New accuracy measures for point and interval forecasts. A case study for Romania's forecasts of inflation and unemployment rate

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Abstract

The objective of this research is to introduce in literature new measures of accuracy for point forecasts (radical of order n of the mean of squared errors, mean for the difference between each predicted value and the mean of the effective values, ratio of radicals of sum of squared errors (RRSSE), the last one being used for forecasts comparisons), different versions of U2 Theil's statistic) and for forecast intervals (number of intervals including the realization, difference between the realization and the lower limit, the upper one, respectively the interval centre). Some classical measures of predictions accuracy were assessed for the inflation and unemployment rate forecasts provided for Romania by Institute for Economic Forecasting (IEF) and National Commission of Prognosis (NCP) on the horizon 2010-2012. Excepting the best forecast, the hierarchy of predictions provided by the classical indicators and by the new ones are different. A novelty in literature is also brought by the methods of building the forecasts intervals. The classical interval based on the root mean squared error method was adapted to the small sample of forecasts. The intervals based on the standard deviation and those constructed using bootstrap technique and bias-corrected-accelerated (BCA) bootstrap method are proposed as an original way in this field.

Resumen

El objetivo de esta investigación es presentar nuevas medidas de precisión para establecer predicciones (radical de orden n del error cuadrático medio, la diferencia media, la media de la diferencia en la predicción de cada valor y la media de los valores efectivos, así como el ratio de radicales de la suma de errores al cuadrado, es decir, RRRSSE por sus siglas en inglés, para las comparaciones predictivas), diferentes versiones del índice de Theil U2) y para los intervalos de predicciones (número de intervalos incluyendo la realización, la diferencia entre la realización y el límite mínimo y máximo respectivamente del centro del intervalo). Evaluamos algunas de las medidas clásicas utilizadas en la precisión de las predicciones de inflación y desempleo en Rumanía, que fueron proporcionadas tanto por el Instituto de Predicciones Económicas (IEF, por sus siglas en inglés) como por la Comisión Nacional de Prognosis (NCP) para el período 2010-2012. Exceptuando las mejores predicciones, la jerarquía de predicciones proporcionada por los indicadores clásicos y modernos es diferente. Como novedad, cabe apuntar la utilización de nuevos métodos de estimación por intervalos. Al intervalo clásico basado en el método de la raíz cuadrada del error cuadrático medio, se añaden los intervalos basados en la desviación típica y aquellos intervalos estimados con el método bootstrap de sesgo corregido y acelerado (BCA por sus siglas en inglés).

Key-words: forecasts, accuracy, U Theil's statistic, forecast intervals

JEL classification: C12, C14, C180

1. Introduction

In this study new accuracy measures were proposed to assess the forecasts of inflation and unemployment rate provided by two specialized institutions from Romania: Institute for Economic Forecasting (IEF) and National Commission of Prognosis (NCP). Our contributions consist of: the proposal of some indicators to assess the point forecasts accuracy, the computing of modified versions of U2 Theil's statistic and the proposal of measures of accuracy for interval forecasts, the last contribution bringing a perspective that have not been taken in consideration in literature till now.

The results provided by these new ways of evaluating the predictions' accuracy by comparisons are different from those based on classical measures of accuracy. Only the best forecast is indicated by the usual measures of accuracy and also by our proposed indicators. Actually, our objective is to analyse the problem of accuracy from more points of view.

The actual tendency in literature is to compare the alternative macroeconomic predictions provided for the same variable by different institutions like IMF, SPF (Survey of Professional Forecasters), OECD or European Commission. It is seldom omitted the comparison with official governmental expectations.

Abreu (2011) was interested to make comparisons between macroeconomic predictions provided by institutions like Consensus Economics, The Economist, OECD, IMF and European Commission.

Bratu (2012) assessed the accuracy of some macroeconomic forecasts for Romania, the expectations being provided by the National Commission of Prognosis and the Institute of Economic Forecasting. The first institution predictions for some variables (inflation, unemployment, GDP deflator, export rate and exchange rate) on the horizon 2004-2011 are better than those of the second institution.

