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The Performance of Unemployment Rate Predictions in Romania. Strategies to Improve the Forecasts Accuracy

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Abstract: The evaluation and improvement of forecasts accuracy generate growth in the quality of decisional process. In Romania, the most accurate predictions for the unemployment rate on the forecasting horizon 2001-2012 were provided by the Institute for Economic Forecasting (IEF) that is followed by European Commission and National Commission for Prognosis (NCP). The result is based on U1, but if more indicators are taken into consideration at the same time using the multi-criteria ranking, the conclusion remains the same. A suitable strategy for improving the degree of accuracy for these forecasts is represented by the combined forecasts. The accuracy of NCP predictions can be improved on the horizon 2001-2012, if the initial values are smoothed using Holt-Winters technique and Hodrick-Prescott filter. The use of Monte Carlo method to simulate the forecasted unemployment rate proved to be the best way to improve the predictions accuracy. Starting from an AR(1) model for the interest variable, the uncertainty analysis was included, the simulations being made for the parameters. Actually, the means of the forecasts distributions for unemployment are considered as point predictions which outperform the expectations of the three institutions. The strategy based on Monte Carlo method is an original contribution of the author introduced in this article regarding the empirical strategies of getting better predictions.

Keywords: forecasts, forecasts accuracy, multi-criteria ranking, combined forecasts, Hodrick-Prescott filter, Holt-Winters smoothing exponential technique, Monte Carlo simulations

JEL Classification: E21, E27, C51, C53

Introduction

It is clear for everybody that efforts should be made to improve the accuracy of our predictions. Nowadays, more institutions provide their own expectations regarding the evolution of a macroeconomic phenomenon. As utilizers of their information, we are interested in choosing the most accurate prediction. The criterion for our choice is an objective one: The degree of accuracy. Comparisons should be made in order to establish the most accurate predictions.

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This paper follows some logical steps: An assessment of unemployment rate forecasts accuracy for what some institutions expect from Romania and the proposal of some empirical strategies to improve the accuracy.

As far as the accuracy assessment is concerned, the contradictory results provided by different measures were solved by taking more accuracy measures into consideration at the same time. A statistical approach was used to reach this goal (the multi-criteria ranking). This procedure provides a classification of institutions according to few accuracy indicators that were considered simultaneously.

Some empirical strategies to improve the accuracy of predictions provided by the selected institutions were proposed: combined forecasts, filtered and smoothed predictions, and construction of point forecasts using Monte Carlo simulations.

2. Literature

The current economic and financial crisis underlined the necessity to increase accuracy of forecasts. The predictions accuracy evaluation is a very large research field, and its complete presentation is not possible. However, recent results will be mentioned. Recent studies based on accuracy comparisons take into account different methods for developing forecasts or different countries for which an indicator is forecasted.

Allan (2012) used quantitative and qualitative methods to assess the forecasts accuracy, getting a rather good degree of accuracy for OECD predictions on the horizon 1984-2010 for GDP growth rate of G7 countries. Dovern and Weisser (2011) observed large differences in terms of accuracy for the variables expectations in the same country or for the same indicator in different countries. Many institutions use their own macroeconomic forecasts (European Commission, IMF, OECD, SPF), but comparisons with government expectations are rarely made. Abreu (2011) studied the problem of directional accuracy, using macroeconomic forecasts provided by OECD, IMF, European Commission, Consensus Economics and *The Economist*.

Franses, Kranendonk and Lanser (2011) concluded that CPB (Netherlands Bureau for Economic Policy Analysis) model forecasts are more accurate than the government forecasts. Gorr (2009) analyzed two periods, the first being evolution of economy in normal conditions, the second evolution in exceptional conditions, for which the ROC curve is more suitable to assess the forecasts accuracy. In order to predict European Union indicators instead of devising a model for the entire zone, Ruth (2008) recommends aggregation of sub-models. Heilemann and Stekler (2007) found out two reasons for the lack of accuracy improvements for G7 predictions: Unsuitable econometric models and unreal expectations regarding the future evolution of a variable.

3. Comparisons of alternative unemployment rate forecasts

In this study, we used the forecasted values of the annual registered unemployment rate made for Romania by European Commission, National Commission for Prognosis and Institute for Economic Forecasting. The forecasting horizon is 2001-2012. The objective is to assess accuracy, bias and efficiency of these predictions and determine the best institution with the highest accuracy.

