

# MODELING AND FORECASTING THE EXCHANGE RATE IN ROMANIA

Author:

Mihaela BRATU\*

**A***bstract.* Econometric modeling of the exchange rate saw successive progresses, the forecasts based on the '70s models having a rather good accuracy, as recent researches showed. *In order to explain the monthly evolution of RON/USA exchange rate during 2007-June 2011, I used three econometric models: a simultaneous equations model, an autoregressive model of order 1 and a model respecting the sense of Granger causality. From the statistical analysis of forecasting accuracy for one-month-ahead forecasts for July and August 2011 based on these models I found that the best predictions are those based on the model that is compatible with the sense of Granger causality. The higher errors are those of the forecasts based on the AR(1) model. The importance of knowing the best exchange rate forecasts is related to the improvement of decision-making and the building of the monetary policy.*

*Keywords:* exchange rate, forecasts, accuracy, Granger causality

*JEL Classification:* E27, C51, C52, C53

## I. Introduction

The determination of the exchange rate and its prediction are key issues at the macroeconomic level, especially for central banks interested in the monetary policy establishment. Although several methodologies have been developed in

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\* Academy of Economic Studies, Faculty of Cybernetics, Statistics and Economic Informatics, Bucharest, email: mihaela\_mb1@yahoo.com

order to determine the exchange rate, the recent researches have invalidated the ideas set out in literature. Thus, Engle (2006) showed that simple econometric models generate predictions with high accuracy. Therefore, we used in this article three econometric models to explain the exchange rate evolution, evaluating the accuracy of the forecasts based on these models.

## **II. The determination of the exchange rate in literature**

Econometric modeling of the exchange rate is applicable both in the analysis of the indicator's past evolution and in making predictions. Engel (2006) shows that since the '70s of the last century models revealed the role in assets price that the exchange rate had. Currently the emphasis is on the assumption of expectations that is taken into account in building the model for the exchange rate. Meese and Rogof (1984) showed that for the '70s exchange rate forecasts based on random walk models have a higher degree of accuracy than those based on a naive model. Empirical models of the 70s and 80s generally take into account too superficially the endogenous character of monetary policy. Authors such as Engel and West (2006), Mark (2007), Clarida and Waldman (2006) and Molodtsova and Papell (2007) evaluated the performance of empirical models based on Taylor rules for monetary policy.

Mark's research (1995) shows that achieving long-term forecasts based on nonlinear models ensures a high degree of accuracy. Many of the models explain the dependent variable (the exchange rate) as a weighted sum of variables that make up this variable, variables called "fundamentals". Campbell and Shiller (1987) made predictions of fundamentals starting from the exchange rate, under their variations to the exchange rate values. If the fundamentals are integrated of first-order and the discount factor is close to 1, Engel and West (2006) showed that the exchange rate followed a random walk process.

Meese and Rogoff (1983 and 1984) and Frankel and Rose (1995) show the difficulty of determining the exchange rate. According to Popescu (2006), many authors have used a panel data set or high volume data series and they concluded that the reduced econometric models provide a good estimate of the exchange rate. In literature there are theories of monetary exchange rate model, the first ones belonging to David Hume. In this model the prices are perfectly flexible, and GDP is an exogenous variable. In order to quantify the impact of the exchange rate on macroeconomic indicators, estimates of exchange rate based on purchasing power parity theory (PPP) were used. Popescu (2006) shows that the Harrod-Balassa-Samuleson model is used as an alternative to this

theory. Numerous methodologies appeared to determine the exchange rate, the best known being: the fundamental equilibrium exchange rate methodology of Williamson, the natural equilibrium real rate methodology of Stein and the one of Fundamental Equilibrium Exchange Rate of Clark and MacDonald (1999). Stein's methodology, called NATREX (Natural Real Exchange Rate), determines the real exchange rate based on variables that explain the current account, investment and saving.

