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Article

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Economic Review: Journal of Economics and Business

Provided in Cooperation with:

Faculty of Economics, University of Tuzla

Suggested Citation: Simionescu, Mihaela; Dragan, Irina (2016) : The Evaluation of Quarterly Forecast Intervals for Inflation Rate in Romania, Economic Review: Journal of Economics and Business, ISSN 1512-8962, University of Tuzla, Faculty of Economics, Tuzla, Vol. 14, Iss. 1, pp. 80-89

This Version is available at:

<https://hdl.handle.net/10419/193859>

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THE EVALUATION OF QUARTERLY FORECAST INTERVALS FOR INFLATION RATE IN ROMANIA*

Mihaela Simionescu**, Irina Drăgan ***

ABSTRACT

The forecast uncertainty was one of the causes of the recent economic crisis and its evaluation became more necessary nowadays. The aim of this paper is to build and assess different types of forecast intervals for quarterly inflation rate in Romania. The Bootstrap Bias-corrected-accelerated (BCA) forecast intervals outperformed the intervals based on historical errors, four out of six values of inflation rate being placed in the first type of intervals during Q3:2013-Q4:2014. The likelihood ratio tests and the chi-square test indicated that there are significant differences between the ex-ante probability of 0.95 and the real probabilities for both types of forecast intervals. As a methodological novelty, Monte Carlo and bootstrap simulations were used for assessing the uncertainty in inflation rate forecasts in Romania.

Keywords: Uncertainty, Forecasts, Forecast intervals, Inflation rate, Monte Carlo simulations, Bootstrap BCA

JEL: E170, C530

1. INTRODUCTION

The forecast uncertainty assessment was the subject of several studies in literature. Still, this research topic should be developed because in real economy the prediction uncertainty cannot be omitted. The uncertainty affects not only the econometric models, but also the forecasts based on this method. The variance of forecast errors is a common measure of assessing the uncertainty associated to point forecasts. On the other hand, experts in forecasting consider that forecast intervals are by their nature a way of

putting in evidence the uncertainty of the predicting process. Some tests for forecast intervals are used to check if there are significant differences between the ex-ante probability and the computed probability.

The objective of this research is to assess the quarterly inflation rate forecasts in the last two quarters of 2013 and in 2014. The point and interval forecasts are based on autoregressive models associated to transformed data sets of inflation rate. Monte Carlo simulations are used to assess the uncertainty, but in this article we propose the use of bootstrap BCA intervals. In this case, the statistics are the average of the inflation rates taken into consideration for building the econometric model. The use of the BCA intervals on predictions is a novelty in literature and the empirical results demonstrated a good performance of this type of intervals for inflation rate in Romania.

2. Literature Review

The problem of forecast uncertainty becomes very important nowadays, because of the great failure of the classical current that explains the actual economic crisis. Novy and Taylor (2012) came to the conclusion that forecast uncertainty is the cause of the USA commercial collapse in the period 2008-2009. For this period of economic instability researchers recommend the come back to nonlinear models.

The policies based on forecasts with high degree of uncertainty were an important cause of the actual economic crisis. This aspect was studied by Bloom and Davis (2013), but also by Bachmann, Elstner and Sims (2010) who showed that the policy uncertainty determined the decrease in companies' profit. Leduc and Liu (2012) observed that the uncertainty reduced the

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economic activity more in the actual crisis than in the previous crisis.

Giordani and Söderlind (2003) used three classic measures of uncertainty: disagreement between forecasters, the variance of aggregated histogram and standard deviation of individual forecasts. Ericsson (2001) considered that the most utilized statistical measures of uncertainty are:

1. Forecast bias;
2. Variance of forecast error;
3. Mean Square Error- MSE as a combination of the two previous indicators.

The forecast interval is built starting from the point forecasts and prediction error and a probability is attached in accordance to the hypothesis regarding the errors distribution. In general, we assume that the random shocks follow a normal distribution $e_t \rightarrow N(0, \sigma_e^2)$, which implies a normally distributed probability density $x_{t+h} \rightarrow N(\hat{x}_{t+h}, \sigma_h^2)$.

Initially the researchers used point forecasts for past periods to have a proxy as an uncertainty measure. These measures are compared to ex-ante uncertainty indicators.

Wallis (2008) showed that Zarnowitz and Lambros (1987) defined the consensus as the degree of agreement regarding the point forecasts of forecasters for a certain variable. The authors defined the uncertainty as the variance of probability distributions.

