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Forecasting Inflation Based on Money Supply and Interest Rates Using a Transfer Function Model

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ABSTRACT

Inflationary pressure remains a major challenge for Indonesia's economic stability, especially amid fluctuations in monetary conditions and policy rates. The purpose of this research is to develop a reliable forecasting model that captures the dynamic interplay between monetary variables and inflation in Indonesia. This study employs a multi-input transfer function approach, incorporating the money supply and interest rates as input variables, using monthly data from January 2001 to November 2025 from *Bank Indonesia* and the *Badan Pusat Statistik* (BPS). The overall research procedure involves conducting stationarity tests, selecting the optimal ARIMA models for the input and output series, determining the appropriate structure of the multi-input transfer function, and generating forecasts. The results of this study yield a transfer function model of the form (0,0,0)(0,2,1)[0,0,2], which demonstrates the best forecasting performance. This model successfully captures the deflationary phenomenon in early 2025 and the subsequent rise in inflation in the months that followed. The forecast for 2026 indicates a fluctuating pattern consistent with macroeconomic dynamics such as liquidity shifts, interest rate adjustments, and global commodity conditions. A MAPE value of 1.3975% indicates excellent forecast accuracy, confirming that the transfer function framework is a reliable and effective method for modeling and forecasting inflation in Indonesia.

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A. INTRODUCTION

The economy is a priority sector because its instability can have widespread impacts on society (Amir, 2024). In the post-pandemic period, global and domestic conditions have become increasingly volatile due to geopolitical tensions, disruptions in global supply chains, fluctuations in international commodity prices, and tighter monetary policy in major economies, all of which have influenced Indonesia's inflation dynamics throughout 2024–2025. Inflation remains a central concern for the government due to its significant impact on economic stability and public welfare. Based on data from the *Badan Pusat Statistik* (BPS) and Bank Indonesia, Indonesia's inflation rate from 2016 to 2025 generally remained under control, with inflation stabilizing around 2–4% between 2016 and 2021, in line with BI's target of 3 ± 1%. A notable surge occurred in September 2022 when year-on-year (YoY) inflation reached 5.95% due to rising energy and food prices and post-pandemic fuel adjustments, while the month-over-month (MoM) inflation for the same month was 1.17%, highlighting the need for clear differentiation between YoY and MoM measures. Entering 2023–2025, inflation eased again to 2.31% (YoY) in August 2025, within BI's target range of 1.5–3.5%, reflecting the ongoing dynamics shaped by global commodity shocks, domestic supply conditions, and policy responses.

Inflation refers to a general and continuous rise in the prices of goods and services over a period, typically measured by the Consumer Price Index (CPI) as year-on-year (YoY) and month-on-month (MoM) inflation. Changes in inflation are important to observe because they affect economic stability and public welfare (Saputra & Febrianti, 2025; Tanial et al., 2022). Uncontrolled inflation can reduce the value of currency, trigger economic instability, and increase poverty rates (Rangkuty et al., 2024; Taufik, 2024). Prameswati et al. (2025) state that inflation is triggered by an imbalance between public demand and the amount of money in circulation. The money supply represents the total amount of money available in an economy, including cash, demand deposits, and savings accounts, which are controlled by the central bank (Amir, 2024). If the amount is excessive, it can trigger high inflation and disrupt long-term economic growth (Tanial et al., 2022). Therefore, an appropriate monetary policy is essential in controlling inflation (Dalimunthe et al., 2025). Apart from the amount of money in circulation, another influential factor is interest rates. Agustin (2021) research shows that interest rates have a significant positive impact on inflation. Interest rates are the cost of borrowing, calculated as a percentage of the loan amount (Ompusunggu et al., 2025), while BI interest rates are the price paid to exchange one rupiah today for one rupiah in the future (Yanti & Soebagyo, 2022). The government needs to be objective in determining interest rate changes in order to maintain public welfare (Tanial et al., 2022).

To support appropriate policy-making, inflation forecasts that can accurately describe future conditions are needed. The development of inflation forecasting methods continues to advance, mainly due to monetary policy requirements that increasingly demand accurate forecasts to maintain economic stability (Coker, 2025; Iftikhar et al., 2025). One relevant method is the transfer function model, which is a multivariate forecasting method that combines ARIMA and multiple regression elements (Khikmah et al., 2023). This method uses past values of output variables while accounting for the influence of input variables, thereby producing more representative future estimates, especially when external factors affect inflation. In the context of the Indonesian economy, the use of transfer function models is important because inflation is influenced not only by its historical behavior but also by macroeconomic indicators such as money supply and interest rates (Astasia et al., 2020). The multi-input transfer function model has advantages because it can simultaneously input multiple variables, capture the cause-and-effect relationships between each variable and inflation, and clearly describe the structure of the delay effect. Compared to univariate ARIMA, simple regression, and single transfer functions, this model is more informative and easier to interpret for economic policy needs (Ananda et al., 2020).

The literature review shows that the analytical methods used in previous studies are still diverse. Taufik (2024) show that simple regression can be applied to explore the direct relationship between an independent variable and a dependent variable as an initial stage in economic analysis. However, in the context of forecasting, multiple regression has a limitation. When the relationship between the independent and dependent variables is not linear, the model will produce inaccurate predictions. Rizal et al. (2025) demonstrate that within the Hybrid ARIMA-ANN model, the ARIMA component plays a crucial role in capturing linear patterns in the time series, thereby providing a stable foundation for predictions before the ANN analyzes non-linear patterns. However, ARIMA has a fundamental limitation: it can only model linear relationships, so when data contain complex non-linear patterns, its forecasting accuracy decreases. Albeladi et al. (2023) noted that LSTM has limitations in time series forecasting, as it yields lower accuracy compared to ARIMA on data with linear patterns, and is less effective at learning stable linear patterns, so the resulting predictions tend to be less accurate. This aligns with the findings of Pratiwi et al. (2025) and Liu (2022), who stated that deep learning-based models, such as LSTM, can experience a decline in accuracy when the data structure is dominated by linear patterns that are better modeled by traditional statistical approaches.

