Jurnal Ekonomi Pembangunan
Vol. 20, No. 02, December 2022, pp. 183 ~ 192

The Impact of Fuel Prices Increasing on Inflation in South Sulawesi using Pulse Function Intervention Analysis

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Article Info

Article history:
Received November 10, 2022
Revised December 27, 2022
Accepted December 30, 2022
Available online December 31, 2022

Key Words:
intervention model; pulse function; ARIMA; input variable.

JEL Classification: A10; H20; H22;

Abstract

South Sulawesi Province is considered capable of controlling inflation, as seen from its not very large volatility. However, this does not mean that the increase in fuel prices does not impact inflation in South Sulawesi. This study aims to obtain the best model to analyze the impact of rising fuel prices on inflation in South Sulawesi using Pulse Function Intervention Analysis and to find out how significant the impact of rising fuel prices on inflation in South Sulawesi is. The data in this study were obtained from the Central Statistics Agency (BPS) of South Sulawesi Province, namely the monthly inflation of South Sulawesi Province for the period January 2014 – September 2022, with a total of 105 observations. The best model in this study is the MA ([12]) bbm1, bbm5, and bbm6 models with AIC 104.09. Statistical test results show that 3 of 6 times increases in fuel prices since 2014 still influence the rising inflation, namely in November 2014, April 2022, and September 2022. The increase in fuel prices in 2014 impacted rising inflation by 1.97 percent, while in 2022, it increased inflation by 0.92 and 0.99 percent.

INTRODUCTION

The provision of fuel oil (BBM) subsidies in Indonesia is one of the government's policies to meet people's needs and maintain price stability. However, since President Soeharto's administration in 1991, the government has taken a policy of reducing fuel subsidies or increasing fuel prices approximately 16 times (Sejarah Harga BBM, 2022). The government announced the recent increase on September 3, 2022 (Jejak Kenaikan Harga BBM, 2022). The rising fuel prices potentially trigger an increase in the price of various goods, especially public needs. The condition of the increasing costs of goods and services in general and continuously within a certain period is none other than inflation (BPS, 2022). Inflation is one of the crucial indicators in determining government policy. High inflation may cause a domino effect, such as decreasing people's purchasing power and increasing poverty (BI, 2020)b.

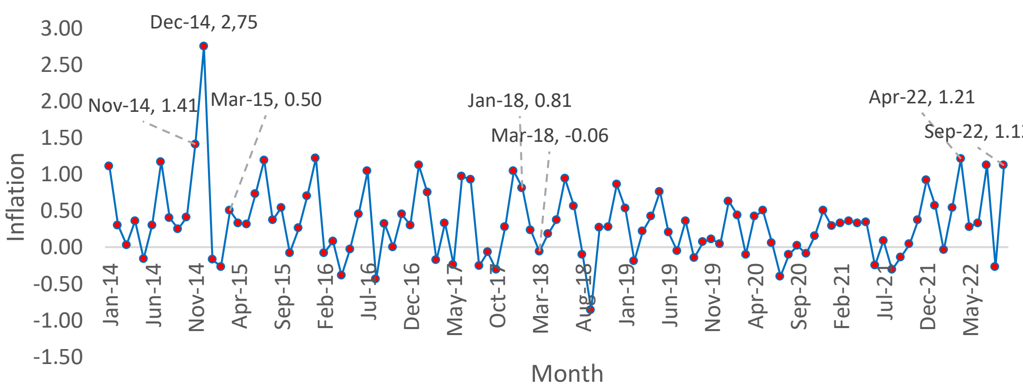
Several studies have shown that the increase in fuel prices affects inflation. Sadewo (2013) conducted inflation modeling using ARIMA with outlier detection and intervention models. The results showed that the October 2005 fuel price hike significantly influenced inflation in Riau Province.

Pusposari (2016) examined the effect of fuel prices on inflation in East Java with a regression model. The study obtained that fuel prices, especially gasoline, significantly impacted inflation. Sumantria and Latifah (2019) stated in their research that inflation had a prominent effect on exports and imports in Indonesia.

Meanwhile, exports and imports are required components of GDP, where exports are a source of economic growth while imports as reductions. Rauf et al. (2020) also examined inflation because it is a time series data that is difficult to predict and can contain trend, seasonal, cyclical, or random components. His research modeled the inflation of primary foodstuffs with ARIMA.

