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MODELING MONTHLY INFLATION IN THE REPUBLIC OF SERBIA, MEASURED BY CONSUMER PRICE INDEX

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Abstract. *This paper presents a framework for the practical modeling of inflation, as one of the key economic indicators. Empirical research of monthly inflation trends in the Republic of Serbia was done covering the period from January 2007 to December 2015. The seasonally adjusted ARIMA model and Holt-Winters smoothing were used for determining the future values of the consumer price index, which has been a measure of inflation in the Republic of Serbia since January 2009. The main objective of the study is to create a model that will be used for analytical and forecasting purposes. The specific objective is the comparative analysis of accuracy of these two methods (Holt-Winters and ARIMA) in determining the future value of the consumer price index. The work relies on the theoretical results of dual relationship between AR (p) and MA (q) processes in determining the future values of consumer price index.*

Key words: *consumer price index, inflation, forecasting, Holt-Winters smoothing method, ARIMA*

INTRODUCTION

Price stability, i.e. stabilization of inflation within the target boundaries, as the first priority of monetary policy, is the basis for sustainable economic growth and rising employment. The paper will, through interpenetration of econometrics and time series analysis, present a framework for the practical modeling of inflation, as one of the key economic phenomena. Economic analyses attach great importance to the monitoring and forecasting of movements in the value of consumer price index (CPI), which has been used as a measure of inflation in the Republic of Serbia since January 2009. However, its calculation and publishing has been done since January 2007. Considering the fact that forecasting time series should be performed for a short period with the purpose of higher reliability, the paper determines the future values of the monthly inflation rate for the second half of 2015.

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The main objective of forecasting the monthly inflation rate is to determine its future value. The paper uses two seasonally adjusted methods: Holt-Winters smoothing and ARIMA. Special attention is given to Box-Jenkins ARIMA modeling methodology. This is because a number of empirical studies conducted in the late 20th and early 21st century show that, in the short term, ARIMA models have extremely high inflation forecasting ability. Forming an effective seasonally adjusted model of great forecasting power relies on interdependence of observations, aimed at determining the future values of consumer price index based on its past values.

In addition to introduction and conclusion, the structure of the work consists of four parts. The first part presents inflation targeting by the National Bank of Serbia. The second part of the paper presents the methodology used for the empirical research of the movements of consumer price index in the Republic of Serbia during the period from January 2007 to December 2015. Research results and discussion form the basis of the third part of the work. This part particularly presents the results of Holt-Winters method and the obtained ARIMA model.

1. The Target Inflation Rate of the National Bank of Serbia

The transition to inflation targeting in January 2009 marked the inflation targeting as the primary objective of Serbian monetary policy. In August 2015, the National Bank of Serbia determined the headline inflation target, as measured by the annual percentage change in the consumer price index for the period from January 2017 to December 2018 in the amount of 4.0%, with permitted fluctuations around that level in the range of ± 1.5 p.p. This decision indicates that the process of price convergence has not been completed and that the exit of the national economy from recession could accelerate it.

Table 1 Inflation target

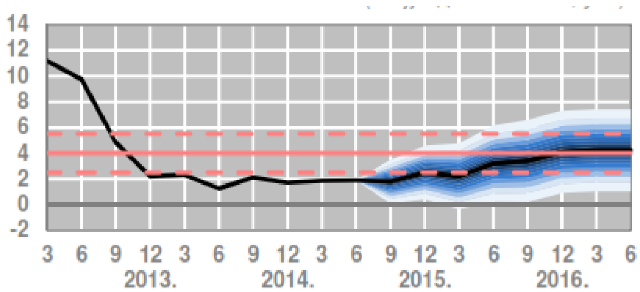
2009.	8.0% ± 2.0 pp
2010.	6.0% ± 2.0 pp
2011.	4.5% ± 1.5 pp
2012-2018.	4.0% ± 1.5 pp

Source: National Bank of Serbia

The main reason why inflation target in developing countries is higher than in developed countries (where price stability is usually quantified as the inflation rate from 2.0% to 2.5%) lies in the process of price convergence. The convergence of price levels in Serbia to the level of prices in the European Union is not finished. The crisis and the fall in domestic demand are the main reasons why the price level in Serbia is lower compared to the price level in the European Union, in relation to the situation five years ago. In fact, domestic prices in 2014 accounted for 52.8% of the average price level in the European Union, and in 2009, for 55.8%.

