The Evaluation of Forecasts Accuracy for Inflation Rate, Exchange Rate and Rate of Money Supply in Romania

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Abstract. The tasks of this research refer to the proposal of some econometric models to describe and predict the evolution of few macroeconomic indicators in Romania: inflation rate, exchange rate and rate of money supply. These econometric models were used as forecasting methods, the ex-post assessment of the predictions being made. Monthly forecasts were provided for index of consumer prices, but they are less accurate than the naïve predictions.

For exchange rate and rate of money supply the forecasts based on own econometric models were more accurate those based on random walk. For exchange rate more types of econometric models were built: GARCH(1,1), moving average model, simultaneous equations model, model with lag. Combined forecasts of exchange rate proved to be a good strategy of improving the accuracy of forecasts based on econometric models.

Key words: econometric model, forecast, accuracy, naïve forecasts, combined forecasts JEL Classification: C130, C150, C52, C53

1 Introduction

The main cause of the recent economic and financial crisis is the low accuracy of macroeconomic forecasts. Therefore, lately more researchers are interested in finding the forecast method that provides the most accurate predictions.

The problem that is studied in this research takes into account the necessity of improving the forecasts' accuracy by using a better econometric model from more proposed models. The level of problem analysis is limited to econometric models for the Romanian economy, a developing country. Previous studies regarding the accuracy of forecasts based on national econometric models were limited to few well-developed countries. For Romanian economy the researches are almost non-existent, excepting some studies of Simionescu (2013). The forecasts' evaluation in terms of accuracy should be done by each researcher that provides predictions regarding the evolution of an indicator. We should not easily accept a forecast or another unless we degree know the of uncertainty that each expectation. characterizes These predictions are used in making decisions and decider has to choose the forecasts with the minimum degree of accuracy or the forecast with the highest accuracy.

The aim of this research consists in selecting the best econometric model used as forecasting method, the selection criterion being the accuracy of forecasts based on these models. Therefore, the aim of the research can be divided in two major purposes. The forecasting method is a quantitative technique that is very used nowadays due to Econometrics' development. The experts in forecasting are also interested in this type of quantitative methods, the fast development of computational techniques making easier the use of complex A first purpose of this article is to models. propose more econometric models for describing the evolution of some macroeconomic variables as inflation rate. exchange rate or rate of money supply. Even if all these models are valid only some of them generate accurate forecasts. Another purpose is to find the econometric model that determined the most accurate predictions by computing specific accuracy measures. The mentioned problem could be solved if we choose the best econometric models. On the other hand, we can use other quantitative methods for making

predictions or just the experts' expectations. In this study we will take into consideration only differences between forecasts based on a single type of method: the econometric model.

2 Literature

The forecasts accuracy should be an important task for the forecasters, because each prediction has a certain degree of confidence. The error in forecasting might be high or low, the main objective being the choice of the prediction with the lowest error. In economic crisis period the accuracy has usually a tendency of decrease, but the interest in choosing the best forecast becomes primordial.

Many international institutions accompany their own forecasts by an assessment of the predictions accuracy. The most utilized forecasts provided bv are European Commission, OECD. IMF. Consensus Economics, Survey of Professional Forecasters (SPF), Congressional Budget Office, Blue Chips.

Liu and Smith (2014) compared the forecasts performance of inflation expectations from Greenbook, median forecasts of Survey of Professional Forecasters and other forecasts made by private forecasters. The conclusion was that Greenbook inflation predictions are better than all the private forecasts.

González Cabanillas and Terzi (2012) analyzed the accuracy of European Commission forecasts before and during the actual economic crisis. The authors also made a comparison with the predictions provided by International Monetary Fund, Consensus Economics and Organization Cooperation and Development. for Α deterioration of the Commission's forecasts accuracy was observed because of the high errors registered in 2009 for many variables like: inflation rate, government budget balance, GDP and investment. Frenkel, Rülke and Zimmermann (2013) observed that the private forecasters have a strategic behavior by placing the predictions away from those provided by OECD and IMF, this phenomenon having a period of 3 months.

