Mihaela Bratu[1]

ASSESSMENT OF MACROECONOMIC FORECASTS ACCURACY IN ROMANIA

The evaluation of macroeocnomic forecasts performance does not include only calculating of statistical measures, rather controversial in literature, like root mean squares error or absolute mean error. In theory and economic practice, 3 directions have been traced regarding the evaluation of forecasts performance: the analysis of accuracy, bias and efficiency. Using the forecasted values on medium run of inflation rate and unemplyment rate through the period from 2000 to 2010 for Romania, we get a better degree of accuracy and a lower efficiency for forecasts made by National Commission of Forecasting as compared to those based of Dobrescu model used by Institute of Economic Forecasting.

Keywords: *macroeconomic forecast; accuracy; error; static/dynamic forecast.*

JEL CLASSIFICATION: C51; E24; E31.

Міхаела Брату

ОЦІНЮВАННЯ ТОЧНОСТІ МАКРОЕКОНОМІЧНИХ ПРОГНОЗІВ У РУМУНІЇ

У статті проведено оцінювання макроекономічних прогнозів з урахуванням не тільки статистичних вимірювань, але й середньої квадратичної похибки та середньої абсолютної похибки. У теорії та на практиці оцінювання точності прогнозування існує 3 напрямки: аналіз точності, необ'єктивності та ефективності. Розглянуто середньотермінові прогнози щодо рівнів інфляції та безробіття у Румунії за 2000-2010 роки. Прогнози Національної комісії прогнозування, за результатами аналізу, є більш точними, але менш ефективними, ніж прогнози Інституту економічного прогнозування.

Ключові слова: *макроекономічне моделювання; точність; похибка; статичне/динамічне прогнозування.*

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Михаэла Брату

ОЦЕНКА ТОЧНОСТИ МАКРОЭКОНОМИЧЕСКИХ ПРОГНОЗОВ В РУМЫНИИ

В статье проведена оценка макроэкономических прогнозов с учетом не только статистических измерений, но и средней квадратической погрешности и средней абсолютной погрешности. В теории и практике оценивания точности прогнозов существует 3 направления: анализ точности, необъективности и эффективности. Были рассмотрены середнесрочные прогнозы по уровням инфляции и безработицы в Румынии для периода 2000-2010 годы. Прогнозы Национальной комиссии прогнозирования, по результатам анализа, более точны, но менее эффективны, чем прогнозы Института экономического прогнозирования.

Ключевые слова: *макроэкономическое моделирование; точность; погрешность; статическое/динамическое прогнозирование.*

1. Introduction. In addition to economic analysis, the elaboration of forecasts is an essential aspect that conducts the way of developing the activity at macroeconom-

[1] Institute for Doctoral Studies, Academy of Economic Studies, Bucharest, Romania.

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ic level. But any forecast must be accompanied by macroeconomic explanations of its performance.

The purpose of this evaluation is related to different aspects: the improvement of a model on which the forecast is based, adjustment of government policies, planning of results. Basically, performance evaluation in this context refers directly to the degree of trust confered to a prediction. Although the literature on forecasting methods and techniques used in describing the evolution of an economic phenomenon is particularly rich, surprisingly few researchers have dealt with the methods used to improve the measurement of forecast uncertainty. This aspect is important because macroeconomic predictions must not be easily accepted, taking into account the negative consequences of macroeconomic forecasts failures, consequences that affect state policies. The decisions of economic policy are based on these forecasts. Hence, there is an evident interest in improving their performance.

In literature there are 3 directions in evaluating the performance of macroeconomic forecasts: accuracy, bias and efficiency. A large number of articles have considered the problem of comparing the accuracy measures, contributions in the field are in particular: Leith and Tanner, 1990; Makridakis, 1993; Yokum and Armstrong, 1995; Tashman, 2000; Makridakis and Hibon, 2000; Koehler, Martin and Witt, 2002; Hyndman, 2006; Witt, 2002; Hyndman, 2006.