The approach of Clark and MacDonald (2000), called FEER (Fundamental Equilibrium Exchange Rate) is based on the concept of balance of macroeconomic equilibrium, the exchange rate determined as being a normative measure corresponding to the ideal conditions in the economy. BEER model uses, to explain the real exchange rate evolution, a reduced equation, the econometric methods used being based on VEC methodology (Vector Error Correction ) of Johansen (1995).

Bacchetta and van Wincoop (2006) used for determining the exchange rate a simple model in which agents have information about future values of fundamentals. Clarida and Waldman (2007) concluded that when a high inflation rate is announced, there is a tendency of appreciation of the exchange rate. The models that follow the Taylor's rule reflect just the observation of the two authors: the tendency of appreciation of the exchange rate amid the increase of inflation rate.

Herciu and Toma (2006) considered that, in Romania, competitiveness can be considerably improved through real exchange rate appreciation and economic freedom growth. The equilibrium real exchange rate can be influenced by: the degree of openness, fiscal policy, trade policy, the intensity of capital flows and the development of the financial system.

Williamson (2007) shows that authors like Mark and Sul (2001) and Groen (2005) used error correction models of panels in order to achieve the long-term forecasts of the exchange rate. These predictions proved to be superior to those based on a random walk model.

Williamson (2008) made several important observations on the current theory to determine the floating exchange rate. The author identified the limits of the standard model of Rogoff and he proposed, as an alternative, a behavioral model. In order to resolve the economic problem of Germany, understanding of foreign exchange market mechanism is indicated.

Using the survey data about market expectations of exchange rate, Hauner, Lee, and Takizawa (2011) showed that they are correlated with the inflation and

productivity differentials. This conclusion implies that the marketing expectations are formed under the influence of Balassa-Samuelson effect and relative PPP theory.

Trenca and Cociuba (2011) used models such as GARCH, TGARCH and GARCH-in to explain the evolution of the exchange rate. In order to choose the best model the authors used criteria such as: Akaike Information Criteria, Bayesian Information Criteria and minimizing the value of the sum of squared errors.

Făt Codruța și Dezsi (2011) showed the superiority of techniques of exponential smoothing in modeling and predicting the exchange rate unlike the ARMA models.

Zapodeanu and Cociuba (2010) proposed an ARCH model to describe the evolution of the exchange rate in Romania.

### **III. The evaluation of forecast accuracy**

Forecast accuracy is a large chapter in the literature aimed at assessing forecast uncertainty. There are two methods used to compare the quality of forecasts: vertical methods (for example, the mean square error of prediction) and horizontal methods (such as distance in time). A comprehensive coverage of the issue taking into account all the achievements of the literature is impossible, but we outline some important conclusions.

To assess the forecast performance, as well as related ordering, statisticians have developed several measures of accuracy. For comparisons between the MSE indicators of forecasts, Granger and Newbold proposed a statistics. Another statistics is presented by Diebold and Mariano for comparison of other quantitative measures of errors. Diebold and Mariano 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 new statistics 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 in 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 the 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:

$$\rightarrow \text{Mean-Square Error (MSE)} = \text{average} (e_t^2) \quad (1)$$

$$\rightarrow \text{Root Mean Square Error (RMSE)} = \sqrt{MSE} \quad (2)$$

$$\rightarrow \text{Mean Absolute Error (MAE)} = \text{average} (|e_t|) \quad (3)$$

$$\rightarrow \text{Median Absolute Error (MdAE)} = \text{median} (|e_t|) \quad (4)$$

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

- Scale-independent errors:

*-> Measures based on percentage errors*

The percentage error is given by:

$$p_t = \frac{e_t}{X_t} \cdot 100 \quad (5)$$

The most common measures based on percentage errors are:

$$* \text{ Mean Absolute Percentage Error (MAPE)} = \text{average} (|p_t|) \quad (6)$$

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\* Median Absolute Percentage Error (MdAPE) = median ( $|p_t|$ ) (7)

\* Root Mean Square Percentage Error (RMSPE) = geometric mean ( $p_t^2$ ) (8)

\* Root Median Square Percentage Error (RMdSPE) = median ( $p_t^2$ ) (9)

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, i.e. too large penalizing made to positive errors in comparison with the negative ones.

