The prediction of inflation in Romania in uncertainty conditions

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Abstract: Based on data of inflation forecasts provided quarterly by the National Bank of Romania, forecast intervals were built using the method of historical forecast errors. Forecast intervals were built considering that the forecast error series is normally distributed of zero mean and standard deviation equal to the RMSE (root mean squared error) corresponding to historical forecast errors. We introduced as a measure of economic state the indicator– relative variance of the phenomenon at a specific time in relation with the variance on the entire time horizon. For Romania, when inflation rates follows an AR (1), we have improved the technique of building forecast intervals taking into account the state of the economy in each period for which data were recorded. We consider really necessary the building of forecasts intervals, in order to have a measure of predictions uncertainty.

Keywords: uncertainty; Inflation; forecast intervals; relative variance; historical forecasts errors; root mean squared error (RMSE)

1 Introduction

Inflation forecasts are made by central bank in order to target the inflation and improve the macroeconomic policies. But, few banks are interested in a detailed measurement of the uncertainty of these forecasts. However, it is very important that a point forecasts is very far from the future reality. Forecasts intervals tend to exceed the obsolete and inefficient deterministic approach. Practically, these intervals reflect the problem of the uncertainty that accompany each prediction. According to Simon government uses various strategies to minimize the uncertainty.

For Krause (2002) the risk management strategies provide recommendations on how to adapt to changing economic conditions. Uncertainty is based essentially on associating probabilities to future events verisimilitude.

Crozier shows that the accompanying of forecasts with instruments for measuring the uncertainty provides autonomy to public environment involved in forecasts developing.

Since predicting a variable by providing numerical values implies a high degree of uncertainty, the researchers have focused on the building of intervals where the predicted value might appear with a certain probability.

All the institutions base their forecasts uncertainty on historical errors, but even in this case Knüppel M. (2009) points out that the studies based on this method of quantifying the uncertainty in literature are almost nonexistent, except those of Williams and Goodman.

Fair (2000) emphasizes that the possibility of an economic crisis should be specified within the forecast interval.

After a brief overview of the main achievements in literature related to the construction of prediction intervals, I built forecasts intervals for quarterly inflation rate predicted by the National Bank of Romania in 2000-2010 using the historical errors method, taking then into account the state of the economy. In addition, given that inflation rates series follows an autoregressive process of order 1, I proposed a new method for building prediction intervals.

2 Forecast Intervals

The problem of building forecast intervals and the determination of distributions was approached quite late in the literature, notable works in this area being written by Cogley, Adolfson, Clark and Jore, Giordani and Villiani. The results showed an important conclusion: in order to build a forecast interval with a certain probability, the model has to include variances deviation in time.

The way to build a forecasts interval is described by Granger, the retrospective presentation of the methods being done by Chatfield (1993). Christoffersen (1998) explains how to evaluate these intervals while the methods for measuring forecasts density are introduced only in 1999 by Diebold, who extends them later for bivariate data. Wallis (2003) is the first one who proposes tests for forecasts intervals, while Otrok and Whiteman (1997, 1998), Robertson (2003) and Cogley (2003) introduce bayesian prediction intervals. Unlike other methods of building prediction intervals that are specified in literature, the Bayesian ones also analyze the impact of estimator error on interval. Stock and Watson (1999, 2003) specify the conditional distribution function for k-steps-ahead forecasts. Their approach is developed by Hansen (2005), who built asymptotic forecasts intervals to include the uncertainty determined by the parameter estimator.

Kjellberg and Villani (2010) numbered the advantages and disadvantages of both types of forecasts, the ones based on models and those built by the experts. Forecast methods based on models describe the complex relationships using endogenous variables by its transparence making easy the identification of mistakes that generated wrong predictions. The disadvantages are related to the difficulty of adapting the model to recent changes in the economy, as well as the too simple form of the models. Chatfield shows that forecast intervals are often too narrow not taking into account the uncertainty related to model specification, problem that is encountered also in the experts' assessment. Unlike the forecasts based exclusive on models, expert assessments modify immediately to any change of information related to the predicted phenomenon. Disadvantages in experts' assessments are related just to the low degree of transparency, the difficulty of using many explanatory variables outside an explicit model.

