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Unravelling Indonesia's CPI Inflation Dynamics through ARIMA-Based Intervention Analysis

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ABSTRACT

Background: The COVID-19 pandemic has significantly influenced the Consumer Price Index (CPI) of Indonesia, resulting in substantial fluctuations in inflation. These variations, driven by both external and unpredictable factors, have profound effects on the broader economy and society. Methods: This study employs the Autoregressive Integrated Moving Average (ARIMA) model to forecast the general CPI inflation in Indonesia. To assess the impact of major events, such as the COVID-19 pandemic, intervention analysis is incorporated into the model. Results: The ARIMA model selected for forecasting the CPI inflation in Indonesia demonstrates strong predictive accuracy, with an AIC value of 250.44 and a MAPE of 11.05%. These results indicate that the model offers a high level of reliability for forecasting inflation. The model was further used to predict CPI inflation for the first four months of 2023 (January to April), providing valuable short-term forecast understanding. Concluding Remarks: The ARIMA model, enhanced with intervention analysis, provides a robust tool for forecasting CPI in Indonesia, highlighting its effectiveness for short-term inflation predictions. With a low AIC and an acceptable MAPE, the model offers actionable insights for policymakers and stakeholders, supporting informed decisions aimed at mitigating the adverse effects of inflation volatility in the post-pandemic economy.

JEL Classifications: C22; E31; E37; I18

Keywords: intervention, time series, COVID-19, CPI, data analysis

I. INTRODUCTION

An important economic indicator that shows how much goods and services have changed in price over time is the Consumer Price Index (CPI) inflation in Indonesia (Bonar et al., 2017). The CPI inflation dynamics in Indonesia are impacted by a variety of economic situations and problems, as befits the largest economy in Southeast Asia. Businesses, economists, and politicians all keep a careful eye on the Consumer Price Index (CPI) inflation rate because of the useful information it gives about the state of the economy (Apituley, 2018; Suparti et al., 2016, 2019). Monetary policy, budgetary planning, investment tactics, and consumer behavior are just a few areas that can feel the effects of changes in consumer price index inflation. For policymakers to effectively manage inflationary pressures and promote sustainable economic growth, they must have a clear grasp of the trends and determinants of CPI inflation in Indonesia (Suhariyanto, 2008; Nazara, 2010; Harianja et al., 2023).

Factors both within and outside of Indonesia have an impact on the key inflation rate (Hutapea et al., 2010; Nessibi, 2016; Watuseke et al., 2019). Because interest rates, taxes, and government expenditure are all variables that can be affected by changes in monetary and fiscal policy, these changes in turn can have a significant influence on consumer price index inflation. Furthermore, developments in Indonesia's CPI inflation are heavily influenced by global economic factors, such as changes in commodity prices, exchange rates, and the dynamics of international trade. Inflation in the consumer price index (CPI) is sensitive to changes in domestic supply and demand factors like production levels, consumer tastes, and the state of the labor market (Pramana et al., 2017; Huang et al., 2020; Kurniawan et al., 2020; Nasution et al., 2020; Squires et al., 2020; Caraka et al., 2023).

In order to comprehend patterns and trends in the Consumer Price Index (CPI), time series analysis is crucial. Economists and policymakers may learn a lot about inflation rates for the future by looking at CPI data from the past. They can see patterns, seasonal changes, and trends. Important insights into the causes of inflationary pressures can be gleaned from time series analysis, which reveals cyclical movements and underlying patterns in CPI inflation (Suhartono et al., 2009; Suhartono, 2011a, 2011b, 2011c; Suparti et al., 2016). Economists can use time series analysis to determine the consistency and unpredictability of CPI inflation, which helps them make better financial policy and economic prediction decisions.