Accuracy herein refers to how close the predicted values are to the real registered values of the analysed variable. An unbiased prediction on a certain horizon implies a null average for the errors. In practice, most of the forecasts are biased. An efficient forecast includes all the available information at a given time. The efficiency supposes comparisons between two or more forecasts, the efficient one being the forecast based on more information.

Armstrong and Fildes (1995) recommended the use of more measures of accuracy. Therefore, more accuracy indicators were computed for the three types of forecasts on the specified horizon.

In order to compare the forecasts, we propose to determine the hierarchy of institutions according to the accuracy of their forecasts, for which we shall use a multi-criteria ranking.

Two methods of the multi-criteria ranking (ranks method and the method of relative distance with respect to the maximal performance) are used in order to select the institution which provided the best forecasts on the horizon 2001-2012, taking into account more calculated measures of accuracy at the same time.

"*p*" is the predicted value for a variable "*var*", while the actual or registered value is denoted by "*a*". The error at time *(t+k)* is: *e(t+k)*. "*n*" represents the number of forecasts or the length of forecasting horizon. The error is computed as a difference between the actual value (*a*) and the predicted one (*p*).

The measures of accuracy that were taken into account at the same time for the multi-criteria ranking are as follows:

Root Mean Squared Error (RMSE)

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{\mathrm{k}=1}^{\mathrm{n}} \mathrm{e}^2(\mathrm{t}+\mathrm{k})} \tag{1}$$

Mean error (ME)

$$\mathrm{ME} = \frac{1}{\mathrm{n}}\sum_{\mathrm{k}=1}^{\mathrm{n}} \mathrm{e}(\mathrm{t}+\mathrm{k}) \tag{2}$$

A positive value for ME implies an underestimation of the indicator, while a negative value is too high in average predictions.

Mean absolute error (MAE)

$$MAE = \frac{1}{n}\sum_{k=1}^{n}|e(t+k)| \tag{3}$$

These measures are not independent of the unit of measurement, unless they are expressed as percentage. RMSE is affected by outliers. If we have two forecasts with the same mean absolute error, RMSE penalizes the one with the highest errors.

U1 and *U2* Theil's statistics

$$U_1 = \frac{\sqrt{\sum_{t=1}^{n}(a_t - p_t)^2}}{\sqrt{\sum_{t=1}^{n} a_t^2} + \sqrt{\sum_{t=1}^{n} p_t^2}} \quad (4)$$

If U1 value is close to zero for U_1 (less than 0.5), we have a high degree of accuracy.

$$U_2 = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{p_{t+1} - a_{t+1}}{a_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{a_{t+1} - a_t}{a_t}\right)^2}} \quad (5)$$

U1 and *U2* Theil's coefficients are used to make comparisons between forecasts. When *U2* indicator is used, naïve forecast is the benchmark.

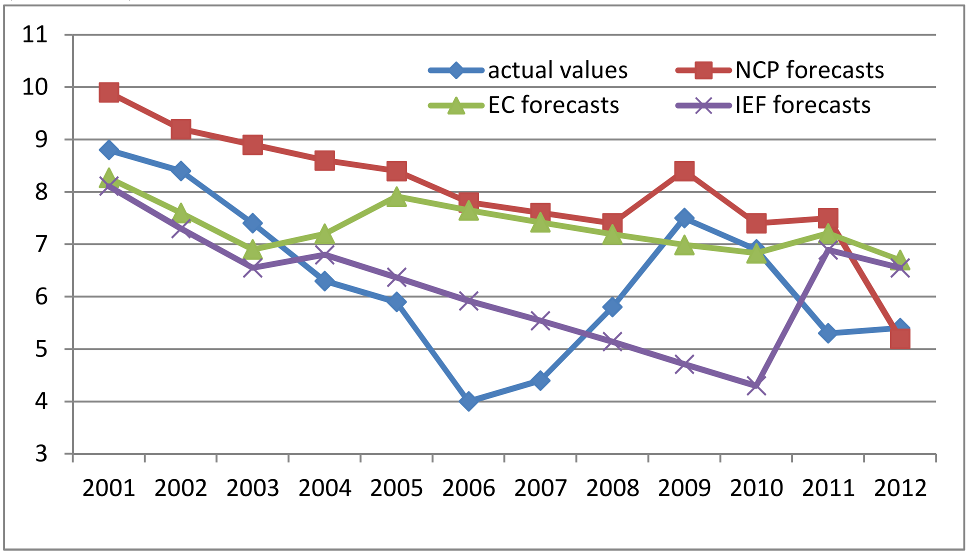
If U_2 =1=> no significant differences as a degree of accuracy between the two forecasts