3 Forecast Intervals Based on Historical Prediction Errors

The building of intervals taking into account the forecasts accuracy is an effective way to highlight the uncertainty that accompanies any forecast made. In the following, we used historical forecast errors to determine the forecast interval for inflation. We also used the projected inflation rates at the end of the year published by the National Bank of Romania for each quarter from 2000 to 2011. Forecast errors for each quarter are calculated by root mean squared errors (RMSE).

Forecast intervals are built considering the hypothesis that the forecast error series is normally distributed of zero mean and standard deviation equal to the RMSE corresponding to historical forecast errors. For a probability of (1-α), forecast interval is calculated:

$$(X_t(k) - z_{\alpha/2} \cdot RMSE(k),\ X_t(k) + z_{\alpha/2} \cdot RMSE(k)), k = 1,..., K \quad (1)$$

$X_t(k)$- punctual forecast for variable X_{t+k} at time t;

$z_{\alpha/2}$- the α/2 quintile of standardized normal distribution.

The table below displays the RMSE and lower and upper limits of the forecast interval for inflation predicted by the central bank with a quarter before ("one-step-ahead").

Table 1 The limits of the inflation rate forecasts intervals in Romania from 2000 Q1 to 2011 Q4 (based on historical forecasts errors)

Quarter	RMSE	Lower limit	Upper limit
2000 T1	0,847201	5,639485	8,960515
2000 T2	3,772844	4,945226	19,73477
2000 T3	6,277642	8,195822	32,80418
2000 T4	4,135102	24,8952	41,1048
2001 T1	2,716564	32,02554	42,67446
2001 T2	2,135833	34,81377	43,18623
2001 T3	3,80091	28,15022	43,04978
2001 T4	1,600179	29,06365	35,33635
2002 T1	0,341496	26,63067	27,96933
2002 T2	1,899812	18,67637	26,12363
2002 T3	0,14037	21,22487	21,77513
2002 T4	0,900789	17,53445	21,06555
2003 T1	1,1338	15,57775	20,02225
2003 T2	2,103242	12,77764	21,02236
2003 T3	0,315486	14,66165	15,89835
2003 T4	1,502289	13,35551	19,24449
2004 T1	0,533843	13,05367	15,14633
2004 T2	1,133521	11,1783	15,6217
2004 T3	0,634717	11,25596	13,74404
2004 T4	0,401726	9,612618	11,18738
2005 T1	0,496708	8,356453	10,30355
2005 T2	0,049909	9,752178	9,947822
2005 T3	0,33049	8,58224	9,87776
2005 T4	1,063651	7,445244	11,61476
2006 T1	0,183536	8,420269	9,139731
2006 T2	0,403424	6,70929	8,29071
2006 T3	0,297119	5,617648	6,782352
2006 T4	0,120033	4,664736	5,135264
2007T1	0,673333	3,180267	5,819733
2007T2	0,506667	3,306933	5,293067
2007T3	0,193333	4,421067	5,178933

Quarter	RMSE	Lower limit	Upper limit
2007T4	1,993333	0,793067	8,606933
2008T1	1,653333	3,059467	9,540533
2008T2	2,363333	1,567867	10,83213
2008T3	2,72	0,0688	10,7312
2008T4	2,51	-0,6196	9,2196
2009T1	0,77	4,4908	7,5092
2009T2	0,586667	4,350133	6,649867
2009T3	0,113333	4,877867	5,322133
2009T4	0,063333	4,375867	4,624133
2010T1	0,433977	3,345429	5,046617
2010T2	0,017011	4,34367	4,410352
2010T3	0,270111	7,23736	8,296195
2010T4	0,310527	7,558561	8,775826
2011T1	0,732516	5,364268	8,235732
2011T2	0,473541	7,77186	9,62814
2011T3	0,618246	3,588238	6,011762
2011T4	0,299992	2,712016	3,887984
2010T3	0,847201	5,639485	8,960515
2010T4	3,772844	4,945226	19,73477
2011T1	6,277642	8,195822	32,80418
2011T2	4,135102	24,8952	41,1048
2011T3	2,716564	32,02554	42,67446
2011T4	2,135833	34,81377	43,18623

Remark: Computations are made using data from reports of inflation of National Bank of Romania between 2000-2011 - www.bnr.ro.