Heilemann and Stekler (2013) assessed the accuracy of inflation and real GDP growth forecasts in Germany for the predictions provided by OECD and three German forecasters. The conclusions revealed that there is not a high improvement of forecasts accuracy during the last 10 years.

Clark and McCracken (2013) made a survey of recent literature related to the assessment of point and density predictions based on Vector Autoregressions. The properties of tests of accuracy are examined using Monte Carlo method and bootstrap techniques. Busetti and Marcucci (2013) used Monte Carlo method to assess the properties of some tests of forecast encompassing and equal mean square forecast errors using nested dynamic regressions. The authors compared the performance of models for GDP short run forecasts in the case of Italy.

Bratu (2012) showed that the filters and Holt Winters method could improve the accuracy of USA inflation forecasts of SPF more accurate predictions for inflation rate in USA, when the initial expectation are provided by SPF, Holt-Winters technique being better.

Deschamps and Bianchi (2012) observed high differences between China economic forecasts for variables like gross domestic product, inflation, consumption and investment.

Allan (2012) recommended the improvement of OECD GDP forecasts for G7 states by using the forecasts combinations. The evaluation of predictions accuracy is based on quantitative and qualitative methods.

Abreu (2011) assessed the accuracy of macroeconomic forecasts provided by OECD, IMF, European Commission, Consensus Economics and The Economist.

Lam, Fung and Yu (2008) compared the exchange rate predictions accuracy, indicating that combined forecasts are more accurate than the expectations based on a single model. Shittu and Yaya (2009) proved that ARFIMA models are a better forecast method than ARIMA models for the exchange rate forecasts in United Kingdom and USA.

Heilemann and Stekler (2007) observed the low accuracy of predictions provided for G7 countries, giving of arguments for this situation the improper forecast methods and non-realistic assumptions for the predictions' accuracy.

3 Modelling and predicting macroeconomic indicators in Romania

Some econometric models corresponding to macro-economic blocks are described, the data referring to Romanian economy. These econometric models are used as forecast predictions methods and are made for endogenous variables: index of consumer prices, exchange rate and rate of money supply. Moreover, some combined forecasts are proposed for exchange rate.

The macro-economic variables used in this study are: index of consumer prices, inflation rate, real GDP rate, interest rate, index of average exchange rate, exchange rate, index of unemployment change, rate of real money supply.

The index of consumer prices measures changes in the price level of a market basket of consumer goods and services purchased by households. The annual percentage change in the index of consumer prices is used as a measure of inflation.

The real GDP rate builds onto the GDP rate by taking into account the effect that inflation has on the economy. It is a measure of the rate of change that the nation's gross domestic product (GDP) experiences from one year to another. The GDP index in current prices is divided by the fixed base index of consumer prices (1990=100) in order to compute the real GDP index. The real GDP rate is calculated by subtracting 100 from the index expressed as percentage.

The interest rate targets are an important tool of monetary policy being taken into account when dealing with variables like investment, inflation, and unemployment. The Central Bank tends to reduce the interest rate when it wants to increase investment and consumption in the country's economy. The reference interest rate of the National Bank of Romania is the monetary policy interest rate fixed by the Administration Council.

The exchange rate between two currencies is the rate at which one currency will be exchanged for another. It is also regarded as the value of one country's currency in terms of another currency. In this research we used the average USD/RON exchange rate. The annual average exchange rate is computed as an arithmetic average of the monthly average USD/RON exchange rates.

The index of unemployment rate is computed as a ratio of the unemployment rate in the current period and the unemployment in the previous period. The unemployment rate is computed as the number of unemployed people over the total active population, the indicator being expressed as percentage.

The money supply represents the total stock of currency and the liquid instruments of a country at a certain moment of time.