Meese and Rogoff's paper, "Empirical exchange rate models of the seventies", is the starting point for many researches in comparing accuracy and bias. Recently, Dovern J. and J. Weisser (2011) examined in their article "Accuracy, unbiaseness and efficiency of professional macroeconomic forecasts: An empirical comparison for the G7" 3 criteria using the empirical data from the G7 economies.

2. 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 we can outline some important conclusions.

In order to evaluate the forecast performance, and also the predictions, statisticians have developed several measures of accuracy. Fildes 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 used a statistics. Another statistic was method presented by Diebold and Mariano to compare quantitative measures of errors. Diebold and Mariano in 1995 proposed a comparison test of two forecasts' accuracy under the null hypothesis that stated the lack of difference. This test was later improved by Harvey and Ashley, who developed a new one based on a bootstrap inference. Later, Christoffersen and Diebold developed a new way to measuring the accuracy that keeps the cointegration relationship between variables.

Armstrong and Fildes (1995) showed 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 showed that it is not sufficient to use a single measure of accuracy.

Mariano R.S. (2000) presented 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 improved 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 Student t. Clark evaluated the power of some tests of equal forecast accuracy, such as modified versions of DM test or those of Newey and West, based on the Bartlett kernel and a fixed length of data series. Meese and Rogoff in their study (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 the conclusion that was later used to improve macroeconomic forecasts performance. They have demonstrated that random walk process generates better forecasts than structural models.

In the evaluation of a forecast based on a model, Clements and Hendry (2005) identified 6 important aspects to be studied: ex-ante and ex-post, evaluation, forecast horizon length, the quality of a model to be conditional or not, internal and external standards, testing the stability and the significance of models, testing parameter stability and assurance of their continuous updating.

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 was made by Hyndman and Koehler (2005) in their reference study "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 ($|r_t|$).

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

->*Relative measures*

For example, the relative RMSE is calculated as:

$$rel\_RMSE = \frac{RMSE}{RMSE_b}, where\ RMSE_b$$

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-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 at average error)

Hyndman and Koehler introduce in 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 an 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: Mean Square Error (MSE), Root Mean Squared Error (RMSE), Generalized Forecast Error Second Moment (GFESM), Mean Absolute Percentage Error (MAPE), Symmetric Median Absolute Percent Error (SMAPE), Mean Error (ME) and Mean Absolute Error (MAE).

On practice, the most used measures for forecast errors 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 is underestimated, which means expected average values are too small. A negative value of the indicator shows expected values are too high on average.

- Mean absolute error (MAE)

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

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

B. Measures for evaluation of relative accuracy of forecasts

Relative accuracy measures are related to comparison of a forecast with a forecast of reference, found in the literature as the "benchmark forecast" or "naive forecast". However, it remains a subjective step to choose the forecast used for comparison. Problems 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-statistics, which uses as 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. Naïve model method assumes that a variable value in the next period is equal to the one recorded at actual moment. Theil proposed the calculation of U, that takes into account both the changes in negative and positive senses of an indicator:

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

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

$$es_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n} \left| X_i - X_{i-1} \right|}$$

and mean absolute scale error as: MASE= mean $|es_t|$.

Naïve 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 also to compare the accuracy of several series. If a scale error is less than 1, the compared forecast is better than the reference one (naïve forecast).

Some authors recommend to use Kullback-Leibler divergence in order to compare the forecasts in terms of accuracy.

Other measures used to evaluate the accuracy are correlation between forecasted values and actual values (measured by coefficient of determination of changes in the series of values and the ones in forecasted series), the percentage of turning points forecast, calculated for binary variables by rank (score) Kuiper, conditional efficiency (for comparing two different forecasts based on the same regression model).

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.

Ericsson (1992) showed that the parameters stability and mean square error of prediction are two key measures in evaluating forecast accuracy, but they are not sufficient and it is necessary to introduce a new statistical test.

Considering the AR (1) process, which is represented as $y_t = \beta y_{t-1} + u_t$, Hoque, Magnus and Pesaran (1988) showed that for small values of β the prediction mean square error is a decreasing function in comparison with the number of forecast periods.