Several other researchers conducted inflation modeling because of its urgency as an economic indicator. Forecast inflation because inflation is an essential indicator for evaluating economic strength. The forecasting compares the methods of the short-term ahead forecast, Singular Spectrum Analysis (SSA), Random Walk (RW), ARIMA, and Holt-Winters. Inflation modeling can link high inflation rates in Nigeria with low economic growth, high prices of imported products, exchange rate depreciation, and external factors such as crude oil prices. His research modeled inflation in Nigeria with ARMA, ARIMA, and GARCH. Predict inflation in Sweden with Bayesian Vector Autoregression (BVAR) because a good inflation forecast is crucial for the effectiveness of monetary policy formulation. Another study also indicated inflation in the European region related to the importance of inflation as a fundamental factor for determining monetary policy. It compares forecasting results with several methods, namely BVAR, UC-SV, and RW.

Figure 1. Time Series Plot of Monthly Inflation in South Sulawesi January 2014 – September 2022



Source: BPS South Sulawesi, 2022

South Sulawesi Province can control inflation with a figure (+/-) of no more than 5 percent. The Regional Inflation Control Team (TPID) of South Sulawesi Province won the title of Best Provincial TPID 2021 for the Sulawesi region and received an award from the Coordinating Minister for the economy at the TPID Central and Regional Coordination Meeting on September 14, 2022. When inflation in other regions was volatile due to rising fuel prices, inflation in South Sulawesi was still relatively stable. Since January 2014, there have been six increases in fuel prices but not too many spikes in the inflation rate. Figure 1 shows the peak of inflation in December 2014, a month after the November 2014 fuel price increase, with an inflation rate of 2.75 percent. In addition, inflation only fluctuated below (+/-) 2 percent. However, the people of South Sulawesi are still voicing their aspirations to criticize the government's policy of increasing fuel prices through various demonstrations. It raises the question of how the impact of rising fuel prices is felt by the people of South Sulawesi, especially concerning the increase in prices of various goods and services needed by the community. This study aims to obtain the best model to analyze the impact of rising fuel prices on inflation in South Sulawesi using Pulse Function Intervention Analysis and to find out how significant the impact of rising fuel prices on inflation in South Sulawesi is.

RESEARCH METHODS

This study uses secondary data provided by the Central Statistics Agency (BPS) of South Sulawesi Province, namely the monthly inflation of South Sulawesi Province for the period January 2014 – September 2022, with a total of 105 observations. Time series data can be affected by external factors or events that occur at a particular time, such as holidays, promotions, pandemics, changes in government policies, and other special events called interventions (Montgomery et al., 2008; Wei, 2006). The analysis was performed using the Pulse Function Intervention Model. The intervention variables in this study were provided by the online news site Kompas, namely the increase in fuel prices that occurred six times during the research data period, namely in November 2014, March 2015, January 2018, March 2018, April 2022, and September 2022.

Intervention analysis is a method for dealing with external factors that time series methods cannot predict. Before modeling the intervention, we have to form an ARIMA model. Autoregressive Integrated Moving Average (ARIMA) is a time series model that includes autoregressive (AR), moving average (MA), and stationary processes. In general, the ARIMA model has the following form (Wei, 2006):

$$\phi_p(B)\,(1-B)^d\,\dot{Z}_t = \theta_q(B)a_t \quad \ldots\ldots \quad (1)$$

where,

$\phi_p(B) = (1 - \phi_1 B - \phi_2 B - \ldots - \phi_p B)$ is the coefficient of the non-seasonal AR component with order p

$\theta_q(B) = (1 - \theta_1 B - \theta_2 B - \ldots - \theta_q B)$ is the coefficient of the non-seasonal MA component with order q

a_t : white noise error, $a_t \sim IIDN(0, \sigma_a^2)$

B: Backward operator

$(1-B)^d$: Differentiation of non-seasonal data with order d as a data stationarization process.