The source of date for index of consumer prices, inflation rate, real GDP rate, unemployment rate is the National Institute of Statistics from Romania. The National Bank of Romania provides the data for annual average exchange rate, rate of money supply and interest rate targets.

For modelling the inflation rate some monthly data series were considered, covering the period 1997: January – 2011: December. Predictions on the horizon 2012: January- 2012: December were made. The data series for prices indices and exchange rate were firstly seasonally adjusted using Tramo/Seats method in EViews.

- *ICP_t* mobile base index of consumer prices in the period ,"t" (monthly data)
- *ler_{t-1}* index for average exchange rate in the previous period "t-1" (monthly data)
- *lu_{t-1}* index of change for the unemployment in the previous period "t-1" (monthly data)
- ε_t error term

The form of the model is: $ICP_t = c_0 \cdot Ier_{t-1}^{c1} \cdot Iu_{t-1}^{c2} \cdot \varepsilon_t$ (1)

For estimating the model's parameters and making the computations easier, the logarithm is applied to data series.

 $\ln _ICP_t = lnc_0 + c_1 \cdot lnIer_{t-1} + c_2 \cdot lnIu_{t-1} + ln\varepsilon_t$ (2)

The considered model is not valid in this form, the following model being used, with seasonally adjusted data series:

 $\ln \widehat{ICP}_{sa_{t}} = 0.408926 \cdot lnler_{sa_{t-1}} + 0.012138 \cdot lu_{sa_{t-1}}$ (3)

Further, we will test the assumptions of the regression model which is linear in parameters. H1. We check that the data are not affected by measurement errors. Therefore, 3 sigma rule is applied.

Each variable, generically denoted by VAR has to have values located in the interval:

$$VAR_t \in (\overline{VAR} - 3\sigma_{VAR}; \overline{VAR} + 3\sigma_{VAR})$$
 (4)

The averages and the standard deviations of the variables used in the regression model are taken from EViews' output.

The data are monthly and the seasonal factors should be eliminated and the stationary should be tested. Tramo/Seats method was used for the seasonal adjustment. The Augmented-DickeyFuller test in all the 3 variants is applied (model with constant, model with trend, model with trend and constant), the ADF statistic being lower than the critical values for 1%, %% and 10% level of significance. Therefore, we can conclude that the adjusted data series are stationary.

Tuble 1. Intervals for the v	alues of the modelled variables
Variable	Interval
logarithm of ICP	(-0.06627;0.100738)
Index of	(0.905042;0.101206)
unemployment	
Logarithm from index	(-0.00243;0.027217)
of exchange rate	
<i>~</i> .	

Table 1: Intervals for the values of the modelled variables

Source: own computations

H2. The hypothesis of errors independence using Durbin-Watson test (DW) (the lack of auto-correlation of order one is checked using DW test). The lower and the upper limits are taken from DW table, being 1.74, respectively 1.78. The value of the statistic computed by EViews program (1.118696) is lower than the inferior limit, fact that indicates a positive autocorrelation. The estimators are not efficient in this case and the errors auto-correlation should be removed.

The same conclusion is obtained when Breusch-Godfrey test is applied. The probability associated to this test is less than 0.05, the errors serial correlation being confirmed. According to Jarque-Bera test, the distribution of the error is not normal.



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Source: graph based on the model's residuals

White test indicates the errors homoscedasticity, the probability of 0.4285 (under 0.05) indicating that there is not enough evidence to reject the null hypothesis that states the homoscedasticity. The Newey-West technique solves the errors auto-correlation problem and the heteroscedasticity one. The standard errors and the t statistic values change in this case. The errors remain normally distributed.