Granger and Jeon (2003) considered 4 models for US inflation: a univariate model, a model based on an indicator used to measure inflation, a univariate model based on two previous models and a bivariate model. Applying the mean square error criterion, the best prediction made is the one based on an autoregressive model of order 1 (AR (1)). Applying distance-time method, the best model is the one based on an indicator used to measure the inflation.

Ledolter (2006) compared the mean square error of ex-post and ex-ante forecasts of regression models with transfer function with the mean square error of univariate models that ignore the covariance and show superiority of predictions based on transfer functions.

Terasvirta, van Dijk, Medeiros (2005) examined 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 a dynamic specification was used and it 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 specific to general.

Heilemann and Stekler (2007) explained 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 (2008), using the empirical studies, obtained forecasts with high degree of accuracy for European macroeconomic variables by combining specific subgroups predictions in comparison with the forecasts based on a single model for the whole Union.

Gorr (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 and Weisser (2011) used a broad set of individual forecasts to analyze 4 macroeconomic variables in G7 countries. Analysis of accuracy, bias and forecasts efficiency resulted in large discrepancies between countries and also in the same country for different variables. In general, forecasts are biased and only a fraction of GDP forecasts are closer to the results registered in reality.

In the Netherlands, experts make predictions starting from the macroeconomic model used by the Netherlands Bureau for Economic Policy Analysis (CPB). For the period 1997-2008 the model of the experts macroeconomic variables evolution was reconstructed and compared with the base model. The conclusions of Franses, Kranendonk and Lanser (2011) were that the CPB model forecasts are in general biased and with a higher degree of accuracy.

Many studies refer to a combination of two methods based on the same model (such as Bayesian mediation model), but a combination between model predictions and expert assessments has not been proposed yet.

3. Evaluation of macroeconomic forecasts accuracy in Romania. In this study we evaluate the accuracy of forecasts made by principal institutions in Romania as for inflation and unemployment rates: Institute of Economic Forecasting and National Commission of Forecasting.

We consider the values of inflation and the unemployment rate projected by National Commission of Forecasting for the period 2004-2010. The indicators mentioned above are calculated for the forecast errors. The values of ME show the underestimation tendency for inflation. Moreover, MAE has the same value, showing the persistence of this underestimation.

The result is confirmed by practice, taking into account the shocks recorded in this period. Thus, in 2004 currency appreciation, restrictiveness of fiscal policy and greater tendency towards savings have contributed to the disinflation process. However, a number of other factors determined the increase of inflationary pressure: the gross average wage growth, the accumulation of arrears and the increase of consumption. Disinflation process resumed in 2005 due to weaker dynamics of administered prices and currency appreciation against the euro. A further acceleration of the disinflation process registered in 2006 due to volatile price downturn, the reduction of the basic component and the increased competition in the retail market.

But in 2007, the inflation trajectory changed, the annual inflation increase was attributed to the shocks like: unexpected increase of volatile prices for agricultural products, increase of food prices, RON exchange rate correction, all of these in the context of excessive demand. If in the first half of 2008 inflationary pressures were generated by supply shocks (food market tensions, the rise in import prices for agricultural raw materials and unprocessed products) and demand shocks (increase in prices for fuel and natural gas). Since August 2008 these factors started to downsize, but influences on the demand generated by easy fiscal policy persisted, the maintenance of laxity in wage policy, expansion of lending. Amid a severe economic contraction in 2009 in Romania, a relatively slow rate of inflation reduction was caused by persistent structural rigidities at the labor and product markets, but also by a number of other factors acting during the year. In 2010 volatile prices for food supply were affected by the influence of external price increases in food goods, because of global supply reduction.

Table 1. **Inflation rate in Romania, 2004-2010**

Inflation rate (%)				
Year	INS	National Commission of Forecasting	Institute of Economic Forecasting (Dobrescu model)	Institute of Economic Forecasting (PEP program)
2004	11,9	9	6,2	12
2005	9	7	13,74	9
2006	6,56	4	6,88	7
2007	4,84	4,5	6,82	5
2008	7,85	3,8	5,88	3,6
2009	5,59	4,5	4,36	
2010	6,09	3,5	4,04	

Sources: National Institute of Statistics – www.insse.ro, National Commission of Forecasting – www.cnp.ro, Dobrescu E. (2006), Macromodels of the Romanian Transition Economy, Expert Publishing house, Bucharest

ME indicator shows an underestimation of the annual inflation rate to 0.29%. The very low RMSE value indicates a low variability of the series of errors.