\* Mean Absolute Percentage Error (sMAPE) = average ( $\frac{|X_t - F_t|}{X_t + F_t} \cdot 200$ ) (10)

\* Symmetric Median Absolute Percentage Error (sMdAPE) = median

( $\frac{|X_t - F_t|}{X_t + F_t} \cdot 200$ )..... (11)

where:  $F_t$  - forecast of  $X_t$ .

-> Measures based on relative errors

It is considered that  $r_t = \frac{e_t}{e_t^*}$  (12)

where:  $e_t^*$  is the forecast error for the reference model.

\* Mean Relative Absolute Error (MRAE) = average ( $|r_t|$ ) (13)

\* Median Relative Absolute Error (MdRAE) = median ( $|r_t|$ ) (14)

\* Geometric Mean Relative Absolute Error (GMRAE) = geometric mean ( $|r_t|$ ) (15)

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

->Relative measures

For example, the relative RMSE is calculated:

$$rel\_RMSE = \frac{RMSE}{RMSE_b} \quad (16), \text{ where } RMSE_b \text{ is the RMSE of "benchmark model".}$$

Relative measures can be defined for MFA MdAE, MAPE. When the benchmark model is a random walk, rel\_RMSE is used, which is actually Theil's U statistics. 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.

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

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

Other authors, like Fildes and Steckler (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.

A. Independent measures of accuracy

In this case, a loss function is usually used, but we can also choose the distance criterion proposed by Granger and Jeon for evaluating forecasts based on economic models. The most used indicators are:

- a) Mean Square Error (MSE)
- b) Root Mean Squared Error (RMSE)
- c) Generalized Forecast Error Second Moment (GFESM)
- d) Mean Absolute Percentage Error (MAPE)
- e) Symmetric Median Absolute Percent Error (SMAPE)
- f) Mean error (ME)
- g) Mean absolute error (MAE).

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

- Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum_{j=1}^n e_x^2(T_0 + j, k)} \quad (17)$$

- Mean error (ME)

$$ME = \frac{1}{n} \sum_{j=1}^n e_x(T_0 + j, k) \quad (18)$$

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

- Mean absolute error (MAE)

$$MAE = \frac{1}{n} \sum_{j=1}^n |e_x(T_0 + j, k)| \quad (19)$$

These measures of accuracy have some disadvantages. For example, RMSE is affected by outliers. Armstrong and Collopy stress that these measures are not independent of the unit of measurement, unless 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 propose 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.

### *B. Measures for the evaluation of the relative accuracy of forecasts*

Relative accuracy measures are related to the comparison of the forecast with a forecast of reference, found in the literature as the 'benchmark forecast' or 'naive forecast'. However, it is a subjective step to choose the forecast used for comparison. Problems that may occur in this case are related to these aspects: the existence of outliers or inappropriate choice of models used for predictions and the emergence of shocks. A first measure of relative accuracy is Theil's U statistic, which uses as a reference forecast the last observed value recorded in



the data series. Collopy and Armstrong proposed instead of U a new similar indicator (RAE). Thompson improved MSE indicator, suggesting a statistically determined MSE-log mean squared error ratio.

A common practice is to compare the forecast errors with those based on a random-walk. "The naive model" method assumes that the variable value in the next period is equal to the one recorded at the present moment. U-Theil proposed the calculation of U, which takes into account both changes in the negative and the positive sense of an indicator:

$$U = \sqrt{\frac{\sum (X_{t+k} - \hat{X}_t(k))^2}{\sum X_{t+k}^2}}. \quad (20)$$

Hyndman and Koehler proposed scale errors based on the mean absolute error of a naive forecasting method. MAE serves, therefore, as denominator. Using this method, the one-step-ahead forecast is generated. Scale error is defined as:

$$es_t = \frac{e_t}{\frac{1}{n-1} \sum_{i=2}^n |X_i - X_{i-1}|} \quad (21)$$

and mean absolute scale error as:  $MASE = \text{mean } |es_t|$  (22)

The naive forecast values are considered to be the current ones recorded during the previous period. MASE is used both to compare forecast methods applied to a given set of data and to compare the accuracy of several series. If the scale error is less than 1, the compared forecast is better than the reference one (naive forecast).

