percentage. Fair, Jenkins, Diebold and Baillie show that these measures include average errors with different degrees of variability. The purpose of using these indicators is related to the characterization of distribution errors. Clements and Hendry have proposed a generalized version of the RMSE based on errors intercorrelation, when at least two series of macroeconomic data are used. If we have two forecasts with the same mean absolute error, RMSE penalizes the one with the biggest errors.

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

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

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

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

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

If $U_2 < 1 \rightarrow$ the forecast to compare has a higher degree of accuracy than the naive one

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

Other authors, like Fildes R. and Steckler H. (2000) use another criterion to classify the accuracy measures. If we consider, $\hat{X}_t(k)$ the predicted value after k periods from the origin time t, then the error at future time (t+k) is: $e_t(t+k)$. Indicators used to evaluate the forecast accuracy can be classified according to their usage. Thus, the forecast accuracy measurement can be done independently or by comparison with another forecast.

The Models Used to Make Macroeconomic Forecasts

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 October 2011. The indicators are expressed in comparable prices, the reference base being the values from January 1999. We eliminated the influence of seasonal factors for the inflation rate using Census X11 (historical) method.

After applying the ADF test (Augmented Dickey-Fuller test) and Phillips Perron 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 December 2011, January and February 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 table below. We developed one-month-ahead forecasts starting from these models, then we evaluated their accuracy.

Table 1. Models used for one-month-ahead forecasts

Reference period of data series	VAR(2)
February 1999-November 2011	RI = - 0.3043822972*RI(-1) - 0.06548906181*RI(-2) + 0.7771089465*RD(-1) - 0.4053252508*RD(-2) - 1.03325251*RS(-1) - 7.209639485*RS(-2) + 0.1457399131 RD = 0.03233284909*RI(-1) + 0.01251360226*RI(-2) + 0.7343577367*RD(-1) + 0.1121099358*RD(-2) + 1.275399865*RS(-1) - 0.1450771904*RS(-2) + 0.01397483645 RS = - 1.783579012e-05*RI(-1) + 0.0008266571782*RI(-2) - 0.001364145251*RD(-1) + 0.001991114806*RD(-2) + 0.0008974988819*RS(-1) + 0.1618077594*RS(-2) - 0.0001927456217
February 1999-December 2011	RI = - 0.3043822972*RI(-1) - 0.06548906181*RI(-2) - 1.03325251*RS(-1) - 7.209639485*RS(-2) + 0.7771089465*RD(-1) - 0.4053252508*RD(-2) + 0.1457399131 RS = - 1.783579012e-05*RI(-1) + 0.0008266571782*RI(-2) + 0.0008974988819*RS(-1) + 0.1618077594*RS(-2) - 0.001364145251*RD(-1) + 0.001991114806*RD(-2) - 0.0001927456217 RD = 0.03233284909*RI(-1) + 0.01251360226*RI(-2) + 1.275399865*RS(-1) - 0.1450771904*RS(-2) + 0.7343577367*RD(-1) + 0.1121099358*RD(-2) + 0.01397483645
February 1999-January 2011	RI = - 0.3043822972*RI(-1) - 0.06548906181*RI(-2) - 1.03325251*RS(-1) - 7.209639485*RS(-2) + 0.7771089465*RD(-1) - 0.4053252508*RD(-2) + 0.1457399131 RS = - 1.783579012e-05*RI(-1) + 0.0008266571782*RI(-2) + 0.0008974988819*RS(-1) + 0.1618077594*RS(-2) - 0.001364145251*RD(-1) + 0.001991114806*RD(-2) - 0.0001927456217 RD = 0.03233284909*RI(-1) + 0.01251360226*RI(-2) + 1.275399865*RS(-1) - 0.1450771904*RS(-2) + 0.7343577367*RD(-1) + 0.1121099358*RD(-2) + 0.01397483645

