A NEW TECHNIQUE BASED ON SIMULATIONS FOR IMPROVING THE INFLATION RATE FORECASTS IN ROMANIA

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Abstract. *The necessity of improving the forecasts accuracy grew in the context of actual economic crisis, but few researchers were interested till now in finding out some empirical strategies to improve their predictions. In this article, for the inflation rate forecasts on the horizon 2010-2012, we proved that the one-step-ahead forecasts based on updated AR(2) models could be substantially improved by generating new predictions using Monte Carlo method and bootstrap technique to simulate the models' coefficients. In this article we introduced a new methodology of constructing the forecasts, by using the limits of the bias-corrected-accelerated bootstrap intervals for the initial data series of the variable to predict. After evaluating the accuracy of the new forecasts, we found out that all the proposed strategies improved the initial AR(2) forecasts and even the predictions of two experts in forecasting. Our own method based on the lower limits of BCA intervals generated the best forecasts. In the forecasting process based on AR models the uncertainty analysis was introduced, by calculating, under the hypothesis of normal distribution, the probability that the predicted value exceeds a critical value.*

Keywords: *accuracy, forecasts, Monte Carlo method, bootstrap technique, biased-corrected-accelerated bootstrap intervals*
JEL classification: *C15, C53*

1. Introduction

The actual economic crisis has grown the importance of getting more accurate forecasts, one of the major causes of this crisis being the uncertainty of macroeconomic forecasts. Therefore, our study is oriented to the presentation of a suitable technique for increasing the degree of accuracy for inflation predictions in Romania. This technique is based on statistical simulations like Monte Carlo experiments or bootstrap simulations.

Clark and McCracken (2008) proved that Monte Carlo experiments and some empirical techniques of forecasts combinations improved the accuracy of predictions based on recursive and rolling schemes.

Monte Carlo method is actually often used in uncertainty analysis. It is a sampling method, supposing the generation of inputs distribution that matches the best the known data series. The simulations values can be analysed as probability distributions or can be transformed in order to get reliability forecasts, confidence intervals, tolerance areas or error bars.

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Efron and Tibshirani (1993) showed that bootstrap technique is another method of generating sample distribution that can be used when the type of repartition is not known. The bootstrap technique supposes the replacements of elements from the sample, each observation having the same probability to be selected. The means of all generated samples are registered. A larger population normally distributed is chosen and its parameters are estimated and the repartition of sample means are determined.

In this paper, we proved that Monte Carlo and bootstrap methods are suitable strategies to be used in order to get better predictions than those based on a simple autoregressive model of order to for the stationary data series on the inflation rate in Romania. Moreover, we proposed an original way of getting new predictions using the limits of the intervals based on bootstrap-corrected-accelerated (BCA) technique for the lagged variable of the AR model. Indeed, the predictions based on our proposed method when the lower limits of BCA intervals were used outperform the other proposed forecasts on the horizon 2010-2012 and even those provided by two experts in forecasting.

The article presents briefly the literature regarding the statistical methods for assessing the forecasts accuracy, indicating some possible strategies of getting better forecasts. Then, the Monte Carlo method (MCM) and bootstrap technique are described in the context of making forecasts. The methods are applied to get more accurate forecasts for Romania inflation rate. We proposed a new methodology to construct forecasts, starting from BCA bootstrap intervals of the modelled variable. This strategy proved to be the best, when lower limits of the intervals are used for Romania forecasted inflation on 2010-2012.

One limit of these empirical strategies is that they depend on the type of data used in making predictions. An empirical strategy of improving the forecasts accuracy might not give the same results for other countries where the evolution of the variables is quite different.

2. Literature review for strategies to improve the forecasts accuracy

It is surprisingly that only few authors were interested to find out some proper methods of improving the accuracy of their predictions, starting from an ex-post evaluation of their expectations.

In literature it is said that one of the key of success for USA predictions is the continuous models updating. Indeed, this is a good and sure strategy of improving the forecasts. In general, the one-step-ahead predictions outperform those made on more years keeping the same forecasting origin.