The research gap in this study stems from the limited application of advanced multivariate time-series models, particularly the Multi-Input Transfer Function model, for inflation forecasting in Indonesia, despite the fact that inflation is influenced by multiple interrelated macroeconomic variables. Most previous studies rely on simpler regression models or univariate approaches, such as ARIMA, without incorporating external variables, such as the money supply and interest rates. Findings from Mutamakkinah et al. (2024), Azizah et al. (2025), and Yundari et al. (2025) also indicate that ARIMA has limitations in capturing dynamic interactions among variables and becomes less effective when external factors are excluded. Therefore, this study fills an existing research gap by applying the multi-input transfer function model, which is considered better at modeling causal relationships and improving forecasting accuracy. The novelty of this study compared to previous studies is the direct application of a Multi-Input Transfer Function model that integrates money supply and interest rates as predictor variables, allowing for a more comprehensive modeling of causal relationships. This approach also uses longer, more up-to-date datasets, enabling more accurate pattern recognition and improved forecasting performance.

This study seeks to forecast inflation in Indonesia by incorporating the effects of the money supply and interest rates using a multi-input transfer function model. The primary contribution of this study is to offer empirical evidence regarding the model's superiority in forecasting inflation, as demonstrated by recent research confirming the superiority of the transfer function model over ARIMA in capturing macroeconomic dynamics (Azizah et al., 2025; Khikmah et al., 2023).The effectiveness of this multivariate approach is further supported by the findings of Iftikhar et al. (2025), making the results of this study a valuable methodological reference and aiding Bank Indonesia in formulating monetary policies that are more responsive to inflation volatility.

B. RESEARCH METHOD

This research applies a multi-input transfer function model to forecast inflation in Indonesia, incorporating money supply and interest rates as explanatory variables. The analysis is based on monthly data from January 2001 to November 2025. The data were sourced from the official websites of *Bank Indonesia* and *Badan Pusat Statistik* (BPS). The stages of the research are as follows:

1. Data were collected for both the input series and the output series. The in-sample period spans from January 2001 to December 2024, while the out-of-sample period extends from January 2025 to November 2025.
2. Prepare the input sequence and output sequence with the following steps:
   a. Create a time series plot for input series $(X_{1,t}$ and $X_{2,t})$.
   b. Examine the stationarity of the data with respect to variance. If the series is found to be non-stationary in variance, a Box–Cox transformation is performed to stabilize the variance and attain stationarity. As stated by Chatfield and Xing (2019), the Box–Cox transformation is defined as in Equation (1):

$$Z_t^* = \begin{cases} \frac{Z_t^\lambda - 1}{\lambda} & \lambda \neq 0 \\ log\ Z_t & \lambda = 0 \end{cases} \tag{1}$$

   c. Assess the stationarity of the data with respect to the mean. If the series is not stationary in mean, differencing is applied to achieve stationarity. Referring to Makridakis et al. (1998), stationarity in mean can be evaluated using the Augmented Dickey–Fuller (ADF) test. To determine the stationarity in mean, the ADF test employs the model specified in Equation (2).

$$\Delta Z_t = \alpha + \gamma Z_{t-1} + \sum_{i=1}^{m} \beta_i \, \Delta Z_{t-i} + a_t \tag{2}$$

   With the following hypothesis:

$$H_0 : \ \gamma = 0$$
$$H_1 : \ \gamma < 0$$

   Test criteria:
   If t-count < t-critical or p-value < α (0.05), the decision is to reject $\mathrm{H_0}$, which means that the data are stationary.
   If t-count > t-critical or p-value > α (0.05), the decision is to fail to reject $\mathrm{H_0}$, which means that the data are not stationary.

3. Form an ARIMA model for stationary input and output series with the following steps:
   a. Determine the order of the ARIMA (p, d, q) model for the series $X_{1,t}$, and $X_{2,t}$ by examining the ACF and PACF plots.
   b. Construct the ARIMA model based on the identified orders p and q. According to Wei (2019), the ARIMA (p, d, q) model can be expressed in Equation (3).

$$\phi_p\,(B)\,(1-B)^d\,Z_t = \theta_q\,(B)\,a_t \tag{3}$$

   Where Z_t represents the Time series data values in period t. The symbol B denotes the backshift operator (time shift), where $BZ_t = Z_{t-1}$. The term $\phi_p(B)$ refers to the autoregressive (AR) polynomial of order p, expressed as $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$. Meanwhile $\theta_q B$ denotes the moving average (MA) polynomial of order q, defined as $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$. The parameter drepresents the differencing order, and a_t is the random error component in period t.
   c. Estimation of ARIMA model parameters for $X_{1,t}$ and $X_{2,t}$.
   d. Performing diagnostic checking of the ARIMA model
   e. The best ARIMA model is selected as the one with the smallest AIC value.

4. Form a multi-input transfer function model with Equation (4) (Wei, 2019):

$$Z_t = \sum_{j=1}^{m} \frac{\omega_j\,(B)}{\delta_j\,(B)} B^{b_j} x_{jt} \ + \ \frac{\theta\,(B)}{\phi\,(B)} \alpha_t \tag{4}$$

a. Perform prewhitening on the input series to obtain the series $\alpha_{1,t}$ and $\alpha_{2,t}$ followed by prewhitening on the output series to obtain the series $\beta_{1,t}$ and $\beta_{2,t}$. These are expressed in Equations (5) and (6):

