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INFLATION FORECAST IN INDONESIA: EXPENDITURE GROUPS OF HOUSING, WATER, ELECTRICITY, GAS, AND FUEL USING TIME SERIES ANALYSIS APPROACH

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ABSTRACT

Inflation stability is a prerequisite for sustainable economic growth. Appropriate information that can be used to manage and control the inflation rate is future inflation prediction. Expenditure groups of housing, water, electricity, gas and fuel have major commodities which have strong influence on inflation spike, so that it is necessary to give more attention in the inflation rate management for those expenditure groups. The aim of this research is to perform inflation model and forecast using time series analysis approach. The data used in this research are Indonesian's monthly inflation data for the expenditure groups of housing, water, electricity, gas and fuel which are taken from BPS Indonesia.

KEY WORDS

Inflation, time series, ARIMA, MSE.

Inflation stability is a prerequisite for sustainable economic growth, which in turn will provide benefits for the improvement of social welfare (Lusia and Suhartono, 2011). Indonesia has a higher inflation value from neighboring countries and is the country with the highest inflation rate in ASEAN since 2013 (Akbarwati, 2015). There are several commodities that play a major role in the inflation rate in Indonesia, including electricity, water and fuel which contribute the highest inflation rate (BPS, 2014). These commodities are joined into the inflation in expenditure groups of housing, water, electricity, gas and fuel. BPS data show that the expenditure groups have the highest basic weight value in general measurement of inflation which reaches 25.41% (Wibowo, 2014).

One of inflation management is to forecast the inflation, (Stock and Watson, 1999). Inflation forecast is a bridge to know the inflation value of the following period, (Faust and Wright, 2013). Obtaining an accurate value of inflation forecast will be important for many parties; namely to establish monetary and fiscal policies, make investment decisions and discover the extent of people's purchasing power (Tzavalis and Wickens, 1996).

Previous research on inflation conducted by Lusia and Suhartono (2011) had a general inflation forecast in Indonesia regardless of certain sub-commodities. In addition, another research conducted by Cahyuni (2012) had a model for inflation in foodstuffs group. Previous research had not specifically addressed the inflation for expenditure groups of housing, water, electricity, gas and fuel. Actually, the groups have a significant impact on the development of Indonesian economy.

Based on the above description, the authors are having monthly inflation forecast in Indonesia to the expenditure groups of housing, water, electricity, gas and fuel by time series analysis approach (McCleary et al., 1980). The inflation values of the following period can be predicted by using time series analysis. The model used in this research is autoregressive integrated moving average (ARIMA). This model assumes that the residual model is white noise and normal distribution. Model estimation is conducted by using Maximum Likelihood Estimator method.

Sketchily, inflation is defined as the rise of prices generally and continuously. The indicator used to measure the inflation rate in Indonesia is Consumer Price Index (CPI). The calculation of inflation for each month is:

$$IR_n = \frac{I_n - I_{(n-1)}}{I_{(n-1)}} \times 100 \quad (1)$$

Where:

IR_n = Inflation rate at month n ;

I_n = Consumer Price Index at month n ;

$I_{(n-1)}$ = Consumer Price Index at month $(n - 1)$.

ARIMA is a model that completely ignores independent variables in making the forecast. ARIMA uses past and present values of dependent variable to generate the forecast. The ARIMA model (p, d, q) is a forecasting model for time series data which has p level of autoregressive model, q level of moving average, and d -difference is taken to make it stationary. The general form of ARIMA equation (p, d, q) is:

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B)\varepsilon_t \quad (2)$$

The complete ARIMA (p, d, q) model can be written as follows:

$$W_t = \phi_1 W_{t-1} + \dots + \phi_p W_{t-p} - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (3)$$

$$W_t = (1-B)^d Z_t$$

METHODS OF RESEARCH

The data used in this research are Indonesian's monthly inflation data for the expenditure groups of housing, water, electricity, gas and fuel from February 2009 to January 2015. The data source is secondary data. The data are obtained from the Central Bureau of Statistics Indonesia (BPS). The steps of data analysis can be explained as follow: identify the stationarity of the data to the mean and variance. If the data are not stationary to variance then Box-Cox transformation is conducted. Meanwhile, if data is not stationary to mean then differencing is conducted; identify the model by looking at ACF and PACF plots based on the data that have already been stationary; conduct the estimation of model parameters by using Maximum Likelihood Estimator method; conduct the significance testing of the parameters with the t-test; conduct the diagnostic checking to see if the residual model is white noise through Ljung Box test and if it has a normal distribution through Kolmogorov-Smirnov test; choose the best model based on the lowest forecasting result of MSE.

RESULTS AND DISCUSSION

Identification of Data Stationarity. Identification of stationarity is conducted firstly by plotting the data.

Figure 1 – Plot Time Series of Data Inflation

Plotting is conducted to see if the data has a trend and has met the stationarity in the mean and variance. Identification of data stationarity can be obtained from the time series plot diagram in figure 1.

Based on the figure above, the data pattern shows an unstable in the mean because the plot shows a fluctuated pattern. The variance pattern of the data is not stationary as well, because the variance width of the data is quite varied. The data is not stationary then it necessary to conduct transformation and differencing to make the mean and variance stationary. The first step of data stationarity is to look at the value in the Box-Cox transformation diagram which is displayed in the following figure.

Figure 2 – Box-Cox Transformation Diagram

The Box-Cox transformation diagram shows a value of -0.5, so the data are transformed by using the transformation formula. The time series plot for the transformation data is displayed in the following figure.

Figure 3 – Plot Time Series of Transformation Data

Next, to see the data stationarity in the mean should check the ACF plot of transformation data. The ACF plot of transformation data is displayed in the following table.

Table 1 – Plot ACF Data Transformation

Autocorrelations																								
Lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error
0	0.437615	1.00000																						0
1	0.226179	0.51684																						0.124035
2	0.111420	0.25461																						0.153636
3	0.049904	0.11404																						0.159995
4	0.044298	0.10123																						0.161241
5	0.046278	0.10575																						0.162216
6	0.024657	0.05634																						0.163273
7	0.047035	0.10748																						0.163572
8	0.044422	0.10151																						0.164655
9	0.039983	0.09137																						0.165615
10	0.092059	0.21037																						0.166388
11	0.097472	0.22274																						0.170431
12	0.054258	0.12399																						0.174852
13	-0.011055	-0.02526																						0.176199
14	-0.069256	-0.15826																						0.176255
15	-0.028050	-0.06410																						0.178428
16	-0.029129	-0.06656																						0.178782

The table above shows that the transformation data have an ACF plot that slowly and exponentially decreases, so the data have not been stationary in the mean and then differencing lag 1 is conducted to the transformation data. The plot time series for differencing lag 1 data is displayed in the following figure.

Figure 4 – Plot Time Series of Differencing Lag 1 Data

Next, ACF and PACF plot are checked on the differencing lag 1 data. ACF plot of differencing lag 1 data is displayed in the following table:

Table 2 – ACF Plot of Differencing Lag 1 Data

			Autocorrelations																					
Lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error
0	0.426238	1.00000																						0
1	-0.094262	-.22115													*	*	*	*	*	*	*	*	*	0.125000
2	-0.053091	-.12456													*	*	*	*	*	*	*	*	*	0.130971
3	-0.052408	-.12295													*	*	*	*	*	*	*	*	*	0.132809
4	-0.0042505	-.00997													*	*	*	*	*	*	*	*	*	0.134576
5	0.010665	0.02502													*	*	*	*	*	*	*	*	*	0.134587
6	-0.044668	-.10480													*	*	*	*	*	*	*	*	*	0.134660
7	0.023776	0.05578													*	*	*	*	*	*	*	*	*	0.135928
8	0.0060456	0.01418													*	*	*	*	*	*	*	*	*	0.136285
9	-0.060679	-.14236													*	*	*	*	*	*	*	*	*	0.136308
10	0.045307	0.10629													*	*	*	*	*	*	*	*	*	0.138612
11	0.050779	0.11913													*	*	*	*	*	*	*	*	*	0.139880
12	0.028214	0.06619													*	*	*	*	*	*	*	*	*	0.141456
13	-0.012840	-.03012													*	*	*	*	*	*	*	*	*	0.141940
14	-0.097400	-.22851													*	*	*	*	*	*	*	*	*	0.142039
15	0.047418	0.11125													*	*	*	*	*	*	*	*	*	0.147672
16	-0.046696	-.10955													*	*	*	*	*	*	*	*	*	0.148976

PACF plot of differencing lag 1 data is displayed in the following table:

Table 3 – PACF Plot of Differencing Lag 1 Data

		Partial Autocorrelations																						
Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1		
1	-0.22115																							
2	-0.18238																							
3	-0.21301																							
4	-0.14089																							
5	-0.08675																							
6	-0.20349																							
7	-0.08526																							
8	-0.07993																							
9	-0.26623																							
10	-0.08065																							
11	0.03613																							
12	0.06151																							
13	0.08217																							
14	-0.16494																							
15	0.01084																							
16	-0.14171																							

ACF and PACF plots of differencing lag 1 data show both ACF and PACF values have not been correlated across the Bartlett line, so it will be difficult to identify the model. Therefore, differencing is necessarily conducted again. The result of plot time series for the data, after the second differencing, is displayed in the figure below:

Figure 5 – Plot Time Series Data of the Second Differencing

The figure above shows that the second differencing of the data has shown a stationary pattern, since the data have been stationary, then the data can be used for the model identification step.

Model Identification. Inflation data that has been stationary then being checked for its ACF and PACF plots. Results of ACF and PACF plots of inflation data are used to estimate a temporary model. The ACF plot of inflation data is displayed in the following table.

Table 4 – ACF Plot of Inflation Data

Autocorrelations																								
Lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error
0	1.052069	1.00000																						0
1	-0.568407	-0.54028																						0.125988
2	0.037806	0.03594																						0.158555
3	-0.051162	-0.04863																						0.158684
4	0.061637	0.05859																						0.158920
5	0.056758	0.05395																						0.159263
6	-0.128355	-0.12200																						0.159553
7	0.082567	0.07848																						0.161027
8	0.055423	0.05268																						0.161633
9	-0.173063	-0.16450																						0.161905
10	0.096810	0.09202																						0.164536
11	0.021440	0.02038																						0.165351
12	0.031155	0.02961																						0.165391
13	0.034381	0.03268																						0.165475
14	-0.233559	-0.22200																						0.165578
15	0.263420	0.25038																						0.170237

The ACF plot of inflation data in Figure 4.9 shows that the autocorrelation value is exit or cut after the lag 1, so it can be concluded that statistically there is a significant correlation in lag 1. Next, PACF plot of inflation data is displayed in the following table:

Table 5 – PACF Plot of Inflation Data

Partial Autocorrelations																						
Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
1	-0.54028												*****									.
2	-0.36148												*****									.
3	-0.35331												*****									.
4	-0.28206												*****									.
5	-0.11962													***								.
6	-0.20743													*****								.
7	-0.15891													*****								.
8	0.01975														*							.
9	-0.17544														*****							.
10	-0.19769														*****							.
11	-0.14035														*****							.
12	-0.07668															***						.
13	0.16475																***					.
14	-0.05892																	*				.
15	0.09901																		***			.

PACF plot of figure 4.10 shows that the PACF value is cut to the 4th lag, then the estimation of appropriate model are ARIMA (0,2,1), ARIMA (1,2,0), ARIMA (2,2,0), ARIMA (3,2,0), ARIMA (4,2,0), ARIMA (1,2,1), ARIMA (2,2,1), ARIMA (3,2,1), and ARIMA (4,2,1).

