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New Strategies to Improve the Accuracy of Predictions based on Monte Carlo and Bootstrap Simulations: An Application to Bulgarian and Romanian Inflation

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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 for Romania and ARMA(1,1) models for Bulgaria 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) and ARMA(1,1) forecasts. These techniques also improved the predictions of experts in forecasting made for Romania and the forecasts of the European Commission made for Bulgaria. Our own method based on the lower limits of BCA intervals generated the best forecasts. In the forecasting process based on ARMA models the uncertainty analysis was introduced, by calculating, under the hypothesis of normal distribution, the probability that the predicted value exceeds a critical value. For 2013 in both countries we anticipate a decrease in the degree of uncertainty for annual inflation rate.

Keywords: accuracy; forecasts; Monte Carlo method; bootstrap technique; biased-corrected-accelerated bootstrap intervals.
JEL classification: C150; C530.
MSC2010: 15C; 20D.

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Nuevas estrategias para mejorar la exactitud de las predicciones de inflación en Rumanía y Bulgaria usando simulaciones Monte Carlo y Bootstrap

RESUMEN

La necesidad de mejorar la precisión de las previsiones ha crecido en el contexto de crisis económica actual, pero son pocos los investigadores que se habían interesado hasta ahora por la búsqueda de estrategias empíricas para mejorar sus predicciones. En este artículo, a través de las previsiones de la tasa de inflación en el horizonte 2010-2012, hemos podido comprobar que las previsiones de un solo paso adelante sobre la base de modelos actualizados AR(2) para Rumanía y ARMA(1,1) para Bulgaria podrían mejorarse sustancialmente mediante la generación de nuevas predicciones utilizando el método de Monte Carlo y la técnica bootstrap para simular los coeficientes de los modelos. Así, en este trabajo presentamos una nueva metodología para la construcción de las previsiones mediante el uso de los límites de los intervalos de rutina de carga de polarización –corrección acelerada para la serie inicial de los datos de la variable a predecir–. Después de evaluar la exactitud de los nuevos pronósticos, encontramos que todas las estrategias propuestas mejoraron los pronósticos iniciales de AR(2) y ARMA(1,1). Estas técnicas también mejoraron las predicciones de dos comisiones de expertos en previsión hechas para Rumanía, así como las previsiones de la Comisión Europea hechas para Bulgaria. Nuestro propio método basado en los límites inferiores de los intervalos de BCA generó los mejores pronósticos. En el proceso de predicción basado en modelos ARMA se introdujo el análisis de incertidumbre, mediante el cálculo, bajo la hipótesis de distribución normal, de la probabilidad de que el valor predicho excediese un valor crítico. Para 2013 anticipamos en ambos países una disminución en el grado de incertidumbre para la tasa de inflación anual.

Palabras clave: precisión; pronósticos; método Monte Carlo; técnica bootstrap; intervalos de rutina de carga con corrección de sesgo acelerado.
Clasificación JEL: D43; L11; L81.
MSC2010: 91B; 93B; 93C.

1. INTRODUCTION

In the context of the actual economic crisis, the necessity of getting more accurate predictions has intensified. It is not enough only to have a mirror of the forecasts accuracy, the research should continue in order to find out the most suitable strategy to improve the macroeconomic predictions. These are often used to fundament the decisional process.

The phrase "strategy of improving the predictions accuracy" was introduced in literature by Mihaela Bratu (2012), who proposed some empirical strategies to get more accurate forecasts for USA inflation rate. The author proposed more methods like: historical accuracy method, combined forecasts, the application of filters and Holt-Winters technique to smooth the predictions, the use of resampling techniques.

Todd Clark and Michael 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.

Peter Buhlmann (2002) 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 is 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 and Bulgaria. 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 institutions from Romania (who want to remain anonymous).

We chose Bulgaria and Romania because they are two European Union countries that make efforts for decreasing the inflation rate. The methodology could be applied for other variables in order to have stationary data set for estimating auto-regressive models.

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, Charles 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. Lars- Eric Oller (2005) deeply analysed the problem of quality data in the context of predictions.

Paul Goodwin (2005) 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.