$$\alpha_t = \frac{\phi_x(B)}{\theta_x(B)} x_t \tag{5}$$

$$\beta_t = \frac{\phi_x(B)}{\theta_x(B)} Z_t \tag{6}$$

b. Calculation of the cross-correlation between each prewhitened input series and the prewhitened output series.
c. Estimation of impulse response weight parameters.
d. Determine the parameter values (b, r, s) of the transfer function model for each input series. The identification of the transfer function orders (b, r, s) is based on the analysis of the cross-correlation function (CCF) and the pattern of the impulse response weights. Specifically, the parameters (b_1, r_1, s_1) are associated with the input series $X_{1,t}$, whereas (b_2, r_2, s_2) correspond to the input series $X_{2,t}$.
e. Identifying, diagnostic checking and selection best model for the ARIMA model order $(pn, 0, qn)$ for the noise series.
f. Estimate the parameters of the initial multi-input transfer function model.
g. Perform diagnostic checks on the final multi-input transfer function model to ensure that the residuals are white noise.
h. Select the best multi-input transfer function model if there are several viable models.
i. Forecast the output series Z_t using the best multi-input transfer function model.
j. In this study, forecasting accuracy is assessed using three error metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). MAE indicates the average absolute deviation between actual and forecasted values, while RMSE represents the square root of the mean squared prediction error, and MAPE presents the error as a percentage, making it easy to compare across models (Saifudin et al., 2026). Model with the lowest MAE, RMSE, and MAPE values were selected as the best model (Hyndman & Athanasopoulos, 2021; Montaño Moreno et al., 2013). Accuracy values were calculated using the Equations (7), (8), and (9) by Montgomery et al. (2011):

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Z_t - \hat{Z}_t}{Z_t}\right| \times 100 \tag{7}$$

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|Z_t - \hat{Z}_t\right| \tag{8}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Z_t - \hat{Z}_t\right)^2} \tag{9}$$

C. RESULT AND DISCUSSION

1. Collect Data for a Series of Inputs and Outputs

This study uses a quantitative time-series design, dividing the data into in-sample (January 2001–December 2024) for model development and out-of-sample (January 2025–November 2025) for forecasting evaluation. Data processing and partitioning were performed in R. The following constitute the data analysis stages conducted in this study.

2. Preparation of Input and Output Sequences

a. Testing the Stationarity of Input and Output Series

Stationarity tests are conducted to ensure that the time series' variance remains constant over the observation period. Data movement patterns are then examined to detect trends, changes in volatility, or other fluctuations that indicate non-stationarity and require confirmation through statistical tests before proceeding to the model identification stage. Data on money supply $(X_{1,t})$ and interest rates $(X_{2,t})$ for the period January 2001–December 2024 are shown in Figures 1 and 2.

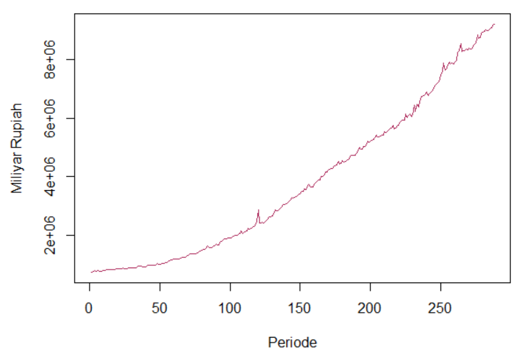

Figure 1. Amount of Money in Circulation

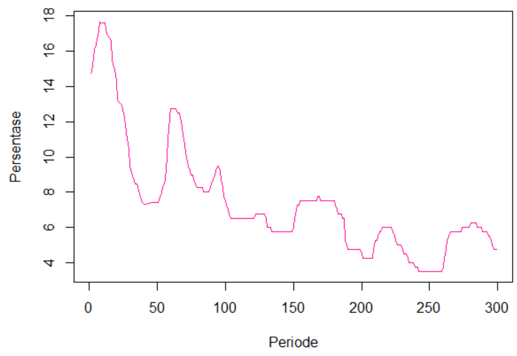

Figure 2. Interest Rate Time Series Plot

Based on Figures 1 and 2 above, the graphs of the money supply and interest rates both show clear trends: the money supply continues to rise sharply, while interest rates decline gradually from the early to the late periods. This non-stationarity is evident from the mean and variance, which change over time, making transformation or differentiation necessary.

b. Tests for Stationarity of the Variance and Mean in Time Series

Stationarity test results show that the series $X_{1,t}$ is not stationary in variance or mean, while the series $X_{2,t}$ is stationary in variance and not stationary in mean. To make the $X_{1,t}$ series stationary, Box-Cox transformation, and first-order differencing are performed, while the $X_{2,t}$ series undergoes first-order differencing. Stationarity test results post-transformation and differencing are shown in Table 1.

Table 1. Stationarity Test Results

Time Series	λ value	P-value (ADF Test)
$X_{1,t}$	0.985	0.01
$X_{2,t}$	-	0.01

Based on Table 1, the data are stationary in terms of both variance and mean, as indicated by the λ value approaching 1 and the p-value $< \alpha$, confirming the appropriateness of the applied transformation. Since the input series has already undergone first-order differencing to achieve stationarity, the same procedure is applied to the output series Z_t by performing first-order differencing. This step ensures that all series used in the subsequent modeling process are on the same level of stationarity, thereby meeting the assumptions required for identifying and estimating the transfer function model.

3. Identification of ARIMA Models

a. Identify The ARIMA Model for the Series $X^*_{1,t}$ Based on the ACF and PACF Plots

The following presents the ACF and PACF plots of the input series $X_{2,t}$ after applying the first-order differencing procedure. These plots are used to observe the remaining autocorrelation structure and to assess whether the differenced series has achieved an adequate level of stationarity. The ACF and PACF results used to identify the appropriate prewhitening model are shown in Figure 3.