Inflation in previous years ranged more broadly than it was defined by the limits of the target tolerance band. Such inflation trend was primarily influenced by the lack of a medium-term framework for the adjustment of regulated prices, with clearly defined rules and dynamics of adjustment, as well as the instability on the market of agricultural products, due to structural problems and lack of adequate systemic measures in agricultural policy. The market of agricultural products has become more liberal in the meantime (customs duties and levies on imports of most agricultural products were abolished), so that the price oscillations on this market decreased. However, the medium-term plan of adjustment of regulated prices is still not defined, which could affect the increased fluctuation of inflation in the coming years. The priority of monetary policy in the coming period is to reduce inflation fluctuations in order to stabilize it within the limits of the target tolerance band. Stabilizing inflation within the target boundaries would bring price stability, which is the basis for sustainable economic growth and rising employment.

The aim of medium-term inflation projections is to show the projected inflation trends in the coming period, the main determinants of those trends, and the risks of its realization. The inflation projection is shown in the form of ranges and central tendencies. The projection assumption is that the monetary policy measures actively keep medium-term inflation within the target tolerance band, which is, in the present context of monetary policy, its main role (The National Bank of Serbia, 2015). According to the projections of the National Bank of Serbia, year-on-year inflation will in 2016 move around the lower limit of the target tolerance, with the possible entry into the target band at the end of this year or early next year. In the second half of 2016, its gradual approximation to 4.0% target can be expected. The most important inflation factors will be regulated prices (higher prices of electricity and low price of cigarettes). In contrast, global prices of primary products (oil and agricultural products), low aggregate demand, low inflation on a global scale, as well as restrictive fiscal policy will continue to have disinflation effect. Risks to the realization of inflation projections relate to developments on a global scale, the movement in prices of primary products, and the deviation from the assumed growth of regulated prices (The National Bank of Serbia, 2015).



Graph 1 Projected inflation (year-on-year rates, in %)
Source: National Bank of Serbia

Short- and medium-term inflation expectations have stabilized within the target band, i.e. economic entities expect that year-on-year inflation in July 2016 and July 2017 will be within the target tolerance band. The stability of inflation expectations is a key prerequisite for the stabilization of inflation and increased efficiency of monetary policy.

2. RESEARCH METHODOLOGY

The forecasting of monthly inflation rate in the Republic of Serbia relies on the official data of the Ministry of Finance on a monthly growth of consumer price index for the period January 2007 – June 2015. The analysis focuses on the price changes in the current month compared to the previous month, based on a total of 102 periods. Bearing in mind the complexity of the forecasting process, the paper will test two methods that are most commonly used in the economic analyses of time series. Integrated approach that includes several methods can be used for determining the future values of consumer price index. The modeling relies on the use of EViews7 software.

The paper will first rely on descriptive statistics to obtain information on the key features of the time series and frequency distribution of consumer price index monthly growth in the period from January 2007 to June 2015. What follows is the Holt-Winters method of forecasting. Seasonally adjusted models that use different parameter values are created, and their comparison performed. To determine the accuracy of forecasts obtained by this method, mean absolute error and root mean squared error are used. Taking into account the data specifics, the additive model is presented, which, together with the multiplicative model, presents two main models of Holt-Winters forecasting method. The additive model is the type of forecast where the expected seasonal increase in the amount of the observed phenomenon for a certain period of time is added to the annual mean. In addition, considerable attention is paid to Box-Jenkins methodology, for the purpose of forecasting the movement of the monthly inflation rate in the Republic of Serbia for the next six months. Box-Jenkins methodology is the three-stage process of constructing a model that includes: identification, estimation, and checking the adequacy of the model. Construction of the model can be considered an iterative process which ends when a satisfactory model is found, consistent with the statistical criteria of model adequacy. After examining 25 different models, one linear, seasonally adjusted ARIMA model will be proposed, which is supposed to be able to provide good results in forecasting future trends in consumer price index in Serbia. The obtained models can be used for analytical and forecasting purposes.