Time series data often contains the seasonal components correlated with the non-seasonal, so the seasonal ARIMA (SARIMA) model can handle it. The combination of ARIMA and seasonal models produces the following Box-Jenkins multiplicative SARIMA model:

$\Phi_P(B^S)\ \phi_p(B)\ (1-B)^d(1-B)^D\ \dot{Z}_t = \theta_q(B)\Theta_Q(B^S)a_t$ .... (2)
Where:
$\Phi_P(B^S) = (1-\Phi_1 B^S - \Phi_2 B^S - \ldots - \Phi_P B^S)$ is the coefficient of the seasonal AR component with order P,
$\Theta_Q(B^S) = (1-\Theta_1 B^S - \Theta_2 B^S - \ldots - \Theta_Q B^S)$ is the coefficient of the seasonal MA component with order Q,
$(1-B)^D$: Differentiation of seasonal data with order D, as a data stationarization process seasonally.
The model in equation (2) can also be ARIMA (p,d,q) (P, D, Q)S.

The initial identification of the ARIMA model uses the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The ACF plot shows the stationarity and the possible order of the MA model, whereas the PACF shows the AR model. The lags that exceed the signature line on the ACF plot show possibility of order q. Likewise, the lags on the PACF plot show the order p. In addition to looking at the plots, we also need to test the stationarity of the data. Next, we need differencing if the data is not stationary in the mean or perform a Box-Cox transformation if the information is not stationary in the variance.

ARIMA and SARIMA models of data that still contain external factors will have errors that do not meet the assumption of white noise. Intervention analysis overcomes this weakness. There are two general forms of intervention variables. The first is a step function intervention, which occurs at time T and leaves an effect in the long term (Montgomery et al., 2008; Wei, 2006).

$S_t^{(T)} = \begin{cases} 0, & t < T \\ 1, & t \geq T \end{cases}$ .... (3)

The second is the pulse function intervention, where the intervention only has an effect at one time.

$P_t^{(T)} = \begin{cases} 1, & t = T \\ 0, & t \neq T \end{cases}$ .... (4)

The intervention model is stated in equation (5).

$Z_t = \sum_{j=1}^{k} \frac{\omega_{sj}(B)B^{bj}}{\delta_{rj}(B)} I_{jt} + N_t$ .... (5)

where,
$Z_t =$ Inflation at time t, with t=1, 2, …, 105
$I_{jt} =$ increase in fuel prices at time t, with j=1, 2, …, 6.
$\omega_{sj}(B) = \omega_{0j} - \omega_{1j}B^1 - \omega_{2j}B^2 - \cdots - \omega_{sj}B^s$
$\delta_{rj}(B) = 1 - \delta_{1j}B^1 - \delta_{2j}B^2 - \cdots - \delta_{rj}B^r$
$N_t = \frac{\theta_q(B)}{\varphi_p(B)(1-B)^d} a_t$

The intervention variable I_{jt} It can be a step function or a pulse function. The increase in fuel prices generally only has a short-term effect, so the pulse function is used. The form $\omega_{sj}(B)B^{bj}/\delta_{rj}(B)$ For the j[th] intervention was determined based on the expected response from the information obtained about the intervention. N_t is the ARIMA (p,d,q) model of the Z time series data before the intervention, called the noise model (Sadewo, 2013; Wei, 2006). The order *b* is the delay time when the intervention I_{jt} Begins to affect Z, the order

s is the length of time an intervention has an effect on Z after a period of b, and the order r is the pattern of the intervention impact after $b+s$ since the intervention occurred at time T (Damayanti & Yosmar, 2021; Ekayanti et al., 2014).

The superiority of the intervention model compared to regression is that it does not require as much input variable data as the response. Still, it can only be in the form of time points where the events occur. The data structure of this study is shown in Table 1.

Table 1. Data Structure of Research

Time/ Observation	Input Variable						Response Variable
(t)	bbm1	bbm2	bbm3	bbm4	bbm5	bbm6	Inflation
1	0	0	0	0	0	0	Z_1
2	0	0	0	0	0	0	Z_2
3	0	0	0	0	0	0	Z_3
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
11	1	0	0	0	0	0	Z_{11}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
15	0	1	0	0	0	0	Z_{15}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
49	0	0	1	0	0	0	Z_{49}
50	0	0	0	0	0	0	Z_{50}
51	0	0	0	1	0	0	Z_{51}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
100	0	0	0	0	1	0	Z_{100}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
105	0	0	0	0	0	1	Z_{105}

Inflation data modeling in this study did not separate in-sample and out-sample data because of several considerations. The input variables are in 105 observations. Several input variables to be analyzed are located at the end of the data series. This study does not do forecasting but tests the significance of the model. Previous research by Zhang et al. (2019) using Intervention Analysis did not separate training and testing data but continued to simulate data until 2030. In addition, research using the ARIMA Intervention Model does not separate in-sample and out-sample data because it focuses on knowing the impact of social restriction policies on silent behavior in South Sulawesi people's homes during the Covid-19 pandemic.