#### IV. Modeling and predicting the exchange rate in Romania.

##### The evaluation of forecasts accuracy

The purchasing power parity theory in its relative form, after Pecian (2005), establishes that in case of two currencies initially in equilibrium the exchange rate evolves to those values that are obtained by variations in the relative prices of the two selected states.

In Romania, a frequent cause of prices increase is the variation in leu/USA dollars exchange rate. Using the Granger causality methodology I checked that

in 2007-2011 the price variation determined changes in exchange rate. I estimated and I tested the parameters of regressions models below:

$$\begin{aligned} IPC_{t/0} &= \alpha_0 + \alpha_1 CS_{t-1} + \alpha_2 IPC_{t-1/0} + \varepsilon_1 \\ CS_t &= \beta_0 + \beta_1 CS_{t-1} + \beta_2 IPC_{t-1/0} + \varepsilon_2 \end{aligned} \quad (23)$$

where  $IPC_t$  – consumer price index with fixed based

$CS_t$  – RON/USD rate exchange.

There are monthly data series for CPI and the exchange rate and it covers the period from 2007 to 2011, as published by the National Institute of Statistics and, the National Bank of Romania respectively. The model that explains the exchange rate evolution in current period based on CPI and the rate exchange in period is the only valid model. The relation between CPI and the exchange rate may be explained in Granger causality terms.

Pairwise Granger Causality Tests			
Date: 11/19/11 Time: 13:45			
Sample: 2007:01 2011:06			
Lags: 2			
Null Hypothesis:	Obs	F-Statistic	Probability
IPC does not Granger Cause CS	52	4.51565	0.01608
CS does not Granger Cause IPC		0.20464	0.81566

A value less than 0.05 for the probability displayed by Eviews implies the rejection of null hypothesis. So, in a probability of 95%, I concluded that the CPI variation is a cause of exchange rate change in 2007-2011.

The data series for exchange rate is stationary, but the elimination of seasonal factors was necessary. I seasonally adjusted the data series for CPI.

### *Models proposed for one-month-ahead prediction of the exchange rate*

In order to explain the exchange rate evolution few models were built.

#### *1. Simultaneous equations model (model A)*

$$CS_t = 3,08 \cdot 10^{-5} \cdot IPC_t + 0,62 \cdot CS_{t-1} \quad (24)$$

$$IPC\_SSA_t = 0,678 \cdot IPC\_SSA_{t-1} + \varepsilon_t \quad (25)$$

The exchange rate (CS) in current period depends on the actual CPI and the exchange rate from the previous period. To determine the CPI we used an autoregressive model. Here  $CS_t$  is an endogenous variable, while  $CS_{t-1}$  is an exogenous one. Actually, this model combines the economic theory with backward looking at the evolution of CPI.

Dependent Variable: CS				
Method: Least Squares				
Date: 11/09/11 Time: 19:26				
Sample(adjusted): 2007:02 2011:06				
Included observations: 53 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
IPC	3.08E-05	9.21E-06	3.344375	0.0016
CS(-1)	0.623725	0.108994	5.722579	0.0000
R-squared	-0.011538	Mean dependent var		27.58172
Adjusted R-squared	-0.031372	S.D. dependent var		4.999774
S.E. of regression	5.077594	Akaike info criterion		6.124558
Sum squared resid	1314.880	Schwarz criterion		6.198908
Log likelihood	-160.3008	Durbin-Watson stat		2.419128