The forecast intervals based on RMSE are independent of the state of the economy. Therefore, Blix and Sellin (1998) proposed the change of the method, so that the interval takes into account of changes in the economy, multiplying RMSE by a factor of uncertainty subjective chosen by the expert in forecasting.

Another approach uses, for the series of observations, a model in which time varies. The series of quarterly inflation rates follows an autoregressive AR process in which the series has a residual variance of stochastic type. It is assumed the hypothesis that errors are identically distributed and follows a standardized normal distribution. Then, the regression model can be written:

$$ri = m + \sum_{k=1}^{K} \phi_k (ri_{t-k} - m) + \alpha_t \cdot e_t \qquad (2)$$

where α_t is the standard deviation of errors.

$$\ln \alpha_t^2 = \ln \alpha_{t-1}^2 + \varepsilon_t, \qquad (3)$$

where ε_t follows a normal distribution and

$\ln \alpha_t^2$ is a random walk .

We introduce a new statistical measure called the relative volatility or relative variance (variance of T moment in relation with the geometric mean of variances corresponding to the interval used to calculate RMSE), calculated by the formula:

$$\beta_T = \frac{\hat{\alpha}_T}{n^{-1} \prod_{t=t_1}^{t_2} \hat{\alpha}_t^{\frac{1}{n}}} \quad (4)$$

$n = t_1 + t_2 - 1$ are the initial moment and the final one of the period for which RMSE is calculated, the time of the interval bounded of the two moments is:

$$(X_t(k) - z_{\alpha/2} \cdot \alpha_t \cdot RMSE(k), X_t(k) + z_{\alpha/2} \cdot \alpha_t \cdot RMSE(k)), k = 1,..., K \quad (5)$$

4 A New Way to Build Forecast Intervals for Romania

Inflation rate for the corresponding month of the previous year in period 2000-2010 were calculated quarterly and they were expressed in prices of December 1999. We made a seasonal adjustment and we transformed the data series in order to become stationary.

Appling the seasonal adjustment based on moving averages we eliminate the seasonal influences. We calculated the logarithm of the adjusted data series and then we differentiated it to get a stationary one, which will be then modeled using the Box-Jenkins procedure.

The Dickey-Fuller test applied to the transformed data series reflects the stationarity for a critical level of 5%. In 2000-2010, the transformed inflation rate follows an AR(1) process: $ri_t = 4{,}79 + 0{,}873 \cdot ri_{t-1} + \varepsilon_t$. This model is used to make a forecast for the first quarter of 2011. In the following table we presented the models corresponding to the previous periods of the quarter for which the forecast is made. In Appendix A we have the outputs from EViews.

Table 2 The models used to make predictions in Romania

The analyzed time period	AR(1) model
2000-2010	$ri_t = 4{,}79 + 0{,}873 \cdot ri_{t-1} + \varepsilon_t$
2000-2011 Q1	$ri_t = 4{,}83 + 0{,}875 \cdot ri_{t-1} + \varepsilon_t$
2000-2011 Q2	$ri_t = 4{,}85 + 0{,}875 \cdot ri_{t-1} + \varepsilon_t$
2000-2011 Q3	$ri_t = 4{,}92 + 0{,}878 \cdot ri_{t-1} + \varepsilon_t$

Remark: own calculations using EViews

Table 3 The limits of the inflation rate forecasts intervals in Romania from 2000 Q1 to 2011 Q4 (based on own method)

Quarter	Variance	e_t	$[e_t - E(e_t)]^2$	δ_T	RMSE	Lower limit	Upper limit
2011 Q1	0,770301	0,1432	0,020506	2,50928	0,732516	3,197346	10,40265
2011 Q2	0,779056	0,1219	0,01486	1,818321	0,473541	7,012344	10,38766
2011 Q3	0,777946	0,038	0,001444	0,117198	0,618246	4,657984	4,942016
2011 Q4	0,779348	0,1357	0,018414	2,175625	0,299992	2,020767	4,579233

Remark: calculations made using data from reports of inflation of National Bank of Romania between 2000-2011; www.bnr.ro.

