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VECTOR AUTOREGRESSION AND MULTIRESPONSE REGRESSION APPROACHES FOR MODELING GOLD, TIN, AND NICKEL PRICES

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ABSTRACT

The mining sector plays a strategic role in the global economy, especially during periods of high economic uncertainty. Between 2020 and 2024, global markets experienced severe volatility due to the COVID-19 pandemic, geopolitical tensions, energy price shocks, and monetary policy tightening. These conditions intensified price fluctuations in major mining commodities such as nickel, gold, and tin. However, limited empirical research has compared different multivariate modeling approaches for analyzing commodity price dynamics during this volatile period. This study examines the dynamic relationships between nickel, gold, and tin prices and key global factors, namely crude oil prices, the USD exchange rate, and silver prices, using monthly data from January 2020 to December 2024. The VAR model captures temporal interdependencies among variables, while the MRR model examines simultaneous relationships among multivariate response variables. The stationarity and cointegration tests show that all variables become stationary after first differencing and exhibit no long-term equilibrium relationship. The Impulse Response Function (IRF) and Variance Decomposition (VDC) analyses reveal that fluctuations in nickel, gold, and tin prices are primarily driven by their own past values, with minor cross-commodity effects. The MRR results indicate that crude oil and silver prices significantly influence metal price variations, while the USD exchange rate has the strongest overall effect. The comparison across three evaluation metrics shows that the MRR model provides better predictive performance than the VAR model. The MRR model yields higher R^2 than VAR, which records R^2 of 0.339, 0.584, and 0.529, with MAPE up to 22.42%. The results demonstrate that the MRR model consistently outperforms the VAR model, providing stronger explanatory power and higher predictive accuracy. These findings highlight the added methodological value of comparing VAR and MRR models and offer practical insights for investors, industry stakeholders, and policymakers in managing commodity price risk under volatile economic conditions.

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1. INTRODUCTION

The mining sector plays a crucial role in a country's development and economy, particularly as a provider of energy resources. In line with various studies, investments in the mining sector still have promising prospects for the future and have a significant impact on the economy and other aspects [1]. Several key commodities, such as nickel, gold, and tin, play a strategic role in industry, technology, and investment. The ever-fluctuating commodity prices significantly impact the global economy. This issue has become more urgent during the 2020–2024 period, which has been marked by global economic uncertainty, geopolitical tensions, and volatility in energy and financial markets, leading to increased instability in commodity prices. These price fluctuations are not only influenced by domestic market dynamics but also by external factors. Several external factors potentially affecting nickel price changes include geopolitical conditions, global supply and demand, and nickel's role in the new energy industry. Geopolitical conflicts, such as the Russia-Ukraine war, China's dependence as the largest nickel consumer, the rising demand for electric vehicle (EV) batteries, and green energy policies all contribute to driving nickel prices.

Price changes are caused by global economic variables, including inflation and currency exchange rates, especially when nickel is sold in US dollars [2]. The US stock market, the mining sector, exchange rates, the price of crude oil, and the US economy as a whole all have an impact on gold prices [3]. A higher dollar tends to reduce gold prices, according to research employing the GARCH model, which also demonstrates a substantial negative association between the USD exchange rate and gold prices [4]. In the meantime, forward prices, interest rates, and inflation all affect tin prices [5]. A stronger USD can raise commodity costs for nations with different currencies, and global oil prices have an impact on metal prices as well [6]. Historical gold prices and exchange rates from 2004 to 2019 had a positive and statistically significant impact on gold prices in Indonesia, according to an earlier study by [7] that used the Autoregressive Distributed Lag (ARDL) technique. Conversely, there was a negative but statistically insignificant correlation between stock prices and the price of oil globally. Additionally, [8] studied how Indonesia's oil and gas export volume was affected by changes in the USD exchange rate between 2019 and 2023. The study's findings suggest that there is no meaningful causal link between Indonesia's oil and gas export volume and the USD exchange rate. This implies that oil and gas export volumes cannot be predicted by changes in the USD exchange rate, and vice versa. For a more thorough examination, further study is necessary because the link between these components is not always consistent. Most existing studies focus on individual commodities or apply a single econometric approach, leaving limited empirical evidence on the joint behavior of multiple metal prices and their shared global determinants. Consequently, more research is required to improve knowledge of the dynamic interactions between these variables, utilizing the Vector Autoregression (VAR) model. In addition to the VAR model, another statistical approach that can be used to analyze the behavior of response variables simultaneously, which are influenced by several predictor variables, is to use Multiresponse Regression (MRR) [9]. This method enables the simultaneous modeling of multiple response variables, such as nickel, gold, and tin prices, while accounting for potential interrelationships among them. By integrating MRR, the analysis not only focuses on temporal relationships, as in VAR, but also on the structural associations among the response variables, providing a broader perspective on how external factors collectively influence multiple commodities. The integration of VAR and MRR allows this study to capture both dynamic time-based interactions and simultaneous relationships among commodities, offering a broader analytical perspective.