Gultekin Isiklar, Kajal Lahiri, and Prakash Loungani (2006) 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.

Michael 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 (1997) suggested some quantitative methods for improving the accuracy: the use of non-linear or general equilibrium model or the non-structural chronological series. Michael Clements and David Hendry (2002) recommend the use of models that are not affected by structural brakes.

Mihaela 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 Mihaela 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 John Scott 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 John Scott 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. Michael Clements and David Hendry (2002) 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 , where a_t is a particular action, $x_{t+1} \to f(x_{t+1})$ is the value of a future time for a random variable with known distribution, and function f is the 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:

$$a_{t,1}^{*} = \arg\min_{a_{t,1} \epsilon A} \int L(a_{t,1}, x_{t+1}) p_{t,1}(x_{t+1}) dx_{t+1} \quad (1)$$

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

$$E\left[L\left(a_{t,1}^{*}, x_{t+1}\right)\right] = \int L\left(a_{t,1}^{*}, x_{t+1}\right) f\left(x_{t+1}\right) dx_{t+1} \tag{2}$$

The chosen density forecast will be preferred to others types if the following condition will be checked: $E[L\left(a_{t,1}^{*}\left(p_{t,1}(x_{t+1})\right), x_{t+1}\right)] < E[L\left(a_{t,2}^{*}\left(p_{t,2}(x_{t+1})\right), x_{t+1}\right)]$, (3)

where $a_{t,i}^{*}$ is the 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:

$$V_h \equiv E[e_{T+h}e_{T+h}^{'}] = V[e_{T+h}] + E[e_{T+h}]E[e_{T+h}^{'}], \tag{4}$$

where e_{T+h} is the 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)*" and the length of the prediction horizon is "*n*". In practice, the following formula is used for MSE:

$$MSE = \frac{1}{n}\sum_{k=1}^{n} e^2(t+k) \tag{5}$$

Other measures that are very used in practice are:

- Root mean squared error (RMSE): $$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n} e^2(t+k)} \tag{6}$$

- Mean error (ME): $$ME = \frac{1}{n}\sum_{k=1}^{n} e(t+k) \tag{7}$$

- Mean absolute error (MAE): $$MAE = \frac{1}{n}\sum_{k=1}^{n} |e(t+k)| \tag{8}$$

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: U_1 (the closer to zero is U_1, the higher is the accuracy of a forecast) and U_2 (a value less than 1 for U_2 implies a better forecast compared to the *naïve* one):

$$U_1 = \frac{\sqrt{\sum_{t=1}^{n}(a_t - p_t)^2}}{\sqrt{\sum_{t=1}^{n} a_t^2} + \sqrt{\sum_{t=1}^{n} p_t^2}} \tag{9}$$

and

$$U_2 = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{p_{t+1} - a_{t+1}}{a_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{a_{t+1} - a_t}{a_t}\right)^2}} \tag{10}$$

If U_1 value is close to zero for U_1 (less than 0.5), we have a high degree of accuracy. An alternative to U_2 is the mean absolute scaled error (MASE), an indicator proposed by Rob Hyndman and Anne Koehler (2006):

$$\text{MASE= average}\left|\frac{e_t}{\frac{1}{n-1}\sum_{t=2}^{n}|a_t - a_{t-1}|}\right| \tag{11}$$

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*:

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

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 1,000 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.
6. An indicator of reliability is computed, starting from a critical chosen by the researcher (q*):

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

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

$$P = 1 - \varphi(R) \quad (14)$$

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

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

However, our methodology is limited to AR and ARMA models. The multivariate approach would be an alternative to our methodology, but in the two chosen countries (Romania and Bulgaria) the dependencies between variables are limited to the particularities of the phenomenon. Even if both countries have post-communist economies, the structural differences have an important impact in the inflation evolution. Lorenzo Cappellari and Stephen Jenkins (2006) computed multivariate normal probabilities for simulation using some Stata programs. Pseudo-random sequences were used to determine draws from standard uniform density.