3. RESEARCH RESULTS AND DISCUSSION

Forecasting the inflation rate in the Republic of Serbia relies on the data on a monthly growth of consumer price index in the period from January 2007 to June 2015. The analysis focuses on changes in prices in the current month compared to the previous month, based on a total of 102 periods (observations). Graphical presentation of time series can point to the key characteristics of time series and frequency distribution. The observed series does not exhibit a pronounced trend, but fluctuations around a constant level. In respect of this time series, there is a greater intensity and degree of fluctuation and slow decline in the monthly consumer price index.

Base series flow represents a pattern of its behavior over time. The existence of a large variability in the time series, i.e. the expressed local fluctuations around the base flow, imposes the need for time series smoothing.

3.1. The seasonally adjusted Holt-Winters forecasting method

Holt-Winters method is used for the forecasting of future values in situations when the time series data has trend and seasonal character. Considering the fact that the trend points to a development tendency, one must distinguish between linear, exponential, and damped trend. The linear trend means that the time series increases (decreases) in equal absolute amounts from period to period, i.e. that the phenomenon exhibits approximately the same absolute change in the same time periods. At the same time, exponential trend means that the time series increases (decreases) in the same relative amounts from period to period. The damped trend is a combination of linear and exponential trend, where, in the first period, there is an increase (decrease) in absolute amount, and in each subsequent period relative changes occur by the exponential trend principle.

Monthly seasonal variation of time series means that the data varies around the monthly average by a certain rule. In this regard, seasonality can be defined as a time series tendency to exhibit behavior that repeats every s periods. Seasonal index for a period shows how much the period deviates from the annual average. To calculate this amount, at least one full data season is needed.

Two main models within Holt-Winters method are additive and multiplicative model. Additive forecasting model is the type of forecast where the expected seasonal increase in the amount of the observed phenomenon for a certain period of time is added to the annual mean. Multiplicative model involves the relative change of the observed variable which is higher if the absolute amount of the observed variable is higher, and vice versa. In parts of the time series which exhibit an additive character, the series shows stable seasonal fluctuations regardless of the overall trend level of a time series. In the case of multiplicative model, the level of seasonal fluctuations varies depending on the overall level of the series.

Additive seasonal model is used when the time series data exhibits additive sensitivity. This model is applicable in time series where the amplitude with the seasonal character is independent of the average series level. Additive version of this method may be described by the following formula:

$$L_j = \alpha(y_j - S_{j-s}) + (1-\alpha)(L_{j-1} + b_{j-1})$$
$$b_j = \beta\left(L_j - L_{j-1}\right) + (1-\beta)b_{j-1}$$
$$S_j = \gamma\left(y_j - L_j\right) + (1-\gamma)S_{j-s}$$
$$F_{j+1} = L_j + b_j + S_{j+1-s}$$
$$j = s + 1, s + 2, \ldots,$$

where α, β, and $\gamma \in [0,1]$ are smoothing parameters, L_j is the smoothing level in time j, b_j is the change in time j; S_j is the seasonal smoothing in time j; s is the number of periods in the season; F_{j+1} is one step ahead of the forecasted value. Initial values are calculated using the following formula:

$$L_s = \frac{1}{S}$$
$$b_s = \frac{1}{s}\left[\frac{y_{s+1} - y_1}{s} + \frac{y_{s+2} - y_2}{s} + \cdots + \frac{y_{s+s} - y_s}{s}\right]$$
$$S_j = y_j - L_s,\ j = 1,2,\ldots,s.$$

Multiplicative seasonal model is used when data has multiplicative seasonality. This model can be represented by the following formulas:

$$L_j = \alpha\left(\frac{y_j}{S_{j-s}}\right) + (1-\alpha)(L_{j-1} + b_{j-1})$$
$$b_j = \beta\left(L_j - L_{j-1}\right) + (1-\beta)b_{j-1}$$
$$S_j = \gamma\frac{y_j}{L_j} + (1-\gamma)S_{j-s}$$
$$F_{j+1} = (L_j + b_j)S_{j+1-s}$$
$$j = s + 1, s + 2, ...$$

The initial values of the model are calculated using the same formula as in the additive version of the model, except for the seasonal variable:

$$S_j = \frac{y_j}{L_s}, \text{j} = 1, 2, ..., s$$

To calculate the initial value of b, data for the first two seasons was needed. Due to the complexity of the basic versions of the two above-mentioned models of Holt-Winters method, their simplified versions are used in practice. Simplified versions can also be used in the analysis of the volatility of the monthly consumer price index. If data in the time series has no clear trend, one can use a simplified version of Holt-Winters method (without variable b).