Novotny and Rakova (2012) made comparisons between forecasts using a regression. The accuracy of Consensus for the Czech Republic predictions on the horizon 1994-2009 was evaluated, observing a lower error from a period to another.

Genrea, Kenny, Meylera and Timmermann (2013) made forecasts combinations starting from SPF predictions for ECB and using performance-based weighting, trimmed averages, principal components analysis, Bayesian shrinkage, least squares estimates of optimal weights. Only for the inflation rate there was a strong evidence of improving the forecasts accuracy with respect to the equally weighted average prediction.

The non-parametric procedure was also used in recent papers to assess the forecasts accuracy.

Jinghui He and Bing Xu (2012) Made forecasts for China textile price index (TPI) using two types of regression models: parametric regression and nonparametric path design, getting a higher accuracy for the predictions based on nonparametric model.

Guégan, Ferrara and Rakotomarolahy (2010) used the semi-parametric models to predict the GDP growth rate, obtaining robust now-casts and predictions.

Fujiwara and Koga (2004) started from a VAR model and constructed a frequency distribution to take into account the uncertainty determined by two elements: the model uncertainty and the forecast uncertainty.

Yang (2010) concluded that for nonlinear relationships a seasonal additive and nonlinear model performs better in terms of forecasts than a period vector autoregressive model. Moreover, the interactions between different univariate sets of data are identified.

If X is the predicted quantitative variable, the error of forecast is computed as the difference between the registered and the predicted value: e_X .

2. New measures of accuracy

The prediction error is computed as the difference between the effective value and the forecasted one of a variable X and it is denoted by e_X. For the number of forecasts on the horizon it is used the notation "n". The most frequently used statistical measures for assessing the forecasts accuracy, according to Fildes and Steckler (2000), are : Root Mean Squared Error (RMSE) : $RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n} e_X^2}$,

Mean error (ME) : $ME = \frac{1}{n}\sum_{j=1}^{n} e_X$ and Mean absolute error (MAE) : $MAE = \frac{1}{n}\sum_{j=1}^{n} \left| e_X \right|$. RMSE is influenced by outliers. These absolute measures depend on the unit of measurement, this disadvantage being eliminated unless if the indicators are expressed as percentage.

U Theil's statistic, used in making comparisons between predictions, can be used in two variants, presented also by the Australian Treasury.

The next notations are used:

a- actual/registered value of the analyzed variable

p- value for the predicted variable

t- time

e- error (difference between actual value and the forecasted one)

n- number of periods

U1 takes value between 0 and 1, a closer value to zero indicating a better accuracy for that prediction. If there are alternative forecasts for the same variable, the one with the lowest value of U1 is the most accurate.

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

U2 is used to make comparisons between the chosen forecast and the naïve prediction. A naïve forecast is the want based on a random walk process. This means that the forecasted value is the one registered in the previous period. If U2 is less than 1, the forecast to compare is more accurate than the naïve one, while a value greater than 1 for U2 implies a better naïve prediction. There are not differences in terms of accuracy between the chosen forecast and the naïve one if U1 is 1.

$$U_2 = \frac{\sqrt{\sum_{t=1}^{n-1}[\text{EMBED Equation.3}]^2}}{\sqrt{\sum_{t=1}^{n-1}[\text{EMBED Equation.3}]^2}}$$

We propose the introduction of new measures of accuracy:

- Radical of order n of the mean of squared errors: $RnMSE = \sqrt[n]{\frac{1}{n}\sum_{j=1}^{n} e_X^2}$

  Actually this indicator comes to correct the too large weight assigned to RMSE for large errors. Therefore, RnMSE is a better measure of forecasts error than the classical RMSE. If two predictions have the same mean absolute error, the RMSE will penalize the one for which the individual errors are higher. If mean squared error (MSE) is used, the unit of measurement has not economic significance.

- The mean for the difference between each predicted value and the mean of the effective values on the forecasting horizon: $\bar{d} = [mean(p]_t - \bar{a}$).