For eliminate the disadvantages of the failure of the linear regression model assumptions, the coefficients will be estimated using the nonparametrical approach of bootstrap. for a number of 10 000 replications a new regression model was obtained with coefficients that were estimated by bootstrapping (the values of the variables were resampled :

$$\ln \underline{ICP}_{sa_{t}} = 0.395425 \cdot lnIer_{sa_{t-1}} + 0.012239 \cdot Iu_{sa_{t-1}}$$
(M1a) (5)

"Bootstrap coefficients" procedure was applied in EViews. In the second variant, the resample of the residual values was done, the model being:

$\ln \widehat{ICP}_{sa_{t}} = 0.408831 \cdot lnIer_{sa_{t-1}} + 0.01212 \cdot Iu_{sa_{t-1}}$ (M2a) (6)

The distribution of exogenous variables for all replications, the case of variables values resampling being shown below.



Figure 2. The distribution of exogenous variables in model M1a with bootstraped estimated coefficients Source: graph based on bootstrap estimated coefficients

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The range is greater for seasonally adjusted unemployment index, both distributions being leptokurtic. For appreciating the effect of introducing new data on the parameters stability, the Chow test is applied. The values for the last 6 months are considered "break points", the computed F statistic being lower than the critical one. Therefore, we can conclude that there is a relative stability of the parameters.

Forecasts are made using the M1a and M2a models on the horizon 2012: January- 2012: December.

 Table 2. Predicted Index of consumer prices based on econometric models on the horizon 2012: January- 2012: December

 Forecast

 Predicted ICP using M1a model:

Forecast	Predicted ICP using M1a model:		Predicted ICP using M2a model:			
horizon						
	Point forecasts	Forecast interv	vals	Point	Forecast intervals	
				forecasts		
		Lower limit	Upper limit		Lower limit	Upper limit
2012: January	1.0101	1.009222	1.010978188	1.0099	1.009021812	1.010778188
2012: February	1.0128	1.011922	1.013678188	1.0128	1.011921812	1.013678188
2012: March	1.0145	1.013622	1.015378188	1.0144	1.013521812	1.015278188
2012: April	1.0150	1.014122	1.015878188	1.0149	1.014021812	1.015778188
2012: May	1.0151	1.014222	1.015978188	1.0151	1.014221812	1.015978188
2012: June	1.0152	1.014322	1.016078188	1.0152	1.014321812	1.016078188
2012: July	1.0145	1.013622	1.015378188	1.0145	1.013621812	1.015378188
2012: August	1.0137	1.012822	1.014578188	1.0137	1.012821812	1.014578188
2012:September	1.0148	1.013922	1.015678188	1.0148	1.013921812	1.015678188
2012: October	1.0146	1.013722	1.015478188	1.0146	1.013721812	1.015478188
2012:November	1.0149	1.014022	1.015778188	1.0148	1.013921812	1.015678188
2012: December	1.0150	1.014122	1.015878188	1.0149	1.014021812	1.015778188

Source: own computations

According to the table, there are not significant differences between forecasts based on the two models and for some months there are the same values for the index of consumer prices on the horizon 2012:January- 2012: December. The forecast intervals based on M1a and M2a models have insignificant differences in length. The parameters bias is a measure of the uncertainty coming from modelling zone. The bias is computed as difference between estimations and the average of the 10 000 estimations based on simulation.

Table 3. Estimations for the M1a model parameters usingbootstrapping procedure and the biases

11 01		
Variable	Estimation of	Bias
	the associated	
	coefficient	
	(M1a model)	
Seasonally adjusted index	0.012138	-0.000101
of unemployment		
Logarithm of seasonally	0.408926	0.013501
adjusted index of		
exchange rate		
Seasonally adjusted index of unemployment Logarithm of seasonally adjusted index of exchange rate	coefficient (M1a model) 0.012138 0.408926	-0.000101 0.013501

Source: own computations

There are extremely low biases, especially for the seasonally adjusted index of unemployment.

Table 4.	Estime	ations for	the M	12a	model	parameters	using
bootstra	pping p	orocedure	and	the	biases		

Variable	Estimation of	Bias
	the associated	
	coefficient	
	(M2a model)	
Seasonally	0.012138	1.8 · 10 ⁻⁵
adjusted index of		
unemployment		
Logarithm of	0.408926	9.5 · 10 ⁻⁵
seasonally adjusted		
index of exchange		
rate		

Source: own computations

When the residuals are resampled, the estimations' bias is lower than in the case of exogenous variables values resampling.