RESULTS AND DISCUSSION

Time series analysis requires stationary data. Figure 1 indicates a stationary data pattern. The results of the stationarity test using the Augmented Dickey-Fuller test in Table 2 indicate that the data is stationary, rejecting H_0 with a p-value of 0.01. Thus, we can continue the modeling without differencing or transformation processes.

Table 2. Stationarity Test Results of Inflation Data

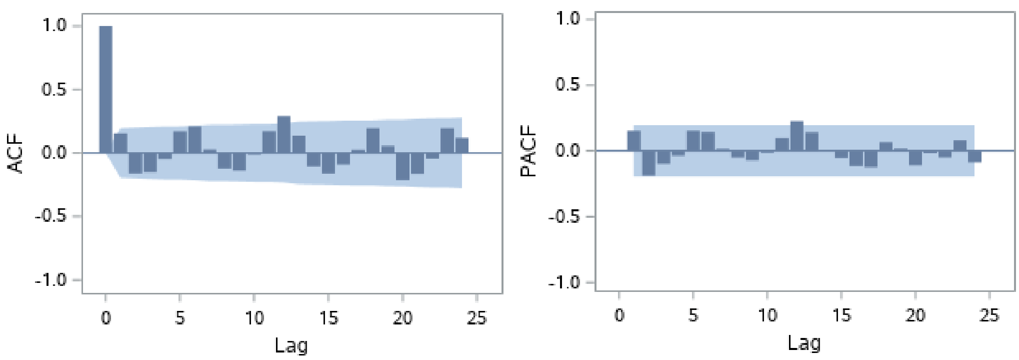
Dickey-Fuller	Lag order	p-value
-4,36	4	0,01

Intervention modeling begins with checking the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, as shown in Figure 2, to obtain the ARIMA model. The ACF plot shows a seasonal pattern and significance at lags 6 and 12. Thus, the result of this identification allows the Seasonal ARIMA (SARIMA) model with a seasonal period of 6 or 12. The PACF plot also shows a seasonal pattern and significance at lags 2 and 12. Table 3 presents the proposed ARIMA models based on the plots.