Simplified additive model can be described as follows:

$$L_j = \alpha(y_j - S_{j-s}) + (1-\alpha)L_{j-1}$$
$$S_j = \gamma\left(y_j - L_j\right) + (1-\gamma)S_{j-s}$$
$$F_{j+1} = L_j + S_{j+1-s}$$
$$j = s + 1, s + 2, ...,$$

The initial values of L_s and S_j in the simplified model are calculated using the above-mentioned formulas.

Simplified multiplicative model can be defined as follows:

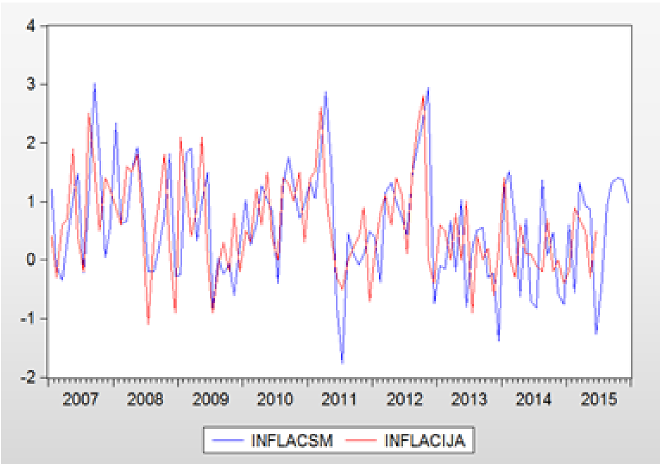
$$L_j = \alpha\left(\frac{y_j}{S_{j-s}}\right) + (1-\alpha)L_{j-1}$$
$$S_j = \gamma\left(\frac{y_j}{L_j}\right) + (1-\gamma)S_{j-s}$$
$$F_{j+1} = L_j S_{j+1-s}$$
$$\text{j} = \text{s} + 1, \text{s} + 2, ...$$

The initial values of L_s and S_j are calculated in the same way as in the original multiplicative model. For the prediction of accuracy of each model, mean absolute error (MAE) and root mean squared error (RMSE) will be used.

Table 2 Additive model of seasonally adjusted Holt Winters method

Parametars:	Alpha		0.8000
	Beta		0.5000
	Gamma		0.0000
Sum of Squared Residuals			87.65239
Root Mean Squared Error			0.927004
End of Period Levels	Mean		0.329324
	Trend		0.216787
	Seasonals:	2014M07	-1.050794
		2014M08	0.158036
		2014M09	0.341865
		2014M10	0.213194
		2014M11	-0.040476
		2014M12	-0.669147
		2015M01	0.271230
		2015M02	-0.057440
		2015M03	0.263889
		2015M04	0.222718
		2015M05	0.531548
		2015M06	-0.184623

In this paper, special focus is on calculating the seasonally adjusted Holt smoothing. In the course of analysis, additive model is created, with the following parameters: $\alpha = 0.8$ $\beta = 0.5$ $\gamma = 0.0$, proven as the best for the needs of forecasting. The forecasted value is calculated as the sum of the mean value of time series, trend component, and seasonal component for the corresponding period.



Graph 2 The monthly inflation rate in the period January 2007 – December 2015, with smoothed and seasonally adjusted values for six months in advance

Applying the Holt-Winters smoothing to the time series with 102 observations (January 2007 – June 2015) results in the forecasted values of the monthly inflation rate for six periods in advance (second half of 2015). According to this model, the projected values are -0.504682, 2.873196, -0.945262, -0.554167, -0.338253, -0.391247, respectively (Graph 3).

Bearing in mind the empirical indicators and high volatility of political and economic cycles in Serbia, which reduces the forecasting power of the model, the results obtained can be considered efficient.