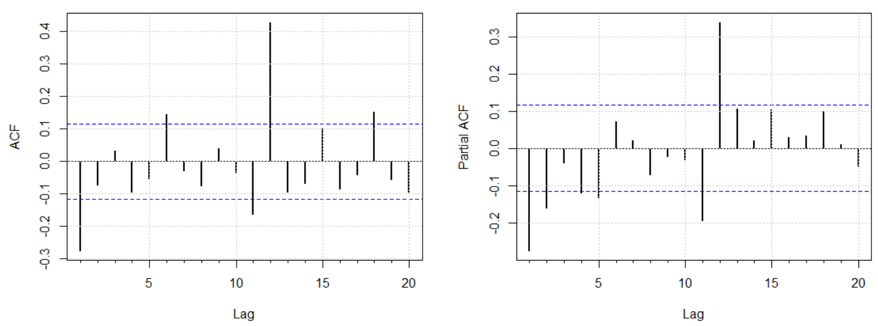

Figure 3. ACF and PACF plots of money supply $(d = 1)$

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Based on Figure 3 above, several ARIMA models can be estimated. These ARIMA models are then estimated and tested for parameter significance. The results of the parameter significance test indicate that the significant ARIMA models are ARIMA (1,1,6), ARIMA (2,1,1), ARIMA (2,1,6), ARIMA (3,1,3), ARIMA (3,1,6), ARIMA (4,1,1), ARIMA (4,1,6), ARIMA (5,1,1), and ARIMA (5,1,6).

b. Estimation of ARIMA model parameters for Series Input $X^*_{1,t}$

The next step is to estimate the ARIMA model's parameters to obtain optimal coefficient values. This process is performed on several previously identified candidate models; however, Table 2 shows only the parameter estimates for the selected ARIMA (5,1,6) model.

Table 2. Estimation of ARIMA Model Parameters for Input Series $X_{1,t}$

Model	Parameters	Estimate	Std. Error	t Statistic	P-value
ARIMA	ϕ_1	-0.356619	0.106292	-3.3551	0.0007934
(5,1,6)	ϕ_2	0.636959	0.107318	5.9352	2.934e-09
	ϕ_3	0.991600	0.010897	91.0015	2.2e-16
	ϕ_4	0.358209	0.107396	3.3354	0.0008518
	ϕ_5	-0.637338	0.107946	-5.9042	3.543e-09
	θ_1	0.056390	0.116004	0.4861	0.6268918
	θ_2	-0.869428	0.057994	14.9916	2.2e-16
	θ_3	-0.896279	0.080754	-11.0988	2.2e-16
	θ_4	-0.044662	0.121747	-0.3668	0.7137362
	θ_5	0.871004	0.054012	16.1261	2.2e-16
	θ_6	-0.030764	0.086397	-0.3561	0.7217825

Table 2 shows the results of the parameter significance test, where there are several insignificant parameters, namely θ_1, θ_4, and θ_6. Overall, most parameters in the ARIMA (5,1,6) model proved significant, so this model remains feasible as a basis for forming a multi-input transfer function model.

c. Diagnostic Checking of the ARIMA Model for Series Input $X^*_{1,t}$

Subsequently, diagnostic tests were conducted on the model, including a white-noise test using the Ljung–Box test and a normality assessment using the Kolmogorov–Smirnov test. The results indicate that the selected model satisfies the white-noise assumption and that the residuals follow a normal distribution, as indicated by a p-value exceeding the chosen significance level of $\alpha = 0.01$. Thus, the model can be deemed suitable for use in forecasting.

d. Selection of the best model for Series Input $X^*_{1,t}$

Of the several ARIMA models tested, the ARIMA (5,1,6) model was chosen as the best specification because it produced the lowest AIC value, namely 6.951. A low AIC value indicates that this model is more efficient at modeling the time series dynamics than the other candidate models. The ARIMA (5,1,6) model can be written as follows:

$$
\begin{aligned}
X^*_{1,t} = {} & 0.643381X^*_{1,t-1} + 0.993578X^*_{1,t-2} + 0.354641X^*_{1,t-3} \\
& - 0.633391X^*_{1,t-4} - 0.99547X^*_{1,t-5} + 0.637338X^*_{1,t-6} + a_t \\
& - 0.056390a_{t-1} + 0.869428a_{t-2} + 0.896279a_{t-3} \\
& + 0.044662a_{t-4} - 0.871004a_{t-5} + 0.030764a_{t-6}
\end{aligned}
$$

e. Identify The ARIMA Model for Series $X_{2,t}$ Based on the ACF and PACF Plots

The following displays the ACF and PACF plots of the input series $X_{2,t}$ after applying first-order differencing procedure was applied. These plots are used to assess whether the differenced series has achieved an adequate level of stationarity. The ACF and PACF results, which serve as a reference for identifying the appropriate prewhitening model, are presented in Figure 4.

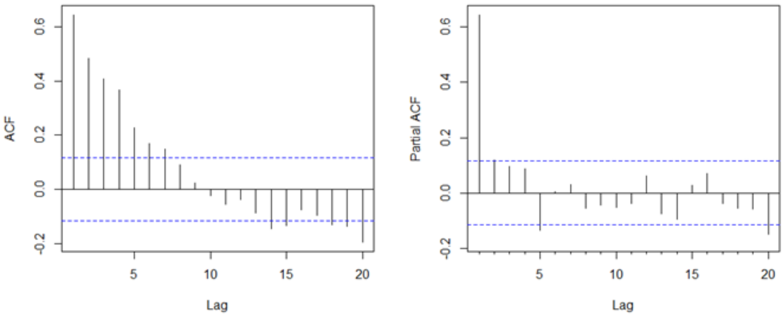

Figure 4. ACF and PACF Plots of Interest Rate Data $(d = 1)$

Based on Figure 4, three candidate ARIMA models were identified: ARIMA (1,1,3), ARIMA (2,1,3), and ARIMA (3,1,3). Based on the parameter significance test results, the statistically significant models are ARIMA(2,1,3) and ARIMA(3,1,3). Therefore, these models were selected for use in the subsequent analysis stage.

f. Estimation of ARIMA Model Parameters for Series Input $X_{2,t}$

The next step is to estimate the ARIMA model parameters to obtain the optimal coefficient values. This process is performed on several previously identified candidate models; however, Table 3 shows only the parameter estimates for the ARIMA (3,1,3) model, which was selected.