Table 3. The Proposed ARIMA Models Based on ACF and PACF

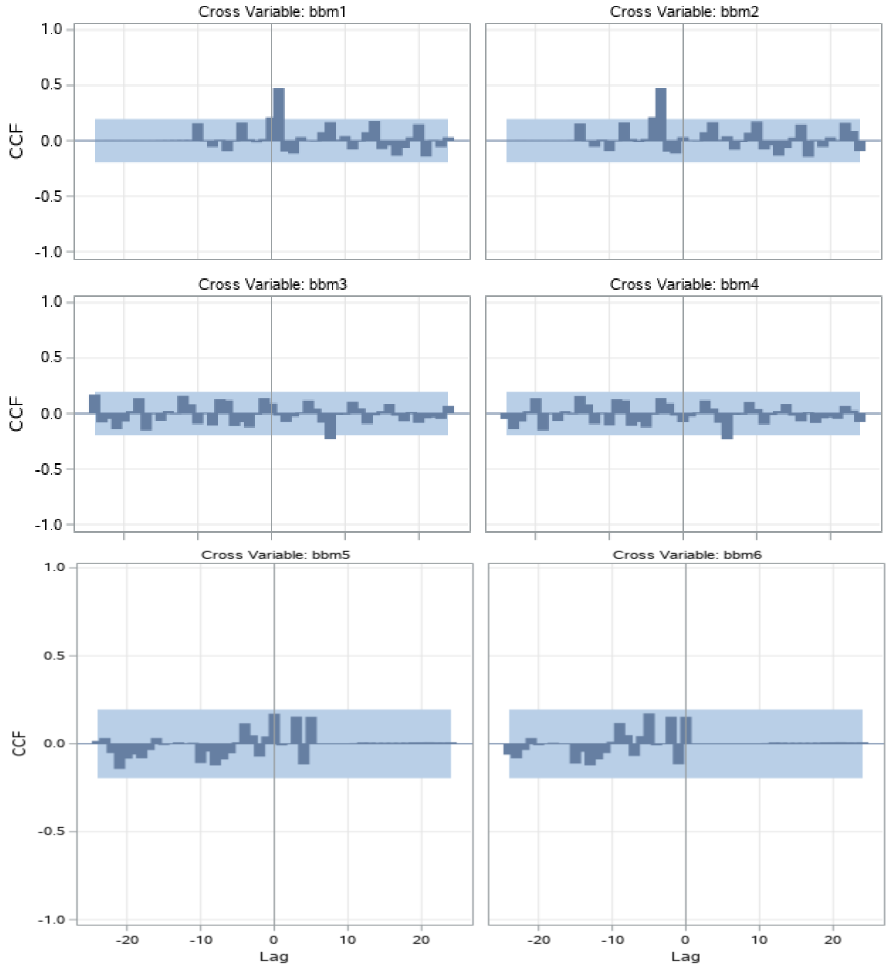
No.	Models	No.	Models
1	ARIMA ([2],0,0) $(1,0,1)^6$	13	ARMA ([2,12],[6,12])
2	ARIMA ([2],0,0) $(1,0,1)^{12}$	14	ARMA ([2],[6])
3	ARIMA (1,0,0) $(1,0,1)^6$	15	ARMA ([2],[12])
4	ARIMA (1,0,0) $(1,0,1)^{12}$	16	ARMA ([12],[6])
5	ARIMA ([2],0,0) $(1,0,0)^6$	17	ARMA ([12],[12])
6	ARIMA ([2],0,0) $(1,0,0)^{12}$	18	ARMA ([6],[6])
7	ARIMA (1,0,0) $(1,0,0)^6$	19	AR ([2,12])
8	ARIMA (1,0,0) $(1,0,0)^{12}$	20	AR ([2])
9	ARIMA ([2],0,0) $(0,0,1)^6$	21	AR ([12])
10	ARIMA ([2],0,0) $(0,0,1)^{12}$	22	MA ([6,12])
11	ARIMA (1,0,0) $(0,0,1)^6$	23	MA ([12])
12	ARIMA (1,0,0) $(0,0,1)^{12}$	24	MA ([6])

Figure 2. ACF and PACF Plots of South Sulawesi Province Inflation Data



In addition to ARIMA modeling, a cross-correlation function (CCF) graph checks between inflation and fuel price increases to identify orders of b, s, and r to obtain an intervention model. The CCF graph in Figure 3 indicates that the first (bbm1), third (bbm3), and fourth (bbm4) hikes affect inflation. However, based on the graph, the effects of bbm3 and bbm4 only be seen after the next 8 and 5 months, respectively.

Figure 3. Cross-Correlation Function (CCF) Plot between Input Variable and Inflation



The modeling based on the ACF, PACF, and CCF plots generates three intervention models. The three models met the criteria for significance, white noise, and residual normality, as shown in Table 4. There are 3 of 6 input variables that affect inflation significantly, namely bbm1 with order b=0, s=2, and r=1; bbm5 with order b=0, s=0, and r=0; and bbm6 with order b=0, s=0, and r=0. The model selection based on the smallest Akaike Information Criterion (AIC) value generates model 3 as the best model, namely MA([12]), with an AIC value of 104.09.

Table 4. Comparison of Intervention Model Testing Results

ARIMA Model	Input Variables	White Noise	Normality	AIC
1. ARMA ([6],[6])	bbm1, bbm5, bbm6	√	√	112,38
2. AR ([12])	bbm1, bbm5, bbm6	√	√	107,40
3. MA ([12])	bbm1, bbm5, bbm6	√	√	104,09

Table 5 present the results of the significance test of model 3 as the best model. The modeling was done by entering all input variables and removing insignificant ones so that three input variables significantly affect South Sulawesi inflation. The MA parameter shows that the residual inflation model in the previous 12 months affects inflation significantly. Furthermore, the first increase in fuel prices that occurred in November 2014 had a significant effect on inflation for that month, as seen from the Scale1 parameter with a shift of 0 (b=0), meaning that there was no delay in the timing of the intervention effect. The significance of the Num1 parameter at lag 2 (s=2) explains that the impact of intervention happened for two months since the increase in fuel prices.

