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MULTIVARIATE TIME SERIES MODELING USING VECTOR AUTOREGRESSION FOR RICE PRICE PREDICTION IN INDONESIA

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ABSTRACT

This study analyzes the dynamic relationship between rice prices and selected economic variables using a Vector Autoregression (VAR) model. The analysis utilizes daily data from January 2022 to December 2023, encompassing rice prices, chicken meat prices, chicken egg prices, the Rupiah-to-USD exchange rate, inflation, and crude oil prices. The estimated VAR model is stable, as all eigenvalues lie within the unit circle. Residual diagnostics based on the Portmanteau (Ljung–Box) test indicate no residual autocorrelation across all equations (LB statistics with df = 1, p-values > 0.05), confirming the adequacy of the model specification. The model demonstrates good predictive performance for the rice-price series, achieving a Mean Absolute Percentage Error (MAPE) of 0.42% over the out-of-sample testing period (the last 20% of observations). Empirical results suggest that rice prices are influenced by dynamic interactions within the system, particularly through their relationships with chicken meat prices and the Rupiah–USD exchange rate. These findings offer valuable policy insights for maintaining rice price stability, a crucial component of national food security.

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1. INTRODUCTION

Rice prices play a crucial role in shaping economic welfare in Indonesia. The price of rice directly affects people's welfare, especially the middle to lower economic groups who spend most of their expenses on rice. An increase in rice price can affect purchasing power and the food supply and is a serious concern for the government, producers, consumers, and other stakeholders [1], [2].

Rice prices sometimes fluctuate greatly. Factors such as planting and harvest seasons, government policies, and changes in supply and demand affect these fluctuations [3]. The area of harvested land, the price of dry grain, and the government's rice import policy also influence rice price. Apart from that, rice prices are also influenced by various economic factors such as exchange rates, inflation rates, and fuel prices [4]. These variables are relevant in determining rice prices and exhibit complex interactions.

Fluctuations in the Rupiah exchange rate and the rate of inflation can have a significant impact on the price of rice in the domestic market. A decrease in the currency exchange rate can increase the price of imported food and raw materials, while an increase in inflation can encourage general price increases [5]. Fuel prices are also an important factor that influences the costs of food production and distribution. Rising fuel prices will increase transportation and distribution costs, which can lead to higher food prices. As a developing country, Indonesia is also influenced by global economic conditions, such as fluctuations in global commodity prices and other global economic instability [6].

Policymakers need to understand the relationships among the rupiah exchange rate, inflation, and food prices, as a failure to do so may lead to inaccurate policy responses, increased price volatility, and heightened food security risks. Therefore, developing models capable of predicting rice prices is essential for effective risk management and the formulation of timely and appropriate policy measures in the food sector. Traditional methods of predicting rice prices are often based on simple statistical approaches or simple trend analysis. However, this approach tends to be less accurate in predicting complex and sometimes non-linear price movements. Therefore, a more sophisticated data-based approach is needed to improve the accuracy of rice price estimates.

Addressing the complex factors that influence rice prices requires a comprehensive, data-driven analytical approach. The Vector Autoregression (VAR) method is a Multivariate Time Series method that can provide a suitable framework for analyzing and predicting simultaneous relationships between interrelated economic variables, thereby enabling the development of prediction models that are more accurate and responsive to market dynamics. The VAR method is a general approach to analyzing relationships and predictions between interrelated economic variables [7]. VAR models can capture complex interrelationships in volatile environments, further confirming their applicability in modelling interconnected systems [8]. VAR allows combining information from various variables that influence rice prices. This makes it possible to model the complex dynamics behind rice prices and make more accurate predictions. Therefore, it is important to understand the dynamics of interactions between these variables to effectively predict food prices.

Previous studies have shown that multivariate time series models are able to capture dynamic relationships between variables more accurately than univariate models, especially in the context of volatile commodity forecasting [9], [10]. Previous research has widely adopted multivariate time series models to analyze and predict food prices. One relevant research was conducted to determine the relationship between rice production and rice productivity in Indonesia [11]. In this research, the researchers used the Vector Autoregression (VAR) approach to model the simultaneous relationship between food prices in the form of rice and external variables of rice productivity. Other research regarding VAR was carried out in predicting COVID-19 cases in India [12] and Pakistan [13] based on three variables, namely confirmed positive cases, death cases, and cases recovered from COVID-19. In the agricultural context, [14] applied the VAR model to investigate the impact of government expenditure, rainfall, consumer price index, food import value, and population on the value of agricultural production in South Africa. Their findings confirmed the existence of long-run relationships among the variables, highlighting the VAR model's strength in capturing complex independence in the economic system. This suggests that VAR can be a powerful tool to forecast agricultural commodity prices, such as rice, especially in economies where food security and market volatility are significant concerns.

This research will focus on the use of multivariate time series forecasting methods to analyze and predict changes in rice prices in Indonesia. The selected variables, namely the price of dry grain, area of harvested land, amount of rice imports, rupiah exchange rate, inflation rate, and fuel prices, were chosen based on their relevance and significant impact on rice prices in the domestic market.

2. RESEARCH METHODS

This study focuses on the Indonesian national rice market, reflecting aggregate price dynamics at the national level. The rice price analyzed corresponds to medium-quality rice, which represents the dominant consumption segment and is commonly used as the benchmark in official price monitoring. The study employs daily data from January 2022 to December 2023. Rice prices, chicken meat prices, and chicken egg prices are defined as average daily retail prices **(**IDR/kg) collected from official government price monitoring systems. The Rupiah to USD exchange rate is defined as the daily middle exchange rate (IDR/USD). Inflation is measured as the officially published inflation indicator reported by the national statistics authority, while crude oil price refers to the international benchmark oil price expressed in USD per barrel.

All prices and macroeconomic data are obtained from Statistics Indonesia (BPS) and the Strategic Food Price Information Center (PIHPS), both accessed through their official online platforms. The empirical analysis is conducted using Python, with the Vector Autoregressive model estimated using the *statsmodels* library. Additional data handling and preprocessing are performed using standard Python libraries, including NumPy and Pandas. Model estimation, diagnostic testing (including stability and Portmanteau tests), and forecasting procedures are fully reproducible. The analysis code is available from the authors upon reasonable request, ensuring transparency and reproducibility of the results.

The rice price forecasting research carried out consists of several stages, and in general, the flow of stages in this research can be seen in Fig. 1.