3.2. Forecasting using ARIMA model

Numerous empirical studies conducted in the late 20th and early 21st century show that, in the long run, aggregate structural models provide efficient forecasts, but that, in the short term, ARIMA models have an extremely high ability to forecast inflation. So, Meyera Aidan, Kenny Geoff & Terry Quinn (1998) use ARIMA models for forecasting inflation in Ireland, and the same are used by Toshitaka Sekine (2001) in Japan, Salam, A. Muhammad, Shazia Salam and Mete Feridun (2006) in Pakistan, Kalezić, Cerović, and Božović (2007) in Montenegro, Nastić (2011) in Bosnia and Herzegovina. By analyzing stochastic characteristics of time series, ARIMA models explain the movement of the variables in time, based on historical data and stochastic errors from the previous period.

This part of the work presents linear, seasonally adjusted ARIMA model, which is supposed to be able to provide good results in forecasting future trends in the consumer price index in Serbia. Analysis relies on monthly data on the movement of the consumer price index in the period from January 2007 to June 2015, so that the series includes 102 observations. Box-Jenkins methodology is applied for forecasting trends in monthly inflation rate in the Republic of Serbia for the second half of 2015 (next six months). Box-Jenkins is a powerful method for mathematical modeling of stochastic processes. It is a methodology for identifying and estimating models that include autoregressive models (AR) and moving average models (MA) for the purpose of forecasting. The main advantage of Box-Jenkins methodology lies in obtaining large data on the analyzed empirical time series using a small number of parameters. It is suitable for modeling of both stationary and non-stationary time series with or without seasonal component. Through the application of theoretical results, the dual relationship between the AR (p) and MA (q) processes in inflation modeling is examined. Basically, Box-Jenkins methodology is the three-stage process of constructing a model that includes: identification, estimation, and checking the adequacy of the model. Construction of the model can be considered an iterative process which ends when a satisfactory model that is consistent with the statistical model adequacy criteria is found. The resulting model can be used for analytical or forecasting purposes.

Seasonal character of the time series is a common phenomenon in economic research, where the number of time periods, s, repeats over time. In the specific case, s is 12 and represents the number of months. In order to solve the problem of the seasonal character of inflation, ARIMA process is generalized and seasonally adjusted. Seasonal autoregressive integrated moving average (SARIMA) model is created as well, which includes trend, seasonal component, and short-time adjustment. It is derived from the standard Box-Jenkins model. Seasonal ARIMA models include seasonal and non-seasonal factors in the multiplicative model according to the following formula:

ARIMA (p,d,q)*(P,D,Q)s

where:

p – Non-seasonal component of autoregressive model (AR)
d – Non-seasonal differentiation
q – Non-seasonal component of moving average model (MA)
P – Seasonal component of autoregressive model (AR)
D – Seasonal differentiation
Q – Seasonal component of moving average model (MA)
S – Number of periods during the year

Box-Jenkins methodology comprises three sequential phases:

1. Model identification;
2. Estimation of model parameters;
3. Diagnostics and projection of the selected models.

The next part of the paper will present the results obtained during the research within each phase of the applied methodology.

3.2.1. Model identification

The first stage involves establishing the necessity of transformation for the purpose of stabilizing the variance and determining the differentiation order, then the inclusion of a determinant into the model when d is greater than 1, and the selection of the appropriate order of ARIMA model, i.e. values p and q. The model is marked as ARIMA (p, d, q) where p and q represent the number of AR and MA model lags, respectively, while d indicates the level of stationarity of the time series. Based on the graphic presentation of the series, the appropriate transformation is selected. The values of autocorrelation and partial autocorrelation are used to determine the order of differentiation, required in order to achieve a stationary time series. Slow and almost linear decrease of autocorrelation function is an indicator of non-stationarity. In addition to this visual determination, the need for differentiation can be determined on the basis of the statistical testing of the presence of one or more unit roots. Accepting the null hypothesis of the existence of unit root indicates non-stationarity of the time series. Basic characteristics of stationary stochastic processes are: constancy of the mean (series level), constancy of variance, and covariance dependence only on the time interval. After prospective transformation and determining the order of differentiation, p and q values are identified on the basis of autocorrelation and partial autocorrelation functions, and/or on the basis of information estimation criteria (Akaike AIC, Schwarz-Bayesian SBC, Hannan-Quinn). These tests measure how well the model describes the data. Relatively the best model is the one with the lowest value of those indicators. Thus, one can conclude that the model identification is based on observing the autocorrelation and partial autocorrelation functions of the time series at the level of differentiation at which the stationarity condition is fulfilled.