Our methodology is also suitable for other macroeconomic variables for which an AR or ARMA model is identified for stationary data. We chose Romania and Bulgaria, because they are two post-communist countries that entered in the European Union at the same time. Both countries have to make constant efforts for achieving a disinflation process. Our methodology could be applied for making predictions on different horizons. In this case we chose the variant of short-run predictions.

According to Bradley Efron (2003), 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. Russel Davidson and James MacKinnon (2002) consider 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.

Phillip Hans Franses, Henk Kranendonk, and Lanser Debby (2011) used Monte Carlo simulation to assess four sources of uncertainty in forecasts based on Saffier model.

Nikolay Gospodinov (2002) used a grid bootstrap method 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 Lorri Thombs and William 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 Clifford Lunneborg (2000), who calculated the acceleration estimate starting from jackknifed 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

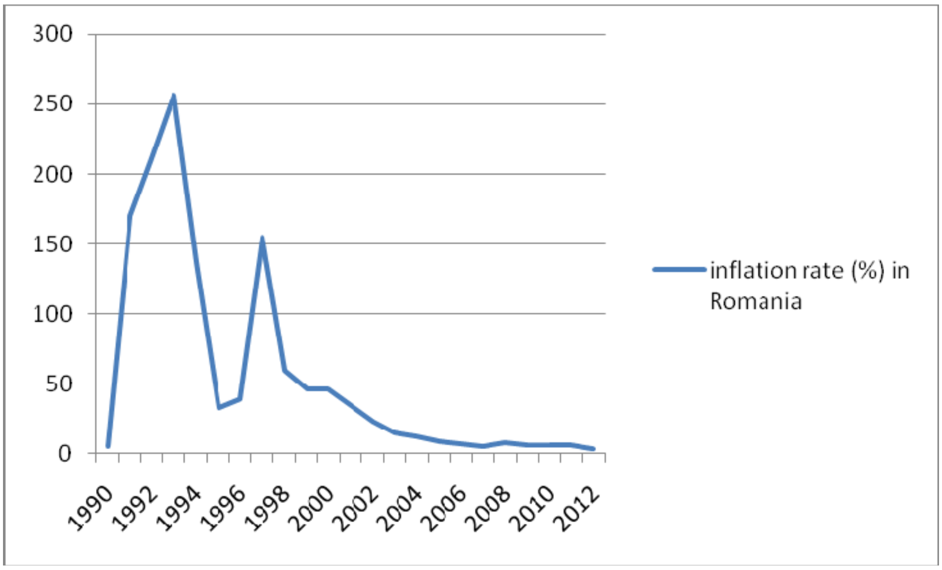
The data set is represented by the inflation rate registered in Romania, respectively Bulgaria in 1990-2012. Actually, we are interested in making predictions on the horizon 2010-2012, evaluating their accuracy in ex-post variant. The variables *ir* (inflation rate in Romania) and *ir'* (inflation rate in Bulgaria) are computed starting from the index of consumer prices in comparable prices (1990=100).

During the transition period from a centralized economy to market economy, Romania tried almost a decade to get one digit inflation rate. During 2000-2007, this country got an annual average disinflation of 5.8% and implemented mix economic policies in order to achieve the financial stability. Romania is numbered between the developing countries that adopt an inflation targeting regime. In 2005 the transition to the new monetary regime was made because of the National Bank independence and the price stability goal was achieved.

We can observe (Figure 1) that in 2012 the inflation rate in Romania decreased with almost 37.7% compared to the value in 1990. From 1997 to 2007, the inflation rate has decreased from a year to another. In 2008, the installation of global economic crisis determined an increase in the inflation rate compared to the previous year. Since 2010, the inflation rate started to decrease slowly.