- ratio of radicals of sum of squared errors (RRSSE)= $\frac{\sqrt[n]{\sum_{t=1}^{n} e_t^2}}{\sqrt[n-1]{\sum_{t=2}^{n}(X_t - X_{t-1})^2}}$ used to compare a forecast with the naïve one.

  The interpretation of this indicator is similar to U1, more closer being to zero, more accurate being the forecast.

3. The accuracy evaluation for point forecasts

The new accuracy measures are computed for the inflation and unemployment rate provided by Institute for Economic Forecasting (IEF) and National Commission of Prognosis (NCP) on the forecasting horizon 2010-2012. But, first off all some usual accuracy indicators are computed.

Table 1: Classical measures of accuracy for the forecasts made by IEF and NCP for inflation and unemployment rate

Accuracy indicator	IEF- inflation rate	IEF- unemployment rate	NCP- inflation rate	NCP- unemployment rate
ME	0.8700	-0.4000	**-0.1558**	-0.9270
MAE	0.9250	1.4000	**0.5043**	1.1770
RMSE	1.1673	1.5732	**0.6289**	1.3020
U1	0.1194	***0.0669***	0.1308	*0.1023*
U2	1.0082	1.6005	**0.8714**	1.2268

Author's computations using Excel

According to U1 indicator IEF unemployment forecasts are the most accurate, while the other indicators (ME, MAE and RMSE) have the lowest values for NCP inflation forecasts. These predictions are also better than the naive ones. The IEF inflation estimations are followed by those of NCP unemployment rate, IEF inflation and NCP inflation.

Table 2: The new measures of accuracy for the forecasts made by IEF and NCP for inflation and unemployment rate

Accuracy indicator	IEF- inflation rate	IEF- unemployment rate	NCP- inflation rate	NCP- unemployment rate
RnMSE	0.8079	1.2697	1.1242	1.4470
$\bar{d}$	0.2043	0.9693	-0.7967	0.2333
RRSSE	0.5867	0.7166	0.8164	0.8167

Author's computations using Excel

According to the new accuracy measures, the best forecasts are provided by IEF for the inflation rate, the difference between the mean of registered values and that of the predictions being only of -0.2043. The same value in absolute terms for the mean of the deviation of each predicted value from the average of the effective values supports the persistence of the overestimation of the average. The hierarchy of the predictions regarding the accuracy is evaluated using the RRSSE indicator and it is same as that provided by the evaluation of U1 statistic of Theil: forecasts of IEF for inflation rate, IEF predictions for unemployment rate, NCP forecasts for inflation, respectively for unemployment. The hierarchy is different from that resulted applying U1 or the other classical measures of accuracy.

The Hodrick–Prescott (HP) filter is very used in macroeconomics to extract the trend of the data series and separate the cyclical component of the time series. According to Hodrick and Prescott (1997), filtered data are more sensitive to long-run changes.

Holt-Winters Simple exponential smoothing technique is used by Bratu (Simionescu) (2013) for data set with linear trend and without any seasonal component.

The U2 statistic can be modified in order to make the comparisons with other forecasts:

- The filtered naïve forecasts;
- The smoothed naïve forecasts;
- The values of the new forecasts.

The filtered forecasts are gotten using Hodrick-Prescott and the smoothed naïve forecasts are obtained using Holt-Winters technique. The formula for the new U2 is:

$$U_2^{*} = \sqrt{\frac{\sum_{t=1}^{n-1}[\text{EMBED Equation.3}]^2}{\sum_{t=1}^{n-1}[\text{EMBED Equation.3}]^2}}$$

a*- filtered actual (effective/real) values

$$U_2^{**} = \sqrt{\frac{\sum_{t=1}^{n-1}[\text{EMBED Equation.3}]^2}{\sum_{t=1}^{n-1}[\text{EMBED Equation.3}]^2}}$$

a**- smoothed actual (effective/real) values

In this study it is utilized a model based on a random value that is generated using resample technique.