The simple econometric models are preferred to the complex one, Engle (2006) showing the superiority of random walk models in front of other complicated models based on fundamentals for the exchange rate.

By using the revised data in constructing the model the predictions accuracy is improved compared to the situation of the models based on the first data. Oller (2005) deeply analysed the problem of quality data in the context of predictions.

McNees (1990) and Donihue (1993) showed that subjective adjustment of the predictions based on models could improve the accuracy compared to the forecasts obtained mechanically only using an econometric model. However, the researchers should be very cautious when they make these adjustment, because some of them might be exaggerate, introducing large errors.

Isiklar (2005) proved that the experts in forecasting need a period up to 5 months to include 90% of the new information that could help them in improving the forecasts accuracy by making their revision.

Clements (2003) considers that it is necessary to find out which of the methods and non-stationarity are independent to location shift, in order to increase the performance of the model used in forecasting. Diebold (1998) suggested some quantitative methods for improving the accuracy: the use of non-linear or general equilibrium model or the non-structural chronological series. Clements and Hendry (2002) recommend the use of models that are not affected by structural brakes.

Bratu (Simionescu) (2012 a) proved that a very good way to improve the forecasts based on Dobrescu macromodel for 2009-2011 is to make predictions using a moving average model for historical errors of the specified model.

According to Bratu (Simionescu) (2012 b), Holt-Winters technique proved to increase the degree of accuracy for the SPF forecasts more than Bandpass or CF filters that gave better results only for some horizon of the inflation rate from 1955Q1 up to 2012Q3.

In literature, only Armstrong (2005) made an inventory of the ways to improve the forecasts accuracy, but most of these are intuitive, not being necessary the use of sophisticated quantitative methods:

1. The use of the suitable forecasting method, its choice depending on the evolution of the used variables (econometric models are recommended when the researcher anticipates large changes in the evolution of the modeled phenomenon);
2. A good knowledge of the studied domain, which is incorporated in methods like neural network, data mining, exponential smoothing techniques, ARIMA models;
3. The use of a model for experts in forecasting expectations;
4. A realistic representation of economic phenomenon;
5. The use of econometric models when the relationships between variables are not known;
6. The construction of a structured problem based on the decomposition of the data series;
7. The use of simple econometric models instead of complex ones;
8. The use of conservative predictions when many sources of uncertainty are identified;
9. The combined forecasts are often used to get more accurate predictions.

The strategies proposed by Armstrong (2005) do not suppose the application of complex quantitative methods to get new accurate forecasts. Some of them are quite subjective and imply the experience of the forecaster in making predictions regarding the evolution of an indicator.

In order to establish the improvement in accuracy some statistical measures for the predictions accuracy should be used. Clements and Hendry (2010) described the frequently used indicators of forecasts accuracy.

1. The use of a particular loss function

If $L(a_t, x_{t+1})$ is a loss function $L(a_t, x_{t+1})$, where a_t -particular action, $x_{t+1} \to f(x_{t+1})$ - the value of a future time for a random variable with known distribution, function f - density forecast, then the optimal condition supposes the minimization of the loss function (density forecast will be denoted by $p_{t,1}(x_{t+1})$) will be:

$$a^*_{t,1} = \underset{a_{t,1} \in A}{\arg\min} \int L(a_{t,1}, x_{t+1}) p_{t,1}(x_{t+1}) dx_{t+1} \quad (1)$$

The expected value of the particular loss function will be computed as:

$$E[L(a^*_{t,1}, x_{t+1})] = \int L(a^*_{t,1}, x_{t+1}) f(x_{t+1}) dx_{t+1} \quad (2)$$

The chosen density forecast will be preferred to others types if the following condition will be checked:

$$E[L(a^*_{t,1}(p_{t,1}(x_{t+1})), x_{t+1})] < E[L(a^*_{t,2}(p_{t,2}(x_{t+1})), x_{t+1})] \quad (3)$$

where $a^*_{t,i}$ – optimal action of the next forecast ($p_{t,i}(x)$).