The monthly data series for average EUR/RON exchange rate is provided by the National Bank of Romania for 1991:January- 2012: December.

Census X12 method is used for seasonal adjustment in the multiplicative form and the new series is denoted by er_t . Augmented Dickey-Fuller test, Phillips-Perron test and the efficient tests for stationary put into evidence the existence of unit root.

The elimination of stationary was done by transforming the data series applying the logarithm: $r_t = \ln er_t - ln_er_{t-1}$.

The data series for r_t is stationary, according to the results of ADF and KPSS tests. After the study of correlogram and Ljung-Box test's statistic, we can conclude that the errors are serial correlated.

An AR(1)-GARCH(1,1) model was estimated for the volatility under the hypothesis of normally distributed innovations :

$$\overline{\sigma_t^2} = 0.001233 + 0.3644$$

$$\cdot \varepsilon_{t-1}^2 + 0.5576 \cdot \sigma_{t-1}^2 - 0.0611 \cdot \varepsilon_{t-1}$$
(7)

The sum 0.3644+0.5576=0.922 is lower than 1 and the data series is covariant-stationary. The unconditional variance is calculated as:

 $\overline{\sigma_{\varepsilon}^2} = \frac{0.001233}{1 - 0.3644 - 0.5576} = 0.0158.$ (8)

A EGARCH(1,1) model was also estimated in the variant with distribution of generalized error, c having the following form: LOG(GARCH) = -0.414198649493 + 0.263166272258*ABS(RESID(-1)/@SQRT(GARCH(-1))) -0.0244707454186*RESID(-1)/@SQRT(GARCH(-1)) + 0.972417255403*LOG(GARCH(-1)) (2.25.) (9)

The negative value of C(5) (-0.024471) shows the existence of asymmetric effect, but it is insignificant.

The rate of real money supply M3 is predicted on the horizon 2011-2013 using annual data series (1994-2012) for variables like: rate of real GDP (1994=100), interest real rate, index of consumer prices. The data are provided by World Bank. The coefficients are estimated using bootstrapping technique with 10 000 replications.

rM_t- rate of real money supply M3

rPIB_t- rate of real GDP

ri_t- interest real rate

ICP_t- index of consumer prices compared to the value in 1994

Year	Econometric model used in making the prediction for that year
2011	$rM_t = 60.0261 - 18.3019 \cdot (\log GDP_r)_{t-1} + 0.6437 \cdot \Delta^2 ri_{t-1} + 68.6307 \cdot \Delta(\log(ICP_{t-1}))$
2012	$rM_t = 59.8337 - 18.1923 \cdot (\log GDP_r)_{t-1} + 0.6457 \cdot \Delta^2 ri_{t-1} + 68.6298 \cdot \Delta(\log(ICP_{t-1}))$
2013	$rM_t = 45.9526 - 3.3051 \cdot (\log GDP_r)_{t-1} + 0.1678 \cdot \Delta^2 ri_{t-1} + 23.3215 \cdot \Delta(\log(ICP_{t-1}))$

Source: own computations

The econometric models put in evidence a negative correlation between rate of real money supply and the logarithm of GDP and a positive correlation of the indicator with logarithm of differenced index of prices, respectively double differenced interest rate. On short-run the money supply should be positively correlated with GDP. In this case, the economic agents anticipate the inflation before the increase in money supply.

Table 6. One-step-ahead forecasts for rate of real money Image: Comparison of the state o
supply (%) on the horizon 2011-2013

Year	One-step-	Registered	
	ahead forecast	value	
2011	6.35	6.5	
2012	6.77	7.5	

2013	5.96	-
Source: own c	omputations	

For 2012 an increase in the money supply was anticipated, but it was not enough large. For 2013, a decrease in the money supply is predicted.

