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Econometric Modeling and Forecasting of Interest Rates in Montenegro

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ABSTRACT

The econometric modelling and forecasting have a growing importance in both the development of modern models and theoretical approaches and as bases for proper policy decision making. This paper investigates the possibility of applying the Box-Jenkins approach and vector autoregressive models in modelling and forecasting interest rates in Montenegro. The motivation for this research lies in the fact that the interest rate level is one of the key determinants of the Montenegrin economic development dynamic due to the specific characteristics of its financial market. The empirical analysis is done on the monthly values data of weighted average lending interest rate of banks on new loans in the period from December 2011 to January 2018.

Our research has proven that the Box-Jenkins approach and VAR models can be successfully used for modelling and forecasting the interest rate level in the Montenegrin, quite a bank-centric, system. Moreover, the results recommend the use of the Box-Jenkins approach and the estimated AR model for forecasting interest rate since it has better performances than the VAR model. The estimated AR model may find its application in helping the decision-makers to create better economic policy decisions. Despite some limitations, regarding specifics of Montenegrin economy and statistical base, to a certain degree our results are in accordance with research done for other countries.

Key words: *forecasting, autoregressive models, interest rate forecasting, Box-Jenkins, VAR, AR*

JEL Classification: C32, C51, C52, E43

INTRODUCTION

The topic of interest rates has been in the focus of the public attention over a long period, and as a consequence of the strong influence of interest rates on economic developments. The interest rate levels and its change significantly determine the companies' decisions to invest, the decisions of individuals on savings and consumption, as well as the decisions of the authorities regarding monetary and economic policy. Numerous scientific and professional papers deal with interest rate issues, due to their wide range of influence and importance in the economy. Papers are often concerned with interest rates modeling and forecasting, as well as exploring the links, relationships and interdependencies of interest rates and many other macroeconomic indicators.

The pronounced specifics of the Montenegrin economy and its underdeveloped financial market make the level of interest rates one of the key determinants of economic development. In the complex structure of interest rates in Montenegro, the average weighted active nominal

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interest rate of banks on newly approved loans is especially highlighted, as a key determinant of the economy dynamism.

Many factors that operated in the past as well as numerous factors that still have impact have led to the formation of banks' high-interest rates in Montenegro. A very small market characterized by high operating costs, with insufficiently strong competitive forces between a large number of banks in the market, as well as a high share of bad loans, high customer risk with high existing indebtedness, and high country risk caused by fiscal imbalances have led to high active interest rates over a long period of time. The very high-interest rates on the part of banks and micro-credit institutions do not allow for the economic growth dynamization and development to the extent necessary to ensure the recovery of the economy after the 2008 economic crisis. Due to the limited instruments of the Central Bank of Montenegro and the absence of an emission function due to the introduction of euroization in Montenegro, the level of interest rates is a critical factor on which further movement the overall economic dynamics will depend.

To address the above-mentioned questions, the paper focuses on econometric modeling and forecasting the active interest rate on newly approved loans in Montenegro. Two theoretical approaches will be tested and two types of models, namely the autoregressive moving averages model and the vector autoregressive model will be evaluated using empirical data available from the Central Bank of Montenegro for the 2011 to 2018 period. Therefore, three research hypotheses are formulated, i.e.

H1: Box-Jenkins approach provides a statistically significant interest rate forecast in Montenegro.

H2: VAR model provides a statistically significant interest rate forecast in Montenegro.

H3: Box-Jenkins approach gives better prognostic results compared to VAR model in case of interest rate in Montenegro.

The purpose of the research is to estimate and compare the models that can be used to model and forecast the interest rates aiming to determine a better model, the model that is best fit for the given case. The approaches used in this paper have been used by numerous other researchers and they usually produce the best results. Forecasts of future interest rate values based on a model that proves to be the best have practical application through influencing decision-makers and increasing the quality of their decisions leading to the desired results. Successful forecasting of future interest rate values helps better the perception of the reality in order to take preventative action on time, to anticipate future changes and adapt behavior to new circumstances. Forecasting allows one to spot an undesirable trend on time so that it can act to eliminate it and achieve the desired results.

The paper is structured as follows: a literature review is presented in the next section. The third section describes the methodology used for time series modeling and forecasting of interest rates. Data analysis and empirical results are presented in the fourth section. Prediction and evaluation of the model's prognostic performance are given in the fifth part. Finally, conclusions and proposal for further research are presented in the last section of the paper.