2. Mean squared error (MSE) and other accuracy measures (root mean squared error, mean error, mean absolute error)

The most used measure to assess the forecasts accuracy is the mean squared error (MSE). For a vector of variables, a matrix V of MSE is constructed as:

$$V_h \equiv E[e_{T+h} e^{'}_{T+h}] = V[e_{T+h}] + E[e_{T+h}] E[e^{'}_{T+h}] \quad (4)$$

e_{T+h} - Vector of one-step-ahead predictions errors

The determinant and the trace of the MSE matrix are considered measures of forecasts accuracy.

Supposing that “p” shows the value of prediction and “a” the actual value (registered value) for a variable X. The error at a given time (t+k) is denoted by “e(t+k)”, the length of the prediction horizon being “n”.

In practice, the following formula is used for MSE: $MSE = \frac{1}{n} \sum_{k=1}^{n} e^2(t+k)$ (5)

Other measures that are very used in practices are:

- Root mean squared error (RMSE): $RMSE = \sqrt{\frac{1}{n} \sum_{k=1}^{n} e^2(t+k)}$ (6)
- Mean error (ME): $ME = \frac{1}{n} \sum_{k=1}^{n} e(t+k)$ (7)
- Mean absolute error (MAE): $MAE = \frac{1}{n} \sum_{k=1}^{n} |e(t+k)|$ (8)

3. Measures of relative accuracy for comparisons between forecasts

These relative measures are used in making comparisons between forecasts. The reference forecast can be the naïve one (the forecast based on random walk) or another prediction. The most used measure of accuracy for making comparisons is the Theil's U statistic, usually computed in two variants: U1 (closer to zero is U1, higher the accuracy of a forecast is) and U2 (a value less than 1 for U2 implies a better forecast compared to the naïve one):

$$U_1 = \frac{\sqrt{\sum_{t=1}^{n}(a_t - p_t)^2}}{\sqrt{\sum_{t=1}^{n} a_t^2} + \sqrt{\sum_{t=1}^{n} p_t^2}} \quad (9) \qquad \text{and} \qquad U_2 = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{p_{t+1} - a_{t+1}}{a_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{a_{t+1} - a_t}{a_t}\right)^2}} \quad (10)$$

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

An alternative to U2 is the mean absolute scaled error (MASE), an indicator proposed by Hyndman and Koehler (2005): MASE= average $\left| \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n}|X_i - X_{i-1}|} \right|$ (11)

3. Methodology

The forecasts are made starting from an autoregressive model (AR) for a stationary data series. It is chosen the variant of one-step-ahead forecasts, the econometric model being updated. Simulations are made starting from these models, getting new forecasts. Supposing we have a model AR of order p:

$$X_t = a_0 + a_1 \cdot X_{t-1} + a_2 \cdot X_{t-2} + \cdots + a_p \cdot X_{t-p} + \varepsilon_t \quad (12)$$

The application of Monte Carlo method supposes several steps:

1. The econometric model estimation (an AR (p) model in this case)
2. The average and the standard deviation of the parameters are determined
3. A normal distribution is generated for each parameter knowing the average and the standard deviation (we chose a number of 1000 replications)
4. The simulated values of the dependent variable are computed knowing the values of the parameters distribution and the observed values.
5. The average and the standard deviation of the simulated values for dependent variable are computed.

An indicator of reliability is computed, starting from a critical chosen by the researcher (q*):

$$R = \frac{q* - m}{\sigma} \tag{13}$$

6. The probability that the predicted inflation rate is greater than the target is:

$$P = 1 - \varphi(R) \tag{14}$$

where phi is the probability of R in a normal standard repartition.

7. The reliability indicator can be based on another reference value and it is denoted by R'. The associated probability is P'.

According to Efron and Tibshirani (1993), the bootstrap technique is used to estimate the sampling distribution of a statistic, the repartition not being known, by repeating the re-sampling of the original data set. MacKinnon (2002) considers it a good alternative to the classical methods used to make estimations or forecasts. When an AR model is used, the bootstrap method supposes the generation of many pseudo-data based on re-sampled residual and on the estimated parameters of the model.