If U_2 <1=> the forecast to compare has a higher degree of accuracy than the naïve one

If U_2 >1=> the forecast to compare has a lower degree of accuracy than the naïve one

A graphical representation of the actual values that were registered, and of the forecasts made by the three institutions can provide us with information about the degree of accuracy.

Figure 1: The Actual Data and the Predicted Values for Unemployment Rate (2001-2012)



Source of data: According to the data published by the National Institute of Statistics, European Commission, National Commission for Prognosis, and Institute for Economic Forecasting

According to the figure 1, the IEF forecasts are positioned closest to the actual values of the unemployment rate, while the NCP ones are far from them on the horizon 2001–2012.

Table 1: Accuracy of Forecasts Made by European Commission, National Commission for Prognosis, and Institute for Economic Forecasting for Unemployment Rate in Romania (2001-2012)

ACCURACY MEASURE	INSTITUTION		
	European Commission (EC)	National Commission for Prognosis (NCP)	Institute for Economic Forecasting (IEF)
ME	-0.5462	-0.5643	-0.7279
MAE	1.2372	1.6369	1.0916
RMSE	1.4959	1.7638	1.3059
U1	0.1074	0.1249	0.0927
U2	1.1587	1.0978	0.9983

Source: own computations

According to all accuracy indicators for forecasts made on the horizon 2001-2012 (with the exception of the mean error), the most accurate predictions for unemployment rate were provided by the Institute for Economic Forecasting which used Dobrescu (2003) macromodel. Forecasts of this institution only outperformed the naïve predictions based on the random walk. The negative values of the mean error imply too high in average predicted values for all institutions. Less accurate forecasts are made by the National Commission for Prognosis.

Ranks method application supposes several steps:

1. Ranks are assigned to each value of an accuracy indicator (the value that indicates the best accuracy receives the rank of 1); statistical units are the four institutions that made forecasts. The rank for each institution is denoted by: $(r_{i_{ind_j}})$, i=1,2,3 and ind_j $-$accuracy indicator *j*. We chose 5 indicators: Mean error, mean absolute error, root mean squared error, *U1* and *U2*.
2. If the ranks assigned to each institution are summed up, the score to each of them is computed.

$$S_i = \sum_{j=1}^{5} (r_{i_{ind_j)}} \quad , \text{i=1,2,3} \qquad (6)$$

3. The institution with the lowest score has the highest performance and it will get the final rank 1.

The results of the ranks method are the same as those provided by most accuracy measures, especially U1 used in making comparisons between forecasts. Actually, if all accuracy indicators calculated are taken into account at the same time, the following hierarchy was achieved: Institute for Economic Forecasting, European Commission and National Commission for Prognosis.

Table 2: Ranks of Institutions According to the Accuracy Measures (Ranks Method)

ACCURACY MEASURE	INSTITUTION		
	European Commission	National Commission for Prognosis	Institute for Economic Forecasting
ME	1	2	3
MAE	2	3	1
RMSE	2	3	1
U1	2	3	1
U2	3	2	1
Sum of ranks	10	13	7
Final ranks	2	3	1

Source: own computations

The second way of ranking consists in the method of relative distance with respect to the maximal performance. Actually, we are interested in computing the distance between each prediction and the one with the highest degree of accuracy. The closer the prediction is to the best one, the higher the accuracy.

A distance of each statistical unit (institution) with respect to the one with the best performance is computed for each accuracy indicator. The distance is calculated as a relative indicator of coordination:

$$d_{i_{ind_j}}=\frac{ind_i^j}{\{\min abs(ind_i^j\}_{i=1,..,4}}, \text{ i=1,2,3 and j=1,2,..,5} \quad (7)$$

The relative distance computed for each institution is presented as a ratio, where the best value for the accuracy indicator for all institutions is the denominator.