We used a graphic illustration of autocorrelation and partial autocorrelation to figure out if the data is stationary or not. With regard to the value of the original data, it can be concluded that series transformation and differentiation is not necessary. This is because stationarity is achieved, as the basic precondition for the creation of ARIMA model. Stationarity is reflected in the fact that the series has a constant variance and the mean value in time.

Testing the stationarity is done through Augmented Dickey-Fuller Unit Root Test (ADF) and Phillips-Perron Unit Root Test (PP). The obtained values of ADF and PP tests are 7.623649 and 7.686779, respectively, and they are greater than the critical values at the error level of 5%. This points to the rejection of the null hypothesis and the existence of the necessary stationarity.

Table 3 Augmented Dickey-Fuller Unit Root Test and Phillips-Perron Unit Root Test

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.623649	0.0000
Test critical values:	1% level	-3.496346	
	5% level	-2.890327	
	10% level	-2.582196	
*MacKinnon (1996) one-sided p-values.			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-7.686779	0.0000
Test critical values:	1% level	-3.496346	
	5% level	-2.890327	
	10% level	-2.582196	
*MacKinnon (1996) one-sided p-values.			

Based on these tests, it can be concluded that it is a stationary time series (which has a constant variance and the mean value in time), which fulfills the basic prerequisite for the creation of ARIMA model. Thus, the series does not need additional transformation, because it is stationary, so that the alternative hypothesis on the absence of unit root is ultimately accepted.

During the analysis, 25 models with different combinations of AR and MA variables are tested. Akaike Info Criterion (AIC) and Schwarz criterion are used for choosing one model, characterized as the best for forecasting.

The minimum values of the selected criteria suggest the selection of ARIMA model (1,0,3) for forecasting the future movement of the monthly inflation rate in the Republic of Serbia. This points to the next stage of the iterative process of time series model construction.

Table 4 Akaike info criterion and Schwarz criterion

	p/q	1	2	3	4	5
Akaike	1	1,906045	1,949938	1,859961	2,050456	2,019729
Schwarz		2,044856	2,089749	1,999772	2,190267	2,159540
Akaike	2	2,161159	2,241530	2,035048	2,176829	2,099177
Schwarz		2,301916	2,382288	2,175805	2,317587	2,239935
Akaike	3	1,915258	1,967084	2,126526	1,4266659	2,041952
Schwarz		2,056977	2,108802	2,268245	2,008377	2,183691
Akaike	4	2,000221	2,078368	2,041140	2,037075	1,994555
Schwarz		2,142916	2,221062	2,183834	2,179710	2,137350
Akaike	5	1,943178	2,019091	2,008594	2,061410	2,040090
Schwarz		2,086863	2,162777	2,152279	2,205095	2,181378

3.2.2. Model parameter estimation

The task of time series analysis is to find a model which describes the stationary time series of the consumer price index. Estimation phase, i.e. model parameter estimation, is the second, most extensive phase. The analyzed model is, after diagnostics, reduced to one model, which will be used to forecast future values of the monthly inflation rate in the Republic of Serbia. Model parameter estimation is performed by Ordinary Least Squares method (OLS). The quality of diagnostics and behavior of residuals are crucial in choosing the most efficient models for forecasting. In order to obtain a more efficient ARIMA model, special attention is paid to the selection of autoregressive variables (lags of dependent variable) and moving average (lags of residual value). The models are estimated in terms of: the coefficient of determination (R2), the value of Durbin-Watson statistic, and F statistical significance.

During the study, 25 models with different combinations of AR and MA variables are tested. The most acceptable model is AR(1) SAR(12) MA(3) SMA(12), i.e. (1,0,3)*(12,0,12)12 with the following parameters:

MODEL: AR(1) SAR(12) MA(3) SMA(12)

Model residuals have white noise characteristics, i.e. are not correlated and move randomly, thereby creating the conditions for obtaining high-quality forecasts outside the sample.