Dependent Variable: IPC_SSA				
Method: Least Squares				
Date: 11/09/11 Time: 19:17				
Sample(adjusted): 2007:03 2011:06				
Included observations: 52 after adjusting endpoints				
Convergence achieved after 2 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.678638	0.102843	6.598790	0.0000
R-squared	-0.558450	Mean dependent var		1788.770
Adjusted R-squared	-0.558450	S.D. dependent var		1314.160
S.E. of regression	1640.569	Akaike info criterion		17.66252
Sum squared resid	1.37E+08	Schwarz criterion		17.70004
Log likelihood	-458.2255	Durbin-Watson stat		2.395494

Inverted AR Roots	.68
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By applying the ADF test to EViews I found that the data series for CPI presented a unit root. I stationarized the data series and I used the new data series to estimate different ARMA models.

The only valid model was AR(1) and it was used to make one-month-ahead forecasts for July and August 2011. The predicted values from (25) equation were introduced into (24) equation, getting after the computations forecasted values of the exchange rate.

## 2. Model that takes into account the sense of Granger causality (model B)

$$CS_t = 0,622 \cdot CS_{t-1} + 3,11 \cdot 10^{-5} \cdot IPC_{t-1} \quad (26)$$

The exchange rate in the current period depends on the same variable and on the CIP, but from the previous period. Actually, we developed a model with lagged variables.

We applied the Granger test of causality to EViews and we found that the previous CPI and exchange rate are causes for the current exchange rate. This relationship is in accordance with the economic theory and the model based on it is valid.

Dependent Variable: CS				
Method: Least Squares				
Date: 11/03/11 Time: 15:00				
Sample(adjusted): 2007:02 2011:06				
Included observations: 53 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
CS(-1)	0.622366	0.108955	5.712124	0.0000
IPC(-1)	3.11E-05	9.25E-06	3.358280	0.0015
R-squared	-0.010024	Mean dependent var		27.58172
Adjusted R-squared	-0.029828	S.D. dependent var		4.999774
S.E. of regression	5.073794	Akaike info criterion		6.123060
Sum squared resid	1312.912	Schwarz criterion		6.197411
Log likelihood	-160.2611	Durbin-Watson stat		2.419021

### 3. Autoregressive model (AR(1))

The data series for the exchange rate was stationary, so I eliminated only the seasonal factors. According to latest researches the nonstructural forecasting tends to generate better results than complex models. One of the recommendations of researchers in forecasting is the utilization of simple models, ARMA procedure generating good results. An AR(1) model was identified for the exchange rate in Romania in 2007- June 2011. There is no autocorrelation between errors. A disadvantage of AR models is that they are 'backward looking'. Actually, the ARMA procedure fails to predict turning points.

$$CSsa_t = 0,98 * CSsa_{t-1} + u_t \quad (27)$$

Dependent Variable: CSSA				
Method: Least Squares				
Date: 11/09/11 Time: 19:11				
Sample(adjusted): 2007:02 2011:06				
Included observations: 53 after adjusting endpoints				
Convergence achieved after 2 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.980036	0.025848	37.91488	0.0000
R-squared	-0.204884	Mean dependent var		27.62359
Adjusted R-squared	-0.204884	S.D. dependent var		4.817304
S.E. of regression	5.287821	Akaike info criterion		6.187377
Sum squared resid	1453.974	Schwarz criterion		6.224552
Log likelihood	-162.9655	Durbin-Watson stat		2.841723
Inverted AR Roots	.98			

I made one-month-ahead forecasts for July and August 2011 and I evaluated their accuracy by using some of the indicators proposed by Hyndman and Koehler (2005) and a test of accuracy.