Table 3. Estimation of ARIMA Model Parameters for Input Series $X_{2,t}$.

Model	Parameters	Estimate	Std. Error	t Statistic	P-value
ARIMA	ϕ_1	-0.019859	0.056305	-3.3551	0.7243156
(3,1,3)	ϕ_2	-0.296204	0.046091	-6.4264	1.306e-10
	ϕ_3	0.790047	0.051653	15.2953	2.2e-16
	θ_1	0.589630	0.093462	6.3087	2.813e-10
	θ_2	0.722773	0.100852	7.1666	7.686e-13
	θ_3	-0.308512	0.088403	-3.4898	0.0004833

Table 3 shows the results of the parameter significance test, where only one parameter, ϕ_1, is insignificant. Overall, most parameters in the ARIMA (3,1,3) model are significant, so this model remains feasible as a basis for constructing a multi-input transfer function model.

g. Diagnostic Checking of the ARIMA Model for Series Input $X_{2,t}$

The results of the diagnostic tests indicate that the ARIMA (1,1,3), ARIMA (2,1,3), and ARIMA (3,1,3) models satisfy the white noise and normality assumptions at the 0.01 significance level. The fulfillment of these two assumptions confirms that these models are statistically valid for use in further modeling.

h. Selection of the best model for Series Input $X_{2,t}$

Of the several ARIMA models tested, the ARIMA (3,1,3) model was identified as the best option because it yielded the lowest AIC value, namely -85.788. The relatively lower AIC value suggests that this model provides a more efficient representation of the time series dynamics than the other candidate models. Accordingly, the ARIMA (3,1,3) model can be expressed as follows:

$$\begin{aligned}X_{2,t} \; = \; & 0.980141X_{2,t-1} - 0.276345\,X_{2,t-2} + 1.086251X_{2,t-3} - 0.790047X_{2,t-4} - 0.589630a_{2,t-1} \\ & - 0.722773a_{2,t-2} - 0.308512a_{2,t-3} + a_t\end{aligned}$$

4. Create A Multi-Input Transfer Function Model

a. Prewhitening the Input Series of Money Supply and Output Series of Inflation

The prewhitening results of the input series $X^*_{1,t}$ and the output series, obtained using the ARIMA (5,1,6) model, provide an overview of the filtering process applied to both variables. In this procedure, $\alpha_{2,t}$ refers to the prewhitened version of the input series $X^*_{1,t}$, while $\beta_{2,t}$ represents the prewhitened output series Z_t. These prewhitening are carried out to eliminate the autocorrelation present in the original data, ensuring that the remaining series reflects only the random component needed for further analysis. The results of this prewhitening process, which form the basis for computing the cross-correlation function in the model identification stage, are as follows:

$$\begin{aligned}
\alpha_{1,t} &= X^*_{1,t} - 0.643381X^*_{1,t-1} - 0.993578X^*_{1,t-2} - 0.354641X^*_{1,t-3} + 0.633391X^*_{1,t-4} \\
&\quad + 0.99547X^*_{1,t-5} - 0.637338X^*_{1,t-6} + 0.056390a_{t-1} - 0.869428a_{1,t-2} \\
&\quad - 0.896279a_{1,t-3} - 0.044662a_{1,t-4} + 0.871004a_{1,t-5} - 0.030764a_{1,t-6} \\
\beta_{1,t} &= X^*_{1,t} - 0.643381X^*_{1,t-1} - 0.993578X^*_{1,t-2} - 0.354641X^*_{1,t-3} + 0.633391X^*_{1,t-4} \\
&\quad + 0.99547X^*_{1,t-5} - 0.6373386X^*_{1,t-6} + 0.056390\beta_{1,t} - 0.869428\beta_{1,t-2} \\
&\quad - 0.896279\beta_{1,t-3} - 0.044662\beta_{1,t-4} + 0.871004\beta_{1,t-5} - 0.030764\beta_{1,t-6}
\end{aligned}$$

b. Prewhitening Interest Rate Input Series and Inflation Output Series

The prewhitening results of the input series $X_{2,t}$ and the output series, obtained using the ARIMA (3,1,3) model, provides an overview of the filtering process applied to both variables. In this procedure, $\alpha_{2,t}$ refers to the prewhitened version of the input series $X_{2,t}$, while $\beta_{2,t}$ represents the prewhitened output series Z_t. These prewhitening are carried out to eliminate the autocorrelation present in the original data, ensuring that the remaining series reflects only the random component needed for further analysis. The results of this prewhitening process, which form the basis for computing the cross-correlation function in the model identification stage, are as follows.

$$\begin{aligned}
a_{2,t} &= X^*_{2,t} - 0.980141X^*_{2,t-1} + 0.276345X^*_{2,t-2} - 1.086251X^*_{2,t-3} + 0.790047X^*_{2,t-4} \\
&\quad + 0.589630a_{2,t-1} + 0.722773a_{2,t-2} + 0.308512a_{2,t-3} \\
\beta_{2,t} &= X^*_{2,t} - 0.980141X^*_{2,t-1} + 0.276345X^*_{2,t-2} - 1.086251X^*_{2,t-3} + 0.790047X^*_{2,t-4} \\
&\quad + 0.589630a_{2,t-1} + 0.722773a_{2,t-2} + 0.308512a_{2,t-3}
\end{aligned}$$

c. Cross-Correlation Between $a_{1,t}$ and Output Series $\beta_{1,t}$

The cross-correlation results provide an overview of the relationship between the input and output series after prewhitening. These results help identify lag values that show significant correlation and are therefore relevant in determining the transfer function structure model is determined based on the cross-correlation analysis. The complete cross-correlation results are presented in Figure 5.

