Journal of Economics and Business Research,
ISSN: 2068 - 3537, E – ISSN (online) 2069 – 9476, ISSN – L = 2068 – 3537
Year XX, No. 2, 2014, pp. 34-40

The Construction and Assessment of Forecast Intervals for Monthly Inflation Rate[1]

M. Simionescu, A. C. Călin, O. C. Popovici

Mihaela Simionescu, Adrian Cantemir Călin, Oana Cristina Popovici
Institute for Economic Forecasting
Romanian Academy, Bucharest, Romania

Abstract
In this research forecast intervals were built for monthly inflation rate during 2014 using an autoregressive model and the historical errors technique. For the first 7 months of 2014 all the actual values of the inflation rate are included in the forecast intervals. However, the historical errors method provided better results, because the intervals' length is smaller. Therefore, there is a high probability for this method to provide the best prediction intervals for the next 5 months of 2014.
Keywords: inflation rate, forecast interval, autoregressive model, historical errors method

[1] This paper has been financially supported within the project entitled "*Routes of academic excellence in doctoral and post-doctoral research",* contract number *POSDRU/159/1.5/S/137926*, beneficiary: Romanian Academy, the project being co-financed by European Social Fund through Sectoral Operational Programme for Human Resources Development 2007-2013.
This work was also cofinanced from the European Social Fund through Sectoral Operational Programme Human Resources Development 2007-2013, project number POSDRU/159/1.5/S/134197 „Performance and excellence in doctoral and postdoctoral research in Romanian economics science domain".

Introduction

Authors like Bachmann, Elstner & Sims and Bloom and Davis showed that the policy uncertainty is the real cause of the decrease in actives profit. [1], [2]

The forecasts uncertainty is the main cause of actual economic crisis. The common current in literature that explains a world economic crisis registered a major failure. Authors like Novy demonstrated that the predictions uncertainty is the real cause of the commercial collapse from US during 2008-2009. Therefore, the construction of forecast intervals is a better solution, but these intervals should be accompanied by a proper assessment of uncertainty. [6]

Three usual uncertainty measures were the most utilized in literature: standard deviation of individual predictions, disagreement between forecasters and the variance of aggregated histogram. [5] According to Ericsson the most used statistical indicators for forecasts' uncertainty are:

1. The bias of the prediction;
2. The variance of forecast error;
3. Mean Square Error (MSE). [4]

The forecast intervals are based on the point predictions, forecast error and a probability that is associated according to the assumption referring to the errors repartition. In the general case, it is made the assumption that the random shocks have a normal distribution $e_t \to N(0, \sigma_\varepsilon^2)$ that supposes a normally distributed probability density $x_{t+h} \to N(\hat{x}_{t+h}, \sigma_h^2)$. It was observed that the actual economic crisis has as important characteristic the higher uncertainty that diminished more the economic activity compared to the previous crisis.

From the very beginning the experts used point predictions for past periods in order to have a proxy as an uncertainty measure. These indicators are compared to ex-ante uncertainty measures.

The consensus is the agreement degree related to the point forecasts made by specialists for a certain variable. The authors defined the uncertainty as variance of probability distributions. [8]

The main aim of this research is to construct and assess the uncertainty of the forecast intervals for inflation rate. Therefore, the research is structured as it follows: after a short introduction, the second section presents the methods for building the prediction intervals. Then, the tests for assessing the forecast intervals are described and the results of evaluation for registered data are made.

Forecast intervals construction

Prediction intervals work under the assumption that the prediction errors follow a normal repartition of zero mean and a standard deviation represented by the indicator called root mean square error (RMSE) based on historical prediction errors. If the probability is (1-α), the prediction interval is determined as:

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

$X_t(k)$ - point prediction of variable X_{t+k} made at the moment t

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

The variable at moment t is denoted by x_t and it is actually an observation of a random variable (X_t). A random walk (first-order autoregressive model – AR (1)) is written as:

$$X_t = \alpha X_{t-1} + \varepsilon_t \qquad (2)$$

α- constant (for stationary data series $|\alpha| < 1$)

ε_t- error at moment t

A model with additive errors is written as:

$$X_t = \mu_t + \varepsilon_t \qquad (3)$$

μ_t- predictable component of the model

$\{\varepsilon_t\}$- sequence of independent normally distributed random variables (null average and constant dispersion: NID(0,σ_ε^2)).

The exponential smoothing calculates a point prediction by creating a weighted average of the latest observation and the most recent point prediction. It is an optimal method (it has the least mean squared error predictions) for the following model (ARIMA (0,1,1):

$$X_t = X_{t-1} + \varepsilon_t + \theta\varepsilon_{t-1} \qquad (4)$$

The 100(1-α)% prediction interval (P.I.) for the h steps ahead forecasts are computed as:

$$\hat{x}_n(h) \mp z_{\alpha/2}\sqrt{Var(e_n(h))} \qquad (5)$$

$z_{\alpha/2}$ – two-tailed percentage point of the normal distribution of null mean and dispersion equaled to 1.

This PI is symmetric about $\hat{x}_n(h)$, the point prediction being unbiased. The uncertainty in predictions for only one variable is assessed using expected means square prediction error (PMSE). If we make the comparison between predictions for different variables, it is recommended the use of MAPE (mean absolute prediction error).