For informing policymaking and predicting future changes in CPI inflation, time series analysis is crucial. Economists can predict future inflation rates using mathematical models and statistical algorithms derived from analyses of past CPI data that reveal patterns (Akerlof, 2002). In order to stabilize the economy, modify monetary policy settings in anticipation of inflationary pressures, and execute other necessary steps, these forecasts are essential. Time series analysis also lets policymakers see how their initiatives have fared in the past and make adjustments based on that. To foster economic growth and stability, governments can benefit from incorporating time series analysis into their decision-making processes

II. MATERIAL AND METHODS

A. Fundamentals of Consumer Price Index in Indonesia

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The Consumer Price Index (CPI) is one of the most fundamental economic indicators in Indonesia because it acts as the main tool for measuring the inflation rate. Inflation itself is a general increase in the price of goods and services over a period, which directly affects people's purchasing power and overall economic stability (Manik and Albarda, 2016). The CPI is calculated based on changes in the prices of a group of goods and services consumed by households, known as the "consumption basket" (Sugema et al., 2010; Darsono et al., 2024). The components of this basket cover various sectors, such as food, housing, transportation, education, and health, thus providing a comprehensive picture of price dynamics at the consumer level. Technically, the CPI has a very significant impact on the economy, especially if it is not controlled. When the CPI rises continuously (high inflation), this can cause a decrease in people's purchasing power because the prices of goods and services become more expensive, while real income does not increase proportionally (Muhammad et al., 2020; Wibowo et al., 2021; Pournaras et al., 2022).

This impact will be felt more severely by low-income groups, most of whose spending is allocated for basic needs such as food and energy. In addition, uncontrolled inflation can erode consumer and investor confidence, which ultimately hampers economic growth (Wicaksonoputro et al., 2018; Anggara et al., 2022). In terms of monetary policy, Bank Indonesia (BI) uses CPI data as the main reference for setting interest rates. If CPI shows a significant increase in inflation, BI may raise the benchmark interest rate (BI Rate) to reduce inflationary pressures by tightening liquidity in the market. However, this interest rate increase can also have a negative impact on the real sector, such as decreasing investment and consumption, because borrowing costs become more expensive. Conversely, if CPI is too low or even shows deflation (decreasing prices), this can indicate weak demand and potentially hamper economic growth. Not only that, but CPI also affects the government's fiscal policy. For example, a high increase in CPI can force the government to increase subsidies or social assistance to protect the public from the impact of inflation (Fibriyani et al., 2024; Hossain et al., 2024; Nurdina et al., 2024; Srinita et al., 2025). This can burden the state budget and reduce fiscal space for infrastructure development or other programs. On the other hand, a stable and controlled CPI creates a more conducive economic environment for business growth, investment, and public welfare. Overall, an uncontrolled CPI can have a detrimental domino effect, ranging from decreasing purchasing power, economic instability, to weakening investor confidence. Therefore, controlling the CPI through appropriate monetary and fiscal policies is key to maintaining economic stability and public welfare in Indonesia.

B. Intervention Time Series

In time series analysis, intervention refers to the intentional manipulation or occurrence of events that affect the observed data (Suhartono et al., 2010, 2019). These interventions may include policy changes, economic events, or external shocks that impact the underlying process that generates the time series data.

The study of intervention time series entails determining and modeling the effects of these interventions on the data. This can be critical for understanding the causal linkages between multiple factors and forecasting future trends. Intervention time series can be analyzed using a variety of methodologies, including structural time series models, regression-based approaches, and intervention analysis tools. These strategies seek to quantify the effects of treatments while controlling for other variables that may influence the findings (Ruchjana et al., 2012; Bonar et al., 2017; Jaya et al., 2018, 2019; Pontoh et al., 2022).