LITERATURE REVIEW

Numerous scientific studies have been carried out aiming to predict the future value of macroeconomic variables such as GDP, inflation, interest rate, etc. Interest rate forecasting is a challenging topic, and many researchers are, therefore, concerned with it. There are certain differences in the subject matter of the research, which vary due to the specific nature of the national economy, the availability of data and the affinity of researchers.

Ahmed, Vveinhardt, Nawaz, and Streimikiene (2017) have used the 6-month KIBOR rate for the four years from 2012 to 2015 to estimate an adequate ARIMA model that can be used for forecasting. They confirmed the assertion that the ARIMA model can be successfully used to forecast the KIBOR rate and that it is of great importance for decision-makers. Alnaa and Ahiakpor (2011) estimated the ARIMA (6,1,6) model using monthly inflation data and the Box Jenkins methodology. Based on the indicator and the calculated RMSE, the effectiveness of the inflation forecasting model was confirmed.

By creating an adequate VAR model, Cologni and Manera (2008) successfully introduced the relationship between oil prices, inflation, and interest rates and provided a useful tool for monetary policymakers. The researchers evaluated the VAR model for the possible impact of changes in oil prices on macroeconomic variables, monetary policy, and the economic system. Different results have been achieved in different countries due to the countries' specificities.

Dua (2008) has shown that different models (ARIMA-GARCH, LVAR, BVAR, VECM) should be used to predict interest rates in India depending on the type of interest rate and the forecast horizon. Research has shown that the multivariate model outperforms univariate models when it comes to longer-term forecasts. The ARIMA and VAR models were used to forecast inflation measured by the Harmonized Index of Consumer Prices (HICP) in Austria. Fritzer, Moser, and Scharler (2002) concluded that over a longer time horizon, the VAR model would provide a more accurate HICP forecast than the ARIMA model, and its use is recommended in further studies. In the case of the inflation forecast, according to Hoa (2017), the forecasting performance of the model depends on the time horizon in which the forecasting is made. It is confirmed that with monthly data the VAR_m2 model gives a better forecast, while for the quarterly data the AR (6) model provides a better inflation forecast.

To obtain an optimal model for short-term interest rates forecasting, Radha and Thenmozhi (2006) compared the forecasting performance of three models: ARIMA, ARIMA-GARCH, and ARIMA-EGARCH. Depending on the type of interest rate, different models have different performances. For commercial papers, the ARIMA-EGARCH model is the best, while for implicit yield 91 day Treasury bill, overnight MIBOR rate and call money rates - the ARIMA-GARCH model gives the best forecasts.

Razak, Khamis, and Abdullah (2017) predict future GDP growth using the VAR and ARIMA models. Out-of-sample model forecast values are compared and the Mean Absolute Percentage Error (MAPE) results confirm that the VAR model is superior to the ARIMA model in this case. According to Zhang and Rudholm (2013) in Sweden, the AR (1) model gives the best GDP per capita forecast over the ARIMA and VAR models, while the VAR model gives the worst forecast.

METHODOLOGY

The two types of time series models, the univariate (ARIMA) and multivariate (VAR), are utilized in this paper for the purpose of interest rate forecasting and models performance comparison.

Time series models known as ARIMA models can be very successfully specified by implementing Box-Jenkins methodology (Box & Jenkins, 1976), a particularly significant specification methodology.

Box-Jenkins methodology is a very popular and frequently used in academic research (Ahmed et al., 2017; Etuk, 2013, Yuan, Liu & Fang, 2016; Iqbal & Naveed, 2016; Seneviratna, & Shuhua, 2013; Moffat & David, 2016; Okafor & Shaibu, 2013; Radha & Thenmozhi, 2006; Xue & Hua, 2016; Yuan, Liu & Fang, 2016). According to Dimitrios (Dimitrios, 2006) the name ARIMA is derived from: AR = autoregressive, I = integrated, MA = moving averages.

A univariate autoregressive model of moving averages (with or without the required series differentiation) in the general notation can be specified as:

$$Y_t = \theta_1 \cdot Y_{t-1} + \cdots + \theta_p \cdot Y_{t-p} + \vartheta_1 \cdot u_{t-1} + \cdots + \vartheta_q \cdot u_{t-q} + u_t$$

If in the process of model specification series were differentiated in order to obtain the required stationarity, we are talking about integrated autoregressive models of moving averages, i.e. ARIMA (p, d, q), where d represents the order of model integration.