For assessing the density or forecast intervals more tests are used, some of them also presented by Simionescu (2014).

I. Likelihood ratio (LR) tests for forecast intervals

We consider time series for the forecast intervals and we set the probability of π for the value to be inside the interval. We registered time series for the results registered in reality and we fix as objective the evaluation of ex-ante probability

correction. If n_1 results are inside the forecast intervals and n_2 outside it, the coverage probability is:

$$p = \frac{n_1}{n}. \quad (2.1.)$$

If the distribution is a binomial one, under the null hypothesis, the likelihood is:

$$L(\pi) = (1 - \pi)^{n_2} \pi^{n_1} \quad (2.2.)$$

while under the alternative hypothesis it is:

$$L(p) = (1 - p)^{n_2} p^{n_1} \quad (2.3.)$$

Christoffersen (1998) established the statistic of likelihood ratio as

$$LR_{UC} = 2(n_2 \ln \frac{1-p}{1-\pi} + n_1 \ln \frac{p}{\pi}) \rightarrow \chi^2_1 \quad (2.4.)$$

This is a test of unconditional coverage that is actually unsuitable for time series. Therefore, Christoffersen (1998) proposed another test that combines the test of unconditional coverage with the independence one.

The independence test is based on the matrix of transition frequencies (n_{ij}) , which is the number of observations that are in state i at moment $t-1$ and in state j at moment t . The maximum likelihood estimations of transition probabilities are computed as a ratio between frequencies in a cell and the total number of frequencies of a line. For a forecast interval two cases are possible: the values are inside or outside the interval, being denoted with 1 and 0. The transition matrix of estimated probabilities is:

$$P = \begin{pmatrix} 1 - p_{01} & p_{01} \\ 1 - p_{11} & p_{11} \end{pmatrix} = \begin{pmatrix} \frac{n_{00}}{n_{0.}} & \frac{n_{01}}{n_{0.}} \\ \frac{n_{10}}{n_{1.}} & \frac{n_{11}}{n_{1.}} \end{pmatrix} \quad (2.5.)$$

The likelihood for P is:

$$L(P) = (1 - p_{01})^{n_{00}} p_{01}^{n_{01}} (1 - p_{11})^{n_{10}} p_{11}^{n_{11}} \quad (2.6.)$$

The null hypothesis of the independence test specifies that the $t-1$ state

is independent of t state, which is equivalent with $\pi_{01} = \pi_{11}$.

The estimator of maximum likelihood of the common probability is $\frac{n_{11}}{n}$.

The likelihood under the null hypothesis assessed at p is:

$$L(p) = (1-p)^{n_{00}} p^{n_{11}} \quad (2.7.)$$

The LR test statistic is:

$$LR_{ind} = -2 \ln \frac{L(p)}{L(\pi)} \rightarrow \chi^2_1 \quad (2.8.)$$

The test proposed by Christoffersen (1998) that combines the unconditional coverage test with the independence one has the statistics:

$$LR_{CC} = -2 \ln \frac{L(\pi)}{L(p)} \rightarrow \chi^2_2 \quad (2.9.)$$

If the first observation is ignored, then:

$$LR_{CC} = LR_{UC} + LR_{ind}. \quad (2.10.)$$

II. Chi-square (χ^2) tests for forecast intervals

Likelihood ratio tests are equivalent to Pearson's goodness-of-fit tests. Wallis (2008) used them for the first time for density and forecast intervals. The chi-square test for unconditional coverage uses the statistics:

$$\chi^2 = \frac{n(p-\pi)^2}{\pi(1-\pi)} \quad (2.11.)$$

If we consider the matrix of observed frequencies, $\begin{pmatrix} a & b \\ c & d \end{pmatrix}$, then

$$\chi^2 = \frac{n(ad-bc)^2}{(a+b)(c+d)(a+c)(b+d)} \quad (2.12.)$$

The conditional coverage test combined with the independence test uses the contingency table of the observed frequencies

with expected frequencies under the null hypothesis of independent lines and using the coverage probability.

The matrix of expected frequencies is:

$$\begin{pmatrix} (1-\pi)(a+b) & \pi(a+b) \\ (1-\pi)(c+d) & \pi(c+d) \end{pmatrix} \quad (2.13.)$$

The proportions column is considered under the test hypothesis; the test has 2 degrees of freedom. The statistics are computed as a sum of square normal standard statistics of the samples proportions, a proportion for each row of the table. For low volume samples the additive relationship of LR statistics cannot be transposed exactly in chi-square test terms.