Estimation of Model Parameter. After the model is obtained, the next step is to estimate the parameter of the model. Summary of parameter estimation results for some appropriate model estimations can be seen in Table 6.

Table 6 – Results of Model Parameter Estimation

Model	Model Parameter	Coefficient	p-value	Description
ARIMA(0,2,1)	θ_1	-0.97009	<0.0001	The model is significant
ARIMA(1,2,0)	ϕ_1	0.27107	<0.0266	The model is significant
ARIMA(2,2,0)	ϕ_1	0.39782	0.0003	The model is significant
	ϕ_2	-0.50789	<0.0001	
ARIMA(3,2,0)	ϕ_1	0.40739	0.0017	The model is not significant
	ϕ_2	-0.51366	<0.0001	
	ϕ_3	0.01707	0.8950	
ARIMA(4,2,0)	ϕ_1	0.41950	0.0010	The model is not significant
	ϕ_2	-0.71741	<0.0001	
	ϕ_3	0.15133	<0.2738	
	ϕ_4	-0.36338	0.0037	
ARIMA(1,2,1)	ϕ_1	-0.45001	0.0025	The model is not significant
	θ_1	-0.99999	0.8656	
ARIMA(2,2,1)	ϕ_1	-0.27263	0.0361	The model is not significant
	ϕ_2	-0.17763	0.1715	
	θ_1	-0.99252	<0.0001	
ARIMA(3,2,1)	ϕ_1	-0.34308	0.0201	The model is not significant
	ϕ_2	-0.23499	0.0755	
	ϕ_3	-0.26354	0.0693	
	θ_1	-0.99995	0.8458	
ARIMA(4,2,1)	ϕ_1	1.08144	<0.0001	The model is significant
	ϕ_2	-0.96923	<0.0001	
	ϕ_3	0.51404	0.0037	
	ϕ_4	-0.35831	0.0062	
	θ_1	0.75711	<0.0001	

Based on table 4.2, it can be seen that ARIMA (0,2,1), ARIMA (1,2,0), ARIMA (2,2,0), and ARIMA (4,2,1) models have been significant, since those models have p-values less than 0.05. From these results, it can be concluded that temporary models that can be used for the next process are ARIMA (0,2,1), ARIMA (1,2,0), ARIMA (2,2,0), and ARIMA (4,2,1) models.

Diagnostic Check. Models whose parameters have been significant, subsequently performs a diagnostic check to see if the residual and the residual variance of the model meet the modeling assumptions. First, test is conducted to see whether the residual model is white noise or not. The test of residual white noise is conducted by using the statistic of Ljung Box test. Results Ljung Box Test can be seen in Table below.

Table 7 – Residual Results of Ljung Box Test

Model	Up to lag	p-value	Description
ARIMA(0,2,1)	6	0.3604	White noise
	12	0.5553	
ARIMA(1,2,0)	6	0.0062	Not white noise
	12	0.0125	
ARIMA(2,2,0)	6	0.1658	White noise
	12	0.2626	
ARIMA(4,2,1)	6	0.4167	White noise
	12	0.3996	

Based on the results obtained from Ljung Box test in table 4.2, it can be concluded that there are four models from the temporary model and there are three models of residual white noise: ARIMA (0,2,1), ARIMA (2,2,0) and ARIMA (4,2,1) models. Residual model is also assumed to have normal distribution; therefore, residual normality test is conducted by using

Kolmogorov-Smirnov test. The results of Kolmogorov-Smirnov test can be seen in Table below.