One frequent strategy is to utilize dummy variables to indicate the timing and quantity of treatments. These dummy variables are included in the time series model, allowing the effects of interventions to be calculated independently of other variables. Intervention time series analysis gives useful insights into data dynamics, allowing policymakers and analysts to make more educated decisions about the impact of interventions on economic or other time-dependent processes (Bartholomew et al., 2024; Dorais, 2024; Valecha et al., 2024; Hyndman and Rostami-Tabar, 2025).

$$Y_t = \frac{\omega_s(B)}{\delta_r(B)} B^b S_t^T + \frac{\theta_q(B)}{\phi_p(B) - (1-B)^d} a_t \tag{1}$$

The intervention time series equation presented is a thorough model for interpreting time series data. The equation captures the response variable Y_t at time (t) as a function of multiple components. The seasonal and regular differencing terms, represented by $\omega_s(B)$ and $\delta_r(B)$ respectively, account for both seasonal and non-seasonal fluctuations in the data.

The backward shift operator (B) increased to the power of (b)reflects the series' temporal structure. The seasonal component S_t^T reflects periodic oscillations, which are vital for analyzing repeating patterns in the data. Furthermore, the autoregressive $\theta_q(B)$ and moving average $\phi_p(B)$) components offer insights into the serial dependencies of the time series.

The equation includes S_t^T and the error term a_t to estimate the influence of external interventions or shocks on observable data. Overall, this intervention time series equation provides a solid foundation for studying and modeling complicated temporal data, allowing researchers to identify underlying trends and make accurate predictions (Makridakis and Wheelwright, 1974; Makridakis et al., 1998).

C. Step Function and Pulse Analysis

In more general terms, intervention analysis is classified into two types: step function analysis and pulse function analysis. Step function intervention analysis is utilized when a variable or process undergoes a permanent change. This signifies that after the intervention, the variable will remain at the newly assigned value. This could include changes in economic policy or market structure, which have a direct impact on the observed data. In this analysis, the intervention is viewed as an abrupt shift that has a direct and lasting impact on the time series, allowing for the study of the intervention's long-term impacts (Makridakis and Wheelwright, 1974).

$$S_t^T = \begin{cases} 0, & for\ t < T \\ 1, & for\ t \geq T \end{cases} \tag{2}$$

Examining the residual plot reveals the order (b, r, s). The value of b is based on watching when the intervention effect starts. The value of s is based on the time it takes for data to stabilize after intervention. r denotes the time lag between b and s.

Table 1
Intervention Pseudocode

1	Input the time series data Y_t
2	Identify the point in time T where the step intervention occurred
3	Split the time series into two segments: before the intervention (Y_t for $t < T$) and after the intervention (Y_t for $t \geq T$)
4	Calculate the mean or level of each segment
5	Determine the difference between the mean or level of the two segments to quantify the effect of the intervention
6	Perform statistical tests (e.g., t-test, F-test) to assess the significance of the difference
7	Optionally, use regression or time series modeling techniques to account for other variables or factors that may influence the data
8	Evaluate the impact of the intervention on the time series and interpret the results
9	Optionally, visualize the data and results using plots or charts to aid interpretation
10	Make conclusions and recommendations based on the analysis

III. DATASET

This study utilizes the General Consumer Price Index (CPI) Inflation Data of Indonesia from 2010 to 2022, obtained from Bank Indonesia's official website. The dataset spans 13 years, with each year consisting of 12 months, resulting in a total of 156 monthly data points. The Consumer Price Index (CPI) serves as a key economic indicator, measuring the average price changes of a basket of goods and services purchased by households over time. This basket typically includes essential items such as food, clothing, housing, transportation, medical care, and other regularly consumed goods and services. By tracking fluctuations in the CPI, policymakers, economists, and researchers can assess the cost of living and determine the inflation or deflation rate within an economy. Inflation, characterized by a sustained increase in the general price level, erodes purchasing power, making goods and services more expensive over time. Conversely, deflation refers to a persistent decline in prices, which can enhance purchasing power but may also signal economic concerns such as reduced consumer demand and slower economic growth. The CPI dataset analyzed in this study offers a comprehensive overview of price trends across various sectors over the past 13 years. By examining historical patterns and trends, this study aims to forecast Indonesia's CPI inflation for the first four months of 2023. The predictive analysis leverages historical inflation trends to provide data-driven insights into future inflation rates, supporting economic planning and policy formulation.