A geometric mean for the distances of each institution is calculated, its significance being an average relative distance for institution *i*.

$$\overline{d_i}=\sqrt[5]{\prod_{j=1}^{5} d_{i_{ind_j}}}, \text{ i=1,2,3} \quad (8)$$

According to values of average relative distances, the final ranks are assigned. The institution with the lowest average relative distance will take the rank of 1. The position (location) of each institution with respect to the one with the best performance is computed as an average relative distance over the lowest average relative distance.

$$loc_i^{\%}=\frac{\overline{d_i}}{\min(d_i)_{i=\overline{1,4}}}\cdot 100 \quad (9)$$

Table 3: Ranks of Institutions According to the Accuracy Measures (Method of Relative Distance with Respect to the Best Institution)

ACCURACY MEASURE	European Commission (EC)	National Commission for Prognosis (NCP)	Institute for Economic Forecasting (IEF)
ME	1	1.0338	1.341
MAE	1.1342	1.550	1
RMSE	1.1465	1.3522	1
U1	1.1597	1.3489	1
U2	1.1623	1.0987	1
Average relative distance	1.1188	1.2628	1.0605
Ranks	2	3	1
Location (%)	105.4970	119.0771	100

Source: Own computations

The method of relative distance with respect to the best institution gave the same results as the previous methods. The lowest average relative distance was registered by the Institute for Economic Forecasting (1.0605). The EC forecasts are the closest to the IEF predictions while the NCP ones are the most distant, the location being 119.0771% compared to the IEF expectations.

The Diebold-Mariano test (DM test) is utilized in order to check if two forecasts have the same accuracy. The following steps are applied:

- The difference between the squared errors of forecasts (e^2) to compare and the squared errors of reference forecasts (e^{*2}): $d_{t,t} = \left(e_{t,t}^2\right) - (e_{t,t}^{*2})$
- The following model is estimated: $d_{t,t} = a + \varepsilon_t$
- We test if "a" differs from zero, where the null hypothesis is that a=0 (equal forecasts). A p-value less than 0.05 implies rejection of the null hypothesis for a probability of 95% in guaranteeing the results.

The following variables are computed: d1, d2 and d3 to make comparisons between EC and NCP forecasts, EC and IEF predictions, or NCP and IEF expectations. All the parameters are zero from the statistical point of view, so in terms of accuracy, there are no significant differences between the forecasts provided by the three institutions. Regression models are estimated in EViews and the results are presented in Appendix 1. Therefore, the accuracy test showed that there are no significant differences between the forecasts provided by the three institutions. If we take into account the results based on accuracy indicators and those of the DM test, we may conclude that those of IEF are the best predictions, followed by EC and NCP. It is necessary to say, though, that the differences between the unemployment rate forecasts are not too big.

By applying qualitative tests for directional accuracy we check if there is a correct prediction of the change. A test of independence between the effective values and the direction of change can be applied in this situation, where the independence is shown by the null hypothesis. A probability of less than 0.05 implies that the null hypothesis be rejected. All the asymptotic significances are greater than 0.05, according to Appendix 2, which is a fact that makes us conclude that the directional changes in the outturn are independent from the predictions.

We also check the bias and the efficiency using t tests. All the forecasts are biased, following the international tendency.

The t test is used to check the biasness. Actually, we test if the free term is different from zero or not. We have to compare the t-statistic with the critical value, or use the approach based on the probability associated to each test. In general, to check if a model is valid, probability should be lower than the level of significance. The lower the probability is, the better the model. We will check if the probability displayed by EViews is lower than the significance level of 0.05.

$$e_{t+1} = a + \varepsilon_{t+1} \tag{10}$$

$e_{t+1} - the\ next\ period\ forecast\ error$

$\varepsilon_{t+1} - the\ future\ error\ for\ regression\ model$

a- the parameter to estimate

Table 4: Unbiasness Test for Unemployment Forecasts (2001-2012) Using t test

Predictions U- unbiased B- biased	Probability associated to errors for IEF forecasts	Probability associated to errors for NCP forecasts	Probability associated to errors for EC forecasts
Unemployment rate	0.0356 (B)	0.012(B)	0.0245 (B)

Source: Own computations

The lower probability is, the higher the degree of bias. Hence, the NCP forecasts are the most biased, being followed by EC and IEF predictions on the horizon 2001-2012.