Table 2. **The average and standard deviations of the inflation rate and unemployment rate in 2004-2010**

Statistical indicators	Inflation Rate (%)	Unemployment rate (%)
Average (2004-2010)	7,38	5,82
Standard deviation	2,62	1,27

Table 3. Indicators of forecast accuracy for inflation and unemployment rates in Romania (2004-2010)

Forecast Errors	Inflation rate	Unemployment rate
RMSE*	0,1	0,09
ME*	0,29	-0,05
MAE*	0,29	0,27
MASE*	0,041	0,038
Theil's U	0,33**	0,14***

* Percentage points
** Compared to Dobrescu model
*** Compared to the MA (1) – model dynamic forecast

Unlike the forecast inflation rate, the negative ME value indicates an overestimation of the unemployment rate by 0.05%. Errors variability is very small because RMSE has the value of only 0.09%. Labor market immediately reacted to the crisis in 2009 through higher unemployment, but also slower annual growth in wages.

For inflation, which recorded only positive rates of growth in the analyzed period, naive model have to extrapolate the latest trend. If Moore proposed the comparison to projections based on an extrapolation method, the development of VAR and ARIMA models impose their use as benchmark models. A value of U less than 1 indicates lower forecast errors than those from the naïve model. The same conclusion is reached when the scale error is calculated as proposed by Hyndman and Koehler.

The U-statistic is calculated, taking as reference the inflation forecasts based on Dobrescu model and those of unemployment rate based on the MA (1) model.

Unemployment rates from 1991 to 2010 in Romania follow the MA(1) process: $r\_unemployment = 7,761 + e_t - 0,805 \cdot e_{t-1}$. We use two forecasting techniques: ex-post (that corresponds to the dynamic forecast) and ex-ante forecasts used for static forecasts.

Dynamic forecast (forecast dynamics) shows the value in period $t+1$ based only on the data up to time t, then for all periods that are already projected using data from period $t + 1$. Static forecast (forecast still) makes forecasts basing only on the registered data.

A dynamic forecasting is made in EViews for 2004-2010. The ex-post technique is applied first, using the first 13 values of the unemployment rate for the model and the rest for prediction. Ex-ante technique of forecasting is based on all the values.

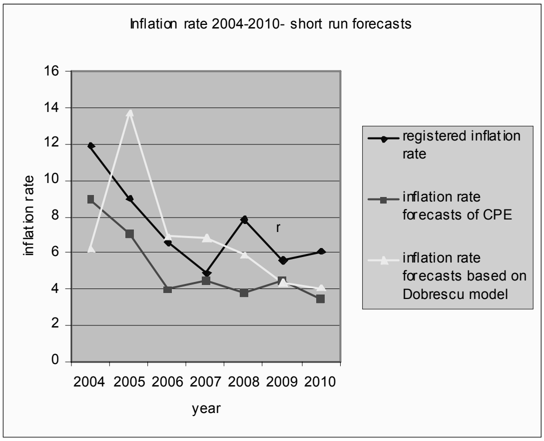
Eviews Program displays a set of indicators to evaluate the model reliability:

- RMSE (Root Mean Squared Error), which must have the smallest value possible;
- MAE (Mean Absolute Error);
- MAPE (Mean Absolute Percent Error), which, in this case, has a relatively low value;
- Theil's inequality coefficient (takes values in (0,1), a value close to 0 indicating a good adjustment; in this case has a low value, so the adjustment is very good);
- Bias Proportion has to be small (in this case is quite large);
- Variance Proportion has to be small; in this case is close to 0;
- Covariance Proportion is desired to be as large as possible; in this case is very small.

Inflation forecast errors of Dobrescu model are higher than those of the Commission of Forecasting. This conclusion was also reached by comparing RMSE and Theil's U coefficient modified by changing the benchmark model.

RMSE for the forecasted inflation rate of Dobrescu model is 1.03% compared to 0.29%, the value calculated for Commission of Forecasting predictions.