Table 5 Statistics of the chosen model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.377193	0.154000	2.449300	0.0164
AR(1)	0.255164	0.105091	2.428034	0.0173
SAR(12)	0.694280	0.064620	10.74410	0.0000
MA(1)	0.145197	0.070204	2.068198	0.0417
SMA(12)	-0.884930	0.034824	-25.41169	0.0000
R-squared	0.479024	Mean dependent var		0.546067
Adjusted R-squared	0.454216	S.D. dependent var		0.807783
S.E. of regression	0.596767	Akaike info criterion		1.859961
Sum squared resid	29.91503	Schwarz criterion		1.999772
Log likelihood	-77.76828	Hannan-Quinn criter.		1.916315
F-statistic	19.30896	Durbin-Watson stat		1.960864
Prob(F-statistic)	0.000000			

3.2.3. Diagnostics and projection of the selected model

There are several criteria to be fulfilled by a good model. These are: cost-effectiveness, identifiability, consistency with data, consistency with theory, eligibility of data, forecasting efficiency, and comprehensiveness (Kovačić, 1995, pp. 158-159). The model diagnostics stage assesses the validity of the chosen model, based on its compatibility with the real data and the quality of its forecasting power.

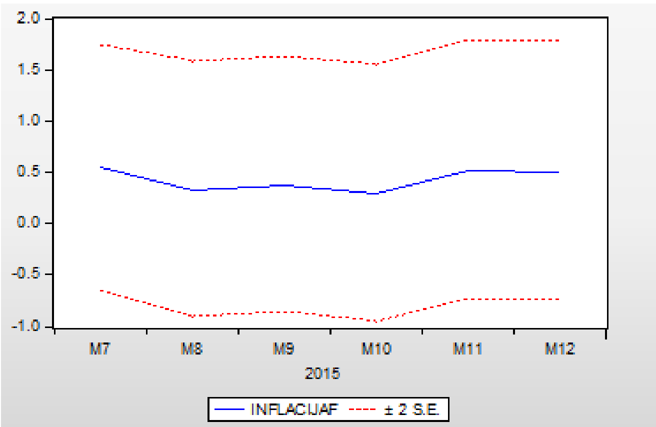
Using a histogram of probability and correlogram (Q-statistics correlogram and residual root correlogram), we found that the selected model has a normal distribution of residuals, whose value of autocorrelation and partial autocorrelation points to random movement of residuals. Justification of the accepted model is also proven by key parameters obtained during the model diagnostics phase – the coefficient of determination (R2), the value of Durbin-Watson statistic, and F statistical significance.

Table 6 Heteroskedasticity test – White test

F-statistic	1.426302	Prob. F(20,68)	0.1408
Obs*R-squared	26.30189	Prob. Chi-Square (20)	0.1561
Scaled explained	27.40062	Prob. Chi-Square (20)	0.1244

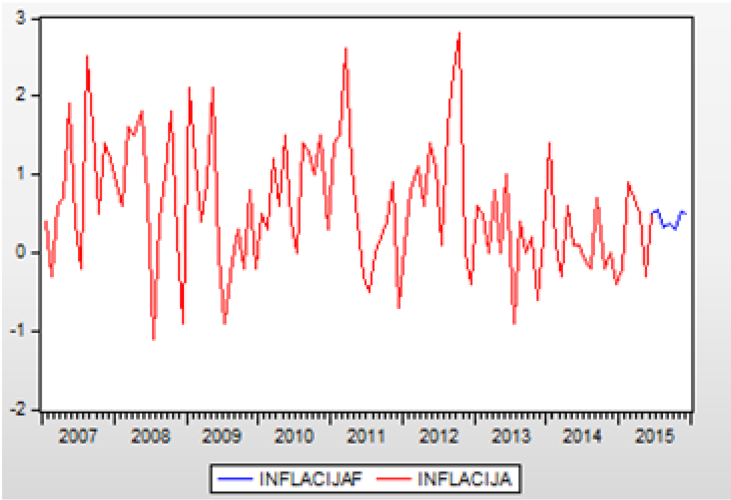
Another indicator supporting the model is the heteroskedasticity test (White test), whose value (26.301) is less than the critical value of $\chi 2$ (0.05, 20), which amounts to 31,410 (Table 6). On the basis of this, the claim on homoscedasticity of model variance is accepted.

For the purpose of forecasting the future values, the original number of observations is modified by the length of the forecasting horizon. In view of the tendency for forecasting the movement of the monthly inflation rate for six months in advance (July-December 2015), the following graph is obtained, which incorporates three scenarios of future trends of the monthly inflation rate.