The informational efficiency tests check the degree of use for the past information. For the variable which should be predicted and which is denoted by "*var*" in this case, the following regression model is built:

$$e_{t+1,t} = a + b \cdot var_{t-1} + \varepsilon_{t+1} \tag{11}$$

$e_{t+1,t} -$ the error for a future time (t+1), but anticipated at a time *t*, which is the forecast horizon

ε_{t+1} - the error of the model at a time (*t+1*)

var_{t-1}- the registered value of the variable "*var*" in the previous period (*t-1*)

Table 5: Informational Efficiency Test for Unemployment Forecasts (2001-2012) Using t test

Predictions E- efficient NE- non-efficient	Probability associated to errors for IEF forecasts	Probability associated to errors for NCP forecasts	Probability associated to errors for EC forecasts
Unemployment rate	0.0127 (E)	0.312(NE)	0.245 (NE)

Source: Own computations in EViews and Excel

According to the t test, the IEF predictions are efficient in the informational approach, while those of EC and NCP are not efficient. So, the last two institutions did not use all the past information.

Empirical Strategies of Improving the Accuracy of Unemployment Rate Forecasts

Bratu (2012) utilized some strategies to improve the accuracy of forecasts (combined predictions, regressions models, historical errors method, application of filters, and exponential smoothing techniques).

More accurate predictions can be achieved by yet another strategy possible, i.e. combined forecasts. The following are most utilized combination approaches:

- optimal combination (OPT);
- equal-weights-scheme (EW);
- inverse MSE weighting scheme (INV).

Bates and Granger (1969) started from two forecasts *p1;t* and *p2*;*t*, for the same variable var(t), derived *h* periods ago. If the forecasts are unbiased, the error is calculated as: $e_{i,t} = X_{i,t} - p_{i,t}$. The errors follow a normal distribution of parameters 0 and σ_i^2. If ρ is the correlation between the errors, then their covariance is $\sigma_{12} = \rho\sigma_1\sigma_2$. The linear combination of the two predictions is a weighted average: $c_t = mp_{1t} + (1-m)p_{2t}$.

The error of the combined forecast is: $e_{c,t} = me_{1t} + (1-m)e_{2t}$. The mean of the combined forecast is zero and the variance is: $\sigma_c^2 = m^2\sigma_1^2 + (1-m)^2\sigma_{2t}^2 + 2m(1-m)\sigma_{12}$. By minimizing the error variance, the optimal value for *m* is determined (m_{opt}):

$$m_{opt} = \frac{\sigma_2^2 - \sigma_{12}}{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12}} \qquad (10)$$

The individual forecasts are inversely weighted to their relative mean squared forecast error (MSE) resulting INV. In this case, the inverse weight (m_{inv}) is:

$$m_{inv} = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2} \qquad (11)$$

Equally weighted combined predictions (EW) are achieved when the same weights are given to all models. The U Theil's statistics were computed for the combined forecasts based on the three schemes, the results being shown in the following table (Table 4).

Table 6: Accuracy of Combined Forecasts for Unemployment Rate (2001-2011)

Accuracy indicator	EC+NCP forecasts	EC+IEF forecasts	NCP+IEF forecasts
U1 (optimal scheme) (m=0.34)	0.0851	0.0674	0.1284
U2 (optimal scheme) (m=0.34)	0.9875	0.7141	1.1083
U1 (inverse MSE scheme) (m=0.459)	0.0879	0.0561	0.1112
U2 (inverse MSE scheme) (m=0.459)	1.0033	0.5894	1.0119
U1 (equally weighted scheme) (m=0.5)	0.0874	0.0747	0.0893
U2 (equally weighted scheme) (m=0.5)	0.9215	0.7939	0.9147

Source: Author's computations

The combined forecasts proved to be a good strategy of improving the accuracy when EC and NCP forecasts, or EC and IEF predictions are combined using OPT and INV schemes. Only if equally weighted scheme is utilized, we got better forecasts for the combined predictions of NCP and IEF. The most accurate forecasts are those resulting from combining EC and IEF expectations. All the combined predictions are better than the naïve ones except for those of NCP and IEF using OPT scheme.