3. An Application for the Uncertainty Assessment of Inflation Rate Predictions

The application uses a time series for inflation rate. For a data series (y_t) that is modelled according to an autoregressive model AR(1), the representation (e_t – error) is:

$$y_t = \theta y_{t-1} + e_t \quad |\theta| < 1. \quad (3.1.)$$

In moving average representation ($a_i = \theta^i$), the h -steps-ahead point forecast is:

$$\hat{y}_{t+h} = \theta^h y_t \quad (3.2.)$$

The forecast error variance is:

$$\sigma_h^2 = \sigma_e^2 \frac{1-\theta^{2h}}{1-\theta^2} \quad (3.3.)$$

The quarterly inflation rates at the end of each year are computed, the series' horizon being Q1:2000-2014:Q4. Quarterly forecasts were made for the last two quarters of 2013 and for all the quarters in 2014. The influence of the seasonal factor is eliminated using the Tramo/Seats method and the new variable is denoted by *irsa*. The data series is not stationary and the following transformation was made in order to get a stationary data set:

$$i_t = \ln(irsa_t) - \ln(irsa_{t-1}) \quad (3.4.)$$

The **Augmented Dickey-Fuller test** (ADF test) was applied to the transformed

data series for different significance levels (1%, 5% and 10%).

Table 3.1. Augmented Dickey-Fuller test for quarterly seasonally adjusted inflation rate (Q1:2000-Q4:2012)

Doubled difference d inflation rate (The speed of change in inflation rate)	Model with trend and constant t	Model including constant	Model without trend and constant t
ADF statistic	-	-	-
	5.96899	6.081928	6.00895
	3	(Prob.=0.000	3
	(Prob.= 0.0000)	0)	(Prob.= 0.0000)
Critical values	-	-	-
1%	4.16575	3.577723	2.61509
	6		3
5%	-	-	-
	3.50850	2.925169	1.94797
	8		5
10%	-	-	-
	3.18423	2.600658	1.61240
	0		8

Source: Authors' calculations

The transformed data series of inflation rate is represented using an autoregressive model of order 1 (AR(1)): $i_t = -0.0315 + 0.285 \cdot i_{t-1} + e_t$. The value of Durbin-Watson statistics is 2.199, a value close to 2, the fact that indicates the error independence. Moreover, the Breusch-Godfrey test for serial correlation leads us to the same conclusion. The probability associated to this test is greater than 0.05. So, we do not have enough evidence to reject the null hypothesis (the hypothesis of the error independence). According to the White test, the error homoscedasticity is checked for a level of significance of 5%. The normality

assumption is not checked, but it could be neglected. The results of the application of these tests are presented in **Appendix 1**.

The process is written as an MA(1) (moving average of order 1):

$$\hat{i}_t = \sum_{i=0}^{t-1} 0.285^i + e_{t-i} \quad (3.5.)$$

The variance of forecast error is:

$$\sigma_h^2 = \sigma_\varepsilon^2 \cdot \frac{1-0.285^{2h}}{1-0.285^2} = \sigma_\varepsilon^2 \cdot \frac{1-0.285^{2h}}{0.9187} \quad (3.6.)$$

The error related to parameter estimation is a part of the forecast error.

The forecast error is written as a sum of two components, in which the first term is the cumulated random error:

$$y_{t+h} - \hat{y}_{t+h} = e_{t+h} + (\theta^h - \hat{\theta}^h)y_t \quad (3.7.)$$

$$e_{t+h} = \varepsilon_{t+h} + \theta\varepsilon_{t+h-1} + \dots + \theta\varepsilon_{t+1} \quad (3.8.)$$

Knowing the variance of parameter θ estimated using the ordinary least squares ($\frac{1-\theta^2}{n}$) and neglecting the correlation between

y_t and the estimations, using a first order approximation of the linear function, we have:

$$\text{var}(\hat{\theta}^h - \theta^h) \approx \frac{(h\theta^{h-1})^2(1-\theta^2)}{n} \quad (3.9.)$$