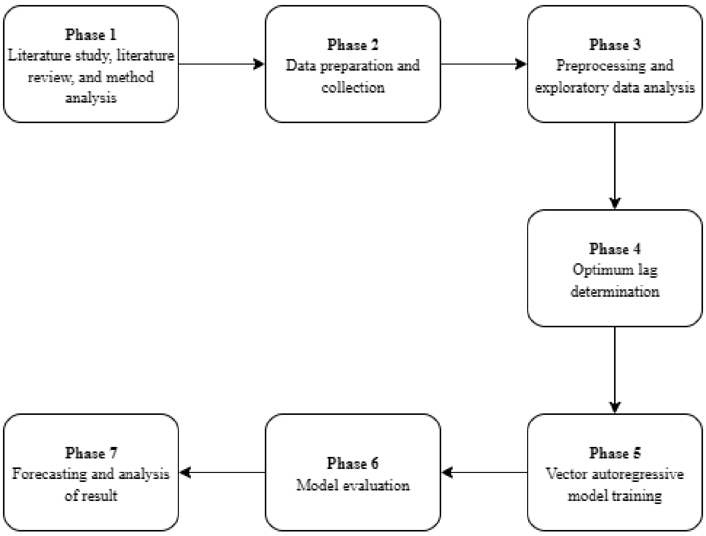


Figure 1. Research Phase for Rice Price Prediction in Indonesia

2.1 Literature Study, Literature Review, and Method Analysis

In the early stages of the investigation, a literature review and a literature study related to multivariable time series forecasting were conducted using the VAR method. These topics include the analysis steps, the model properties and assumptions, and the evaluation of the forecast results. Then, a review of the literature on rice prices is necessary as the object of this research. This study is needed to identify variables and parameters related to the object of research. Surveys of traditional markets that are used as the object of research also need to be carried out to obtain information about the fluctuation of rice prices.

2.2 Data Preparation and Collection

The next stage is data preparation and collection. The data in this study is a time series data type taken from time to time. The data used in this study were obtained from Statistics Indonesia (Badan Pusat Statistik, BPS) and the Strategic Food Price Information Centre (PIHPS). The datasets include variables such as rice prices, inflation rates, the rupiah–USD exchange rate, and crude oil prices. All data are publicly available from the official websites of the respective institutions, and no special access permissions were required. Proper references to these sources are provided in the reference list to ensure reproducibility.

The scale of the data used is in daily periods. The period of data used to create the model is from January 2022 to December 2023. Inflation data published by Statistics Indonesia (BPS) are available at a monthly frequency. To ensure consistency with the daily frequency of the VAR model, the monthly inflation rate was assigned to all days within the corresponding month, resulting in a stepwise daily series. This approach preserves the officially reported inflation information while avoiding artificial smoothing or noise introduced by interpolation. While this transformation implies that inflation exhibits limited day-to-day variation, it remains suitable for capturing short-run interactions and lagged effects within the multivariate VAR framework. The potential limitation of reduced intra-month variability is acknowledged and does not affect the validity of the model estimation. The following is an overview of the dataset's form, as presented in Table 1.

Table 1. Shape of Rice Price Dataset and Influencing Variables

Variable	Definition	Unit	Market Coverage	Frequency	Observations (n)	Missing Values
Time (t)	Observation date	Date	National	Daily	730	0
Rice Price	Average retail price of medium-quality rice	IDR/kg	National average (BPS & PIHPS)	Daily	730	0
Chicken Meat Price	Average retail price of broiler chicken meat	IDR/kg	National average (BPS & PIHPS)	Daily	730	0
Chicken Egg Price	Average retail price of broiler chicken eggs	IDR/kg	National average (BPS & PIHPS)	Daily	730	0
Rupiah to USD Exchange Rate	IDR per USD exchange rate	IDR/USD	National (Bank Indonesia)	Daily	730	0
Inflation	Monthly consumer price inflation rate	% (monthly)	National (BPS)	Monthly → Daily*	730	0
Crude Oil Price	Brent crude oil spot price	USD/barrel	Global market	Daily	730	0

*Monthly inflation values are repeated for each day within the corresponding month.

Table 1 provides a detailed description of the variables used in this study, including their definitions, units of measurement, data coverage, and frequency. All price variables represent national average retail prices, ensuring consistency across markets. The dataset consists of 730 daily observations covering the period from January 2022 to December 2023. Missing values were handled during the data collection stage; however, no missing observations remained after data cleaning. Monthly inflation data published by Statistics Indonesia (BPS) were converted into a daily series by assigning the same monthly value to all days within the respective month.

2.3 Data Preprocessing and Exploratory Data Analysis

After collecting the data, the next step is to do the data preprocessing. In general, the preprocessing process includes handling missing value data. In addition, a pattern check is performed on the data to determine whether the data has a stationary pattern or not. Data that is not stationary needs to be transformed or differenced so that the data becomes stationary. The requirement for using the VAR model is that the data must be stationary [15],[16].

Before modeling the short-run relationships among the variables, it is essential to first assess whether a long-run equilibrium or cointegration relationship exists among them. The Johansen cointegration test is employed as it can handle multiple variables simultaneously and estimate the number of potential cointegrating relationships. The results of this test will determine whether a Vector Error Correction Model (VECM) is appropriate or if an alternative approach should be used to analyze the short-run dynamics among the variables.

2.4 Optimum Lag Determination

Lag represents the relationship between variables based on historical data. In a VAR model, the value of a variable at time t can be affected by the value of itself and other variables at time $t-1$, $t-2$, and so on. The selection of the optimal number of lags (p) is very important so that the model is not too simple or complex. This selection is done by information criteria, such as Akaike Information Criterion (AIC) [17].

2.5 Multivariate Time Series Model Training

The prepared dataset will be used to train the multivariate time series method through the VAR model. The VAR is a forecasting model that simultaneously predicts changes in several observed variables. In the VAR method, the relationship between variables is viewed as a dynamic system that affects each other or is bidirectional [18].

The equation for VAR with k variables and p lags can be explained as follows [19]:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \varepsilon_t \tag{1}$$

where:

Y_t : vectors of size $n \times 1$, consisting of n variables in the VAR model at time t;
Y_{t-1} : vectors of size $n \times 1$, consisting of n variables in the VAR model at time $t-1$;
α : intercept vector of size $n \times 1$;
$\beta_1, \beta_2, \dots, \beta_p$: matrices of regression coefficients of Y from lag 1 to p, each of size $n \times n$;
ε_t : vector of errors or forecasting errors.