We test the bias of the combined forecasts. Only the combined forecasts based on CE and IEF expectations are biased; all other predictions are unbiased. The combined forecasts are thus a very good strategy leading to unbiased forecasts.

Each combined forecast based on INV scheme provided different information when comparisons of two forecasts from this group are made. The combined forecasts of CE and IEF, and those of NCP and IEF, too, are relatively efficient with respect to the combined predictions of CE and NCP. As far as efficiency is concerned, these efficient combined forecasts have a better performance than the original ones made by the institutions.

Application of filters to the predicted data is another technique possible to use for improving the forecasts accuracy; this technique was used by Bratu (Simionescu) (2013). The author also recommends the use of exponential smoothing methods like Holts-Winters.

Hodrick-Prescott filter and Holt-Winters exponential technique were applied to the original predictions, and the accuracy of new forecasts was evaluated.

The Hodrick–Prescott (HP) filter is used very often in macroeconomics to extract the trend of the data series and separate the cyclical component of the time series. The smoothed data thus achieved are more sensitive to long-term changes.

The initial data series is composed of trend and cyclical component:

$$inf_t = tr_t + c_t \tag{12}$$

Hodrick & Prescott (1997) suggest solving the minimization problem:

$$\min_{\{tr_t\}t=1,T} \quad \sum_{t=1}^{T}(inf_t - tr_t)^2 + \gamma \sum_{t=2}^{T-1}(\nabla^2 tr_{t+1})^2 \tag{13}$$

γ- penalty parameter

The solution to the above equation can be written as:

$$inf_t = (\gamma F + I_T) \cdot tr_T \tag{14}$$

inf_t- vector of the initial data series of the inflation rate

$$F=\begin{bmatrix} 1 & -2 & 1 & 0 & \dots & & & & & & & \\ -2 & 5 & -4 & 1 & 0 & \dots & \cdots & & & & & 0 \\ 1 & -4 & 6 & -4 & 1 & 0 & & & & & & \\ & & \vdots & & & & \ddots & & \vdots & & & \\ & & & & & & & & & & & \dots \\ & & & & & & \cdots & 0\ 1 & -4 & 6 & -4 & 1 & 0 \\ & & & & & & & 0\ 0 & 1 & -4 & 6 & -4 & 1 \\ 0 & & 0 & & & & \dots & 0 & 0 & 1 & -4 & 5 & -2 \end{bmatrix}$$

The trend is calculated as:

$$tr_T = [(\gamma \cdot F + I_T \quad)]^{-1} \cdot inf_T \tag{15}$$

Holt-Winters Simple exponential smoothing method is recommended for data series with linear trend and without seasonal variations, the forecast being determined as:

$$inf_{n+k} = a + bk \tag{16}$$

$$a_n = \alpha inf_n + (1-\alpha)(a_{n-1} + b_{n-1}) \tag{17}$$

$$b_n = \beta(a_n - a_{n-1}) + (1-\beta)b_{n-1} \tag{18}$$

Finally, the prediction value on the horizon “*k*” is:

$$\widehat{inf_{n+k}} = \widehat{a_n} \text{ +b} \tag{19}$$

Table 7: Accuracy of Filtered and Smoothed Forecasts for Unemployment Rate (2001-2011)

Accuracy measure	EC Filtered forecasts	NCP Filtered forecasts	IEF Filtered forecasts	EC smoothed forecasts	NCP smoothed forecasts	IEF smoothed forecasts
U1	0.1324	0.105	0.1045	0.1299	0.1294	0.1188
U2	1.3973	0.9303	1.0727	1.3421	1.182	1.2669

Source: Author’s computations

Except for the NCP filtered forecasts, all the predictions based on HP filter and HW technique are less accurate than the naïve forecasts. Indeed, the NCP forecasts accuracy has improved because a smaller value for U1 was registered for the filtered predictions. The Holt-Winters smoothing technique did not improve the forecasts accuracy. The HP filter application is thus a good strategy for improving the NCP forecasts only. However, the combined predictions remain a better strategy. The filters or the smoothing techniques give good results only if there is no change in forecasts direction compared to the real values.