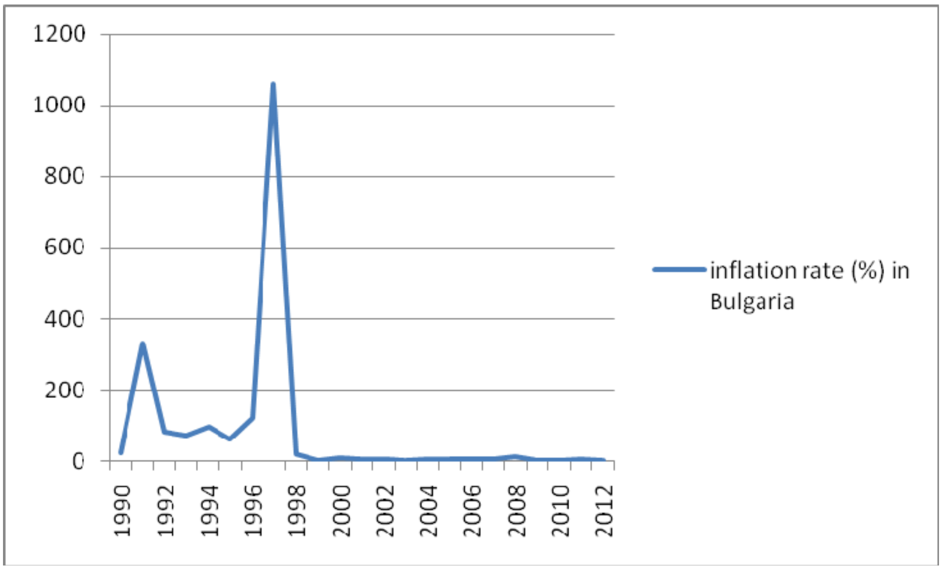
Bulgaria (Figure 2) faced an economic collapse during 1996 because of the reforms of the Bulgarian Socialist Party. The currency board regime was introduced in the spring of 1997, fact that generated a very high inflation rate and the lev collapse. Until the middle of 2007 the disinflation process went well.

Figure 1: The evolution of inflation rate (%) in Romania during 1990-2012



Source: own graph

Figure 2: The evolution of inflation rate (%) in Bulgaria during 1990-2012



Source: own graph

In 2012 the inflation rate in Bulgaria decreased with 87.45% compared to 1990. A trend of increase or decrease in inflation for many years cannot be observed in Bulgaria. In 2008, like in Romania, on the crisis background, the inflation rate increase compared to 2007.

The data series for Romania has one unit root according to Phillips-Perron test, being necessary a differentiation of order 1. For Bulgaria the inflation rate series is stationary. Some valid models were built for Romania (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. For Bulgaria, the most suitable process was an ARMA(1,1), the residual terms being a white noise. The results are presented in Appendix 1 and Appendix 2. The equations of the autoregressive models and autoregressive moving average models are presented in the following table:

Table 1: Econometric models (AR(2) and ARMA(1,1)) used to make one-step-ahead forecasts for inflation rate in Romania and Bulgaria (horizon 2010-2012)

Year in the forecasting horizon	Model used to make forecast in Romania	Model used to make forecast in Bulgaria
2010	$\Delta ir_t = -9.933 - 0.415 \cdot \Delta ir_{t-2} + \varepsilon_t$	$ir'_t = 133.29 - 0.99ir'_{t-1} + 1.88\varepsilon_{t-1} + \varepsilon_t$
2011	$\Delta ir_t = -9.952 - 0.416 \cdot \Delta ir_{t-2} + \varepsilon_t$	$ir'_t = 129.18 - ir'_{t-1} + 1.88\varepsilon_{t-1} + \varepsilon_t$
2012	$\Delta ir_t = -9.965 - 0.418 \cdot \Delta ir_{t-2} + \varepsilon_t$	$ir'_t = 73.77 - 0.81ir'_{t-1} + 0.97\varepsilon_{t-1} + \varepsilon_t$

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 and Bulgaria (2010-2012). The parameters used to generate the MC simulations are the average and the standard deviation of the parameters of AR(2), respectively ARMA(1,1) models. 1,000 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) and ARMA(1,1) models and those based on simulations starting from these models. Moreover, the accuracy for Romanian's forecasts is compared with that of the predictions provided by the two institutions from Romania.

The inflation forecasts based on AR(2) model are more accurate only than the expectations of Forecaster 2 (F2) on the horizon 2010-2012, but less accurate than Forecaster 1 (F1) prediction. 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 F1 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.

Table 2: 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	F1 inflation rate predictions (%)	F2 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

For Bulgaria we compare the predictions with those made by the European Commission (EC).