Supposing that the past values of an indicator and the forecasts provided by a certain institutions are known, the future values are determined using the following model:

New_prediction= forecast_provided_by_an_institution + random_value (M1)

a**- new forecasts based on the proposed model

$$U_2^{***} = \sqrt{\frac{\sum_{i=1}^{n-1}[\text{EMBED Equation.3}]^2}{\sum_{i=1}^{n-1}[\text{EMBED Equation.3}]^2}}$$

The transformed U2 statistic is computed for the new forecasts of reference. The values of modified U2 are displayed in the following table, the indicators being denoted U2*, U2** and U3***.

These accuracy measures were introduced to make comparisons with other forecasts instead of naïve predictions. Usually, a type of prediction that proved to be more accurate in the past is chosen as benchmark. In our case, the reference predictions are some values which proved to be quite good approximations of the reality in the past.

Table 3: The U2 transformed statistic for the forecasts made by IEF and NCP for inflation and unemployment rate

Forecasts	U2*	U2**	U2***
IEF inflation rate	0.6773	0.8230	0.6773
IEF unemployment rate	0.6347	0.8829	0.6347
NCP inflation rate	1.0752	1.3064	1.3064
NCP unemployment rate	0.8935	1.2431	1.2431

Source: Author's computations using Excel

U2* statistic values show that, excepting the NCP inflation rate, all the other predictions are better than the filtered naïve forecasts based on Hodrick-Prescott filter. The indicators forecasted by IEF are more accurate than the smoothed naïve ones in Holt-Winters variant and even than the forecasts resulted from the proposed model. For NCP predictions the situation is exactly the opposite.

4. The accuracy evaluation for forecast intervals

In this article some methods to construct the forecast intervals for inflation rate average forecasts are proposed. The forecasts average for the inflation rates of the specific sample is denoted by $\overline{infl}$. The inflation rate forecast at time t is $infl_t$, while n is the number of forecasts.

Firstly, to construct the forecasts intervals we take into account the predictions provided by NCP in the pessimistic and optimistic versions and those of IEF for main, respectively desirable scenario.

The samples of forecasts have low volume, so the t-Student distribution is used. The average of all the predictions that were proposed by forecasters is computed and the standard deviation corrected with the number of forecasts will be utilized in constructing new forecast intervals:

$\overline{infl}$(t)- $t_{\alpha,n-1} \cdot \frac{s_t}{\sqrt{n}}$ <forecasts< $\overline{infl}$(t)+ $t_{\alpha,n-1} \cdot \frac{s_t}{\sqrt{n}}$

s_t – standard deviation of the forecasts

$$s_t = \sqrt{\frac{\sum_{t=1}^{n}\left(infl_t - \overline{infl_t}\right)^2}{n-1}}$$

The level of significance is 0.05 and the confidence level is 0.95. This interval is proposed instead of classical one, because a correction is necessary for the small sample of forecasts. In order to get an unbiased estimator for the forecasts variance, the number of degrees of freedom is used instead of “n” as denominator. Other forecasts intervals are constructed using the RMSE of the previous year, where the RMSE is computed differently as the root mean squared of differences between each prediction of a year made by a certain institution and the real value of the indicator.

$\overline{infl}$(t)- $t_{\alpha,n-1} \cdot RMSE_t$ <forecasts< $\overline{infl}$(t)+ $t_{\alpha,n-1} \cdot RMSE_t$

A resampling technique is applied to build forecasts intervals and it consists in replicating the sample of predictions a huge number of times. Basically, a proxy population is made starting only from a sample. This is actually an artificial population.

The bias-corrected-accelerated interval (BCA) is a complex bootstrap technique used to construct confidence intervals. In this case, Davison and Hinkley (1997) showed that estimates for bias and acceleration are provided using the initial sample and the bootstrap samples. One accuracy measure for forecast intervals could be the number of intervals in which the real value is placed.