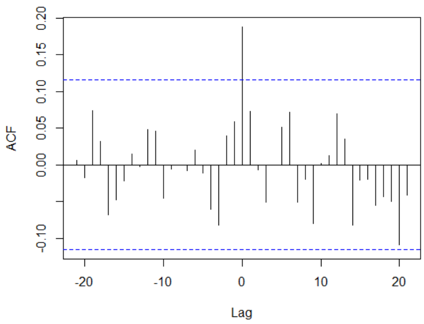

Figure 5. Cross Correlation between $a_{1,t}$ and $\beta_{1,t}$

Based on Figure 5, the cross-correlation analysis between the prewhitened input series $a_{1,t}$ and the prewhitened output series $\beta_{1,t}$. was conducted. The identification results suggest two alternative transfer function models for describing the relationship between the input and output series. namely the model with order $(b_1, r_1, s_1) = (0, 0, 0)$ and the model with order $(b_1, r_1, s_1) = (0, 2, 0)$.

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d. Cross-Correlation Between $a_{2,t}$ and Output Series $\beta_{2,t}$

The cross-correlation results illustrate the relationship between the prewhitened input and output series at different lag values. These results help identify the lags that exhibit significant correlation and are therefore relevant in determining the structure of the transfer function model. The complete cross-correlation output is presented in Figure 6.

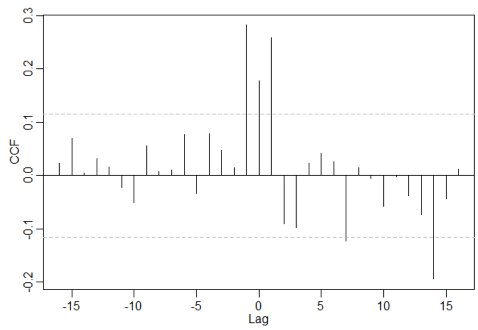

Figure 6. Cross Corelation between $a_{2,t}$ and $\beta_{2,t}$

Based on Figure 6 above, the identification results indicate two possible transfer function model orders that may be used to describe the relationship between the series $X_{2,t}$ and Z_t namely the model with order $(b_2, r_2, s_2) = (0, 2, 1)$ and the model with order $(b_2, r_2, s_2) = (0, 2, 0)$.

e. Direct Estimation of the Impulse Response Weight of the Input Series $X^*_{1,t}$ with Output Series Z_t

The impulse response weight estimates how changes in the input series X_{1t} affect the output series $Z_t$in subsequent time periods. This estimation provides information on the timing, magnitude, and duration of the influence transmitted from $X^*_{1,t}$ to Z_t. The estimated impulse response weight is shown in Figure 7.

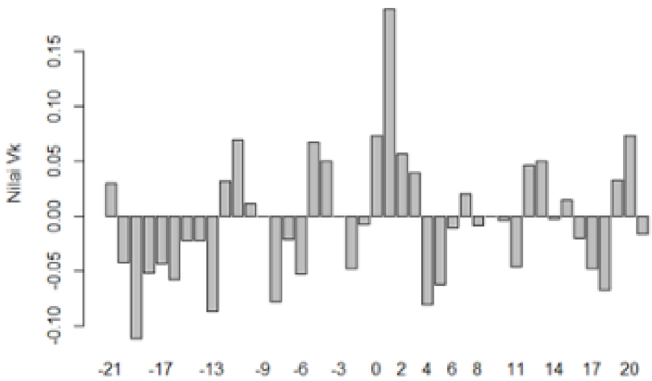

Figure 7. Estimation of Impulse Response Weight $X^*_{1,t}$ and Z_t

Based on Figure 7, the influence of the input variables on the output variable appears to occur immediately, without any observable delay. The response pattern also shows a gradual decline over time, indicating a direct effect that weakens progressively. Accordingly, the most appropriate initial transfer function specification is $(b_1, r_1, s_1) = (0, 2, 0)$.

f. Direct Estimation of the Impulse Response Weight of the Input Series $X_{2,t}$ with Output Series Z_t

The estimation of the impulse response weights illustrates how variations in the input series X_{1t} influence the output Z_t series across subsequent time periods. This estimation provides information on the timing, magnitude, and duration of the influence transmitted from $X_{2,t}$ to Z_t. The estimated impulse response weight is shown in Figure 8.

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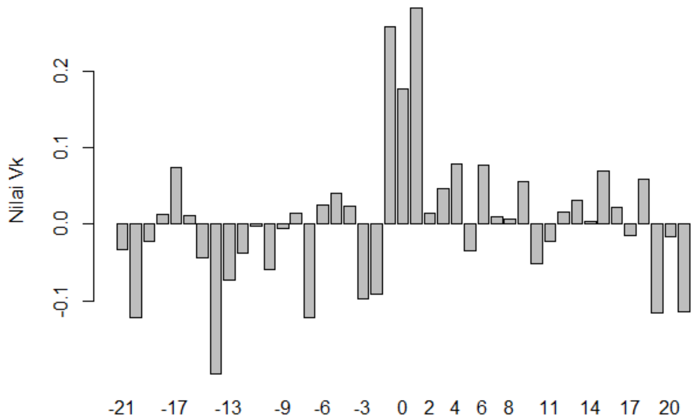

Figure 8. Estimation of Impulse Response Weight $X_{2,t}$ and Z_t

Based on Figure 8, the impulse response shows how the effect of the input series on the output evolves over time. The shape of the response suggests that the effect appears after a short delay and then gradually decreases. Therefore, the initial transfer function model that best matches this pattern is the one with the order combination $(b_2, r_2, s_2) = (0, 2, 1)$.