Time series models that include more than one series are multivariate (multidimensional) models. In these models, the behavior of the dependent variable is explained by the action of several observed series, unlike univariate (one-dimensional) models where the behavior of the dependent variable is explained by the influence of the previous values of one series. The vector autoregressive (VAR) model is the most represented and commonly used model in the class of multivariate models. The attraction of the VAR approach, as proposed by Sims (1980), is mainly that there is no reliance on the restrictions of economic theory to indicate which variables occur in each equation. In VAR, every variable in the system is assumed to be endogenous. This contrasts to the standard theory-based method in which causal relationships between the variables is implied.

So, when we are not sure that a variable is truly exogenous, each must be treated symmetrically. Take for example the time series y_t affected by present and past values of x and, at the same time, the time series x_t affected by present and past values of y. In this case, we will have a simple multivariate model:

$$y_t = \beta_{10} - \beta_{12}x_t + y_{11}y_{t-1} + y_{12}x_{t-1} + u_{yt}$$

$$x_t = \beta_{20} - \beta_{21}y_t + y_{21}y_{t-1} + y_{22}x_{t-1} + u_{xt}$$

where both y_t and x_t are assumed to be stationary and u_{yt} and u_{xt} are uncorrelated white noise errors. The VAR model has been used extensively for forecasting and has achieved excellent results in scientific research (Carriero, Kapetanios & Marcellino, 2009; Gerdesmeier, Roffia & Reimers, 2017; Sarantis & Stewart, 1995; Salazar & Weale, 1999).

The data are obtained from the Central bank of Montenegro. The data are of the time-series form, i.e. the monthly data from December 2011 to January 2018. The method of analysis in this paper is the Ordinary Least Square (OLS) which is used to estimate structural parameters of the model in such a way, so as to minimize the sum of the deviations of the actual observation from their model estimated values. It is one of the most commonly used methods in estimating econometric models and it produces the best, linear, unbaised estimates (BLUE) (Koutsoyiannis, 1997). Empirical work based on time series assumes that the underlying time series is stationary. The stationarity is an essential property in defining a time series process. A stationary time series is the one whose parameters, such as mean, variance, autocorrelation, etc. are all constant over time. Hence, according to standard econometric procedure it is necessary to firstly check the data for possible non-stationarity. This need arises from the fact that if a time series data is non-stationary, the regression performed on variables with unit root would be "spurious" (Granger and Newbold, 1974) or "dubious" (Phillips, 1987). Stationarity can be tested by using several tests. In this paper the Augmented Dickey Fuller (ADF) test is implemented. Secondly, it should be tested whether the identified non-stationary series are co-integrated. The variables are said to be co-integrated if they satisfy the condition that there exist at least (k1) co-integrating equations i.e. stationary linear combinations of individually non-stationary variables (Maddala and Kim, 1998). Several diagnostic tests have to be done in order to check for the specification of the model, as well as for the possible problems of heteroscedasticity, autocorrelation, multicolinearity and residual normality. For that purpose Jarque-Bera (JB) test, Breusch-Godfrey test, VAR Residual Serial Correlation LM test, Breusch-Pagan-Godfrey test, VAR Residual Heteroscedasticity Tests, Empirical Distribution Test and VAR Residual Normality Tests are employed.

ANALYSIS AND RESULTS

This part of the paper presents the results of the empirical research that focuses analysing and modeling the empirical data on interest rates in Montenegro. The interest rate dynamics is monitored from the 12th month (December) of 2011 (the first available data on interest rate (IR) published by the CBM) to the 1st month (January) of 2018 (the last available data). The banks' average weighted active nominal interest rate on newly approved operations is recorded on an annual basis. The monthly consumer price growth rate (CPI) from December 2011 to January 2018 is also monitored, as the second time series. The descriptive statistics for the two-time series analyzed are presented in Table 1.

Table 1. Descripotive statistics

Series	**IR**	**CPI**
Sample	2011M12 2018M01	2011M12 2018M01
Observations	74	74
Mean	7.914	0.135
Median	8.210	0.100
Maximum	10.190	1.100
Minimum	5.270	-0.800
Std. Dev.	1.380	0.407
Skewness	-0.212	0.279
Kurtosis	1.707	3.178
Jarque-Bera	5.706	1.060
Probability	0.057	0.588

Source: Own elaboration.