We proposed a simultaneous equations model for the exchange rate, taking into account the Granger causality between variables:

$$ICP_{t/0} = \alpha_0 + \alpha_1 er_{t-1} + \alpha_2 ICP_{t-1/0} + \varepsilon_1$$

$$er_t = \beta_0 + \beta_1 er_{t-1} + \beta_2 ICP_{t-1/0} + \varepsilon_2$$
(10)

where ICP_t – fixed base index of consumer

prices and er_t – monthly average exchange rate We also built a moving average model of order 1 and a model with lag, all the coefficients being estimated by stochastic simulations.

Table 7: Econometric models used to predict the exchange rate

Type of	Form of the model	
model		
Simultane	$er = 0.412 + 1.14 \cdot 10^{-5} \cdot ICP$	
ous		
equations	(E1)	
model	$ICP_{t} = 11362, 9 \cdot er_{t-1} + 0,8522 \cdot ICP_{t-1}$	
	(E2)	
MA(1)	$er = 0.117 + 0.356 \cdot \varepsilon_{-1} + \varepsilon_{-1}$	
model		
Model	$er = 0.4306 \pm 6.03 \cdot 10^{-6} \cdot ICP \pm 5.43 \cdot 10^{-6}$	10-
with lag	$r_{t} = 0, 1000 + 0,00 + 0,00 + 0,00 + 0,00 + 0,00 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 + 0,000 +$	10
-		

The models are used to make predictions for 2012: October- 2012: December.

Table 8. Exchange rate forecasts based on the mentioned models

Month	Simultaneous	Model	MA(1)
	equations	with	model
	model	lag	
October	4.8122	4.5271	3.9422
2012			
November	4.8307	4.5588	4.5206
2012			
December	4.8279	4.5659	5.1819
2012			

Source: own computations

The combined forecasts are another possible strategy of getting more accurate predictions. The most utilized combination approaches for combined predictions are presented in the following scheme:

- variable Xt;
- f1;t and f2;t, two forecasts corresponding to variable Xt;
- forecast error: $e_{i,t} = X_{i,t} f_{i,t}$. (under the assumption of normal distribution of errors with parameters 0 and σ_i^2 .);

combined forecast:

$$c_t = m \cdot f_{1t} + (1 - m) \cdot f_{2t}$$

• optimal combination (OPT):

$$m_{opt} = \frac{\sigma_2^2 - \sigma_{12}}{\sigma_1^2 + \sigma_2^2 - 2 \cdot \sigma_{12}}$$
(11)

• equal-weights-scheme (EW): the same weights to all models

• inverse mean square error weighting

scheme (INV):
$$m_{inv} = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}$$
 (12)

The variance-covariance matrix is computed in order to determine the weights that are necessary in making the combined forecasts on 3 months.

Table 9. Combined forecasts of the exchange rate (horizon 2012: October- 2012: December) using the econometric models

econometric moae	els		
Predictions	OPT	INV	EW
based on	scheme	scheme	scheme
simultaneous			
equations			
models and			
models with			
lag			
October 2012	5.0171	4.8157	4.8212
November	4.7793	4.8306	4.8304
2012			
December	4.6721	4.6969	4.6968
2012			

Predictions			
based on			
simultaneous			
equations			
models and			
MA(1)			
October 2012	5.4374	4.8229	4.8397
November	4.7721	4.8306	4.8304
2012			
December	5.0383	5.0049	5.0051
2012			
Predictions			
based on			
MA(1) models			
and models			
with lag			
October 2012	4.9475	4.5343	4.5456
November	4.5516	4.5588	4.5588
2012			
December	4.9321	4.8740	4.8742
2012			

Source: own computations

For December 2012 the forecasts based on models with lag and MA(1) models are lower than those for November 2012. For the other combined forecasts the values in December are greater than the previous month.