Suppose the VAR model consists of three variables with lag $p = 1$, then Eq. (1) can be written as:

$$\begin{bmatrix} y_{1(t)} \\ y_{2(t)} \\ y_{3(t)} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \begin{bmatrix} y_{1(t-1)} \\ y_{2(t-1)} \\ y_{3(t-1)} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1(t)} \\ \varepsilon_{2(t)} \\ \varepsilon_{3(t)} \end{bmatrix}. \tag{2}$$

Training is carried out until the model with the optimal lag is found. The optimal model selection is done by comparing the AIC value. Based on [8], before conducting VAR analysis, it is necessary to select the optimal lag first. The optimal lag length can be determined using the following AIC formula:

$$AIC = 2k - 2\ln(L), \tag{3}$$

where k is number of parameters in the model and L is the likelihood function of the data.

The smaller the AIC value in Eq. (3), the more optimal the model with that lag.

2.6 Model Evaluation

After predicting future values using a forecasting method, it is important to evaluate the accuracy of the forecasting results. Forecasting result evaluation methods referring to [20], including:

1. Mean Absolute Error (MAE)

   MAE is the average value of the absolute difference between the true value and the value predicted by the model. MAE can be calculated with the following formula:

   $$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right|, \tag{4}$$

   where Y_t is the true value and $\hat{Y}_t$ is the predicted value.

2. Mean Absolute Percentage Error (MAPE)

   MAPE is the average of the absolute percentage difference between the actual value and the predicted value of the model. The MAPE value can be written as:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|Y_t - \hat{Y}_t|}{Y_t}. \tag{5}$$

3. Root Mean Squared Error (RMSE)

   RMSE is the root of Mean Squared Error (MSE). RMSE is calculated with the following formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}. \tag{6}$$

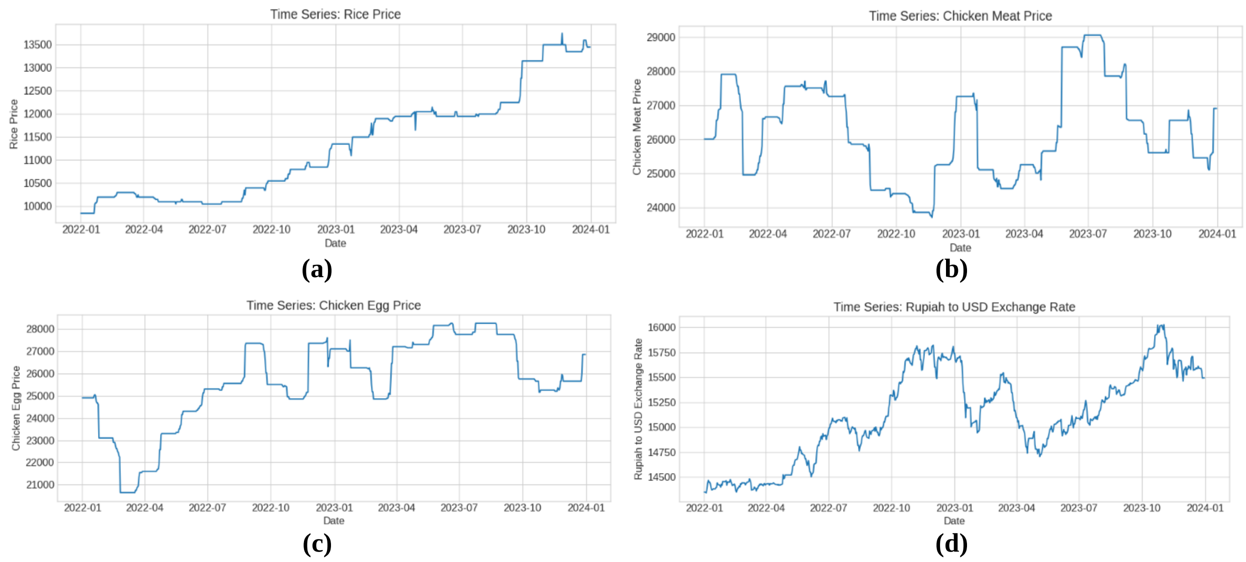
The smaller values of MAE in Eq. (4), MAPE in Eq. (5), and RMSE in Eq. (6) indicate that the model is more accurate in predicting the actual values.

2.7 Forecasting and Analysis of Results

The next step after obtaining the best model is to use the model to forecast the price data of each basic need in the future. The period chosen in this study is for 7 days ahead. The last process is to analyse the data on the results that have been built. The analysis will focus on the model diagnosis test, as well as the time required for training and prediction on new data. At this stage, the data pattern visualization of the forecast results is also carried out.

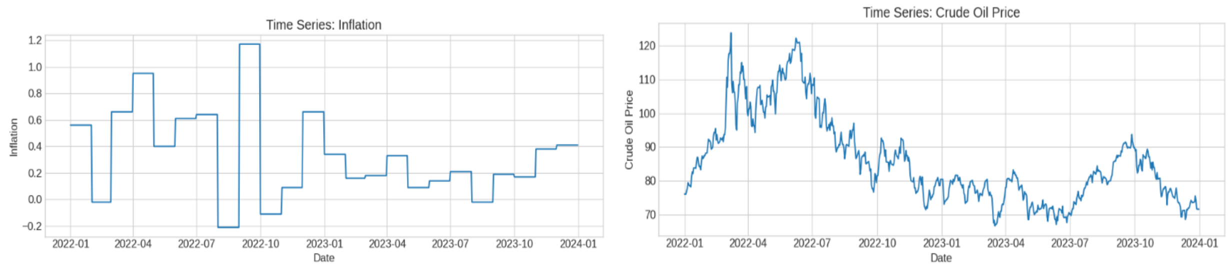
3. RESULTS AND DISCUSSION

This research will focus on the use of multivariate time series forecasting methods to analyze and predict changes in rice prices in Indonesia. The selected variables, namely super quality rice price, chicken meat price, chicken egg price, Rupiah to USD exchange rate, inflation, and crude oil price, are chosen based on their relevance and significant impact on rice prices in the domestic market. Below are the initial data plots for the variables used to see the data overview, Fig. 2.



(a) (b)

(c) (d)



(e) **(f)**

Figure 2. Initial Data Plot of the Observed Variables Before Preprocessing: (a) Rice Price, (b) chicken meat price, (c) chicken egg price, (d) Rupiah to USD exchange rate, (e) inflation, and (f) crude oil price
(Application Source: Python)

Based on Fig. 2, variables such as rice price, chicken meat price, chicken egg price, Rupiah to USD exchange rate, inflation rate, and crude oil price have a dynamic relationship affecting rice prices. Fig. 2 indicates that domestic rice prices exhibit relative rigidity over time, while oil prices and exchange rates display more pronounced fluctuations. This divergence suggests a limited short-term responsiveness of rice prices to global indicators, which justifies the inclusion of these variables in the VAR model to formally test the extent, direction, and lagged nature of their dynamic interactions rather than assuming strong contemporaneous linkages.