Table 5. Significance Test Results of the MA ([12]) Intervention Model

Parameters	Estimation	p-*value*	Lag	Variables	Shift
MA	-0. 5028	<0.0001	12	inflasi	0
Scale1	1. 9742	<0.0001	0	bbm1	0
Num1	0.8641	<0.0001	2	bbm1	0
Den1	0.9996	<0.0001	1	bbm1	0
Scale5	0.9178	0.0253	0	bbm5	0
Scale6	0.9929	0.0158	0	bbm6	0

After the inflation spike in November 2014, several increases in fuel prices did not affect inflation significantly. The hike in fuel prices in March 2015, January 2018, and March 2018 were excluded from the model because they had no significant effect. It may be due to the effectiveness of the policies implemented by the government through the work of the Regional Inflation Control Team (TPID) in suppressing the inflation rate. These policies include trying to strengthen the logistics system, carrying out coordination between regions in terms of maintaining the availability of commodities needed by the community, as well as other steps that are the task of TPID, as stated in the Decree of the President of the Republic of Indonesia Number 23 of 2017.

After about eight years of stable inflation in South Sulawesi, the fifth fuel price increase that occurred in April 2022 turned out to have a significant effect on inflation. This effect happened immediately in that month but did not last long. The Scale5 parameter with a shift of 0 (b=0, s=0, r=0) shows that. The effect of rising fuel prices on inflation that took place shortly is also possible because the government has again implemented various policies that can reduce inflation.

Furthermore, the sixth fuel price increase in September 2022 significantly affected inflation that month, as seen from the Scale6 parameter with a shift of 0 (b=0). Inflation in September 2022, which reached 1.12 percent, was due to price increases in most expenditure groups, especially transportation, with an inflation rate of 9.85 percent. Of the 11 expenditure groups, only two groups were deflated: the food, beverages, and tobacco group and the information, communication, and financial services group (BPS South Sulawesi Province, 2022). However, we don't know how long this effect will last because the last data used was September 2022.

The Scale parameter shows the overall regression factor of the input variables. From the estimation results, the model is as written in equation (6). The model shows that the increase in fuel prices in November 2014 impacted on increasing inflation in South Sulawesi in that month by 1.97 percent. The hike in fuel prices in April 2022 resulted in an increase in inflation for the month by 0.92 percent, and the rising in fuel prices in September resulted in an increase in inflation for the month by 0.99 percent. Meanwhile, the residual MA model in the previous 12 months affects inflation by 0.50 percent.

$$Z_t = 1,9742\, I_{1t} + 0,9178\, I_{5t} + 0,9929\, I_{6t} + N_t$$
$$N_t = (1 + 0,5028\, B^{12})a_t$$
$$I_{1t} = \begin{cases} 1, & t = 11 \\ 0, & t \neq 11 \end{cases}$$
$$I_{1t} = \begin{cases} 1, & t = 100 \\ 0, & t \neq 100 \end{cases}$$
$$I_{1t} = \begin{cases} 1, & t = 105 \\ 0, & t \neq 105 \end{cases} \quad \text{.......... (6)}$$

In general, an increase in fuel prices can increase the inflation rate. However, with substantial efforts, the impact of inflation can be minimized so that it does not last long. Even with mitigation as early as possible, a high inflation spike will not happen. The results of the study by Sadewo (2013) used an intervention model which concluded that the increase in fuel prices in January 2002 and October 2005 affected inflation significantly. In addition, the research of Wulandari et al. (2016) found that the most suitable model for general inflation rates and inflation according to the seven expenditure groups in the city of Surabaya is the BBM intervention model except for the inflation for the processed food, beverages, cigarettes and tobacco groups, the clothing group and the health group.

The increase in fuel prices that occurred in 2022 turned out to affect South Sulawesi's inflation. Even though the government has made various efforts to control inflation, this is due to the economic pressure still present in South Sulawesi after the Covid-19 pandemic. This economy becomes more easily affected by the intervention.

CONCLUSION

Based on the results of this study, we found that the best model from the comparison of several intervention models is the MA([12]) bbm1, bbm5, and bbm6 model with AIC 104.09. Three of the six times increase in fuel prices since 2014 still have leverage on rising inflation, namely in November 2014, April 2022, and September 2022. The fuel prices rising in 2014 affected the increase in inflation of 1.97 percent. While in 2022, fuel prices rising has an impact on the increase in inflation by 0.92 and 0.99 percent. The results reinforce the assumption that rising fuel prices can trigger inflation. Even though South Sulawesi is considered quite capable of controlling inflation, in a vulnerable economic condition, inflation is sometimes still out of control. These results provide recommendations to local governments, both provincial and district/city, to pay more attention to overcoming inflation so that inflation does not have a dominant and lasting impact.