IV. RESULTS

The General Consumer Price Index (CPI) inflation data for Indonesia is a time series dataset that frequently exhibits significant fluctuations. Figure 1 shows several dramatic fluctuations in the inflation data. However, for instructional purposes, this study will concentrate on a single period of high fluctuation, from June to August 2014. Several main variables contributed to Indonesia's considerable decline in inflation between June

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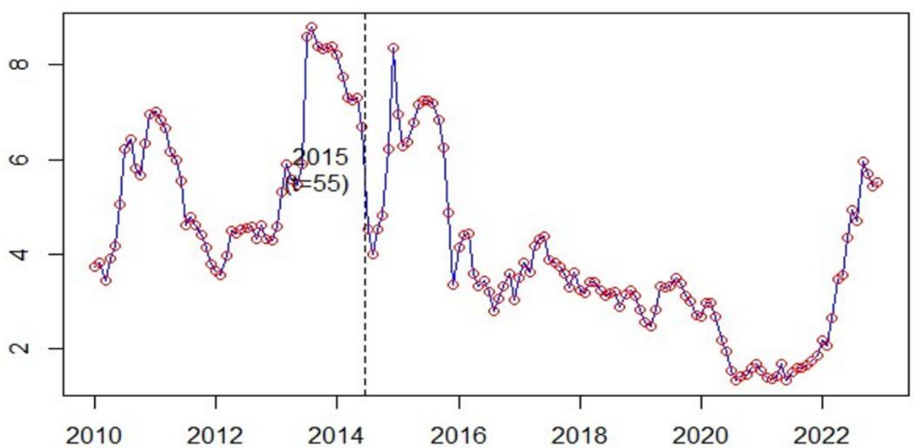
and August 2014. First, seasonal differences frequently influence inflation trends. In Indonesia, the mid-year period corresponds with the conclusion of the harvest season for many agricultural products, resulting in more supply and lower pricing. This seasonal surge of commodities can reduce overall price levels, resulting in reduced inflation rates. Furthermore, during this time, the government may have enacted special price-stabilization measures, such as subsidies or price limits on vital commodities, which would have helped to reduce inflation even further.

Second, monetary policy decisions by Bank Indonesia, the country's central bank, could have had a considerable impact on inflation rates. Leading up to mid-2014, if the central bank tightened monetary policy by raising interest rates or taking other measures to restrict the money supply, inflationary pressures would have been reduced. Higher interest rates can restrict consumer spending and borrowing, lowering demand for goods and services and contributing to a fall in inflation. As a result, any policy initiatives aimed at reducing inflation would have begun to take effect during this time period, resulting in the observed drop.

Figure 1
CPI



T=55.

Foreign economic forces and global market conditions may have had an impact. Global oil prices remained relatively steady in mid-2014, which may have aided in regulating transportation and production costs in Indonesia, resulting in lower inflation. Furthermore, better trade conditions or an appreciation of the Indonesian rupiah could have cut the cost of imported products, contributing to lower inflation. Overall, seasonal variables, domestic policy actions, and foreign economic conditions all likely contributed to the considerable decline in inflation recorded from June to August 2014. The ARIMA model will be formed using pre-intervention data with t-values < 55. The ARIMA (Auto Regressive Integrated Moving Average) model is a popular time series forecasting tool. However, before an ARIMA model can be developed, the data utilized for forecasting must be stable.