Table 3: Accuracy indicators for the inflation rate forecasts in Bulgaria (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	EC inflation rate predictions (%)	Predicted inflation rate using ARMA (1,1) model
MSE	0.348757	0.4827	0.3277	0.4663	0.447232	0.402699
RMSE	0.5835	0.5582	0.5573	0.6323	0.6688	0.6346
ME	0.5228	0.5024	0.4522	0.6228	0.6453	0.2453
MAE	0.5073	0.4774	0.4522	0.5935	0.645333333	0.621333333
U1	0.0735	0.0693	**0.0337**	0.1004	0.1098	0.0977
MASE	0.7783	0.8724	0.6477	0.7834	0.8307	0.9039

Source: own computations

The results in the above table for Bulgaria show that the method proposed by us using the lower limit of the BCA intervals gave the most accurate forecasts, as in the case of Romania. It is interesting that all the proposed predictions are better than the naïve ones, according to the values of MASE. Moreover, the predictions based on lower limits of BCA intervals are underestimated due to the equal values for MAE and MASE. The forecasts for Romania based on this method are more accurate. However, our predictions based on AR(2) model for Romania are less accurate than those based on ARMA(1,1) model for Bulgaria on the horizon 2010-2012.

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. According to Siok Kun Sek and Wai Mun Har (2012), the inflation targeting became frequently used starting to the 90's years in the context of prices stability. But Philip Arestis and Malcolm Sawyer (2013) showed that the recent financial crisis threw many doubts regarding the target inflation regime.

The difference between the targets in Romania 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 in Romania

Year for which the inflation is projected	Probability *P*	Probability *P'*
2012	0.5082	0.512
2013	0.517	0.532

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. The usual interpretation supposes that there are more chances that we have in 2013 a higher inflation rate in Romania than the value from 2012. However, the results are marked by doubts because the probability is very close to 0.5. There is a probability of almost 0.5 to have a lower inflation rate in 2013 compared to 2012.

For Bulgaria we compare the predictions for a year with the inflation target for that year and with the previous year value of the inflation rate.

Table 5: The probabilities of getting inflation rates greater than target inflation, respectively the previous inflation rate in Bulgaria

Year for which the inflation is projected	Probability *P*	Probability *P'*
2012	0.7429	0.6594
2013	0.7603	0.6723

Source: own computations

For Bulgaria we got a high probability of getting a greater inflation rate in 2012 and 2013 compared to the target or the previous year inflation. Indeed, in 2012 Bulgaria registered a higher inflation rate, with 33.5% greater the target and with 25.8% higher than the previous year indicator. For 2013 there is likely to have an increase in inflation in Bulgaria compared to the value registered in 2012. If we make the comparison between the reference values, we have a lower uncertainty is you make the comparison with the previous year inflation. The results for Bulgaria are marked by lower uncertainty, the probabilities being farther from 0.5. There are high chances to have a higher inflation rate in 2013 in Bulgaria compared to the value in 2012 and to the target for 2013. In the context of economic crisis, it is more likely to have an increase in inflation rate in a country with transition economy like Bulgaria.

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 for Romania and ARMA(1,1) model for Bulgaria are very good strategies of improving the inflation rate forecasts 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 ARMA models that were 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) and ARMA(1,1) 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 in Romania 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. For Bulgaria we have a lower degree of uncertainty if we make the comparison of the predicted values with those registered in the previous year. For both countries we anticipate a diminish of the degree of uncertainty in 2013 compared to 2012.