Taking as reference the Dobrescu model forecast inflation rate the U-statistics has the value of 0.33, which means that the Commission's forecasts are better. This conclusion is also the result from the graphic analysis below.



Data sources: Table 1

To make a comparison of forecasts characteristics, the loss-function values are analyzed. Root mean squared error (RMSE) calculates the forecast deviation from the actual values recorded. It is estimated that a prediction is much closer to real evolution as much as RMSE value is lower. Static forecast is superior to the dynamic one for unemployment rate which follows a MA (1), because of the lower value of RMSE.

Table 4. **Unemployment rate in Romania, 2004-2010**

Unemployment rate (%)					
Year	National Commission of Forecasting	Static Forecast MA (1)	Dynamic Forecast MA(1)	Institute of Economic Forecasting (Dobrescu model)	Institute of Economic Forecasting (PEP program)
2004	6,3	7,559	7,756	8,02	8
2005	5,9	6,746	7,761	7,9	7,9
2006	4	7,079	7,761	7,65	7,8
2007	4,4	5,281	7,761	7,42	7,6
2008	5,8	7,051	7,761	7,19	7,4
2009	7,5	6,753	7,761	6,99	
2010	6,9	8,361	7,761	6,83	

Sources: National Commission of Forecasting – www.cnp.ro, Dobrescu E. (2006), Macromodels of the Romanian Transition Economy, Expert Publishing House, Bucharest

Commission of Forecasting makes predictions using quarterly model of Romanian economy. In the long run and short run, index of prices used to calculate inflation is estimated according to the index of M2 and the exchange rate.

RMSE for unemployment rate forecasts of Commission of Forecasting (1,27) is lower than the one of MA(1) model, which has the value of 2,24 for the dynamic forecast in EViews.

EViews static forecast is better than the dynamic one taking into consideration all indicators used for reliability evaluation, but the RMSE is higher for predicted values of Commission of Forecasting. The modified U-statistics is calculated in order to compare forecasts of the Commission with those based on the MA (1) model and the value of 0.07 resulted when static forecast is chosen as benchmark and 0.14 for a dynamic forecast used as reference. We obtained smaller forecast errors for the unemployment rate provided by the Commission of Forecasting in comparison with the errors resulting from the moving average model.

Dobrescu (2003) grouped the constraints affecting economic performance into two categories, one taking into account demand factors (limited access to foreign markets and the decline in real terms of capacity absorption) and the other one – the supply factors (the activity of companies lacking performance). For the period 2003-2007, Dobrescu developed some scenarios of the evolution of main macroeconomic indicators, the workings being made in PEP program (Pre-Accession Economic Program).

For the period 2004-2010 the unemployment rate projected in the Dobrescu model achieved the RMSE value of 0.46. That means an error greater than the one of the forecast by Commission of Forecasting. IPE also used the PEP program to forecast the unemployment rates between 2004 and 2008. RMSE has the value of about 0.58, higher than 0.54, the result when Dobrescu model is used.

An optimal macroeconomic forecast is unbiased and efficient, in the macroeconomic framework taking into account the rational expectations hypothesis. This implies a zero average prediction error.

6. Conclusions. Forecast performance evaluation is an important indicator of the extent to which projections made accomplished their purpose to be closer as much as possible to the registered values. Forecasts accuracy in Romania for inflation and unemployment rate is evaluated for the institutions specialized in forecasting, and comparisons were made showing the superiority of forecasts made by National Commission of Forecasting.

Macroeconomic forecasts evaluation is necessary to inform the public about the way in which state institutions predict economic phenomenon. In the future our attention will focus on particular institutions in accord with the criterion of forecasts accuracy.

Bibliography:

1. *Armstrong, J. S., Fildes R.* (1995). On the selection of Error Measures for Comparisons Among Forecasting Methods, Journal of Forecasting, 14, p. 67-71.

2. *Bowles C., Friz R., Genre V., Kenny G., Meyler A., Rautanen T.* (2007). The ECB Survey of Professional Forecasters (SPF): A review after eight years' experience, Ocassional Paper Series, nr. 59/ April 2007.