Table 1. One-month-ahead forecasts for the exchange rate based on the specified models

	Simultaneous equations model (model A)	Model that takes into account the sense of Granger causality (model B)	Autoregressive model (AR(1)) (model C)
July 2011	24.22	28.11	23.82
August 2011	29.93	30.14	29.09

Table 2. Measures of forecasts accuracy

	RMSM	ME	MAE	MASE	U Theil's statistics	Rel_RMSM between models A and B
Model A	3.89	-2.38	2.85	0.76	0.13	3.04
Model B	1.28	-0.34	1.02	0.27	0.04	
Model C	4.15	-3,006	3.22	0.85	0.14	

Analyzing the accuracy indicators, I got the highest degree of accuracy for the predictions based on the model that respects the Granger causality relation and the lowest one for forecasts based on the autoregressive model. The subunit values of the MASE indicator and of the U Theil's statistics show the superiority of forecasts based on specified models compared to those based on random walk. Using the relative RMSM indicator I compared in terms of accuracy the predictions based on the A and B models. The value 3.04, higher than 1, brings us to the conclusion that the best model for forecasts is the one that respects the Granger causality. The negative values for MAE show the tendency to overestimate the exchange rate for all forecasts. In literature some researchers concluded that if the predictions based on econometric models are overestimated, the structural shocks were not included. Indeed, our simple econometric models do not take into account the structural shocks in horizon forecasts, but the results are quite good, accomplishing the task of a simple model that determined the best predictions.

A generalization of the Diebold-Mariano test (DM) is used to determine whether the MSFE matrix trace of the model A is significantly lower than that of the model of B. If the MSFE determinant is used, according Athanasopoulos and Vahid (2005), the DM test cannot be used in this version, because the difference between the two models MSFE, determinants cannot be written as an average.

In this case, a test that uses a bootstrap method is recommended. The DM statistics is calculated as:

$$DM_t = \frac{\sqrt{T} \cdot [tr(MSFE_A)_h - tr(MSFE_B)_h]}{s} = \frac{1}{s} \cdot \sqrt{T} \cdot \left[ \frac{1}{T} \sum_{t=1}^T (em_{1,h,t}^2 + em_{2,h,t}^2 - er_{1,h,t}^2) \right] \quad (28)$$

$T$  - number of years for which forecasts are developed

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

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

$s$  - 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. On 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.

The DM statistics value (32.24) is higher than the critical one, so, if we use model B we have a better forecasts accuracy than using model A.

## V. Conclusions

Econometric models for the determination of the exchange rate were developed in order to analyze the evolution of this indicator, but also for making predictions. Given that the theory provides several possible models to explain the same variables, it is important to choose the model that generates best predictions in terms of accuracy. The last researches highlight that the simple models are the best for predicting macroeconomic variables. Therefore, I used some alternative simple econometric models to analyze and predict the exchange rate in our country.

I proposed three possible models to explain the evolution of the exchange rate in Romania: a simultaneous equations model, an autoregressive model of order 1 and a model respecting the sense of Granger causality. These models were not proposed before by Romanian researchers who preferred GARCH models. Data series are monthly and cover the period from 2007 to June 2011. The model

related to the Granger causality has generated the one-month-ahead forecasts for July and August 2011 at the highest degree of accuracy. Therefore, we can conclude that a good formalization of the economic theory by using econometric models tends to generate predictions that are close to the future reality.

AR models generated the worst predictions. We found out the explanation for this. As we can see, all the predictions based on the models used overestimated the exchange rate values. The cause is the fact that the turning points were not predicted by our models, which is one of the major deficiencies of ARMA models.

So, I recommend forecasting the exchange rate in Romania using a model with lagged variables, because it is consistent with the economic theory and the predictions based on it generated the higher degree of accuracy. To assess the accuracy I used not only the most known statistical indicators, but also an adapted Diebold-Mariano test (a generalization of the classical test). Actually, in literature different authors, like Engel (2006), showed that to evaluate forecasts accuracy it is necessary to use more statistical indicators and a test to verify the equality of prediction accuracy.

Knowing of best estimates and predictions of the exchange rate is necessary in order to build the monetary policy and to take the best decisions regarding the evolution of the economic mechanism. Central banks are the most interested institutions in predicting the exchange rate using the best econometric models.

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