This study does not do forecasting because it focuses more on the purpose of knowing the impact of rising fuel prices on inflation in South Sulawesi. It is inadequate to separate in-sample and out-sample data due to fulfilling that objective. As a suggestion for further research, inflation forecasting can be done with the Intervention Model if the data is sufficient.

REFERENCE

BI. (2020, September 21). *Inflasi*. Bank Indonesia. https://www.bi.go.id/id/fungsi-utama/moneter/inflasi/default.aspx

BPS. (2022, September 21). *Inflasi*. Badan Pusat Statistik. https://www.bps.go.id/subject/3/inflasi.html#subjekViewTab1

Damayanti, S., & Yosmar, S. (2021). Model Intervensi Fungsi Step Untuk Peramalan Harga Saham Pt. Garuda Indonesia (Persero) Tbk Di Masa Pandemi Covid-19. *Jurnal Riset Dan Aplikasi Matematika*, *5*(1), 10–18. https://doi.org/10.26740/jram.v5n1

Ekayanti, R., Mara, M. N., & Sulistianingsih, E. (2014). Analisis Model Intervensi Fungsi Step untuk Peramalan Kenaikan Tarif Dasar Listrik (TDL) Terhadap Besarnya Pemakaian Listrik. *Buletin Ilmiah Mat. Stat. Dan Terapannya (Bimaster)*, *03*(3), 175–184. http://dx.doi.org/10.26418/bbimst.v3i03.7353

Jejak Kenaikan Harga BBM. (2022, September 3). *Jejak Kenaikan Harga BBM di Era Pemerintahan Jokowi*. Kompas.Com. https://nasional.kompas.com/read/2022/09/03/19593621/jejak-kenaikan-harga-bbm-di-era-pemerintahan-jokowi

Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2008). *Introduction to Time Series Analysis and Forecasting*. John Wiley & Sons.

Pusposari, L. F. (2016). Pengaruh Harga BBM Terhadap Inflasi Di Jawa Timur. *J-PIPS*, *Vol. 3, 1*, 47–67. https://doi.org/10.18860/jpips.v3i1.6854

Rauf, R. A., Lamusa, A., Bahri, S., Laihi, M. A. A., & Effendy, E. (2020). Model Peramalan Inflasi Bahan Makanan Primer dengan Pendekatan Box-Jenkins: Studi kasus di Kota Palu. *AGRIEKONOMIKA*, *9*(1), 16–27. https://doi.org/10.21107/agriekonomika.v9i1.6440

Sadewo, E. (2013). Pemodelan Inflasi Provinsi Riau Menggunakan ARIMA Dengan Deteksi Outlier dan Model Intervensi. *ResearchGate*, *January 2013*, 1–10. https://doi.org/10.13140/RG.2.2.11823.12963

Sejarah Harga BBM. (2022, August 29). *Sejarah Harga BBM Naik: Dari Masa Soekarno Hingga Jokowi*. Timesindonesia.Co.Id. https://www.timesindonesia.co.id/read/news/425605/sejarah-harga-bbm-naik-dari-masa-soekarno-hingga-jokowi

Sumantria, F., & Latifah, U. (2019). The Influence of Interest Rate, Money Circulation, Inflation, and CPI Against Export And Import in Indonesia 2012-2018. *Jurnal Ekonomi Pembangunan (JEP)*, *17*(02), 108–118. https://doi.org/10.22219/jep.v17i2.10242

Wei, W. W. S. (2006). *Time Series Analysis Univariate and Multivariate Methods* (Second Edition). Pearson Education.

Zhang, Y., Wu, P., Shan, B., Pan, T., Chen, W., Yan, T., Zeng, M., Lin, Y., & Qiu, L. (2019). Research on Intervention Analysis Model of Medium-to-long-term Electric Power Substitution Policy. *IOP Conference Series: Earth and Environmental Science*, *252*(3), 1–6. https://doi.org/10.1088/1755-1315/252/3/032080