Fig. 2 shows the daily rice prices in Indonesia from January 2022 to December 2023. The x-axis indicates the observation dates, with monthly ticks for clarity, while the y-axis shows the prices in levels. All series are plotted in their original levels, not differenced. The figure was generated using Python with the matplotlib library, ensuring accurate and clear visualization of the daily price dynamics over the two-year period.

3.1 Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Test Results

The results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests in Table 2 provide insights into whether the data for each variable has a unit root, indicating whether the data is stationary or non-stationary.

Table 2. Summary of ADF and PP Test Results

Variable	ADF Test Statistic	ADF p-Value	5% CV	10% CV	Lag Selection	Regression Type	PP Test Statistic	PP p-value	Conclusion
Rice price	0.2802	0.9764	-2.87	-2.57	AIC	None	0.4249	0.9824	Non-stationary
Chicken Meat price	-2.1564	0.2225	-2.87	-2.57	AIC	None	-2.4778	0.1210	Non-stationary
Chicken Egg price	-1.5909	0.4882	-2.87	-2.57	AIC	None	-1.6249	0.4702	Non-stationary
Rupiah to USD Exchange Rate	-1.9701	0.2998	-2.87	-2.57	AIC	None	-1.7858	0.3875	Non-stationary
Inflation	-3.9007	0.0020	-2.87	-2.57	AIC	None	-4.3995	0.0003	**Stationary**
Crude Oil Price	-1.2240	0.6632	-2.87	-2.57	AIC	None	-1.6871	0.4378	Non-stationary

The stationarity of the variables was assessed using both the ADF and Phillips-Perron PP tests. Table 2 reports the ADF test statistics, the corresponding critical values at 5% and 10% significance levels, the selected lag based on the AIC criterion, and the regression specification (with or without trend). The results indicate that most variables, including rice price, chicken meat price, chicken egg price, Rupiah to USD exchange rate, and crude oil price, have ADF statistics higher than the critical values and p-values greater than 0.05, which implies a failure to reject the null hypothesis of a unit root. Therefore, these variables are non-stationary in levels.

On the other hand, inflation is the only exception, for which both the ADF and PP test statistics are lower than the critical values, and the p-values are below 0.05, allowing rejection of the null hypothesis. This confirms that inflation is stationary at levels. The Phillips-Perron (PP) test was also performed, and the results are consistent with the ADF test, further supporting the stationarity conclusion. These results indicate that all non-stationary variables need to be differenced before inclusion in the VAR model to ensure valid estimation of short-run dynamics.

3.2 Data Transformation

Stationarity tests indicate that not all variables are stationary in their level form. To satisfy the stationarity requirement of the VAR model, non-stationary variables were transformed using first differencing. The ADF and PP test was then reapplied to the transformed series to confirm stationarity. A summary of the ADF and PP test results after transformation is presented in Table 3. Let X_t denote the original value of a time series variable at time t. The first-differenced series is defined as

$$\Delta X_t = X_t - X_{t-1}. \tag{7}$$

This transformation was applied to all variables identified as non-stationary at level, including crude oil prices and chicken egg prices. Variables that were found to be stationary at level were retained in their original form. All subsequent VAR model estimations were conducted using the stationary series (either differenced or level, depending on the ADF test results). For interpretability of the forecasting results, the predicted values obtained from the VAR model were later transformed back to their original scale using inverse differencing, defined as:

$$\hat{X}_t = X_{t-1} + \widehat{\Delta X}_t, \tag{8}$$

where X_{t-1} represents the last observed actual value prior to the forecast period.

Summary of ADF test results after differencing for various time series data can be seen at Table 3 below.

Table 3. Summary of Augmented Dickey-Fuller (ADF) Test Results After Differencing

No.	Variable	ADF p-value	PP p-value	Conclusion
1.	Rice price	0.0000	0.0000	Stationary
2.	Chicken Meat price	0.0000	0.0000	Stationary
3.	Chicken Egg price	0.0000	0.0000	Stationary
4.	Rupiah to USD Exchange Rate	0.0000	0.0000	Stationary
5.	Crude Oil Price	0.0000	0.0000	Stationary

Based on Table 3, it is observed that after differencing, the ADF test was conducted again, and it was found that the data were stationary (p-value < 0.05). This can also be seen from the graph in Fig. 3.

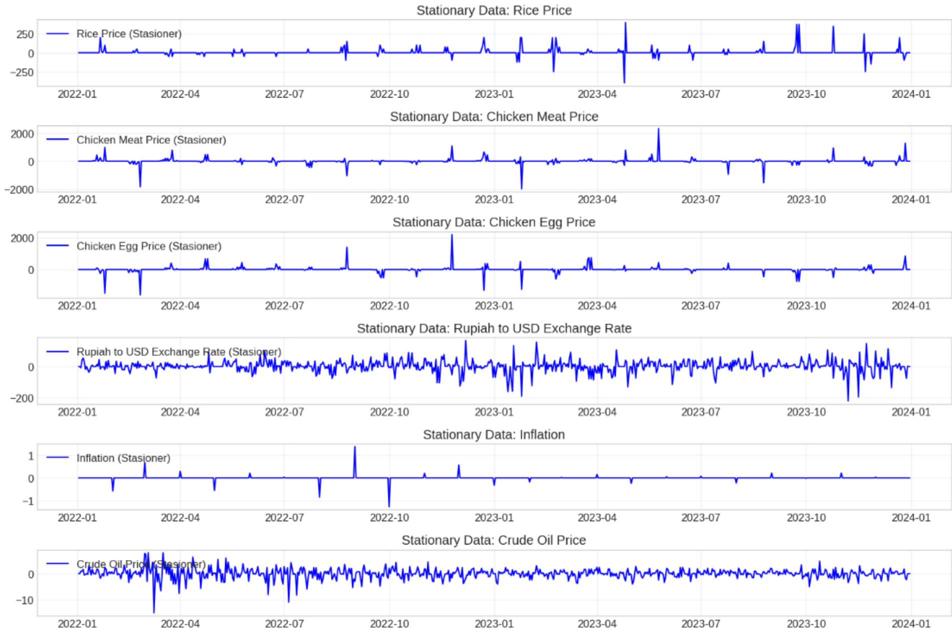


Figure 3. Plot of Stationarity
(Application Source: Python)

The results of the Johansen cointegration test can be seen in Table 4 below.