4 The assessment of forecasts accuracy

 $\hat{X}_t(k)$ is the forecasted value after k time periods compared to the origin time t. The error at a future time (t+k) is: $e_t(t+k)$ being computed as the difference between the effective value and the predicted one. Some accuracy indicators are computed for the

predictions based on econometric models:

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum_{j=1}^{n} e_{X}^{2} (T_{0} + j, k)}$$
(13)

Mean error

$$ME = \frac{1}{n} \sum_{j=1}^{n} e_{X} \left(T_{0} + j, k \right)$$
(14)

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If ME has a positive value, then there are too small in average predictions, while the negative value of ME supposes overestimated values.

Mean absolute error (MAE)

$$MAE = \frac{1}{n} \sum_{j=1}^{n} | e_{X}(T_{0} + j, k) |$$
(15)

Theil (1966) proposed the comparison of forecasts with the naïve ones (based on random walk model) and he used U statistic that later was developed in 2 forms:

a- the registered results p- the predicted results t- reference time e- the error (e=a-p) n- number of time periods

U1Theil's coefficient

$$U_{1} = \frac{\sqrt{\sum_{t=1}^{n} (a_{t} - p_{t})^{2}}}{\sqrt{\sum_{t=1}^{n} a_{t}^{2}} + \sqrt{\sum_{t=1}^{n} p_{t}^{2}}}$$
(16)

A value close to zero for U_1 implies a higher accuracy.

U2 Theil's coefficient

$$U_{2} = \sqrt{\frac{\sum_{t=1}^{n-1} (\frac{p_{t+1} - a_{t+1}}{a_{t}})^{2}}{\sum_{t=1}^{n-1} (\frac{a_{t+1} - a_{t}}{a_{t}})^{2}}}$$
(17)

If $U_2 = 1 \Rightarrow$ no differences between predictions If $U_2 < 1 \Rightarrow$ the forecast to compare is better If $U_2 > 1 \Rightarrow$ the forecast to compare is less accurate

400

Accuracy		
indicator	ICP forecasts based on :	
	M1a model	M2a model
ME	-0.010615	-0.010558
MAE	0.010615	0.010558
RMSE	0.011289	0.011241
U1	0.005595	0.005571
U2	2.672410	2.660085

Table 10.	Measures	of forecasts	accuracy for ICP
		55	2.2

Source: own computations

An overestimation of the ICP and GDP forecasts was registered on 2010-2012. The equal values in absolute change for ME and MAE of inflation show the persistence of this overestimation. Even if all the inflation forecasts are less accurate than the naive ones, a slow superiority was obtained for predictions based on M2a model.

Table 11. Ex-ante accuracy measures for forecast in 2013 of rate of money supply

Accuracy indicator	Rate of monetary supply
Error	1.54
Absolute error	1.54
Percentage error	0.2053
U1 Theil's coefficient	0.1144

Source: own computations

The forecast evaluation for 2013 is made under the assumption of keeping the same value registered in 2012. The forecast error of the rate of monetary supply will increase with 20.53% in 2013 compared to the effective value in 2012.

Table 12. Accuracy indicators for rate of monetary supply (horizon: 2011-2012)

Accuracy indicator	Rate of monetary supply
ME	0.44
MAE	0.44
RMSE	0.5269

U1	0.0388
U2	0.7151
Source: own computations	

Source: own computations

For the rate of monetary supply the predictions are better than the naive ones, U1 statistic having an extremly low value (0.04). The monetary supply underestimation is persistent, MAE and ME having the same value.

According to Appendix 1 and Appendix 2, the accuracy of dynamic and static forecasts made for exchange rate (2012: January- 2012: December) using GARCH(1,1) model is rather low. However, the dynamic predictions are better than the statis ones. The Appendix 3 and Appendix 4 show lower accuracy for forecasts based on EGARCH(1,1) model, the dynamic one being better again than the static prediction.