According to Jarque-Bera value the analyzed IR and CPI time series are normally distributed. In Table 2 the ordinary and partial autocorrelation function of the interest rate time series are presented. The autocorrelation coefficient declines slowly from 0.893 on the first lag to 0.186 on the 20th lag when it is not statistically significant. The standard error of the autocorrelation coefficient is calculated as $\sqrt{1/74}$ =0.1162. Based on the Z critical values, the 95% confidence interval for the autocorrelation coefficient is $\rho_k \pm 1.96 * 0.1162 = \rho_k \pm 0.2277$.

Table 2. Correlogram of interest rate

Lags(k)	**AC**	**PAC**	**Q-Stat**	**Prob**
1	0.893	0.893	61.464	0.000
2	0.841	0.214	116.72	0.000
3	0.819	0.195	169.89	0.000
4	0.799	0.105	221.23	0.000
5	0.775	0.04	270.17	0.000
6	0.761	0.078	318.08	0.000
7	0.72	-0.105	361.62	0.000
8	0.702	0.054	403.6	0.000
9	0.65	-0.185	440.16	0.000
10	0.603	-0.091	472.08	0.000
11	0.563	-0.069	500.35	0.000
12	0.548	0.077	527.63	0.000
13	0.499	-0.112	550.62	0.000

Lags(k)	AC	PAC	Q-Stat	Prob
14	0.433	-0.192	568.21	0.000
15	0.403	0.088	583.7	0.000
16	0.38	0.027	597.68	0.000
17	0.327	-0.077	608.24	0.000
18	0.283	-0.057	616.26	0.000
19	0.231	-0.066	621.72	0.000
20	0.186	-0.05	625.31	0.000

Source: Own elaboration.

The results of Augmented Dickey-Fuller (ADF) unit root test are presented in Table 3. Based on the calculated probabilities, the null hypothesis is rejected for both time series at a 5% significance level. Therefore, it is concluded that none of the two time series have a unit root and, hence, they both are stationary.

Table 3. Unit root test

Series	Unit root test	t-Statistic	ADF test statistic	Prob.
IR	Augmented Dickey-Fuller	-3.473	-6.284	0.000
CPI	Augmented Dickey-Fuller	-2.901	-6.393	0.000

Source: Own elaboration.

After examining and confirming the normality and stationarity of the interest rate series several different models were estimated using the Box-Jenkins methodology. Based on statistical and econometric criteria, which will be shown below, it is concluded that the AR (1) model is superior to the other estimated ones. The chosen estimated model is shown in Table 4.

Table 4. AR (1) model

Dependent variable: Interest rate				
Method: least squares				
Sample (adjusted): 2012M01 2018M01				
Included observations: 73 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	10.2292	0.2068	49.4735	0.0000
@TREND	-0.0610	0.0048	-12.7987	0.0000
@MONTH=12	-0.6417	0.1613	-3.9785	0.0002
AR(1)	0.4823	0.1021	4.7244	0.0000
R-squared	0.9030	Akaike info criterion		1.2566
Adjusted R-squared	0.8988	Schwarz criterion		1.3822
S.E. of regression	0.4417	Hannan-Quinn criterion		1.3067
F-statistic	214.1232	Durbin-Watson stat		2.1871
Prob(F-statistic)	0	Inverted AR Roots		0.48

Source: Own elaboration.

In the specified model, the dependent variable IR (average weighted interest rate on newly approved loans) depends on the value of the interest rate in the previous period (AR(1)), the effect of the trend and the impact of the dummy variable (MONTH=12). All independent variables in the model are statistically significant, at a 5% significance level. A coefficient of determination of 0.90 indicates that 90% of the variation of the dependent variable is explained by the model, so from the standpoint of that criterion the model is good, as confirmed by the F-statistic. Values of information criteria: Akaike, Schwarz, and Hannan-Quinn are smaller in the model compared to other models evaluated. The estimated AR (1) model will be used as a benchmark in comparison to the corresponding VAR model.

After analyzing a larger number of VAR models that meet the econometric criteria and are specified and estimated with and without a constant, with a larger and smaller number of lags, the model with the best characteristics is chosen as the final one. The specified model is representative of multivariate time series models and is used to be compared to a previously selected estimated model to represent the class of univariate time series models.

Table 5. VAR model

Dependent variable: Interest rate				
Sample (adjusted): 2012M03 2018M01				
Included observations: 71 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	
IR(-1)	0.4840	-0.1168	[4.14436]	
IR (-2)	0.2631	-0.1215	[2.16606]	
IR (-3)	0.2454	-0.1146	[2.14133]	
CPIM(-1)	-0.1319	-0.1560	[-0.84567]	
CPIM(-2)	-0.3090	-0.1593	[-1.94057]	
CPIM(-3)	0.2377	-0.1546	[1.53713]	
R-squared	0.8879	Akaike info criterion		1.4490
Adjusted R-squared	0.8793	Schwarz criterion		1.6402
S.E. of regression	0.4796	Mean dependent		7.8625
F-statistic	103.0033	S.D. dependent		1.3806

Source: Own elaboration.