Table 4. The Johansen Cointegration Test Results

r	Trace Statistics	Critical Value (5%)	Max-Eigen Statistic	Critical Value Max (5%)
$r \leq 0$	59.765464	95.7542	26.660021	40.0763
$r \leq 1$	33.105442	69.8189	14.561099	33.8777
$r \leq 2$	18.544343	47.8545	7.687319	27.5858
$r \leq 3$	10.857024	29.7961	5.992985	21.1314
$r \leq 4$	4.864039	15.4943	3.212413	14.2639
$r \leq 5$	1.651625	3.8415	1.651625	3.8415

Table 4 reports the results of the Johansen cointegration test using both the trace and maximum eigenvalue statistics at the 5% significance level. For all null hypotheses ($r \leq 0$ to $r \leq 5$), the test statistics are lower than their respective critical values, indicating a failure to reject the null hypothesis of no cointegration. These results confirm that no long-run equilibrium relationship exists among the variables, and the estimated cointegration rank is zero. Accordingly, the Vector Error Correction Model (VECM) is not appropriate, and a VAR model estimated on first-differenced data is employed to capture short-run dynamics.

3.3 Optimal Lag Selection

Lag selection is done using the AIC Table 5. The VAR model with lag 1 was chosen as the best model if the relationship between variables at lag 1 provides optimal predictions without overfitting, based on the criteria outlined in Table 5.

Table 5. AIC Test

Lag	AIC	Lag	AIC
1	**32.3950**	11	32.9059
2	32.4662	12	32.9809
3	32.5421	13	33.0526
4	32.6040	14	33.1074
5	32.6763	15	33.2057
6	32.7360	16	33.2855
7	32.6389	17	33.3735
8	32.7072	18	33.4511

Lag	AIC	Lag	AIC
9	32.7703	19	33.5392
10	32.8432	20	33.5799

The results of the optimal lag test visualization in the VAR model are also shown in Fig. 4.

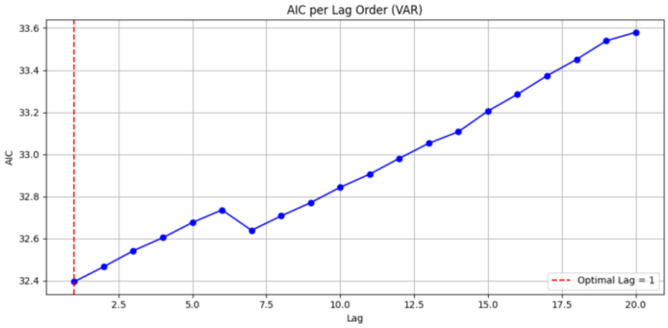


Figure 4. Optimal Lag Test Visualization
(Application Source: Python)

Based on the results in Fig. 4, it can be observed that the AIC reaches its lowest point at lag 1. After lag 1, the AIC value tends to increase consistently as the lag length extends up to lag 20. This pattern indicates that the model with lag 1 provides the best balance between model complexity and prediction error. In other words, using lags greater than 1 does not offer significant improvements to the model's goodness-of-fit; instead, it increases the AIC value, which reflects reduced model efficiency. Therefore, the optimal lag selected in this VAR model is lag 1, which is expected to effectively capture the dynamics of relationships among variables without causing overfitting.

3.4 Granger Causality

Based on the Granger causality test p-value matrix, causal relationships between variables are identified using the standard Granger causality framework. Let y_t and x_t denote two stationary time series. The Granger causality test evaluates whether past values of x_t provide statistically significant information for predicting y_t beyond the information contained in past values of y_t alone. The unrestricted VAR representation is given by:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=1}^{p} \beta_i x_{t-i} + \varepsilon_t. \tag{9}$$

The null hypothesis of no Granger causality is defined as:

$$H_0: \beta_1 = \beta_2 = \cdots = \beta_p = 0. \tag{10}$$

This hypothesis is tested using an F-test. A p-value less than 0.05 indicates rejection of the null hypothesis at the 5% significance level, implying that x_t Granger-causes y_t. This can be seen in Table 6 below.

Table 6. Granger Causality Test

	Rice price_x	Chicken meat price_x	Chicken egg price_x	Rupiah to USD Exchange rate_x	Inflation_x	Crude oil price_x
Rice price_y	-	0.2587	0.1463	0.1037	0.2907	0.3915
Chicken meat price_y	**0.0213**	-	0.6925	0.0855	0.0860	0.6891
Chicken egg price_y	**0.0009**	0.7684	-	0.1179	0.8345	0.4442
Rupiah to USD Exchange rate_y	**0.0334**	0.6440	**0.0363**	-	0.6982	**0.0118**
Inflation_y	0.1851	0.1877	0.0000	0.6303	-	0.6035

	Rice price_x	Chicken meat price_x	Chicken egg price_x	Rupiah to USD Exchange rate_x	Inflation_x	Crude oil price_x
Crude oil price_y	0.4319	**0.0179**	0.0518	0.4242	0.0791	-

Table 6 presents the results of the Granger causality tests among the variables. In this table, the suffix _x denotes the predictor variable, while _y represents the response variable. Thus, each reported p-value tests whether the variable in the column (_x) provides statistically significant predictive information for the variable in the corresponding row (_y).

The Granger causality test results in Table 6 indicate that rice price acts primarily as a driving variable rather than a dependent one. Specifically, rice price Granger-causes chicken meat price, chicken egg price, and the Rupiah to USD exchange rate, with p-values of 0.0213, 0.0009, and 0.0334, respectively. In contrast, no variable is found to Granger-cause rice price at the 5% significance level, suggesting that rice price dynamics are relatively exogenous within the system during the observed period.

On the other hand, inflation_y and crude oil price_y do not exhibit a statistically significant causal effect on rice price, as indicated by their higher p-values of 0.1851 and 0.4319. This means that, within this dataset, changes in inflation and crude oil prices do not directly influence rice price movements in a predictive sense. The matrix also reveals some interesting inter-variable causal relationships. For example, inflation_y is significantly influenced by chicken egg prices_x with a p-value of 0.0000. Additionally, crude oil prices_y are affected by chicken meat price_x with a p-value of 0.0179. These insights could be useful for building a more interconnected and accurate forecasting model using VAR.

3.5 VAR Modelling

VAR modeling is conducted by splitting the data into a training set and a testing set, with a composition of 80% and 20%, respectively. The dataset was split into 80% training and 20% testing sets to ensure sufficient observations for VAR parameter estimation while preserving an adequate out-of-sample period for forecast evaluation. This proportion is commonly used in time-series forecasting where temporal order must be maintained. The VAR model with optimal lag 1 was selected based on the Akaike Information Criterion (AIC), Table 4. This model is used to predict rice price variables based on chicken egg price, chicken meat price, Rupiah to USD exchange rate, inflation, and crude oil price.