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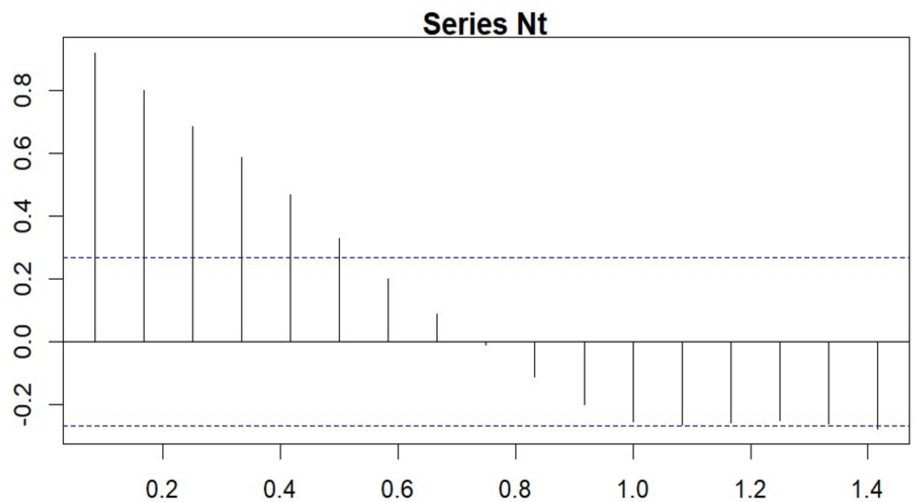
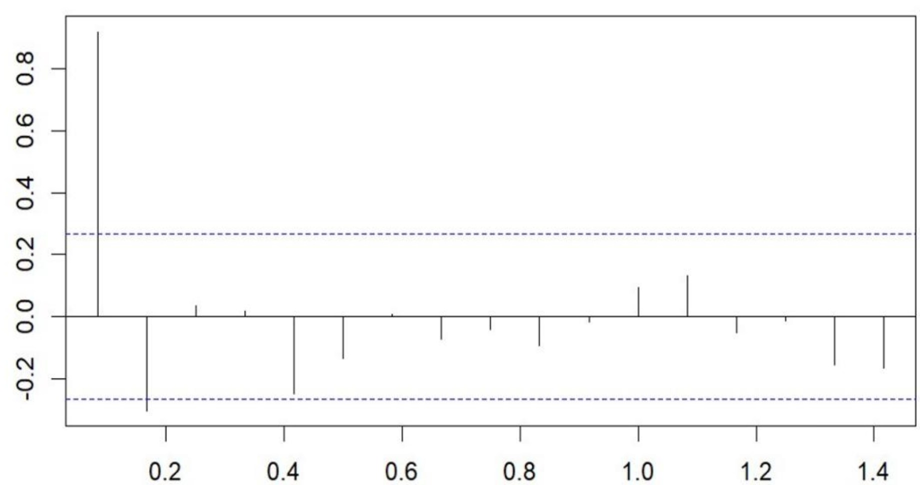
Data is deemed stationary if it fits two criteria: stationarity with respect to variance and stationarity with respect to mean. Stationarity with respect to variance indicates that the variance of the data does not fluctuate over time; the variations in the data are within a consistent range. Meanwhile, stationarity with regard to the mean indicates that the average of the data remains constant and does not reveal any increasing or decreasing tendencies over time.

Figure 2
Autocorrelation Function (A) and Partial Autocorrelation Function (B)



(A)



(B)

According to Figures 2a and 2b, the Autocorrelation Function (ACF) plot exhibits a pattern that gradually diminishes over time, which indicates a lack of persistent long-term correlation in the data. On the other hand, the Partial Autocorrelation Function (PACF) plot shows a clear cut-off at lag 1, suggesting that only the immediate previous observation significantly impacts the current value. Based on this observation, we have selected an AR (1) model, where the parameter (p) = 1. To ensure that the CPI inflation data is suitable for time series modeling, we performed a Box-Cox transformation to test for stationarity in both the mean and variance of the data. Stationarity is a crucial property in time series analysis as it ensures that the statistical properties of the data (mean, variance, and autocorrelation structure) remain constant over time, allowing for reliable forecasting. We applied the Box-Cox transformation using the optimal lambda value, which is the value that minimizes the transformation's impact while stabilizing variance and mean. After applying this transformation, the CPI inflation data became stationary, as shown in Figure 3**.** These results validate the effectiveness of the Box-Cox transformation in stabilizing the variance and mean, preparing the data for further modeling and analysis. The achieved stationarity is essential for accurate predictions and robust statistical inference in time series forecasting.