Based on the estimated model, we can see that the interest rate value at time t depends on the interest rate value from period t-1, t-2 and t-3, as well as the value of the price growth rate from period t-1, t-2 and t-3. The model does not contain a constant. The estimated model largely describes interest rate variations by endogenous variables, so a model determination coefficient of 0.887 indicates that approximately 89% of interest rate variations are explained by the model. The estimated VAR model meets all the validity conditions of the model. The diagnostic test results shown in Table 6 prove that the model is characterized by the absence of autocorrelations, the absence of heteroscedasticity, and normality of the distribution of residuals.

FORECAST RESULTS AND MODELS EVALUATION

The real and projected interest rates based on the autoregressive AR (1) model are shown in Figure 1. Model AR (1) will be used in comparison with the specified vector autoregression model (VAR) to determine a superior model for interest rate forecasting in Montenegro. The forecast with a deviation of +/- 2 standard deviations is presented, that is, an interval forecast of the interest rate for the next six months is given with a probability of 95%. We note that the real value of the interest rate is within the interval, with the exception of the 5th month.

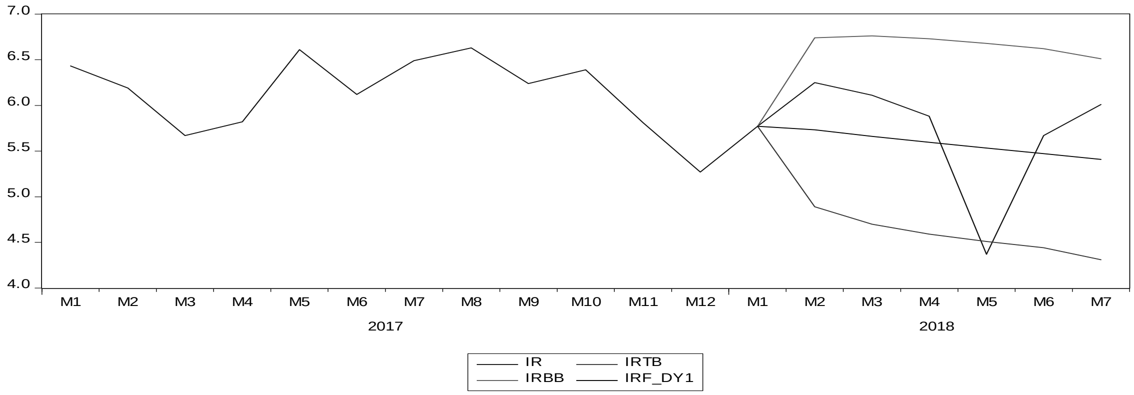

Figure 1. Actual and model AR (1) forecast interest rate for the period 2018m1-2018m7

Source: Own elaboration

The real value of the interest rate for the period 2017m1 to 2018m7 as well as the forecasted value of the interest rate for the period 2018m2-2018m7 with deviations of plus/minus two standard deviations is presented in the Figure 2. We note that the real value of the interest rate does not go beyond the 95% confidence interval and is within the limits of plus/minus two standard deviations presented.

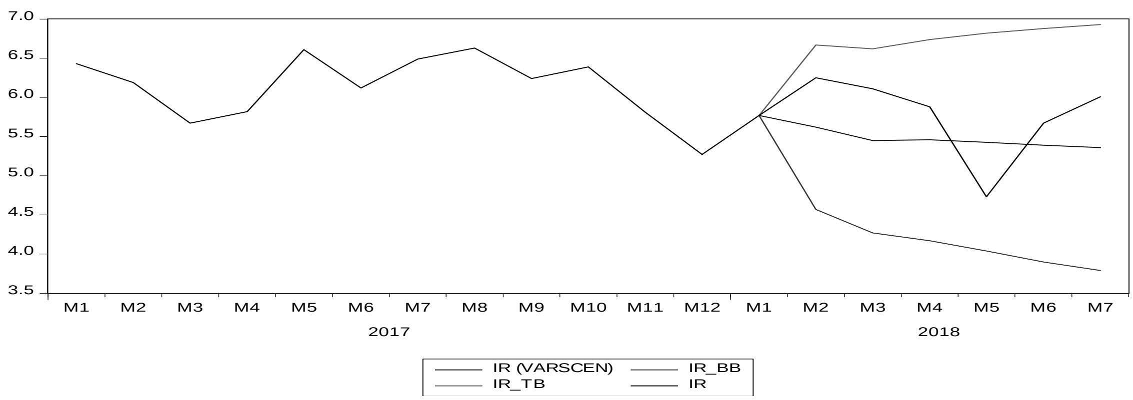

Figure 2. Actual and model VAR forecast interest rate for the 2018m1-2018m7 period.