Table 7. Estimation of Model Parameter

Parameter	Rice Price	Chicken Meat Price	Chicken Egg price	Rupiah to USD Exchange Rate	Inflation	Crude Oil Price
α	7.344197	-8.417413	7.692818	2.016322	0.013597	0.024192
$Y_{1,t-1}$	-0.136449	-0.425068	-0.514335	-0.055228	-0.000016	0.001023
$Y_{2,t-1}$	-0.006728	0.048952	0.008365	0.006177	0.000006	-0.000314
$Y_{3,t-1}$	-0.011931	-0.050309	0.007667	-0.022452	-0.000004	-0.000023
$Y_{4,t-1}$	0.074230	-0.107046	-0.083394	0.073519	-0.000031	-0.000550
$Y_{5,t-1}$	-5.429310	36.085236	-7.081097	-0.741982	0.958888	-0.101809
$Y_{6,t-1}$	-0.827464	0.614953	2.555589	-1.901347	-0.000631	0.026833

The estimated VAR(1) parameters, corresponding to the model structure defined in Eq. (1), are presented in Table 7.

3.6 VAR(1) Model Analysis

The VAR(1) model captures the dynamic interrelationships among six key economic variables: rice price, chicken meat price, Rupiah to USD exchange rate, inflation, and crude oil price. Each equation in the model explains one variable as a function of the lag (one-period delay) of all six variables.

Based on the results in Table 7, the rice price is negatively affected by the lagged values of the chicken meat price, the chicken egg price, inflation, and the crude oil price. The strongest effect comes from the crude oil price (-5.429), suggesting that an increase in global oil prices significantly lowers rice price in the following period, possibly due to rising distribution costs and substitution in consumption. Chicken meat price is strongly and positively influenced by lagged inflation (36.08) and crude oil price (0.61). This indicates that rising inflation and oil prices may drive chicken meat prices up. In contrast, the lagged rice price has a negative effect, possibly reflecting substitution between carbohydrate and protein sources in household consumption. Chicken egg price is negatively influenced by lagged rice price (-0.514), inflation (-7.08), and crude oil price (s2.55). This implies that inflationary pressures and distribution costs significantly impact chicken egg prices, reflecting the sensitivity of livestock-based commodities to external shocks. The Rupiah–USD exchange rate is negatively associated with lagged inflation (-0.74) and crude oil prices (-1.90), indicating an empirical relationship observed in the VAR estimation rather than a direct causal effect. The effect of rice crude oil price is positively affected by lagged inflation (0.026), with minimal influence from other variables. This may indicate a mild feedback loop between inflation and global oil prices, though the impact is relatively limited.

All non-stationary variables were transformed using first differencing prior to VAR estimation to satisfy the stationarity assumption. Model estimation and forecasting were conducted on the differenced series. For interpretability and evaluation purposes, the forecasted values were subsequently transformed back to their original scale using inverse differencing. The VAR(1) model reveals dynamic linkages among key economic indicators in Indonesia. Inflation and crude oil prices play a dominant role in influencing food prices and the exchange rate. The rice and chicken meat prices also show mutual interactions, possibly indicating household-level consumption adjustments in response to economic conditions. These findings offer valuable insights for short-term forecasting and policymaking, particularly in the areas of food price stabilization and monetary management. The visualization graph of the results of fitting the VAR model to the training data using lag order 1 with parameter estimation using the OLS method is presented in Fig. 5.