Table 8 – Results of Kolmogorov-Smirnov Test

Model	Statistic Test	p-value	Description
ARIMA (0,2,1)	0.043267	>0.15	Residuals are normally distributed
ARIMA (1,2,0)	0.081879	>0.15	Residuals are normally distributed
ARIMA (2,2,0)	0.055423	>0.15	Residuals are normally distributed
ARIMA (4,2,1)	0.058485	>0.15	Residuals are normally distributed

Table 8 shows that the four residual models tested have a normal distribution. From the results of diagnostic check that has been conducted before, it can be concluded that from the first estimation of four models, there are three temporary models that nearly meet the assumptions of ARIMA model (0,2,1), ARIMA (2,2,0) and ARIMA (4,2,1). Next, the three models will be re-selected for one the best model that will be taken for forecasting.

Best Model Selection. From the three temporary models: ARIMA (0,2,1), ARIMA (2,2,0) and ARIMA (4,2,1), the best model is the model that has the lowest forecasting value of MSE. The comparison results of forecasting results of MSE are shown in Table 9 below.

Table 9 – Results of MSE Forecasting

Model	MSE Forecasting
ARIMA(0,2,1)	0.293764
ARIMA(2,2,0)	0.395519
ARIMA(4,2,1)	0.331832

Based on the results in table 9, it is known that the ARIMA model (0,2,1) has the lowest MSE forecasting value of 0.293764; therefore it can be concluded that the best model for inflation forecast of housing, water, electricity, gas and fuel groups is ARIMA model (0,2,1).

ARIMA (0,2,1) model can be probabilistically written by the following equation:

$$\begin{aligned}
 (1 - B)^2 Z_t^* &= (1 - \theta_1 B) \varepsilon_t \\
 (1 - 2B + B^2) Z_t^* &= (1 - \theta_1 B) \varepsilon_t \\
 Z_t^* - 2Z_{t-1}^* + Z_{t-2}^* &= \varepsilon_t - \theta_1 \varepsilon_{t-1} \\
 Z_t^* &= \varepsilon_t - \theta_1 \varepsilon_{t-1} + 2Z_{t-1}^* - Z_{t-2}^* \\
 \frac{1}{\sqrt{Z_t}} &= \varepsilon_t - \theta_1 \varepsilon_{t-1} + \frac{2}{\sqrt{Z_{t-1}}} - \frac{1}{\sqrt{Z_{t-2}}} \\
 Z_t &= \frac{1}{\left(\varepsilon_t - \theta_1 \varepsilon_{t-1} + \frac{2}{\sqrt{Z_{t-1}}} - \frac{1}{\sqrt{Z_{t-2}}} \right)^2} \\
 Z_t^* &= \frac{1}{\sqrt{Z_t}}
 \end{aligned}$$

So, the equation of ARIMA (0,2,1) model for inflation value of expenditure groups of housing, electricity, water, gas, and fuel is:

$$Z_t = \frac{1}{\left(\varepsilon_t + 0,97009\varepsilon_{t-1} + \frac{2}{\sqrt{Z_{t-1}}} - \frac{1}{\sqrt{Z_{t-2}}} \right)^2}$$

CONCLUSION AND SUGGESTIONS

Based on the results of the research and discussion that have been described in the previous chapters, it can be drawn some conclusions as follows:

The best model that can be used for Indonesian's monthly inflation forecast for expenditure groups of housing, water, electricity, gas and fuel is ARIMA (0,2,1) model.

The equation of ARIMA (0,2,1) model for Indonesian's monthly inflation forecast for expenditure groups of housing, water, electricity, gas and fuel is:

$$Z_t = \frac{1}{\left(\varepsilon_t + 0,97009\varepsilon_{t-1} + \frac{2}{\sqrt{Z_{t-1}}} - \frac{1}{\sqrt{Z_{t-2}}} \right)^2}$$

The forecasting value of MSE of ARIMA (0,2,1) model is 0.293764.

The value of inflation is often fluctuating and is influenced by many external factors; for example, the hikes of fuel price, the changes of socio-political policy, natural disasters etc. Therefore, the forecasting of inflation value for further research is suggested to use time series analysis approach which includes other external factors, such as transfer function model, intervention, etc.

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