Source: Own elaboration.

It is demonstrated in the Figure 3. that the VAR model forecast is slightly lower than the AR(1) model forecast, and in this sense, the VAR model underestimates the interest rate to a greater extent than the AR(1) model does. Deviation from this phenomenon occurs only in the fifth month when a sharp decrease in the interest rate to the level of 4 is noted, probably due to some external shock, possible CBM incentive measures or significant changes in the European capital market. A sharp decrease in the interest rate that occurred in the fifth month is not a common occurrence: The sample data indicate that such an occurrence is recorded for the first time in 2018 and requires a more detailed analysis.

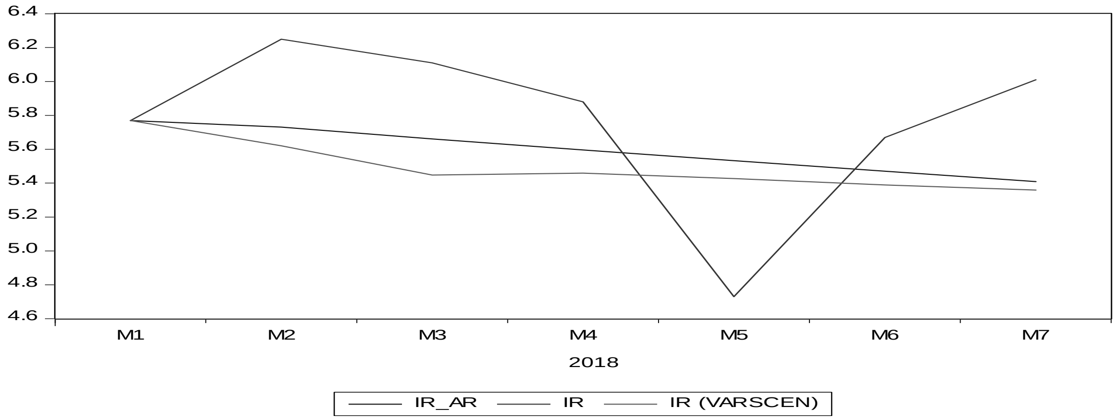

Figure 3. Real and forecast interest rates based on AR (1) and VAR models.

Source: Own elaboration

An overview of the probabilities for the diagnostic tests: autocorrelation (Breusch-Godfrey test and VAR Residual Serial Correlation LM Tests), heteroscedasticity (Breusch-Pagan-Godfrey test and VAR Residual Heteroscedasticity Tests) and residual normality (Empirical Distribution Test and VAR Residual Normality Tests) for the both evaluated models are given in Table 6. The tests are given in the appendix. With a 5% error rate, the null hypothesis is confirmed, so the models are characterized by the absence of autocorrelation, heteroskedasticity, and the normal distribution of residuals.

Table 6. Diagnostic test results (probabilities)

MODEL	**Autocorrelation (prob.)**	**Heteroscedasticity (prob.)**	**Residual normality (prob.)**
AR(1)	0.0994	0.2881	0.7338
VAR	0.7191	0.806	0.3646

Source: Own elaboration.

After the statistical and econometric validity of the model is established, a comparison of the model's forecasting performance is investigated. In Table 7 the real and forecasted values of interest rate and the most important calculated statistics are given based on which the choice of the optimal model is made.