Table 4: Forecasts intervals for unemployment rate on the forecasting horizon 2001-2012

Year	Forecasts intervals based on:					
	Bootstrap technique	BCA bootstrap method	Previous registered value	Forecasts' standard deviation	Real values	Historical RMSE
2001	8.11-9.9	*8.1895-9.9*	*5.775-9.850*	*8.547-9.514*	8.8	*7.416-10.672*
2002	*7.3-9.2*	*7.375-9.2*	*6.315-9.285*	*7.841-8.808*	8.4	*6.65-9.99*
2003	*6.55-8.9*	*6.725-8.9*	*4.999-10.541*	*7.212-8.412*	7.4	*5.733-9.891*
2004	*6.8-8.6*	*6.9-8.25*	*4.663-9.922*	*7.354-8.245*	6.3	*6.256-9.343*
2005	6.37-8.4	6.37-8.2775	*1.855-12.225*	7.313-8.226	5.9	6.188-9.351
2006	5.92-7.8	5.92-7.7625	*2.575-10.99*	6.563-7.728	4	5.782-8.802
2007	5.54-7.6	5.54-6.38	*3.832-10.418*	6.563-7.728	4.4	5.389-8.69
2008	*5.14-7.4*	*5.14-7.3475*	*3.799-9.166*	*6.26-7.304*	5.8	*4.973-8.591*
2009	*4.71-8.4*	*4.71-8.0475*	*6.534-8.015*	*6.297-7.952*	7.5	*4.259-9.99*
2010	*4.3-7.4*	*4.9325-7.4*	*5.775-9.850*	*5.778-7.185*	6.9	*4.048-8.916*
2011	6.89-7.5	6.89-7.427	6.315-9.285	7.136-7.412	5.3	6.795-7.753
2012	5.2-6.7	5.2-6.625	*4.999-10.541*	8.547-9.514	8.8	4.555-7.269

Source: Own computations using Excel

6 out of 11 values of the unemployment rate are placed in the bootstrap intervals and in the historical RMSE intervals, 7 in the BCA bootstrap intervals and respectively in the intervals based on the standard deviation. The most values (10 out of 11) are located in the intervals based on the previous registered value.

Other measures of accuracy for forecast intervals can be computed. The differences between the realization for a specific year and the lower limit of each interval or the upper one or the interval centre could be considered as suitable measures of predictions accuracy. A lower difference implies a better forecast interval.

d1= realization - lower limit

d2= realization - upper limit

d3= realization - centre

Starting from these deviations we can compute their average or their absolute average on the forecasting horizon.

Table 5: Forecasts intervals for inflation rate (2001-2012)

Year	Forecasts intervals based on:					
	Bootstrap technique	BCA bootstrap method	Previous registered value	Forecasts' standard deviation	Real values	Historical RMSE
2001	*33.8-37.2*	*33.8-36.35*	*-16.7-87.2*	*33.832-36.667*	34.5	*32.158-38.341*
2002	26-28.3	26-27.85	*14.36-39.48*	25.995-27.854	22.5	23.752-30.097
2003	17-19	17-18.825	*11.32-25.32*	17.549-19.1	15.3	*9.716-26.933*
2004	*11.9-14.8*	12.3525-14.4	*10.3-16.89*	12.594-14.61	11.9	*7.650-19.554*
2005	*9-13.74*	*9-12.6075*	*5.92-14.54*	*8.315-12.159*	9	*6.427-14.047*
2006	7-8.6	7-8.2	*5.25-10.13*	7.02-8374	6.56	*3.191-12.203*
2007	5-8.14	5-7.535	*3.58-8.34*	*4.713-7.216*	4.84	*3.415-8.514*
2008	*3.6-8.5*	3.6-7.275	*1.657-*	*3.715-8.2*	7.85	*2.668-9.251*

			10.262			
2009	*4.5-8.25*	*4.5-7.3125*	*1.386-10.038*	*4.257-7.167*	5.59	*-0.035-11.46*
2010	6.2-8.29	6.2-7.8175	*4.347-9.197*	*5.936-7.608*	6.09	*3.852-9.692*
2011	*3.8-9.11*	*3.8-7.7825*	*1.721-9.184*	*3.385-7.521*	5.8	*3.338-7.568*
2012	4.9-8.77	5.05-8.0775	*3.57-8.814*	4.725-7.659	3.6	*2.004-10.38*

Source: Own computations using Excel

Only 5 of the forecast intervals based on bootstrap method include the real values of inflation rate and 3 of those based on BCA bootstrap technique are suitable. 7 out of 11 forecast intervals based on standard deviation contain the inflation rate values. All the intervals constructed using the inflation rate of the previous year include the realizations of inflation. Excepting the interval from 2002, all the others built using the previous RMSE include the real values. The new accuracy measures are shown in **Appendix 1** for the inflation rate predictions and in **Appendix 2** for unemployment rate.