3. *Clements M.P., Hendry D.F.* (2005). Evaluating a Model by Forecast Performance, Oxford Bulletin of Economics and Statistic, Volume 16, Supplement s1, p. 931-956.

4. *Corder J.K.* (2003). Managing Uncertainty. The Bias and Efficiency of Federal Macroeconomic Forecasts, Department of Political Science, Western Michigan University, the 7th National Public Management Conference. Georgetown University. Washington, DC, October, 2003.

5. *Dobrescu E.* (2006). Macromodels of the Romanian Transition Economy, Expert Publishing House, Bucharest

6. *Dobrescu E.* (2003). Macroeconomic estimators for the Romanian "Pre-accesion Economic Program" (the 2003 version), Romanian Journal of Economic Forecasting, 2003, Volume 4, Issue 4, Supplement

7. *Dovern J., Weisser J.* (2011). Accuracy, unbiasedness and efficiency of professional macroeconomic forecasts: An empirical comparison for the G7, International Journal of Forecasting, Volume 27, Issue 2, April-June 2011, p. 452-465.

8. *Ericsson N.R.* (1992). Parameter constancy, mean square forecast errors, and measuring forecast performance: An exposition, extensions, and illustration, Journal of Policy Modeling, Volume 14, Issue 4, August, p. 465-495.

9. *Fildes R., Steckler H.* (2000). The State of Macroeconomic Forecasting, Lancaster University, EC3/99, George Washington University, Center for Economic Research, Discussion Paper No. 99-04.

10. *Franses P.H., Kranendonk H. C., Lanser D.* (2011). One model and various experts: Evaluating Dutch macroeconomic forecasts, International Journal of Forecasting, Volume 27, Issue 2, p. 482-495.

11. *Granger C.W.J., Jeon Y.* (2003). Comparing forecasts of inflation using time distance, International Journal of Forecasting, Volume 19, Issue 3, July-September 2003, p. 339-349.

12. *Gorr W.L.* (2009). Forecast accuracy measures for exception reporting using receiver operating characteristic curves, International Journal of Forecasting, Volume 25, Issue 1, January-March 2009, p. 48-61.

13. *Heilemann U., Stekler H.* (2007). Introduction to "The future of macroeconomic forecasting", International Journal of Forecasting, Volume 23, Issue 2, April-June 2007, p. 159-165.

14. *Hyndman R. J., Koehler A.B.* (2005). Another Look at Measures of Forecast Accuracy, Working Paper 13/05, Available at http://www.buseco.monash.edu.au/depts/ebs/pubs/wpapers.

15. *Kjellberg D., Villani M.* (2010). The Riksbank's communication of macroeconomic uncertainty, Economic Review, 1/2010

16. *Ledolter J.* (2006). Increase in mean square forecast error when omitting a needed covariate, International Journal of Forecasting, Volume 23, Issue 1, January-March 2007, p. 147-152.

17. *Mariano R.S.* (2000). Testing forecast accuracy, University of Pennsylvania, available at http://projects.chass.utoronto.ca/link/200010/papers/testforecast.pdf

18. *Ruth K.* (2008). Macroeconomic forecasting in the EMU: Does disaggregate modeling improve forecast accuracy?, Journal of Policy Modeling, Volume 30, Issue 3, May-June 2008, p. 417-429.

19. *Terasvirta T., van Dijk D., Medeiros M.C.* (2005). Linear models, smooth transition autoregressions, and neural networks for forecasting, macroeconomic time series: A re-examination, International Journal of Forecasting, Volume 21, Issue 4, October-December 2005, p. 755-774.

20. *Wojciech C., Svetlana M.* (2009). Nonlinear Inflationary Persistence and Growth: Theory and Empirical Comparative Analysis, Romanian Journal of Economic Forecasting, 2009, Volume 10, Issue 2, p. 5-22

21. National Commission of Forecasting, 2010. Database. Available at http://www.cnp.ro/ro/prognoze [accessed May 2011].

22. National Institute of Statistics. Database. Available at http://www.insse.ro/cms/rw/pages/anuarstatistic2009.ro.do [accessed May 2011].

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