Figure 3
Optimum λ

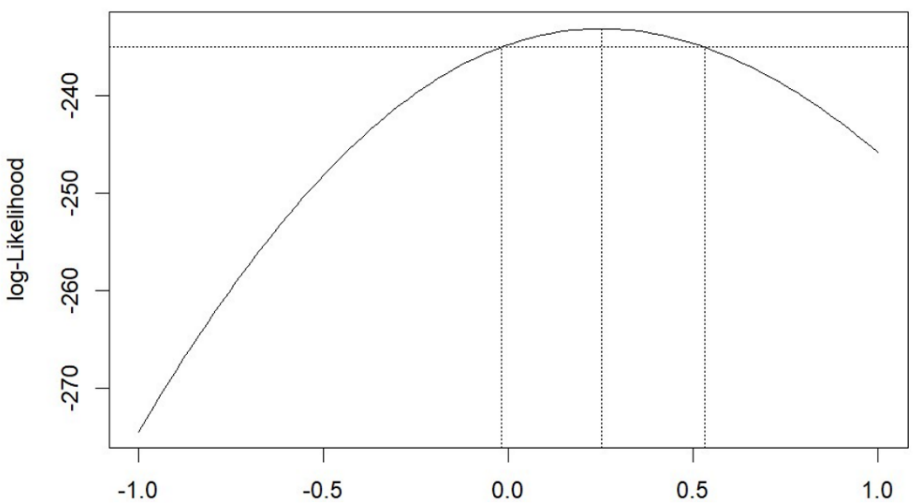


Figure 4 shows converted data with properties of stationarity, such as consistent variance and a stable mean throughout time. This is critical for ensuring that the statistical features of the data are consistent across time points, allowing for more robust modeling and forecasting tools.

The achievement of stationarity in the inflation data opens the door to additional research, such as the construction of forecasting models, such as ARIMA or SARIMA. These models rely largely on the assumption of stationarity to make accurate predictions. By translating the data into a stationary format, analysts can gain a better understanding of the underlying patterns and trends, resulting in more informed decision-making.

Furthermore, the successful translation of inflation data demonstrates the

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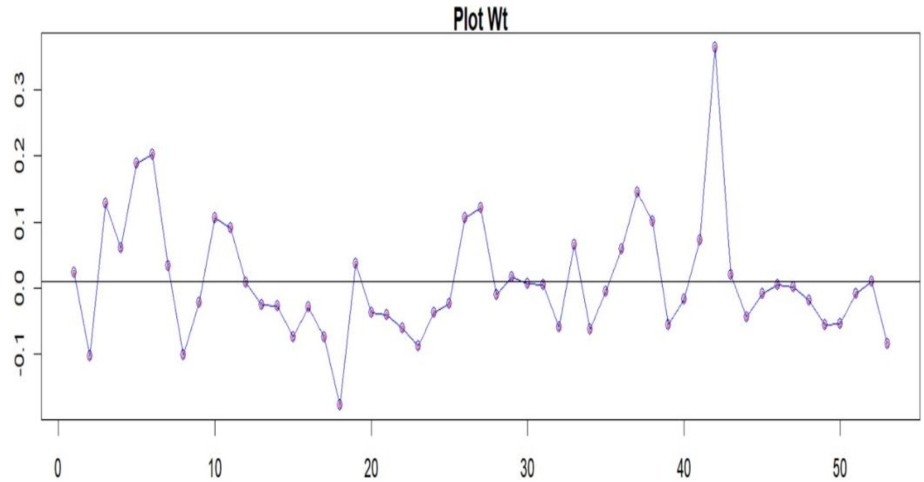
usefulness of the Box-Cox approach in dealing with non-stationarity difficulties. By finding and adopting the best transformation parameters, analysts may reduce the impact of non-stationarity and ensure the accuracy of their studies.