For the forecast intervals of inflation rate based on bootstrap technique, the lowest value is registered by d2, but when absolute values of deviation are taken into account d2 is the highest.

BCA bootstrap method gave the best results for d1 (0.069), the lowest value for all methods. In average, the deviation between the realization and the inferior limit is 0.069% while the one between the realization and the intervals' centres is around 1.23%.

d3 registered the lowest value compared to d1 and d2 when the method applied is based on the previous registered value.

If the forecast intervals are based on standard deviation, d1 registers again the best value. It maintains to be the minimum even if the absolute values of the deviations are computed.

According to the values of d1, d2 and d3 and the corresponding values for absolute deviations, the BCA bootstrap technique provided the best intervals for inflation rate.

A negative value but better than d1 and d2 is registered when the historical RMSE is utilized.

For unemployment rate forecast intervals the better value is registered for d3 when BCA bootstrap method is applied. d1 is a good measure of accuracy for this method. d2 has the lowest value for intervals based on bootstrap method.

So, the new accuracy measures recommend the forecast intervals based on BCA bootstrap technique for inflation (d1) and for unemployment rate (d3).

5. Conclusions

This research enlarges the perspective of measuring the forecasts accuracy, by proposing some new measures for point forecasts and also for forecast intervals. The proposed measures draw attention about different results that may be registered when more predictions are compared. U1 Theil's statistic and the new indicator (ratio of radicals of sum of squared errors) gave different results regarding the hierarchy of forecasts. However, the indicators showed the same forecast as the most accurate. Therefore, the new measure could be used to identify the most accurate forecast. Our indicator reduces the too large weight assigned to large errors.

The BCA bootstrap techniques gave the best results from same accuracy measures of the prediction intervals for Romanian inflation and unemployment. The measures of accuracy proposed for forecast intervals are a novelty in this field.

APPENDIX 1

The new accuracy measures for forecast intervals of inflation

	Forecasts based on BCA bootstrap technique					
	Accuracy measures					
Year	d1	d2	d3	|d1|	|d2|	|d3|
2001	0.7	-1.85	-0.575	0.7	1.85	0.575
2002	-3.5	-5.35	-4.425	3.5	5.35	4.425
2003	-1.7	-3.525	-2.6125	1.7	3.525	2.6125
2004	0	-2.5	-1.25	0	2.5	1.25
2005	0	-3.6075	-1.80375	0	3.6075	1.80375
2006	-0.44	-1.64	-1.04	0.44	1.64	1.04
2007	-0.16	-2.695	-1.4275	0.16	2.695	1.4275
2008	4.25	0.575	2.4125	4.25	0.575	2.4125
2009	1.09	-1.7225	-0.31625	1.09	1.7225	0.31625
2010	-0.11	-1.7275	-0.91875	0.11	1.7275	0.91875
2011	2	-1.9825	0.00875	2	1.9825	0.00875
2012	-1.3	-4.4775	-2.88875	1.3	4.4775	2.88875
average	**0.069167**	-2.54188	**-1.23635**	1.270833	2.637708	1.639896

APPENDIX 2

The new accuracy measures for forecast intervals of unemployment rate

	Forecasts based on					
	Accuracy measures					
Average	d1	d2	d3	|d1|	|d2|	|d3|
Bootstrap method	0.5558	**-1.5250**	-0.4846	1.4925	1.8750	1.3171
BCA bootstrap method	**0.4673**	-1.3348	**-0.4337**	1.4207	1.6973	**1.2429**
Previous forecast value	1.8387	-3.3823	-0.7718	2.0078	3.3823	1.2457
Forecasts' standard deviation	-0.4926	-1.5440	-1.0183	**1.0889**	**1.5440**	1.1632
Historical RMSE	0.9547	-2.4797	-0.7625	1.7137	2.7352	1.3896

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