Where by $\text{var}(y_t) = \frac{\sigma_\varepsilon^2}{1-\theta^2}$, then the forecast error variance is:

$$E(y_{t+h} - \hat{y}_{t+h})^2 \approx \sigma_\varepsilon^2 \left(\frac{1-\theta^{2h}}{1-\theta^2} + \frac{(h\theta^{h-1})^2}{n} \right) \quad (3.10.)$$

For the quarterly inflation rate registered in the first two quarters of 2013, the forecast error variance is:

$$E(i_{t+h} - \hat{i}_{t+h})^2 \approx 0.048 \cdot \left(\frac{1-0.285^{2h}}{1-0.285^2} + \frac{(h \cdot 0.285^{h-1})^2}{2} \right) \quad (3.11.)$$

Table 3. 2. Components of the forecast error variance

	The forecast error variance	The first component of the forecast error variance	The second component of the forecast error variance
h			
1	1.50000	1.00000	0.50000
2	1.24368	1.08123	0.16245
3	1.11751	1.08782	0.02969
4	1.09265	1.08836	0.00429
5	1.08895	1.08840	0.00054
6	1.08847	1.08841	0.00006

Source: own computations

We computed the total forecast error variance and we made its decomposition, highlighting the following conclusions:

- The first component of the forecast error variance increases in time from a quarter to another, while the second component decreases very fast ;
- In the last predicted quarter the second component of the forecast error variance decreased by 99.98% compared to the first quarter. The model is updated to make the forecast for the next quarters, but it remains the same. The Monte Carlo simulations are made in order to assess the prediction uncertainty.

The application of Monte Carlo method in this case supposes several steps:

1. The econometric model estimation (an AR (p) model in this case):

$$i_t = -0.0315 + 0.285 \cdot i_{t-1} + e_t$$
2. The average and the standard deviation of the parameters are determined

Table 3. 3. Average and standard deviation of the parameters

Coefficient	Mean	Standard deviation
Constant	-0.03188	0.044604
Slope	0.285030	0.119174

Source: own computations

3. A normal distribution is generated for each parameter knowing the average and the standard deviation (we chose a number of 1000 replications)
We use the following code in R:

```
> simulation0<-rnorm(1000,-
0.031488,0.044604)
> simulation1<-rnorm(1000,
0.285030, 0.119174)
```

4. The simulated values of the dependent variable are computed knowing the values of the parameters distribution and the observed values. The observed values are retained in the vector i.

$$> dep <- simulation0 + simulation1 * i$$
5. The average and the standard deviation of the simulated values for dependent variable are computed.

$$> x <- mean(dep)$$

$$> y <- sqrt(var(dep))$$

$$> x$$

$$[1] 0.1661683$$

$$> y$$

$$[1] 0.1144252$$
6. An indicator of reliability is computed, starting from a critical chosen by the researcher (q^*):

$$R = \frac{q^* - m}{\sigma} \quad (3.13.)$$

The q^* values are computed using the National Bank of Romania (NBR) inflation projections in the first two quarters of 2013.

$$q^* = \log(i_{NBRproj\ Q4:2013}) - \log(i_{NBRproj\ Q3:2013}) = \log(3) - \log(3.2) = 0.477 - 0.505 = -0.028$$

$$R = \frac{-0.028 - 0.1661}{0.1144} = -1.6969$$

7. The probability that the transformed inflation rate is greater than the q^* is:

$$P = 1 - \varphi(R) = 0.5455$$

Where φ is the probability of R in a normal standard repartition. Here \log is the natural logarithm.

$$\log \frac{i_t}{i_{t-1}} > -0.028 \quad \Rightarrow \ln \frac{i_t}{i_{t-1}} > -0.028 \\ \Rightarrow \frac{i_t}{i_{t-1}} > 0.972.$$

Actually, we computed the probability (0.5455) that the inflation rate in the fourth quarter of 2013 be more than 0.972 of the inflation that was registered in the previous quarter.

If we analyse the situation in the third quarter of 2013 compared to the last second quarter of 2013, q^{**} will be: $q^{**} = \log(3.2) - \log(3) = 0$. R will be -1.452. There is a probability of 0.574 that the inflation rate in the third quarter of 2013 be greater than the value registered in the second quarter of 2013.

The bootstrap technique is used to estimate the sampling distribution of the statistics, 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 is 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 (the transformed data set) used in constructing the AR(p) model, the average is computed (-0.00611).

2. Bootstrap Bias-corrected-accelerated (BCA) intervals are determined for the data series, choosing the average of the mentioned data set as statistics. We used a number of 1000 replications and the following BCA intervals were gotten in Excel by using the "Resampling" add-in.