Exponential smoothing method can be utilized for data set with no obvious tendency or seasonality. The PMSE in this case is given by:

$$Var(e_n(h)) = [1 + (h-1)a^2]\sigma_\varepsilon^2 \quad (6)$$

a- smoothing parameter

$Var(e_n(h))$ - variance of the one-step-ahead prediction errors

For the random walk, the variance of predictions error is computed as:

$$Var(e_n(h)) = h\sigma_\varepsilon^2 \quad (7)$$

The evaluation of inflation forecast intervals

The data refers to the monthly inflation rate in Romania in the period from January 1991 to July 2014. The forecasts horizon is 2014: January-2014: December. An ex-post assessment was made for the period till July 2014. The data are stationary at 1% level of significance, according to ADF test.

Table no.1. ADF test for inflation rate in Romania (1991: January-2013: December)

Include in the equation	Computed statistic	Critical values		Conclusion
Intercept	-3.486089	1% Critical Value*	-3.4561	Stationary data series
		5% Critical Value	-2.8723	
		10% Critical Value	-2.5725	
Trend and intercept	-4.960956	1% Critical Value*	-3.9953	Stationary data series
		5% Critical Value	-3.4277	
		10% Critical	-3.1369	

		Value		
none	-2.990155	1% Critical Value*	-2.5732	Stationary data series
		5% Critical Value	-1.9408	
		10% Critical Value	-1.6163	

Source: own computations

The models used in making predictions have the following form:

$$inflation_t = 2.878 + 0.671 \cdot inflation_{t-1} + \varepsilon_t \quad (8)$$

The results of estimations are in Appendix 1.

Table no. 2. Point forecasts and prediction intervals based on autoregressive model for the next month (2014: January-2014: December)

Month	Point forecast	Lower limit	Upper limit
2014- January	0.806	-1.154	2.766
2014- February	0.776	-1.184	2.736
2014- March	0.654	-1.306	2.614
2014- April	0.558	-1.402	2.518
2014- May	0.455	-1.505	2.415
2014- June	0.422	-1.538	2.382
2014- July	0.332	-1.628	2.292
2014- August	0.206	-1.754	2.166
2014- September	0.200	-1.76	2.16
2014- October	0.178	-1.782	2.138
2014- November	0.167	-1.793	2.127
2014- December	0.012	-1.948	1.972

Source: authors' computations

All the registered values are located in the indicated forecast intervals. Moreover, the historical errors method is applied for the same variables.

Table no. 3. Point forecasts and prediction intervals based on historical errors method for the next month (2014: January-2014: December)

Month	Point forecast	Lower limit	Upper limit	Actual values
2014- January	0.875	-1.085	2.835	0.330000
2014- February	0.776	-1.184	2.736	0.850000
2014- March	0.563	-1.397	2.523	0.330000
2014- April	0.226	-1.734	2.186	0.030000
2014- May	0.286	-1.674	2.246	0.270000
2014- June	0.116	-1.844	2.076	-0.040000
2014- July	0.034	-1.926	1.994	-0.270000
2014- August	0.045	-1.915	2.005	-0.050000
2014- September	0.157	-1.803	2.117	0.330000
2014- October	0.572	-1.388	2.532	0.850000
2014- November	0.357	-1.603	2.317	0.330000
2014- December	0.226	-1.734	2.186	0.030000

Source: authors' computations

All the registered values are located in the indicated forecast intervals, but this method provided narrow intervals, which is an improvement.

Conclusions

For monthly inflation rate some forecast intervals are constructed for 2014 and the results conduct us to the conclusions that all the actual values were located in the forecast intervals in the first 7 months of 2014, but the historical errors method provided narrower intervals.

References

[1] Bachmann, R., Elstner, S, Sims, E.R. (2010). Uncertainty and Economic Activity: Evidence from Business Survey Data, *NBER Working Papers,* Vol. 16143, National Bureau of Economic Research, Inc., p. 45-76

[2] Bloom, N., Davis S. J. (2012). Has Economic Policy Uncertainty Hampered the Recovery? Working Papers 2012-003, *Becker Friedman Institute for Research* in Economics

[3] Christoffersen, P.F. (1998). Evaluating Interval Forecasts. *International Economic Review,* Department of Economics, University of Pennsylvania and Osaka University Institute of

Social and Economic Research Association, Vol. 39(4), p. 841-62, November

[4] Ericsson, N. (2001). Forecast Uncertainty in Economic Modeling, Board of Governors of the Federal Reserve Discussion Paper No. 697

[5] Giordani, P., Söderlind, P. (2003). Inflation forecast uncertainty, *European Economic Review*, Vol. 47(6), p. 1037-1059

[6] Novy, D. (2013). International trade without CES: Estimating translog gravity. *Journal of International Economics*, Elsevier, Vol. 89(2): p. 271-282

[7] Stuart, S., Ord, J.K., Arnold, S.F. (1999). Kendall's Advanced Theory of Statistics, Vol. 1: Distribution Theory (6th ed.).

[8] Wallis, K. F. (2008). Forecast uncertainty, its representation and evaluation. World Scientific Publishing Co. Pte. Ltd., Econometric Forecasting and high-frequency data analysis, p. 10-453.

Appendix 1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.878234	0.608905	4.726902	0.0000
AR(1)	0.671625	0.043887	15.30364	0.0000
R-squared	0.461752	Mean dependent var		2.985855
Adjusted R-squared	0.459781	S.D. dependent var		4.508494
S.E. of regression	3.313726	Akaike info criterion		5.241270
Sum squared resid	2997.753	Schwarz criterion		5.267574
Log likelihood	-718.6746	F-statistic		234.2013
Durbin-Watson stat	2.350876	Prob(F-statistic)		0.000000
Inverted AR Roots	.67			