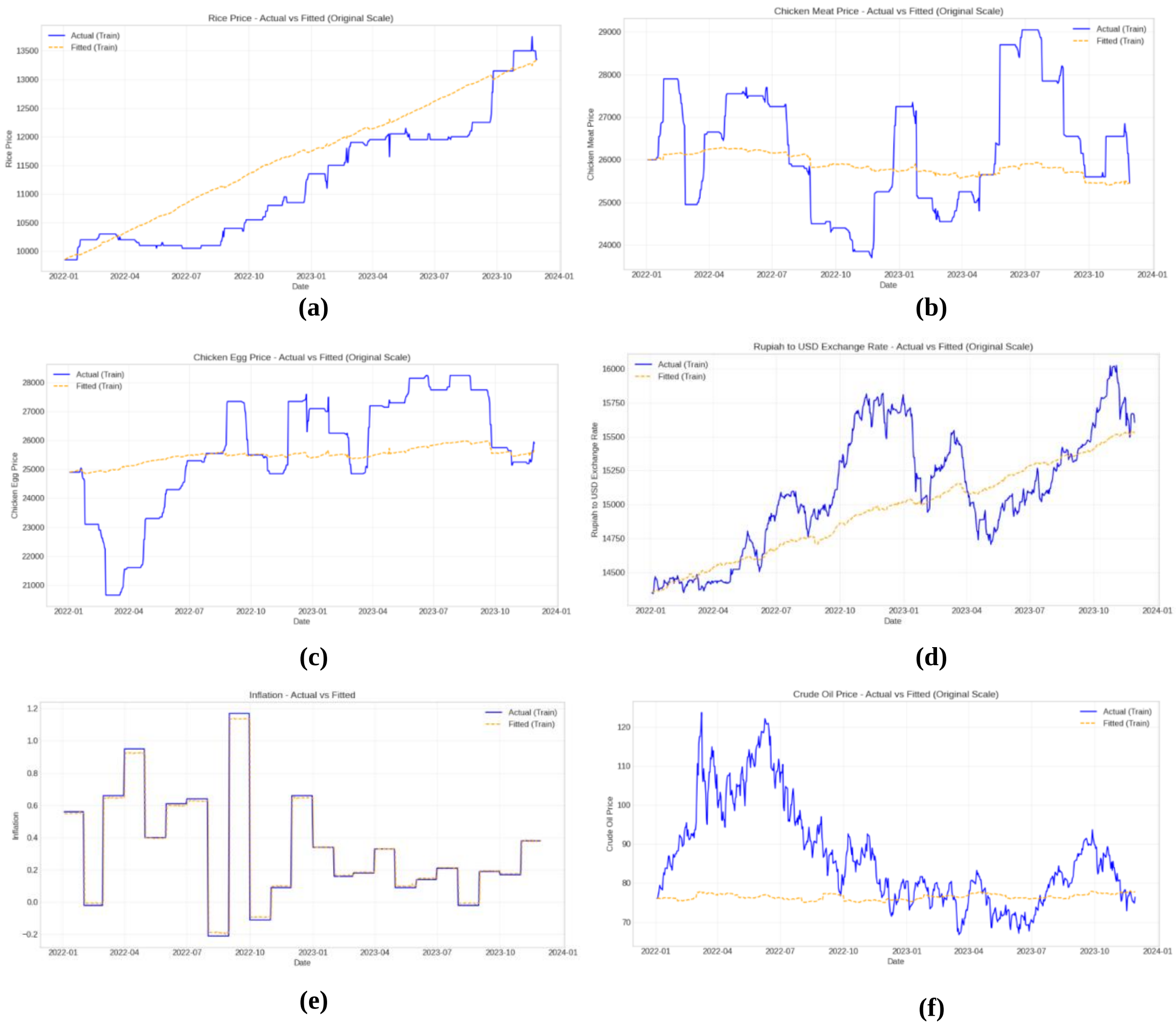


Figure 5. Fitted Model VAR(1) – Data Training: (a) Rice Price, (b) chicken meat price, (c) chicken egg price, (d) Rupiah to USD exchange rate, (e) inflation, and (f) crude oil price

(Application Source: Python)

Based on Fig. 5, the VAR(1) model was trained using historical data on six key economic variables: rice price, chicken meat price, chicken egg price, Rupiah to USD exchange rate, inflation, and crude oil price. The plots comparing actual and fitted values reveal varying degrees of accuracy across variables.

The model performs well in capturing the long-term upward trend of rice prices, with the fitted values closely tracking the actual values, despite minor fluctuations. However, for chicken meat prices, the model shows a weaker performance. It fails to capture the sharp and irregular price movements, indicating that this variable may require a more complex model to account for sudden shifts. Similarly, the chicken egg price series displays significant volatility, which is only partially reflected in the fitted line, suggesting the model struggles with this type of discrete price behaviour.

For the rupiah to USD exchange rate, the model adequately captures the long-term depreciation trend, but underestimates short-term volatility, especially during periods of sharp exchange rate movement. In contrast, the model shows an excellent fit for inflation, with the fitted values nearly overlapping the actual ones. This suggests that inflation dynamics are more stable and well-suited to modelling with a VAR(1) structure. Lastly, for crude oil prices, the model does not perform well. The fitted values remain flat and do not reflect the high volatility observed in the actual data, which implies that crude oil prices are likely influenced by exogenous global shocks not fully captured in the model.

The VAR(1) model is effective in modelling relatively smooth and trend-based variables like rice prices and inflation. However, it is less suitable for highly volatile or irregular variables such as meat and egg prices or crude oil. Future modelling efforts may consider higher-order VAR models or nonlinear approaches for improved accuracy on those variables. Next, the graph for the testing data is presented in Fig. 6.

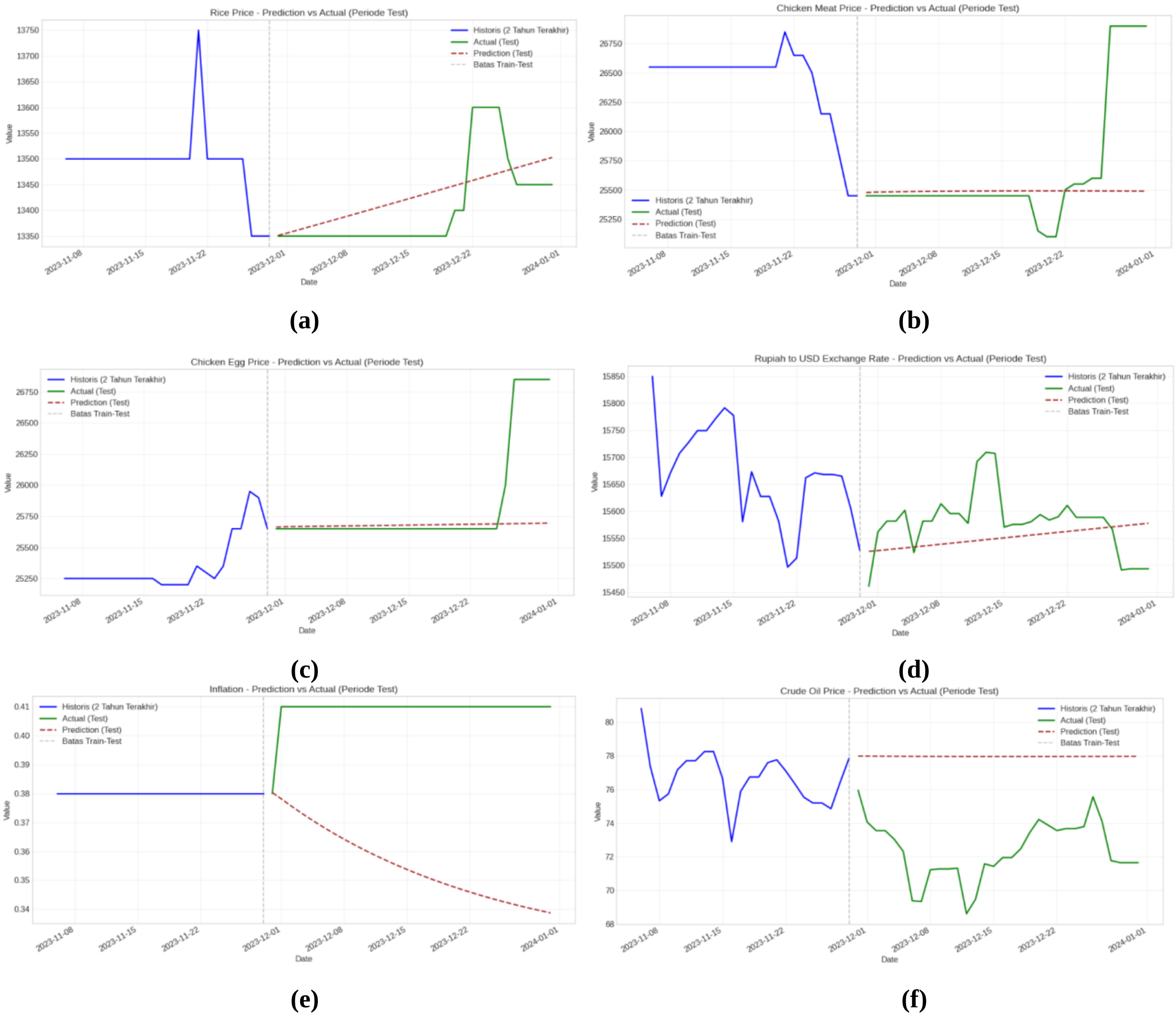


Figure 6. Fitted Model VAR(1) – Data Testing: (a) Rice Price, (b) chicken meat price, (c) chicken egg price, (d) Rupiah to USD exchange rate, (e) inflation, and (f) crude oil price

(Application Source: Python)

The VAR(1) model was applied to forecast six economic indicators: rice price, chicken meat price, chicken egg price, exchange rate (Rupiah to USD), inflation, and crude oil price. The model performed well for more stable variables, such as the chicken egg price and exchange rate, where predictions closely aligned with actual values. However, it struggled with volatile indicators like rice, chicken meat, and crude oil prices, failing to capture sudden spikes or irregular fluctuations. For inflation, the model predicted a downward trend that did not occur, as actual values remained flat. Overall, the model's accuracy varies across variables, indicating that while it is effective for stable time series, improvements are needed to handle high volatility and abrupt changes.