Gospodinov (2002) used the grid bootstrap method proposed by Hansen (1999) to determine forecasts with unbiased median in the cases of the processes with a high degree of persistence.

The bootstrap method supposes the application of the following steps:

1. The estimation of the AR(p) model, calculating the bias-corrected estimators.
2. The residual are scaled again using the procedure proposed by Thombs and Scuchany (1990).
3. The pseudo-data series are generated starting from the estimated residuals; the "p" starting values are the first two ones from the original dataset.
4. The parameters of the AR(p) models are estimated again starting from the pseudo-data series.
5. The bootstrapped forecasts are computed using these estimates.

In this article we propose another procedure based on simulations to construct forecasts using an AR(p) model:

1. For the stationary data series used in constructing the AR(p) model, the average is computed.
2. Bias-corrected-accelerated (BCA) intervals are determined for the data series, choosing as statistic the average of the mentioned data set.

The bias-corrected-accelerated interval (BCA) is a complex bootstrap technique used to construct confidence intervals. The steps of BCA bootstrap method are described by Lunneborg (2000), who calculated the accelaration estimate starting from jacknifed estimates. Then, a bootstrap sampling was generated starting from the initial sample and the bias was estimated. Finally, the z scores from the normal repartition are included to build the BCA confidence interval.

3. The limits of BCA intervals are retained as point values used in making predictions for the interest variable, forecasts based on the estimated AR(p) model.

4. Empirical results

The data set is represented by the inflation rate registered in Romania in 1991-2012. Actually, we are interested in making predictions on the horizon 2010-2012, evaluating their accuracy in ex-post variant. The variable ir (inflation rate) is computed starting from the index of consumer prices in comparable prices (1990=100). The data series has one unit root according to Phillips-Perron test, being necessary a differentiation of order 1. Some valid models were some AR(2) models, for which the errors are not correlated, the distribution is a normal one and the homoscedasticity hypothesis is checked according to White test without cross terms. The results are presented in **Appendix 1**. The equations of the autoregressive models are presented in the following table:

Table 2.

Econometric models (AR(2)) used to make one-step-ahead forecasts

Year in the forecasting horizon	Model used to make forecast:
2010	$\Delta ir_t = -9.933 - 0.415 \cdot \Delta ir_{t-2}$
2011	$\Delta ir_t = -9.952 - 0.416 \cdot \Delta ir_{t-2}$
2012	$\Delta ir_t = -9.965 - 0.418 \cdot \Delta ir_{t-2}$

Source: own computations

The Monte Carlo (MC) method and bootstrap techniques that were presented in the previous section are used to construct one-step-ahead forecasts for inflation rate in Romania (2010-2012). The parameters used to generate the MC simulations are the average and the standard deviation of the parameters of AR(2) model. 1000 replications were chosen and their average represents the new point forecast. The add-in "Bootstrap coefficients" available in EViews 7.2. is used to estimate the bootstrapped parameters.

We assessed the accuracy of predictions based on AR(2) models and those based on simulations starting from these models. Moreover, the accuracy is compared with that of the predictions provided by two forecasters.

Table 3. Accuracy indicators for the inflation rate forecasts in Romania (2010-2012)

Accuracy measure	Predicted inflation rate using Monte Carlo (MC) simulations (%)	Predicted inflation rate using bootstrap technique (%)	Authors' method based on lower limit of BCA intervals	Authors' method based on upper limit of BCA intervals	Expert 1 inflation rate predictions (%)	Expert 2 inflation rate predictions (%)	Predicted inflation rate using AR(2) model
MSE	0.10260	0.04830	0.00617	0.32070	0.66936	3.61273	2.98420
RMSE	0.32031	0.21977	0.07853	0.56630	0.81814	1.90072	1.72748
ME	0.25333	0.19000	0.01000	-0.45667	-0.27433	0.29333	-1.57333
MAE	0.25333	0.19000	0.07667	0.45667	0.73233	1.63333	1.57333
U1	0.03153	0.02146	**0.00755**	0.05240	0.07715	0.18050	0.14551