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APPENDIX 1. Tests for stationary, serial correlation, homoscedasticity and normality for the AR(2) model used in making prediction for 2012 in Romania

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

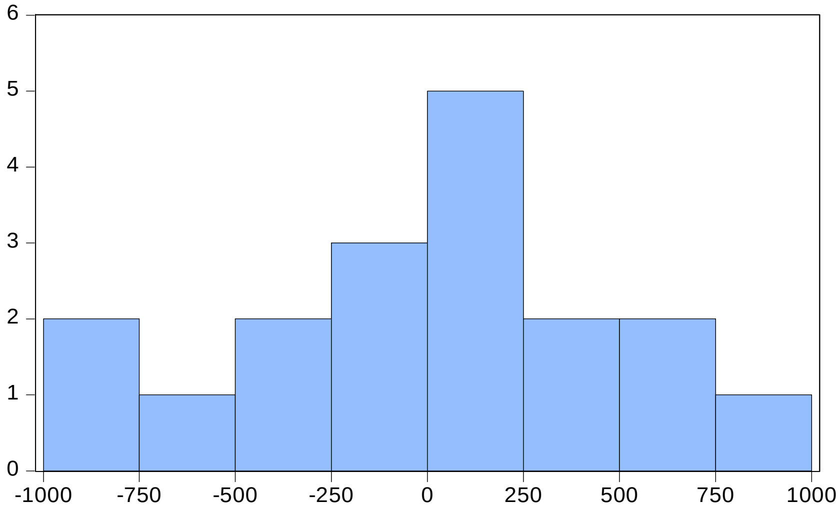
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-5.919457	0.0001
Test critical values:	1% level	-3.808546	
	5% level	-3.020686	
	10% level	-2.650413	

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



Series: Residuals
Sample 1994 2011
Observations 18

Mean	-1.33e-11
Median	14.29253
Maximum	861.8586
Minimum	-890.0679
Std. Dev.	493.1938
Skewness	-0.102955
Kurtosis	2.472509
Jarque-Bera	0.240484
Probability	0.886706

APPENDIX 2. Tests for stationary, serial correlation, homoscedasticity and normality for the AR(2) model used in making prediction for 2012 in Bulgaria

Null Hypothesis: IR has a unit root
Exogenous: None
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.875263	0.0005
Test critical values:	1% level	-2.674290	
	5% level	-1.957204	
	10% level	-1.608175	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: IR has a unit root
Exogenous: Constant
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.300557	0.0031
Test critical values:	1% level	-3.769597	
	5% level	-3.004861	
	10% level	-2.642242	

Null Hypothesis: IR has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.874324	0.0041
Test critical values:	1% level	-4.440739	
	5% level	-3.632896	
	10% level	-3.254671	

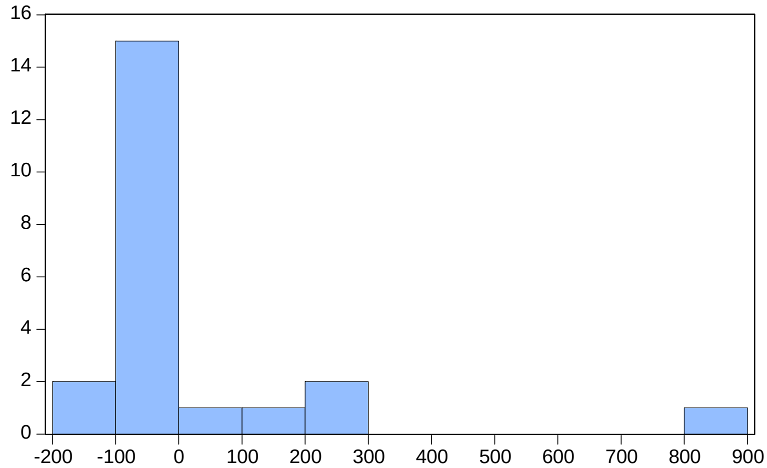
*MacKinnon (1996) one-sided p-values.

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.069112	Prob. F(1,18)	0.7956
Obs*R-squared	0.054854	Prob. Chi-Square(1)	0.8148

Heteroskedasticity Test: White

F-statistic	1.87865	Prob. F(9,12)	0.2000
Obs*R-squared	2.47317	Prob. Chi-Square(9)	0.1152
Scaled explained SS	8.20477	Prob. Chi-Square(9)	0.4680



Series: Residuals
Sample 1991 2012
Observations 22

Mean	7.449320
Median	-52.07800
Maximum	809.2951
Minimum	-189.8926
Std. Dev.	208.5512
Skew ness	2.792020
Kurtosis	11.11914
Jarque-Bera	89.01008
Probability	0.000000