Another empirical and interesting strategy to improve the forecasts accuracy is based on Monte Carlo and bootstrap simulations. Firstly, the coefficients of an econometric model are estimated using the bootstrap technique with 10000 replications. The horizon of the data series is 1990-2000. The unemployment rate is denoted by ur and an AR(1) was estimated for the unemployment data series, which is stationary according to Phillips-Perron test (Appendix 3). The AR(1) model with simulated coefficients is: $ur_t = 9.986 + 0.262 \cdot ur_{t-1}$. Monte Carlo simulations are carried out for the estimated coefficients. Actually, for the estimators the average and the standard deviations of the estimators are taken into account and normal distributions are generated using these parameters (1000 replications). Knowing the values of the unemployment rate in the previous period and the simulated coefficients, the distribution of the unemployment as forecasted is created, and the average of this distribution is considered as a point forecast. These steps are followed to predict each unemployment rate on the horizon 2001-2012. The U1 value for these point forecasts based on Monte Carlo simulations is 0.0535, which implies a higher degree of accuracy for the forecasts based on simulations. In fact, those predictions are better than those provided by all institutions.

Conclusions

In our study, we assessed unemployment forecasts performance for the predictions provided during 2001-2012 as made by three institutions: European Commission, National Commission for Prognosis, and Institute of Economic Forecasting. The best accuracy is provided by IEF, followed by EC and NCP. This hierarchy resulted from the application of multi-criteria ranking, but also from the measurement of accuracy indicators, as U1, used in making comparisons between forecasts.

Combined forecasts which take advantage of the three classical schemes are a good strategy of improving the accuracy, as most of the predictions combined were better than the initial ones. Filtered forecasts based on HP filter, or the smoothed ones based on Holt-Winters technique succeeded in improving the NCP forecasts only.

Accuracy of forecasts should be a priority for the public that uses these predictions in underlying the decisional process. Combined forecasts – and filtered and smoothed predictions in some cases, too – are a very good strategy of achieving improvement in accuracy for the unemployment rate predictions.

The best technique for getting more accurate predictions than those provided by the three institutions lies in using Monte Carlo simulations. In this context, this is an original approach introduced by the author.

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Appendix 1

Results of Diebold-Mariano Test in EViews

Dependent Variable: D1
Method: Least Squares
Date: 11/22/12 Time: 13:02
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.874545	1.187738	-0.736312	0.4785
R-squared	0.000000	Mean dependent var		-0.874545
Adjusted R-squared	0.000000	S.D. dependent var		3.939283
S.E. of regression	3.939283	Akaike info criterion		5.666382
Sum squared resid	155.1795	Schwarz criterion		5.702555
Log likelihood	-30.16510	Durbin-Watson stat		1.518619

Dependent Variable: D2
Method: Least Squares
Date: 11/22/12 Time: 13:02
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.530909	0.624816	0.849704	0.4154
R-squared	0.000000	Mean dependent var		0.530909
Adjusted R-squared	0.000000	S.D. dependent var		2.072281
S.E. of regression	2.072281	Akaike info criterion		4.381685
Sum squared resid	42.94349	Schwarz criterion		4.417857
Log likelihood	-23.09927	Durbin-Watson stat		1.521367

Dependent Variable: D3
Method: Least Squares
Date: 11/22/12 Time: 13:03
Sample: 2001 2011
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.405455	0.886219	1.585900	0.1438
R-squared	0.000000	Mean dependent var		1.405455
Adjusted R-squared	0.000000	S.D. dependent var		2.939256
S.E. of regression	2.939256	Akaike info criterion		5.080698
Sum squared resid	86.39227	Schwarz criterion		5.116871
Log likelihood	-26.94384	Durbin-Watson stat		1.686150

Appendix 2

Results of Tests for Directional Accuracy

Test Statistics

	ur	Ec
Chi-Square	.818[a]	1.273[b]
Df	9	8
Asymp. Sig.	1.000	.996

Test Statistics

	ur	Ncp
Chi-Square	.818[a]	.000[b]
Df	9	10
Asymp. Sig.	1.000	1.000

Test Statistics

	ur	Ief
Chi-Square	.818[a]	1.273[b]
Df	9	8
Asymp. Sig.	1.000	.996

Appendix 3

Null Hypothesis: UR has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.590651	0.0314
Test critical values:	1% level	-4.420595	
	5% level	-3.259808	
	10% level	-2.771129	