Reference period of data series	ARMA
February 1999-November 2011	$ri_t = 0,153 - 0,218 \cdot ri_{t-1} + \varepsilon_t$ $rs_t = 0,753 \cdot rs_{t-1} - 0,701 \cdot \varepsilon_{t-1} + \varepsilon_t$ $rd_t = 0,126 + 0,913 \cdot rd_{t-1} + \varepsilon_t$
February 1999-December 2011	$ri_t = 0,1534 - 0,218 \cdot ri_{t-1} + \varepsilon_{1t}$ $rs_t = 0,749 \cdot rs_{t-1} - 0,695 \cdot \varepsilon_{2t-1} + \varepsilon_{2t}$ $rd_t = 0,125 + 0,913 \cdot rd_{t-1} + \varepsilon_{3t}$
February 1999-January 2011	$ri_t = 0,154 - 0,217 \cdot ri_{t-1} + \varepsilon_t$ $rs_t = 0,761 \cdot rs_{t-1} - 0,715 \cdot \varepsilon_{t-1} + \varepsilon_t$ $rd_t = 0,123 + 0,914 \cdot rd_{t-1} + \varepsilon_t$

Reference period of data series	Models having variables with lags
February 1999-November 2011	$ri_t = 0,111 + 0,224 \cdot rd_{t-1} + \varepsilon_t$ $rd_t = 0,097 + 0,248 \cdot ri_{t-2} + 0,254 \cdot ri_{t-1} + \varepsilon_t$
February 1999-December 2011	$rd_t = 0,096 + 0,248 \cdot ri_{t-2} + 0,255 \cdot ri_{t-1} + \varepsilon_t$ $ri_t = 0,11 + 0,226 \cdot rd_{t-1} + \varepsilon_t$
February 1999-January 2011	$rd_t = 0,095 + 0,249 \cdot ri_{t-2} + 0,257 \cdot ri_{t-1} + \varepsilon_t$ $ri_t = 0,11 + 0,226 \cdot rd_{t-1} + \varepsilon_t$

Source: own calculations using EViews.

The forecasts based on these models are made for December 2011, January and February 2012 in the version of one-step-ahead forecasts.

Table 2. One-month-ahead forecasts based on econometric models

Inflation rate	VAR(2) models	ARMA models	Models with lags
December 2011	28,8438	28,83771	28,83325
January 2012	28,91652	28,91941	28,90285
February 2012	29,02535	29,02783	29,01578

Unemployment rate	VAR(2) models	ARMA models
December 2011	0,072676	0,072984
January 2012	0,069938	0,069827
February 2012	0,071453	0,071988

Interest rate	VAR(2) models	ARMA models	Models with lags
December 2011	0,064843	0,175941	0,171848
January 2012	0,101606	0,170376	0,143031
February 2012	0,047752	0,148866	0,143098

Source: own calculations using Excel.

The Assessment of Forecasts' Accuracy

A generalization of Diebold-Mariano test (DM) is used to determine whether the MSFE matrix trace of the model with aggregation variables is significantly lower than that of the model in which the aggregation of forecasts is done. If the MSFE determinant is used, according Athanasopoulos and Vahid (2005), the DM test can not be used in this version, because the difference between the two models MSFE determinants can not be written as an average. In this case, a test that uses a bootstrap method is recommended.

The DM statistic is calculated as:

$$DM_t = \frac{\sqrt{T} \cdot [tr(MSFE_{VAR(2)\ \mathrm{model}})_h - tr(MSFE_{ARMA\,\mathrm{model}})_h]}{s} = \frac{1}{s} \cdot \sqrt{T} \cdot [\frac{1}{T} \sum_{t=1}^{T} (em^2_{1,1,t} + em^2_{2,1,t} + em^2_{3,1,t} - er^2_{1,1,t} - er^2_{2,1,t} - er^2_{3,1,t})] \tag{1}$$

T-number of months for which forecasts are developed

$em_{i,h,t}$ – the h-steps-ahead forecast error of variable i at time t for the VAR(2) model

$er_{i,h,t}$ – the h-steps-ahead forecast error of variable i at time t for the ARMA

s – the square root of a consistent estimator of the limiting variance of the numerator

The null hypothesis of the test refers to the same accuracy of forecasts. Under this assumption and taking into account the usual conditions of central limit theorem for weakly correlated processes, DM statistic follows a standard normal asymptotic distribution. For the variance the Newey-West estimator with the corresponding lag-truncation parameter set to $h - 1$ is used.

On 3 months we compared in terms of accuracy the predictions for all the three variables, predictions made starting from VAR(2) models and ARMA models. The value of DM statistics (32,18) is greater than the critical one, fact that shows there are significant differences between the two predictions. The accuracy of forecasts based on VAR models is higher than that based on ARMA models.