The inflation variance is: $\mathrm{var}(r\_\inf) = \frac{\sigma_e^2}{1+0{,}873^2} = \frac{0{,}008}{1{,}509} = 0{,}770$

We introduce as a measure of economic state the indicator δ – relative variance of the phenomenon at a specific time in relation with the variance on the entire time horizon, which for T moment is calculated as: $\delta_T = \frac{[e_T - E(e_t)]^2}{\mathrm{var}(r\_\inf)} = 2{,}509.$

In this case we got a rather high relative variance, fact that shows the necessity of growing the value of RMSE with 105,9% if we take into account the state of the economy in the first quarter of 2011 and with 117,5% to take into account the economy state in the last quarter of 2011.

5 Conclusions

In this paper we built forecasts intervals for the inflation rate in Romania, using the quarterly predicted values provided by the National Bank of Romania for 2000-2011. First, we used the historical errors method, which is the most used method, especially by the central banks. Forecast intervals were built considering that the forecast error series is normally distributed of zero mean and standard deviation equal to the RMSE (root mean squared error) corresponding to historical forecast errors. We introduced as a measure of economic state the indicator – relative variance of the phenomenon at a specific time in relation with the variance on the entire time horizon. Then, we calculated the relative volatility in order to know the change that must be brought to the root mean squared error in order to take into account the state of economy.

6 Appendix

Dependent Variable: RISA_LOG_D
Method: Least Squares
Date: 12/21/11 Time: 18:23
Sample(adjusted): 2000:3 2011:1
Included observations: 43 after adjusting endpoints
Convergence achieved after 4 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.834181	0.142621	33.89522	0.0000
AR(1)	0.875405	0.007426	117.8860	0.0000

R-squared	0.997058	Mean dependent var	3.512943
Adjusted R-squared	0.996987	S.D. dependent var	1.647275
S.E. of regression	0.090425	Akaike info criterion	-1.923194
Sum squared resid	0.335245	Schwarz criterion	-1.841278
Log likelihood	43.34868	F-statistic	13897.10
Durbin-Watson stat	0.256727	Prob(F-statistic)	0.000000
Inverted AR Roots	.88		

Dependent Variable: RISA_LOG_D
Method: Least Squares
Date: 12/21/11 Time: 19:56
Sample(adjusted): 2000:3 2011:2
Included observations: 44 after adjusting endpoints
Convergence achieved after 4 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.859274	0.173252	28.04739	0.0000
AR(1)	0.875543	0.009038	96.86868	0.0000

R-squared	0.995544	Mean dependent var	3.555961
Adjusted R-squared	0.995438	S.D. dependent var	1.654779
S.E. of regression	0.111769	Akaike info criterion	-1.500377
Sum squared resid	0.524676	Schwarz criterion	-1.419278
Log likelihood	35.00830	F-statistic	9383.541
Durbin-Watson stat	1.067378	Prob(F-statistic)	0.000000
Inverted AR Roots	.88		

Dependent Variable: RISA_LOG_D
Method: Least Squares
Date: 12/21/11 Time: 20:07
Sample(adjusted): 2000:3 2011:3
Included observations: 45 after adjusting endpoints
Convergence achieved after 4 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.925383	0.147067	33.49071	0.0000
AR(1)	0.878851	0.007429	118.2991	0.0000

R-squared	0.996937	Mean dependent var	3.598781
Adjusted R-squared	0.996866	S.D. dependent var	1.658932
S.E. of regression	0.092877	Akaike info criterion	-1.871659
Sum squared resid	0.370923	Schwarz criterion	-1.791363
Log likelihood	44.11232	F-statistic	13994.68
Durbin-Watson stat	0.244269	Prob(F-statistic)	0.000000
Inverted AR Roots	.88		

Dependent Variable: RISA_LOG_D
Method: Least Squares
Date: 12/21/11 Time: 17:56
Sample(adjusted): 2000:3 2010:4
Included observations: 42 after adjusting endpoints
Convergence achieved after 4 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.790741	0.141322	33.89940	0.0000
AR(1)	0.873714	0.007459	117.1353	0.0000
R-squared	0.997093	Mean dependent var		3.469461
Adjusted R-squared	0.997020	S.D. dependent var		1.642056
S.E. of regression	0.089631	Akaike info criterion		-1.939776
Sum squared resid	0.321351	Schwarz criterion		-1.857029
Log likelihood	42.73529	F-statistic		13720.69
Durbin-Watson stat	0.270451	Prob(F-statistic)		0.000000
Inverted AR Roots	.87			

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