MASE	0.18515	0.12911	0.04470	0.33916	0.49078	1.02386	1.01455

Source: own computations

The inflation forecasts based on AR(2) model are more accurate only than the expectations of Expert 2 on the horizon 2010-2012, but less accurate than Expert 1 forecasts. A great improvement of AR model predictions was obtained by making simulations. The hierarchy of strategies to improve the accuracy, according to U1, starting with the best one, is the following: own method based on the lower limit of BCA intervals, the strategy based on bootstrap technique, the application of MC method, own method based on the upper limit of BCA intervals. It is interesting that the application of these strategies succeeded in getting predictions even more accurate than the Expert 1 ones, which were initially better than simple AR(2) forecasts. If the initial predictions were less accurate than the naïve ones, our methods generated better forecasts than those based on random walk. The appreciations based on MCM, bootstrap method and lower limits of BCA intervals are underestimated compared to those based on AR models, that are overestimated (a negative value for mean error). For all the computed accuracy measures our method that uses lower limits of BCA intervals registered the best values.

The critical values (q*) used to calculate the reliability indicators are: the difference between the targeted inflation in Romania in the previous two years in our case and the differences between the two previous values of inflation rate.

The difference between the targets is based on the inflation rates expressed in comparable prices. A value of 0.5 percentage points corresponds to this difference if we take into account the inflation rate compared to the previous year.

Table 4. The probabilities of getting inflation rates greater than some reference values

Year for which the inflation is projected	Probability P	Probability P’
2012	0.5082	0.5082
2013	0.517	0.517

Source: own computations

The degree of uncertainty is higher for the prediction in 2013 compared to that made for 2012. A higher probability was obtained for 2013. This implies that there is a greater probability that the predicted value in 2013 outperforms the value from 2012 with more than 0.5 percentage points (the difference between targets in 2013 and 2012). This probability is also higher in 2013, if we take into consideration as critical value the difference between the previous two registered inflation rates. If we take the critical value as the difference between the last two values in the data series, we got a lower degree of uncertainty compared to the difference between targets.

5. Conclusions

This research comes to enrich the literature related to the strategies of improving the forecasts accuracy. Only few studies were interested in finding some quantitative methods to get better predictions. The simulations based on MCM and bootstrap technique used to predict the inflation starting from an AR(2) model are very good strategies of improving the inflation rate forecasts in Romania on the horizon 2010-2012.

The novelty is given by the method proposed by the two authors to get new predictions. Actually, this strategy proved to outperform the MCM and normal bootstrap method. For the variable that will be predicted, BCA intervals are built and its limits are introduced in AR(2) model estimated using the initial data. The forecasts based by simulated data using the lower limit proved to be more accurate than those based on classical MCM and bootstrap technique.

We also include the analysis of uncertainty in the forecasting process based on AR(2) models. The uncertainty study is based on Monte Carlo simulations, a probability that the prediction exceeds a critical value being computed. If the critical values are the difference between the inflation targets based on the two previous periods and the difference of actual values of the two previous years, the uncertainty is higher for the prediction in 2013 compared to that made for 2012.

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Appendix

Tests for stationarity, serial correlation, homoscedasticity and normality for the AR(2) model used in making prediction for 2012

Null Hypothesis: D(IR) has a unit root
Exogenous: Constant
Bandwidth: 18 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-5.919457	0.0001
Test critical values:	1% level	-3.808546	
	5% level	-3.020686	
	10% level	-2.650413	

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	3.669302	Prob. F(2,15)	0.0504
Obs*R-squared	6.241817	Prob. Chi-Square(2)	0.0441

Heteroskedasticity Test: White

F-statistic	0.733709	Prob. F(2,16)	0.4956
Obs*R-squared	1.596169	Prob. Chi-Square(2)	0.4502
Scaled explained SS	1.016480	Prob. Chi-Square(2)	0.6016