VAR(2), ARMA models and the ones with lags have the tendency to underestimate the forecasted values of inflation rate. The predictions of inflation based on models with lag have the higher accuracy, the value close to zero for U1 confirming this observation as the other accuracy indicators that registered the lowest values. As the U2 Theil's statistic has values lower than one for al one-step-ahead forecasts, these predictions are better than those based on naïve model.

Table 3. Indicators of forecasts accuracy for the inflation rate

Inflation rate	Models used to build the forecasts		
Indicators of accuracy	VAR(2)	ARMA	Models with lag
RMSE	0,0746185	0,07450409	0,06625522
ME	0,0638	0,0635	0,0525
MAE	0,0638	0,0635	0,0525
MPE	0,0022	0,0015	0,0012
U1	0,001291	0,001289	0,001147
U2	0,93003	0,928368	0,825577

Source: own calculations using Excel.

For the unemployment rate the VAR(2) and ARMA models overestimate the forecasted values. The values registered by the indicators are contradictory, because some of the indicators of accuracy indicate a higher precision for predictions based on VAR(2) models (RMSE,MPE,U1), and the others consider that ARMA models should be used in forecasting the unemployment rate (MAE,ME). The unemployment rate forecasts based on VAR models are better than those obtained using the naïve model.

Table 4. Indicators of forecasts accuracy for the unemployment rate

Unemployment rate	Models used to build the forecasts	
Indicators of accuracy	VAR(2)	ARMA
RMSE	0,00214523	0,00220985
ME	-0,00031	-6,7E-05
MAE	0,002095	0,002056
MPE	-0,00387	-0,00047
U1	0,014997	0,015422
U2	0,995366	1,024536

Source: own calculations using Excel.

Table 5. Indicators of forecasts accuracy for the interest rate

Interest rate	Models used to build the forecasts		
Indicators of accuracy	VAR(2)	ARMA	Models with lag
RMSE	0,03403586	0,09931423	0,08942674
ME	0,034067	0,127728	0,115326
MAE	0,034067	0,127728	0,115326
MPE	1,099826	3,646275	3,24019
U1	0,387935	0,628847	0,602318
U2	3,258689	11,30977	10,36556

Source: own calculations using Excel.

The best forecasts for the interest rate are those based on VAR(2) models, all the indicators of accuracy having registered the lowest values. For all the presented models we observed the underestimation tendency for the predicted values. The forecasts based on proposed models have a lower acccuracy than those based on naive models.

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.

Simple exponential smoothing method (M1)

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

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

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

$$\min \frac{1}{n} \sum_{i=0}^{n-1} (R^{'}_{n+1} - \hat{R}^{'}_{n+1})^2 = \min \frac{1}{n} \sum_{i=0}^{n-1} e^2_{n+1} \tag{3}$$

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

$$\hat{R}^{'}_{n+1} = \alpha \times \sum_{i=1}^{n} (1-\alpha)^i \times \hat{R}^{'}_{n+1-s} \tag{4}$$

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:

$$R_{n+k} = a + b \times k \tag{5}$$

$$a_n = \alpha \times R_n + (1-\alpha) \times (a_{n-1} + b_{n-1}) \tag{6}$$
$$b_n = \beta \cdot (a_n - a_{n-1}) + (1-\beta) \cdot b_{n-1}$$

Finally, the prediction value on horizon k is:

$$\hat{R}_{n+k} = \hat{a}_n + \hat{b}_n \times k \tag{7}$$

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:

$$\hat{R}^{'}_{n+k} = (a_n + b_n \times k) \times c_{n+k} \tag{8}$$

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

$$\begin{aligned} a_n &= \alpha \times \frac{R^{'}_n}{c_{n-s}} + (1-\alpha) \times (a_{n-1} + b_{n-1}) \\ b_n &= \beta \times (a_n - a_{n-1}) + (1-\beta) \times b_{n-1} \\ c_n &= \gamma \times \frac{R^{'}}{a_n} + (1-\gamma) \times c_{n-s} \end{aligned} \tag{9}$$

The prediction is:

$$\hat{R}^{'}_{n+k} = (\hat{a}_n + \hat{b}_n \times k) \times \hat{c}_{n+k} \tag{10}$$

Holt-Winters additive exponential smoothing method (M4)

This technique is used when the trend is linear and the seasonal variation follows a multiplicative model. The smoothed data series is (14):