g. Noise Series Estimation and ARMA Model Identification for Noise Series

The residuals from the initial multi-input transfer function model with order $(p_n, 0, q_n) = (0, 0, 0)$ are used as estimators of the noise series. This step aims to identify the remaining lag dependency patterns, which will serve as a basis for selecting the most appropriate ARIMA model for the noise series. Based on the results of the parameter significance test and noise series diagnostic checks, the best model for the noise series is ARIMA(0,0,2) with an AIC value of 615.122, and this model is then used to form the multi-input transfer function model. The ARIMA noise series order (0,0,2) can be written with the following equation:

$$\hat{n}_t = \alpha_t - 0.19047\alpha_{t-1} - 0.1134\alpha_{t-2}$$

h. Parameter Estimation for the Multi-Input Transfer Function

Based on the identification of order (b, r, s) that has been carried out, four multi-input transfer function models can be formed by combining the order of each input series, namely (b_1, r_1, s_1) for the first input and (b_2, r_2, s_2) for the second input, which are combined with the ARIMA noise series model $(p_n, 0, q_n)$. At this stage, the ARIMA noise series model used is (0,0,2). The candidate multi-input transfer function models are presented in Table 4.

Table 4. Results of the Significance Test of the Multi-Input Transfer Function Model Parameters

No	Transfer Function Model	Parameter	Estimate	T statistic	p-value
1	$(0,0,0)(0,2,1)[0,0,2]$	ω_{10}	-0.009392995	-1.463829	0.1432
		ω_{20}	0.695107118	7.794147	0.00
		ω_{21}	0.6909771	-6.815070	0.00
		δ_{21}	0.5217259	10.864061	0.00
		δ_{22}	-0.4530752	-3.193882	0.0014
		θ_1	0.9047	12.656789	0.00
		θ_2	0.1134	1.551917	0.1206
2	$(0,0,0)(0,2,0)[0,0,2]$	ω_{10}	-0.003516231	-0.03919389	0.968
		ω_{20}	0.1410598	2.44881630	0.014
		δ_{21}	-0.3771277	-23.40287389	0.00
		δ_{22}	-0.9845196	-74.01689394	0.00
		θ_1	0.715336478	11.90163759	0.00
		θ_2	0.237517090	3.90698338	0.00009
3	$(0,2,0)(0,2,1)[0,0,2]$	ω_{10}	-0.000413376	-4.2033539	0.00
		ω_{20}	0.6711099	0.1618356	0.871
		ω_{21}	-0.6744509	-0.1572284	0.875

No	Transfer Function Model	Parameter	Estimate	T statistic	p-value
		δ_{11}	0.6342154	14.8043218	0.00
		δ_{12}	-0.6130716	-14.2469025	0.00
		δ_{21}	0.6934177	5.9559505	0.00
		δ_{22}	-0.4777651	-3.6526265	0.0002
		θ_1	0.878742138	15.4529834	0.00
		θ_2	0.145141208	2.4845641	0.0129
4	$(0,2,0)(0,2,0)[0,0,2]$	ω_{10}	-0.007474179	-134.22776244	0.00
		ω_{20}	0.2188987	0.07276494	0.941
		δ_{11}	0.006555695	10.51865701	0.00
		δ_{12}	0.959214219	28.55090217	0.00
		δ_{21}	-0.373197	-20.31535197	0.00
		δ_{22}	-0.9742714	-69.86587701	0.00
		θ_1	0.790373662	19.99851562	0.00
		θ_2	0.232889216	5.73193489	0.00

i. Diagnostic Checking on the Final Multi-Input Transfer Function Model

The four multi-input transfer function models, namely (0,0,0)(0,2,1)[0,0,2], (0,0,0)(0,2,0)[0,0,2], (0,2,0)(0,2,1)[0,0,2], and (0,2,0)(0,2,0)[0,0,2], have been tested using the Ljung-Box test for white noise. Based on the test results, all models produce p-values that are higher than the predetermined level of significance ($\alpha = 0.01$). Thus, the residuals of each model satisfy the white noise assumption, making these transfer function models suitable for the next stage of analysis.

j. Select the Best Multi-Input Transfer Function Model

For forecasting, choosing the appropriate model involves considering both parameter properties and the Akaike Information Criterion (AIC), with preference given to the model with the lowest AIC, which is considered the most efficient and best able to explain the data. Based on a comparison of the AIC values for each model, model (0,0,0)(0,2,1)[0,0,2] has the lowest AIC value of -248.5186, so that model is selected as the best model to use in the forecasting process. The multi-input transfer function model with order $(b_1, r_1, s_1)(b_2, r_2, s_2)[p_n, 0, q_n]$ = (0,0,0)(0,2,1)[0,0,2] can be expressed in equation form as follows:

$$\begin{aligned}Z_t &= 0.5217259Z_{t-1} - 0.4530752Z_{t-2} - 0.009392995x_{1t} + 0.049x_{1,t-1}\\ &\quad - 0.00425573x_{1,t-2} + 0.6951071180x_{2,t} - 0.6951071180x_{2,t-1} + \alpha_t - 0.19047\alpha_{t-1} - 0.1134\alpha_{t-2}\end{aligned}$$

k. Forecasting Inflation Using the Multi-Input Transfer Function Model

The next step is to generate forecasts for the out-of-sample data, which represents observations not included in the model estimation process. This step is important for assessing the model's ability to produce accurate predictions on new data and evaluating its overall performance. The inflation forecast results for the year 2025, which serve as the basis for this evaluation, are presented in Table 5.

Table 5. Results of the Input Series Model Parameter Significance Test $X_{2,t}$

Period	2025 Forecast (%)	2025 Actual (%)
January	-1.026.813.213	-0.76
February	-0.782283085	-0.48
March	2.342.415.257	1.65
April	180.746.098	1.17
May	-1.948.648.672	-0.37
June	0.066527379	0.19
July	1.171.956.053	0.3
August	-0.386136368	-0.08
September	-0.073369469	0.21
October	3.392.519.168	2.86
November	337.808.516	2.72

Based on Table 5, in early 2025, Indonesia experienced deflation, which generally occurs due to a decline in demand after a surge in consumption at the end of the year, stable food commodity supplies, and no price pressure from government-

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regulated goods. This phenomenon is also reflected in the forecast results, where the forecast value points in the same direction as the actual data, which is negative at the beginning of the year. The alignment between the forecast and actual data indicates that the model can capture the seasonal dynamics and economic conditions that influence inflation during this period. Based on the forecast data, a comparison plot can be made as shown in Figure 9.