Graph 3 Projected values of the monthly inflation rate until the end of 2015

Optimistic and pessimistic scenarios are defined as ± two standard errors of the real movement of the consumer price index. Graph 4 shows the movements of monthly inflation rate from January 2007 to December 2015. It shows both actual and projected values of the monthly inflation rate for the period July-December 2015.



Graph 4 Actual and projected values of the monthly inflation rate

Part of the graph showing the projected values shows that the monthly rate of inflation will have cyclical character. First, one can see a downward trend, with quick upward trend towards the end of the year.

Table 7 Projected values according to the chosen model

July 2015	0.543769
August 2015	0.328622
September 2015	0.377211
October 2015	0.288579
November 2015	0.522074
December 2015	0.507158

The selected model has been used to forecast the movement of the monthly inflation rate for the period July-December 2015. Based on actual and projected data, the average annual inflation rate in 2015 has been calculated, which amounts to 0.58%. Finally, the analysis has resulted in the projected values of monthly inflation developments by the end of 2015, which can be seen in Table 7.

CONCLUSION

Application of theoretical results has given practical framework for modeling inflation, as one of the key economic indicators of a country. Empirical research into the developments of consumer price index, which measures inflation in the Republic of Serbia, has been done for the period January 2007 – December 2015. Using seasonally adjusted ARIMA models and Holt smoothing method has resulted in the future values of the consumer price index. The comparative analysis of accuracy of the two methods (Holt-Winters method and ARIMA) in determining future values of the observed indicator has been performed. In the course of the research, a total of 30 models have been tested in respect of both methods. A comparative analysis of the model has been reduced to the calculation of mean absolute error and root mean squared error.

The results of seasonally adjusted Holt smoothing have been presented, and the additive model chosen, with parameters $\alpha = 0.8$ $\beta = 0.5$ $\gamma = 0.0$, estimated as the best for forecasting future levels of consumer price index. Based on Akaike Info Criterion (AIC) and Schwarz Criterion, a single ARIMA model has been selected, proven as the best for the needs of forecasting. ARIMA model has been estimated in terms of the following diagnostics parameters: coefficient of determination (R2), the value of Durbin-Watson statistic, F statistical significance, and residuals. The most acceptable model turned out to be AR(1) SAR(12) MA(3) SMA(12), i.e. (1,0,3)*(12,0,12)12. Residuals of the selected model have characteristics of white noise, i.e. are not correlated and move randomly, thereby creating the conditions for obtaining high-quality forecasts outside the sample as well. Therefore, one can conclude that the selected model can be used for further analytical and forecasting purposes.

Based on the above, it can be concluded that the selected models have a sufficient level of reliability and that the results obtained are a fairly reliable indicator of the monthly inflation rate movements in Serbia. It is undisputed that the efficiency and predictive power of the obtained models will be tested in the future. At the same time, one should not ignore that the great volatility of the political and economic cycles in developing countries, such as Serbia, reduces the predictive power and ability to construct an efficient model.

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MODELIRANJE MESEČNE STOPE INFLACIJE U REPUBLICI SRBIJI MERENE INDEKSOM POTROŠAČKIH CENA

U radu je predstavljen okvir za praktično modeliranje inflacije kao jednog od ključnih ekonomskih pokazatelja. Empirijsko istraživanje kretanja mesečne stope inflacije u Republici Srbiji urađeno je za period januar 2007- decembar 2015. godine. Korišćenjem sezonski prilagođenog ARIMA modela, i metoda Holtovog izravnanja utvrđene su buduće vrednosti indeksa potrošačkih cena koji je mera inflacije u Republici Srbiji od januara 2009.godine. Osnovni cilj rada je kreiranje modela koji će se koristiti u analitičke i prognostičke svrhe. Uz to, specifični cilj je uporedna analiza preciznosti dva metoda (Holt-Winters metod i ARIMA) u određivanju buduće vrednosti indeksa portošačkih cena. U radu su primenjeni teorijski rezultati dualne veze između AR (p) i MA(q) procesa u određivanju buduće vrednosti indeksa potrošačkih cena.

Ključne reči: *indeks potrošačkih cena, inflacija, prognoziranje, Holt-Winters-ov metod izravnaanja, ARIMA*