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

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

$$\begin{aligned} a_n &= \alpha \times (R^{'}_n - c_{n-s}) + (1-\alpha) \times (a_{n-1} + b_{n-1}) \\ b_n &= \beta \times (a_n - a_{n-1}) + (1-\beta) \times b_{n-1} \\ c_n &= \gamma \times (R^{'}_n - a_n) + (1-\gamma) \times c_{n-s} \end{aligned} \tag{11}$$

The prediction is:

$$\hat{R}^{'}_{n+k} = \hat{a}_n + \hat{b}_n \times k + \hat{c}_{n+k} \tag{12}$$

Double exponential smoothing method (M5)

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

$$S_n = \alpha \times R_n + (1-\alpha) \times S_{n-1}$$
$$D_n = \alpha \times S_n + (1-\alpha) \times D_{n-1} \quad (13)$$

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

Table 6. Forecasts of the exchange rate based on the specified models and techniques

Inflation rate	M1	M2	M3	M4	M5
December 2011	28.7098	28.8060	28.9149	28.8388	28.6947
January 2012	28.7098	28.9070	28.8114	28.9050	28.7316
February 2012	28.7815	28.8886	28.7183	28.8619	28.7950

Unemployment rate	M1	M2	M3	M4	M5
December 2011	0.0730	0.0731	0.0733	0.0732	0.0729
January 2012	0.0730	0.0732	0.0743	0.0741	0.0727
February 2012	0.0741	0.0701	0.0710	0.071	0.0695

Interest rate	M1	M2	M3	M4	M5
December 2011	0.0546	0.0493	0.0492	0.0516	0.0580
January 2012	0.0546	0.04936	0.0516	0.0492	0.0580
February 2012	0.0497	0.0444	0.0439	0.0513	0.0514

Source: own computations using EViews

Table 7. Measures of forecasts accuracy

Inflation rate	RMSE	ME	MAE	MPE	U1	U2
M1	0,139623	-0,13108	0,131084	-0,00454	0,002424	1,742829
M2	0,020535	0,002416	0,018917	8,49E-05	0,000356	1,204907
M3	0,145544	-0,04992	0,138771	-0,00172	0,002523	1,088624
M4	0,044529	0,003783	0,038084	0,000134	0,000771	1,142016
M5	0,128728	-0,12435	0,124351	-0,00431	0,0022	0,731673
Unemployment rate	RMSE	ME	MAE	MPE	U1	U2
M1	0,001933	0,0017	0,0017	0,023938	0,013327	0,887748
M2	0,002547	0,000467	0,0024	0,007075	0,017708	1,174125
M3	0,002594	0,0012	0,002533	0,01723	0,017942	1,201461
M4	0,002493	0,0011	0,002433	0,015828	0,01726	1,15401

Inflation rate	RMSE	ME	MAE	MPE	U1	U2
M5	0,002655	3,33E-05	0,002367	0,001069	0,018517	1,223844
Interest rate	RMSE	ME	MAE	MPE	U1	U2
M1	0,013872	0,015633	0,015633	0,496562	0,195873	1,594589
M2	0,013563	0,006923	0,01062	0,347335	0,157418	1,15881
M3	0,014619	0,007633	0,011233	0,368146	0,16851	1,208536
M4	0,015703	0,0077	0,013367	0,428523	0,176185	1,534473
M5	0,020443	0,012768	0,018467	0,576079	0,216784	1,798754

Source: own computations using Excel

All the techniques tend to underestimate the values of the variables, excepting the simple and the double exponential smoothing method for the inflation rate. For the inflation rate and the interest rate the Holt-Winters Simple exponential smoothing method (M2) generated the best forecasts and for the unemployment rate the simple exponential smoothing method (M1). Only the predictions of the inflation rate based on M5 and of the unemployment rate based on M1 are better than those based on naive model. The forecasts based on econometric models are better in terms of accuracy than those got using exponential smoothing techniques, because of the values of U1 that are closer to 1.

Conclusions

Analyzing the results of this research, we can use VAR models in making predictions about macroeconomic variables as unemployment rate or interest rate in Romania and the model with lags for the inflation rate. We got a higher accuracy for the forecasts based on econometric models unlike the ones based on smoothing techniques. This result implies that it is important to take into account all the previous values of the variables in making predictions, not only the recent ones like in the case of smoothing exponential methods.

To improve the policy we can use monthly forecasts based on econometric models instead of those obtained using smoothing methods. The policy is improved by choosing the most accurate forecast which will help the government or the bank in taking the best decisions.

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