Table 13. Accuracy of exchange rate forecasts based on proposed econometric models on the horizon 2012: October- 2012: December

Accuracy indicator	Simultaneous equations	Model with	MA(1) model
	model	lags	
U1	0.0322	0.0057	0.0588
U2	0.1450	0.8495	0.0813

Source: own computations

The predictions based on the models with lags are the most accurate on the horizon 2012: October- 2012: December. All the forecasts made using the proposed econometric models are better than the naive forecasts.

Table 14. Accuracy of combined exchange rate forecasts based on proposed econometric models on the horizon 2012: October- 2012: December

Accuracy	Combined forecasts based on		
measure	simultaneous equations models		
	and	models with	lags
Scheme:	OPT	INV	EW
U1	0.0343	0.0279	0.0281
U2	0.1358	0.1682	0.1671
	Combine	ed forecasts	based on
	simultaneous equations models		
	and $MA(1)$ models		
	OPT	INV	EW
U1	0.0640	0.0402	0.0406
U2	0.0707	0.1155	0.1142
	Combined forecasts based on		
	MA(1) models and models with		
	lags		
	OPT	INV	EW
U1	0.0365	0.0243	0.0244
U2	0.1278	0.1954	0.1956

Source: own computations

All the combined forecasts based on the exchange rate models are better than the naive ones. All the combined predictions based on INV scheme are more accurate than those based on MA(1) models. Excepting the forecasts of simultaneous equations models and MA(1) models, the forecasts based on INV scheme are better than those based on simultaneous equations models.

5 Conclusions

We used different econometric models to predict the evolution of inflation rate, exchange rate and rate of menetary supply in Romania. The assessment of these predictions was based on some accuracy measures as mean errors, mean absolute errors, root mean squared errors, U1 and U2 statistics. The evaluation of forecasts accuracy was done in the ex-post version to draw a certain conclusion regarding the past forecasting process.

The naive forecasts provided for inflation rate more accurate appreciations. For exchange rate and rate of money supply our econometric models were better than those based on random walk. Combined forecasts of exchange rate proved to be a good strategy of improving the accuracy of forecasts based on econometric models.

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Appendices

APPENDIX 1

Dynamic exchange rate forecast for 2012: January- 2012: December using GARCH(1,1) model

Forecast: RF Actual: R Forecast sample: 2012M01 2012M12 Adjusted sample: 2012M02 2012M12 Included observations: 11

Root Mean Squared Error	0.008201
Mean Absolute Error	0.007341
Mean Absolute Percentage Error	165.6112
Theil Inequality Coefficient	0.563165
Bias Proportion	0.140644
Variance Proportion	0.831891
Covariance Proportion	0.027465

APPENDIX 2

Static exchange rate forecast for 2012: January- 2012: December using GARCH(1,1) model

Forecast: RF Actual: R Forecast sample: 2012M01 2012M12 Adjusted sample: 2012M03 2012M12 Included observations: 10

Root Mean Squared Error

0.009167

Mean Absolute Error	0.008075
Mean Absolute Percentage Error	199.0254
Theil Inequality Coefficient	0.598940
Bias Proportion	0.017818
Variance Proportion	0.111400
Covariance Proportion	0.870782

APPENDIX 3

Dynamic exchange rate forecast for 2012: January- 2012: December using EGARCH(1,1) model

Forecast: RF Actual: R Forecast sample: 2012M01 2012M12 Included observations: 12

Root Mean Squared Error	0.007846
Mean Absolute Error	0.006914
Mean Absolute Percentage Error	112.6913
Theil Inequality Coefficient	0.715303
Bias Proportion	0.013196
Variance Proportion	0.697093
Covariance Proportion	0.289711

APPENDIX 4

Static exchange rate forecast for 2012: January- 2012: December using EGARCH(1,1) model

Forecast: RF Actual: R Forecast sample: 2012M01 2012M12 Included observations: 12

Root Mean Squared Error	0.008574
Mean Absolute Error	0.007695
Mean Absolute Percentage Error	184.4470
Theil Inequality Coefficient	0.613872
Bias Proportion	0.000761
Variance Proportion	0.099602
Covariance Proportion	0.899637