Table 7. Real values and AR (1) / VAR model interest rate forecasts with the most important statistics

Most important statistics		**February 2018**	**March 2018**	**April 2018**	**May 2018**	**June 2018**	**July 2018**
	Interest rate (real)	**6.25**	**6.11**	**5.88**	**4.37**	**5.67**	**6.01**
	AR model forecast	5.73	5.66	5.59	5.53	5.47	5.41
	VAR model forecast	**5.62**	**5.45**	**5.46**	**5.43**	**5.39**	**5.36**
E	AR(1)	0.52	0.45	0.29	-1.16	0.20	0.60
	VAR	**0.63**	**0.66**	**0.42**	**-1.06**	**0.28**	**0.65**
MSE	AR(1)	0.27	0.24	0.19	0.48	0.39	0.38
	VAR	**0.40**	**0.42**	**0.34**	**0.53**	**0.44**	**0.44**
RMSE	AR(1)	0.52	0.48	0.43	0.69	0.62	0.62

	VAR	**0.63**	**0.64**	**0.58**	**0.73**	**0.66**	**0.66**
MAE	AR(1)	0.52	0.49	0.42	0.61	0.52	0.54
	VAR	**0.63**	**0.65**	**0.57**	**0.69**	**0.61**	**0.62**

Source: Own elaboration.

Based on the calculated statistics, and especially the most commonly used MSE (mean squared error) statistics in model comparisons, it can be concluded that a first-order autoregressive model containing a trend and a dummy variable is superior to the estimated vector autoregressive model. The AR(1) model prediction error is higher only for the fifth month, which is caused by external shock and falling interest rate, as discussed previously. The values of all statistics for the first-order AR(1) model are less than the values of the VAR model statistics, which is consistent with the aim to specify a model with minimal forecast error and the best forecast performances.

Many other researchers who have researched within their national economies using the same methodology have come to similar results. It has been confirmed that the ARIMA model can be successfully used in forecasting the KIBOR interbank rate, and recommendations have been made for its use in other countries when forecasting interest rates (Ahmed, R.R., et al. 2017). Interest rate forecasting in India was addressed by a group of researchers who came to the conclusion that different models (ARIMA-GARCH, LVAR, BVAR, VECM) should be used depending on the type of interest rate and the forecast horizon (Dua, P. 2008). In order to obtain the optimal model to forecast the short-term interest rate, the forecasting performance of the ARIMA, ARIMA-GARCH and ARIMA-EGARCH models was compared (Razak, N. A. A., et al., 2017).

CONCLUSION

The two most frequently used types of time series models, the univariate and multivariate, are investigated in this paper for the purpose of interest rate forecasting and models performance comparison for the case of Montenegro. Box-Jenkins methodology and vector autoregressive model approach have the greatest application and often give the best forecasts, compared even to more complex econometric models.

Applying the Box-Jenkins methodology, several univariate autoregressive models are specified, estimated and evaluated. Based on the econometric criteria, primarily on information criteria and adjusted coefficients, the best model from the class of autoregressive models is selected, namely AR (1). Accordingly, the first research hypothesis stating the Box-Jenkins approach provides a statistically significant interest rate forecast in Montenegro is confirmed.

Alternative VAR model as one of the classes of multivariate models is specified. After VAR model estimation and evaluation, the second research hypothesis claiming the VAR model provides a statistically significant interest rate forecast in Montenegro is proved. Hence, it can be concluded that both approaches lead to the estimation of adequate models that can be used in modeling and forecasting interest rates in Montenegro.

To determine the optimal prognostic model, the forecast performance of previously estimated models, AR (1) in the class of univariate models and VAR models in the class of multivariate models, are compared. The comparison is done on the bases of actual forecast error, the mean square error, the root mean square error and the mean absolute error. The results of this analysis indicate that for interest rate forecasting in Montenegro Box-Jenkins approach produces better prognostic results in comparison to the VAR model approach, i.e. the third research hypothesis is true.

In this paper only two types of models have been analyzed, and it must be remembered that there could have been different results had other types of models been included in the analysis. The obtained results relate to time series that are short and of questionable quality, regarding the Montenegrin economy that is small, open and with specific foreign exchange regime (eurozation). The results could be different if the sample size and data quality is increased, so models need to be tested at different periods. Therefore the presented results must be taken with caution.

Despite the mentioned limitations, the results and conclusions presented in this paper are in accordance, to a certain degree, with the research conducted in other countries and can be valuable in decision making policy and further research regarding interest rate forecasting in Montenegro. Future aspects of this research may focus on the application of other methodologies and the estimation of new models with better forecasting performances, such as autoregressive distributed lag models, artificial neural network models, error correction models, generalized autoregressive conditional heteroskedastic models, conditional volatility models, etc.

REFERENCES

Ahmed, R., Vveinhardt, J., Ahmad, N., & Streimikiene, D. (2017). Karachi inter-bank offered rate (KIBOR) forecasting: Box-Jenkins (ARIMA) testing approach. *E&M Economics and Management*, *20*(2), 188-198.