Figure 4
CPI After Difference



Before estimating the parameters of the ARIMA model, it is important to explore and compare several candidate model specifications. Model selection was guided by the statistical significance of model parameters and the Akaike Information Criterion (AIC). As shown in Table 1, the ARIMA (0,1,1) model with drift yielded the lowest AIC value (233.3114), indicating better model fit in a general sense. However, the drift term in this model was not statistically significant and introduced bias into the model interpretation. Therefore, the ARIMA (0,1,1) model without drift was selected instead, despite having a higher AIC value, because it offered a more parsimonious structure with reduced bias and better forecasting performance for the General CPI inflation data.

Table 2
ARIMA Selection

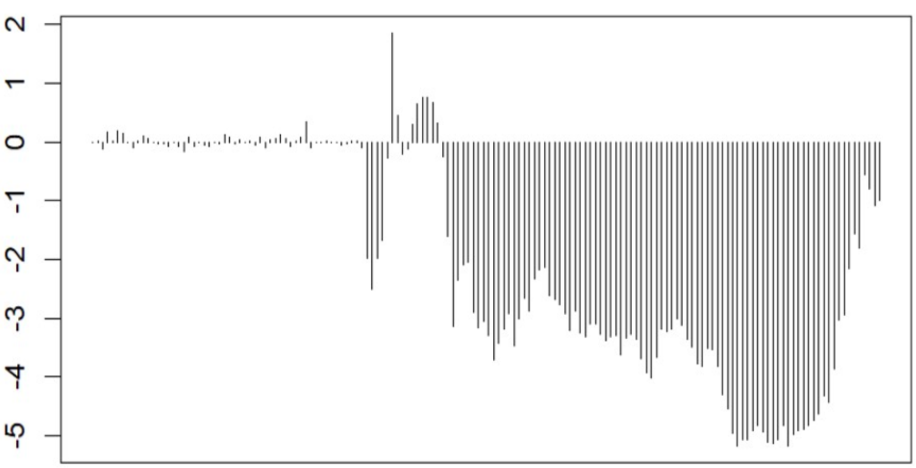
ARIMA	Drift	AIC
(0,1,0)	With drift	236,1509
(1,1,0)	With drift	234,0414
(0,1,1)	With drift	233,3114
(0,1,1)	Without drift	250,4359
(1,1,1)	With drift	235,8706
(0,1,2)	With drift	235,7134
(0,1,1)	With drift	240,4512

After determining the optimal model to utilize, the next step is to ensure that it fits the residual normality and non-autocorrelated white noise assumptions. The

Kolmogorov-Smirnov test yielded a p-value of 0.07269 when applied to the residual normality assumption. This result demonstrates that the p-value is greater than the 5% significance level, implying that the ARIMA (0,1,1) model meets the assumption of residual normality.

The non-autocorrelated white noise assumption was then tested using the Ljung-Box test, which yielded a p-value of 0.7699. A p-value larger than 5% implies that the ARIMA (0,1,1) model meets the assumption of non-autocorrelated white noise. The ARIMA (0,1,1) model meets both required assumptions; thus, the researcher decides to utilize it for further investigation. This means that the model can be used to characterize and forecast future CPI inflation trends. Thus, the analytical results from this model can provide a solid foundation for policymakers and stakeholders to make educated judgments about economic policies and company planning. Figure 5 reflects the final order of the intervention model adopted. Figure 6 shows that the plot of the general CPI inflation data closely approaches the anticipated data. The similarity between these two charts suggests that the forecasting model is appropriate. However, to determine its quality, researchers use the Mean Absolute Percentage Error (MAPE) statistic. If the MAPE is less than 10%, the forecasting model can be considered excellent.