The previous procedures are applied to make forecasts for Q3:2013-Q4:2014.

Table 3. 4. Bootstrap BCA intervals for transformed inflation and quarterly inflation on horizon Q3:2013-Q4:2014

Quarter	Bootstrap BCA intervals for transformed inflation		Bootstrap BCA intervals for inflation (%)	
	Lower limit	Upper limit	Lower limit	Upper limit
Q3:2013	-	0.073	4.936	5.705
	0.071			
Q4:2013	-		4.621	5.323
	0.068	0.072		
Q1:2014	-		3.237	4.553
	0.053	0.098		
Q2:2014	-		3.056	4.228
	0.033	0.102		
Q3:2014	0.014	0.275	3.017	4.126
Q4:2014	0.065	0.549	2.998	3.754

Source: own calculations

The bias-corrected-accelerated interval (BCA) is a complex bootstrap technique used to construct confidence intervals. The steps of the BCA bootstrap method are described by 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.

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

In order to eliminate the disadvantage of non-normal distribution of the error, the parameters of AR(1) model are estimated by bootstrapping simulations. The add-in "Bootstrap coefficients" available in EViews 7.2. is used to estimate the bootstrapped parameters (1000 simulations). These new estimators are used in predicting the transformed inflation rate data series.

The new regression model has the following form:

$$i_t = -0.0355 + 0.293 \cdot i_{t-1} + e_t \quad (3.14.)$$

Using this AR(1) model and applying the Monte Carlo method as in the previous example, we computed a probability of 0.4236 that the inflation rate in the last quarter of 2014 be greater than the inflation rate in the previous quarter with 0.854 percentage points. On the other hand, we assume with a probability of 0.4188 that the inflation registered in the third quarter of 2014 is greater than that of the second quarter of 2014.

We also construct forecast intervals based on the historical forecasting error method, under the assumption of normally distributed errors of average zero and standard deviation equalled to the error.

$$(Y_t(k) - \frac{z\alpha}{2} \cdot e(k), Y_t(k) + \frac{z\alpha}{2} \cdot e(k))$$

, k=1,2,...,K (3.15.)

$Y_t(k)$ - point forecast of our variable Y

for period (t+k) (the prediction is made at moment t)

$\frac{z\alpha}{2}$ - $\alpha/2$ quintiles of the standard

normal distribution

e- error

For the last two quarters of 2013 and for 2014, we have the following computations:

In this particular case, the forecast error is computed starting from the fact that each AR process could be written as an MA process. For a moving average process in describing the evolution of our indicator, the prediction at a future time $n+h$ has the following form, according to Simionescu (2014):

$$i_{t+n} = \sum_{j=0}^{h-1} c_j e_{n+h-j} + \sum_{j=h}^{\infty} c_j e_{n+h-j} \quad (3.16.)$$

c_j - the coefficient

j- the index of time

e- the error

The best forecast (f) is in this case:

$$f_{n,h} = \sum_{j=h}^{\infty} c_j e_{n+h-j} \quad (3.17.)$$

In our case, for one-step-ahead predictions, h equals 1 and the prediction is $f_{n,1} = c_1 e_n$.

The forecast error is given by:

$$e_{n,h} = i_{n+h} - f_{n,h} = \sum_{j=0}^{h-1} c_j e_{n+h-j} \quad (3.18.)$$

The mean of forecast errors is considered to be null. The errors' variance is:

$$\text{var}(e_{n,h}) = \sigma_{\text{eps}}^2 \sum_{j=0}^{h-1} c_j^2 \quad (3.19.)$$

In our particular case, the variance is: e_n^2

Considering the hypothesis that the error distribution is a normal one, the forecast interval is determined as:

$$f_{n,h} \pm 1.96 \sqrt{\text{var}(e_{n,h})} \quad (3.20.)$$

In our case, the forecast interval has the following form:

$$c_1 \cdot e_n \pm 1.96 \cdot e_n \quad \text{that becomes} \quad e_n \cdot (c_1 \pm 1.96) \quad (3.21.)$$

The conversion of AR model to MA one is made in R using the following code:

```
>ARMAtoMA(ar = c(-0.0315,0.285),
ma = 1, 1)
[1] 0.9685
```

Table 3. 5. Forecast intervals based on the historical forecasting error method on Q3:2013-Q4:2014