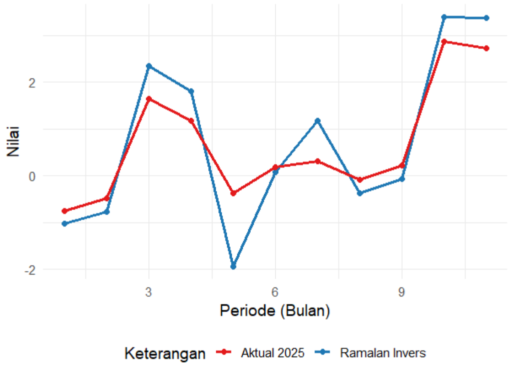

Figure 9. Comparison Plot of 2025 Forecast Data and 2025 Actual Data

Based on Figure 9, the projected inflation pattern for 2025 generally aligns with actual data. The monthly fluctuations show a similar trend, including a period of deflation at the beginning of the year and a rise in inflation from the middle to the end of the year. Although there are slight differences in some months, the discrepancies are not significant; therefore, the model is deemed capable of accurately capturing inflation dynamics from January through November 2025. After comparing these forecast results, the next step is to forecast inflation for 2026, which is presented in Table 6 for the period January–December 2026.

Table 6. Indonesia Inflation Forecast Results for 2026

Period	Prediction Value
January	-1.336233161
February	0.494903789
March	0.258976578
April	-1.15817614
May	-0.769939194
June	2.63069352
July	1.305930204
August	-2.556004816
September	-0.875080112
October	1.016388386
November	-0.321886632
December	-0.416569993

Based on the forecast results in Table 6, inflation in 2026 is expected to fluctuate throughout the year, alternating between deflation and inflation. Deflation is projected in January, April, May, August, September, November, and December, whereas positive inflation is expected in February, March, June, July, and October. The highest inflation spike is expected to occur in June, while the deepest deflation will occur in August. Overall, this pattern indicates unstable price dynamics and reflects the influence of seasonal factors and changing macroeconomic conditions throughout the year.

1. Forecasting Accuracy

To evaluate the accuracy of inflation forecasts, various error measures quantify the difference between forecasted and observed values. These indicators reflect the average magnitude of forecast errors and provide a clearer picture of the model's overall performance. The MAPE, MAE, and RMSE values obtained are presented in Table 7.

Table 7. Forecasting Accuracy

Period	Prediction Value
January	-1.336233161
February	0.494903789
March	0.258976578
April	-1.15817614
May	-0.769939194
June	2.63069352
July	1.305930204
August	-2.556004816
September	-0.875080112
October	1.016388386
November	-0.321886632
December	-0.416569993

Based on Table 7, the main finding of this study is that the employed forecasting model achieved very high accuracy during the period from January 2025 to November 2025. This is evidenced by MAPE of 1.3975%, MAE of 0.5684691, and RMSE of 0.687995. The MAPE value of 1.3975% indicates that the average forecasting error is approximately 1.40% of the actual values, which is highly accurate. Furthermore, the RMSE is only slightly higher than the MAE, suggesting that there are no significant extreme errors in the forecasts. Therefore, the predicted values are very close to the actual observed conditions.

The results of this study are consistent with previous studies that confirm the effectiveness of transfer function models in achieving high forecasting accuracy. Azizah et al. (2025) demonstrated that transfer function models yielded an MAE of 84.19, an RMSE of 110.37, and a MAPE of 1.65%, which are lower than those of standard ARIMA models. Similar results were obtained by Mutamakkinah et al. (2024) who demonstrated that transfer function models outperform standard ARIMA models in rainfall forecasting, with an MAPE of 38.21% compared to 43.23% for ARIMA.

Compared to previous studies, the forecasting accuracy in this study is better than the results reported by Mutamakkinah et al. (2024) and slightly higher than those reported by Azizah et al. (2025). These differences are likely due to variations in data characteristics, the observation period, the number of input variables, and the model order specification. Overall, these findings reinforce the evidence that transfer function models can capture dynamic relationships among variables and produce reliable forecasts.

D. CONCLUSION AND SUGGESTION

The main finding of this study is that the multi-input transfer function model with orders (0,0,0), (0,2,1), and [0,0,2] effectively captures Indonesia's inflation dynamics in 2025. The model successfully identifies early-year deflation and the subsequent upward inflation trend. The 2026 forecasts also indicate a relatively volatile pattern, reflecting interactions among money supply (M2), BI interest rates, global commodity prices, and seasonal effects.

The uniqueness of this study lies in applying a multi-input transfer function that integrates multiple monetary variables to model short-term inflation dynamics, thereby improving forecasting accuracy and deepening the understanding of inflation–monetary relationships. These findings offer policymakers practical value in anticipating inflationary pressures and formulating more responsive policies.

One limitation of this study is the use of only two input variables, money supply (M2) and the BI rate, despite inflation being influenced by other factors such as exchange rates, global commodity prices, fiscal policy, and inflation expectations. This situation can certainly limit the model's ability to capture inflation dynamics comprehensively and accurately. Therefore, future research is encouraged to include additional macroeconomic variables and to explore broader multivariate or nonlinear models to further improve forecasting accuracy.

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DECLARATIONS

AUTHOR CONTRIBUTION

All authors contributed equally to this research, including problem identification, data collection, analysis, and manuscript writing

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COMPETING INTEREST

The authors declare that there are no competing financial interests or conflicts of interest related to this research.

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