Figure 5
Orde Intervention



During the estimation of intervention parameters, it was discovered that the proposed model is significant. The resultant p-value of 0.06262 satisfies the condition of residual normality, as does the assumption of non-autocorrelated white noise with a p-value of 0.2422.

The MAPE value of 11.05373% was achieved while testing the model's accuracy. Although the MAPE value did not go below 10% and the accuracy level is 89%, researchers believe the model is still useful for projecting data in the future. Figure 6 describes the coherence between anticipated and actual data, demonstrating the intervention model's success. The close likeness of the two graphs suggests that the model accurately represents the underlying patterns and trends in inflation data. While the

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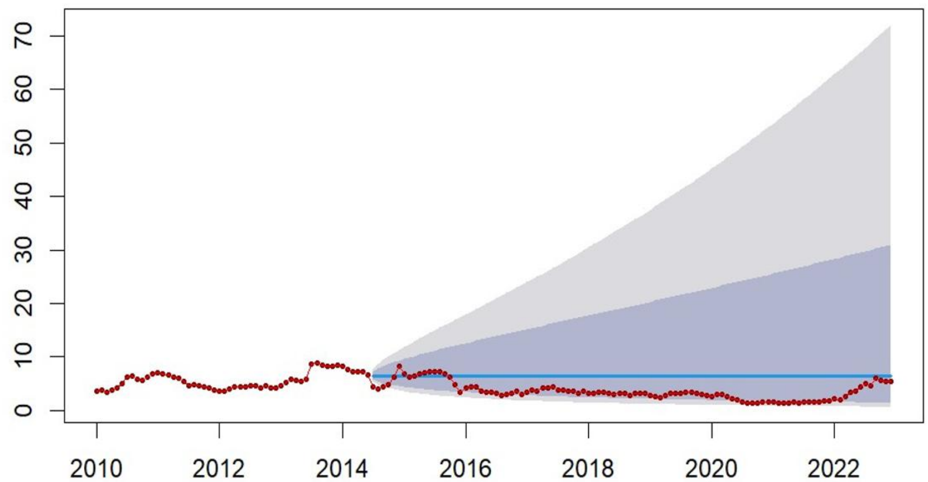
MAPE value is somewhat higher than the required threshold, the model's total accuracy of 89% gives confidence in its reliability for future forecasting efforts.

$$y_t = (0.8368 - 0.3163B^1)S_1^{(55)} + a_t$$
$$S_t^{(55)} = 1, t \geq 55 \tag{1}$$
$$S_t^{(55)} = 0, t < 55$$

Figure 6
Actual Data vs Prediction



V. CONCLUSION

Several conclusions can be drawn from the discussion of the use of intervention analysis on Indonesia's General Consumer Price Index (CPI) inflation data from 2010 to 2023. To begin, the use of the ARIMA (0,1,1) model without drift demonstrates its applicability for capturing the dynamics of CPI inflation in Indonesia. Despite its unusually high AIC value of 250.4359, the model is nevertheless relevant and adheres to crucial assumptions like residual normality and non-autocorrelated white noise. This model selection has practical significance for time series forecasting of CPI inflation. Understanding the impact of actions or external factors on inflation patterns enables stakeholders to make more informed decisions about monetary policy, investment strategies, and pricing. Accurate forecasting of CPI inflation leads to improved budgeting, risk management, and economic policy formation. In addition to its practical consequences, further study could explore the effectiveness of various intervention tactics on CPI inflation and the robustness of forecasting models in different economic scenarios. Comparative studies of different time series forecasting methodologies, as well as the inclusion of new variables or exogenous factors, have the potential to improve the accuracy and reliability of CPI inflation projections. Finally, the use of the ARIMA (0,1,1) model without drift for intervention analysis of CPI inflation data in Indonesia reveals its importance and applicability for predicting. Practical consequences include informed policymaking and

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business decisions, while future research could focus on improving forecasting accuracy and gaining a better understanding of inflation dynamics

Conflicts of Interest

The authors declare that they have no conflict of interest.

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