Here's a simplified Table 8 summarizing the model evaluation metrics for data testing.

Table 8. Performance Metrics for Model Evaluation

Parameter	Rice Price	Chicken Meat Price	Chicken Egg Price	Rupiah to USD Exchange Rate	Inflation	Crude Oil Price
MAE	56.6909	288.4171	212.3927	53.3901	0.0536	5.5818
MAPE	0.4218	1.0882	0.7960	0.3423	13.0975	7.7725
RMSE	67.8342	570.6249	461.2124	66.5373	0.0557	5.8418

Based on Table 8, the VAR(1) model demonstrates strong predictive performance for variables with stable trends, such as rice prices and the rupiah to USD exchange rate, indicated by very low MAPE values of 0.4218% and 0.3423%, respectively. It also performs reasonably well for chicken egg prices with an MAPE of 0.7960%. However, the model struggles to capture the sharp fluctuations in chicken meat prices (MAPE 1.0882%), inflation (MAPE 13.0975%), and crude oil prices (MAPE 7.7725%). The higher error values for these variables suggest that the VAR(1) model is less suitable for volatile data or series influenced by external shocks, indicating a need for more complex or nonlinear modelling approaches to improve accuracy.

3.7 Stability of the VAR Model

The stability test of the VAR model aims to ensure that the VAR model is stable and produces reliable prediction results. In the context of VAR, stability refers to all eigenvalues of the VAR coefficient matrix being inside the unit circle (modulus < 1). If all eigen moduli < 1, then the model is considered stable. If any eigen modulus value ≥ 1, the model is considered unstable.

From the analysis results in Table 7, it was found that the optimal lag is at lag 1. To ensure the stability of the estimation model, a stability test was performed, and the results can be found in Table 9.

Table 9. Stability Test Results

Eigenvalues of VAR(1)	Status
0.9593	Stable
0.1605	Stable
0.0066	Stable
0.0909	Stable
0.0493	Stable
0.0493	Stable

The analysis results show that all root moduli are inside the unit circle, indicating that the model is stable. Thus, the model can be used for short- and medium-term predictions with a high level of confidence.

3.8 White Noise Test

The purpose of the white noise residual assumption test is to determine whether there is a correlation between the residual vectors from the VAR(1) that have been formed. The multivariate white noise test using the portmanteau test is shown in Table 10.

Table 10. White Noise Testing

Variable	p-value	Decision
Rice Price	0.92088	Accept H_0

Variable	p-value	Decision
Chicken Meat Price	0.982924	Accept H_0
Chicken Egg Price	0.952629	Accept H_0
Rupiah to USD Exchange Rate	0.936944	Accept H_0
Inflation	0.586813	Accept H_0
Crude Oil Price	0.99478	Accept H_0

Table 10 shows that at the 5% significance level, all the p-value $> \alpha = 5\%$. This indicates that the VAR(1) model meets the multivariate white noise assumption.

3.9 Rice Price Prediction Result

Based on the rice price prediction results, the analysis indicates that short-term price trends remain stable, with predicted values ranging between 13,455.11 and 13,482.76 (in price units), as shown in Table 11. These predictions show no significant fluctuations over time, reflecting a stable price pattern. However, long-term predictions demonstrate increasingly wider confidence intervals.

Table 11. Rice Price Forecast Results

Date	Rice Price (IDR/Kg)
1 January 2024	13455.1181
2 January 2024	13459.5972
3 January 2024	13464.2138
4 January 2024	13468.8275
5 January 2024	13473.4586
6 January 2024	13478.1031
7 January 2024	13482.7608

Based on the prediction results, rice prices from January 1 to January 7, 2024, exhibit a gradually increasing trend. The price is forecasted to be 13,455.12 on January 1 and rises steadily each day, reaching 13,482.76 by January 7. This consistent upward movement indicates a stable and moderate price growth over the one-week period, without any sharp spikes or drops. The smooth progression suggests that the model effectively captures the short-term trend in rice prices and reflects an absence of significant external shocks or volatility during the first week of January 2024.

4. CONCLUSION

This study applies a Vector Autoregression (VAR) framework to examine the short-run dynamics between rice prices and selected economic variables using daily data from January 2022 to December 2023. The estimated VAR(1) model is dynamically stable, with all eigenvalues located inside the unit circle, and passes residual diagnostic checks based on the Portmanteau (Ljung–Box) test, indicating no residual autocorrelation. The model exhibits strong out-of-sample predictive performance for rice prices, achieving a Mean Absolute Percentage Error (MAPE) of 0.42%. The empirical findings indicate that rice price movements are predictively linked to interactions within the system, particularly with chicken meat prices and the Rupiah–USD exchange rate, underscoring their relevance for short-term price monitoring and policy assessment.

Several limitations should be noted. The analysis relies on a relatively short sample period and employs a daily inflation proxy. In addition, potential seasonality, structural breaks, and long-run cointegration are not explicitly modeled. Therefore, the results should be interpreted as predictive rather than causal.

Author Contributions

Atika Ratna Dewi: Conceptualization, Methodology, Data Curation, Formal Analysis, Writing Original Draft Preparation. Andreas Rony Wijaya: Software, Resources, Visualization, Validation. Mirza Ghanimi:

Investigation, Project Administration, Funding Acquisition. Talitha Veda Azaria Ramadhani: Supervision and Writing–Review and Editing. All authors have read and agreed to the published version of the manuscript, discussed the results together, and contributed to the refinement of the final draft.

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Declarations

The authors declare that there are no conflicts of interest regarding the publication of this study.

Declaration of Generative AI and AI-assisted Technologies

AI-assisted technology (e.g, ChatGPT) was used to support light paraphrasing and sentence restructuring for clarity. The authors confirm that the underlying ideas, arguments, data analyses, and conclusions are original and were not generated by AI. All AI-assisted edits were critically reviewed and validated by the authors.

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