Alnaa, S. E., & Ahiakpor, F. (2011). ARIMA (autoregressive integrated moving average) approach to predicting inflation in Ghana. *Journal of economics and international finance*, *3*(5), 328-336.

Box, G. E., & Jenkins, G. M. (1976). Time series analysis: Forecasting and control San Francisco. *Calif: Holden-Day*.

Carriero, A., Kapetanios, G., & Marcellino, M. (2009). Forecasting exchange rates with a large Bayesian VAR. *International Journal of Forecasting*, *25*(2), 400-417.

Cologni, A., & Manera, M. (2008). Oil prices, inflation and interest rates in a structural cointegrated VAR model for the G-7 countries. *Energy economics*, *30*(3), 856-888.

Dimitrios, A. (2006). Applied Econometrics: a modern approach using EViews and Microfit.

Dua, P. (2008). Interest rate modeling and forecasting in India (No. id: 1521).

Etuk, E. H. (2013). Monthly Nigerian Interbank Call Rates Modeling by Seasonal Box-Jenkins Approach. *Journal of research in Marketing*, *1*(1), 22-29.

Fritzer, F., Moser, G., & Scharler, J. (2002). Forecasting Austrian HICP and its components using VAR and ARIMA models (No. 73).

Gerdesmeier, D., Roffia, B., & Reimers, H. E. (2017). Forecasting Euro Area Inflation Using Single-Equation and Multivariate VAR–Models. *Folia Oeconomica Stetinensia*, *17*(2), 19-34.

Granger, C.W.J. and Newbold, P. (1974). Spurious Regression in Econometrics*. International Journal of Social Science*, Vol.5, No.1.

Hoa, T. T. (2017). *Forecasting inflation in Vietnam with univariate and vector autoregressive models* (No. BOOK). The Graduate Institute of International and Development Studies, International Economics Department.

Iqbal, M., & Naveed, A. (2016). Forecasting inflation: Autoregressive integrated moving average model. *European Scientific Journal*, *12*(1), 83-92.

Koutsoyiannis, A. (1997). Theory of Econometrics: Introductory to Exposition of Econometric Methods, 2nd edition., Macmillan Publishers Ltd, London

Maddala, S.G. and Kim, I.M. (1998). Unit Root, Cointegration, and Structural Change, Cambridge University Press, New York

Moffat, I. U., & David, A. E. (2016). Modeling inflation rates in Nigeria: Box-Jenkins' approach. *International Journal of Mathematics and Statistics Studies*, *4*(2), 20-27.

Okafor, C., & Shaibu, I. (2013). Application of ARIMA models to Nigerian inflation dynamics. *Research Journal of Finance and Accounting*, *4*(3), 138-150.

Phillips, P.C.B. (1987). Time Series Regression With Unit Root. *Econometrica*, Vol. 55, No. 2.

Radha, S., & Thenmozhi, M. (2006). Forecasting short term interest rates using ARMA, ARMA-GARCH and ARMA-EGARCH models. In *Indian Institute of Capital Markets 9th Capital Markets Conference Paper*.

Razak, N. A. A., Khamis, A., & Abdullah, M. A. A. (2017). ARIMA and VAR modeling to forecast Malaysian economic growth. *Journal of Science and Technology*, *9*(3).

Salazar, E., & Weale, M. (1999). Monthly data and short-term forecasting: an assessment of monthly data in a VAR model. *Journal of Forecasting*, *18*(7), 447-462.

Sarantis, N., & Stewart, C. (1995). Structural, VAR and BVAR models of exchange rate determination: a comparison of their forecasting performance. *Journal of Forecasting*, *14*(3), 201-215.

Seneviratna, D. M. K. N., & Shuhua, M. (2013). Forecasting the Twelve Month Treasury Bill Rates in Sri Lanka: Box Jenkins Approach. *IOSR Journal of Economics and Finance (IOSR-JEF)*, *1*(1).

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, 1-48.

Xue, D. M., & Hua, Z. Q. (2016). ARIMA Based Time Series Forecasting Model. Recent Advances in Electrical & Electronic Engineering (Formerly Recent Patents on Electrical & Electronic Engineering), 9(2), 93-98.

Yuan, C., Liu, S., & Fang, Z. (2016). Comparison of China's primary energy consumption forecasting by using ARIMA (the autoregressive integrated moving average) model and GM (1, 1) model. *Energy*, *100*, 384-390.

Zhang, H., & Rudholm, N. (2013). Modeling and forecasting regional GDP in Sweden using autoregressive models. *Dalama University*.

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