Quarter	Intervals for transformed inflation		Intervals for inflation (%)		Actual values (%)
	Lower limit	Upper limit	Lower limit	Upper limit	
Q3:201	-	2.466	1.29	5.40	1.9
3	0.834		9	8	
	0.204	0.604	1.30	5.07	
Q4:201			4	4	1.6
3					
Q1:201	0.337	0.892	1.443	4.937	1.0

4					
Q2:201	0.459	0.883	1.025	4.753	0.7
4					
Q3:201	0.525	1.023	1.32	5.02	1.5
4			5	3	
Q4:201	0.783	1.227	1.432	5.448	0.8
4					

Source: own computations

We propose to compare the forecast intervals based on different methods. As we can see three out of six intervals included the actual value, but those based on the Bootstrap BCA method included four values.

The ex-ante fixed probability π is 0.95.

Table 3. 6. Forecast intervals for quarterly inflation rate (horizon: Q3:2013-Q4:2014)

Quarter	Bootstrap BCA Intervals for inflation (%)		Intervals for inflation (historical forecasting error method) (%)		Real values (%)
	Lower limit	Upper limit	Lower limit	Upper limit	
Q3:201	1.83	5.705	1.29	5.408	1.9
3	6		9		
	1.52	5.323	1.30	5.074	
Q4:201	1		4		1.6
3					
Q1:201	1.22	4.985	1.44	4.937	1.0
4	5		3		
Q2:201	1.10	3.875	1.02	4.753	0.7
4	4		5		
Q3:201	1.03	3.448	1.32	5.023	1.5
4	7		5		
Q4:201	0.77	2.785	1.43	5.448	0.8
4	9		2		

Source: own computations

The coverage probabilities are 0.66 for bootstrap BCA intervals and 0.5 for intervals based on the historical forecasting error method. The statistics of likelihood ratio test are 4.634 for the bootstrap BCA intervals and 9.964 for the intervals based on the historical errors method.

The critical value for one degree of freedom and at a significance level of 0.05 is

3.841, which is lower than the computed values. Hence, there are not significant differences between the ex-ante probability and the real probability at a 5% significance level.

The statistics of chi-square test of unconditional coverage have the values 36.63 for the bootstrap BCA intervals and 20.21 for the intervals based on the historical forecasting error method.

The computed values are higher than the critical one, which indicates a low degree of goodness between the ex-ante fixed probability and the empirical one.

4. CONCLUSIONS

The uncertainty assessment became very important nowadays because of the effects of economic crisis determined by the high degree of forecast uncertainty. For quarterly inflation rate in Romania we proposed more ways of evaluating the forecasts uncertainty.

We explained the evolution of the transformed data series of the inflation using an AR(1) model. The uncertainty was evaluated by making the decomposition of the forecasts variance in the first two quarters of 2013. The total variance and its components registered a decrease in the second quarter compared to the first one.

The Monte Carlo simulations were used to assess the uncertainty, evaluating the probability that the inflation prediction in a quarter changes compared to the previous quarter. There is a probability of 0.4236 that the inflation rate in the last quarter of 2014 be greater than the inflation rate in the previous quarter with 0.854 percentage points. On the other hand, we assume with a probability of 0.4188 that the inflation registered in the third quarter of 2014 is greater than that of the second quarter of 2014.

For forecast intervals, a form of highlighting the uncertainty of predictions, we used to methods of forecasting: bootstrap BCA and the historical errors method based on the optimal forecast. According to likelihood ratio tests and chi-square tests, there are significant differences between the ex-ante probability associated to each interval (0.95) and the actual probabilities.

In a future research we might extend the study on other macroeconomic variables like real GDP rate or interest rate. On the other hand, a comparative analysis with density forecasts would be very useful.

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APPENDIX 1

Breusch-Godfrey and White test

Breusch-Godfrey Serial Correlation LM Test:				
F-	2.51	Prob.		0
statistics	2402	F(1,47)	.1197	
Obs*R-	2.53	Prob.		0
squared	7144	Chi-Square(1)	.1112	
Heteroskedasticity Test: White				
F-	0.	Prob.		0
statistic	121115	F(2,47)	.8862	
Obs*R-	0.	Prob.	Chi-	0
squared	256369	Square(2)	.8797	
Scaled	0.	Prob.	Chi-	0
explained SS	978739	Square(2)	.6130	