Sims first proposed VAR in 1980 as a method for describing the combined dynamic behavior of a group of variables without the requirement for stringent constraints that are necessary to determine the underlying structural parameters. This method has become one of the most commonly used approaches in time series modeling [10], [11]. Without prescribing a particular causal structure, a VAR model of order pp is a technique for analyzing the dynamic interactions among several variables in a system. In this model, each endogenous variable is represented as a combination of its own past values as well as the past values of other variables in the system, allowing for simultaneous analysis of intervariable relationships. As a result, VAR makes it possible to describe variable interactions in a flexible way, where each variable is impacted by both its own and other variables' historical values [12]. VAR makes it possible to analyze how commodity prices, such as those of nickel, gold, and tin, affect one another over time in the mining industry. Furthermore, the simultaneous correlations between the prices of nickel, gold, and tin (endogenous variables) and silver, global oil, and USD exchange rates (exogenous variables) may be captured by the VAR model. Commodity prices such as nickel, gold, and tin show notable delayed effects in the real world of economics. The price of nickel fluctuates a lot; it peaked in March 2022 at US$33,924 per ton, fell to US$21,481 per ton in July, then rose once more to US$28,946 per ton by the end of the year before steadily falling to US$16,103 per ton in January 2024. Geopolitical and economic uncertainty causes gold, a hedging asset, to fluctuate sharply [13]. In the meantime, export regulations and changes in the price of other industrial metals have a significant impact on tin pricing. The VAR model makes it possible to represent dynamic interactions between economic variables without imposing rigid causality assumptions by taking temporal delays into account. This adaptability makes it possible to comprehend patterns of short- and long-term interactions between commodity prices and other economic variables. However, VAR alone does not explicitly model the simultaneous dependence among multiple response variables, which motivates the complementary use of the MRR approach.

This research is in line with the Sustainable Development Goals (SDGs), particularly SDG 8 (Decent Work and Economic Growth) which emphasizes the importance of commodity price stability in supporting the global economy, SDG 9 (Industry, Innovation, and Infrastructure) which highlights the influence of metal prices on industrial investment and technological development, and SDG 12 (Responsible Consumption and Production) which highlights the need for efficient and sustainable management of natural resources Modeling Nickel, Gold, and Tin Prices with a Vector Autoregression Approach [14]. In line with existing research, no studies have specifically examined the impact of global crude oil prices, USD exchange rates, and silver prices on nickel, gold, and tin prices using the VAR model. Therefore, the researcher is interested in modeling nickel, gold, and tin prices using the VAR approach. The findings of this study are expected to provide valuable insights for investors, industry players, and policymakers in navigating the dynamics of the commodity market. To enhance the depth of analysis, this study also applies the MRR method alongside the VAR model. This dual-method approach enables both the exploration of dynamic temporal interactions and the assessment of simultaneous relationships among the response variables, resulting in a more comprehensive understanding of the factors influencing nickel, gold, and tin prices. This study is unique in that it integrates two complementary statistical approaches: VAR and MRR. While VAR captures the dynamic temporal interactions among variables over time, MRR enables simultaneous modeling of multiple correlated response variables. This combination provides a distinctive analytical framework that not only reveals the time-based causal dynamics but also uncovers the structural relationships among commodity prices. Such a dual approach offers deeper insights into the interconnected behavior of nickel, gold, and tin prices compared to previous studies that relied solely on single-response or univariate time-series models. By incorporating MRR alongside VAR, this study offers a novel comparative framework that enhances the understanding of both dynamic and simultaneous price relationships.

2. RESEARCH METHODS

2.1 Vector Autoregressive

By describing each endogenous variable as a function of the lagged values (up to order p) of all endogenous variables within the system, the reduced-form VAR technique avoids the need for structural modeling. The following is a representation of a p-order VAR model's general form (VAR(p)) [15].

$$\boldsymbol{y_t} = \mu + \boldsymbol{A_1 y_{t-1}} + \boldsymbol{A_2 y_{t-2}} + \cdots + \boldsymbol{A_p y_{t-p}} + \boldsymbol{C x_t} + \boldsymbol{\epsilon_t} \tag{1}$$

with $\boldsymbol{y_t} = \left(y_{1t}, y_{2t}, \dots, y_{qt}\right)'$ is a $q \times 1$ vector of endogenous variables; $\boldsymbol{x_t} = (x_{1t}, x_{2t}, \dots, x_{rt})'$ is a $r \times 1$ vector of exogenous variables; $\boldsymbol{A_1}, \boldsymbol{A_2}, \dots, \boldsymbol{A_p}$ are $q \times q$ matrices of estimated lag coefficients; $\boldsymbol{C}$ is a matrix $q \times r$ of estimated coefficients of exogenous variables; $\boldsymbol{\epsilon_t} = \left(\epsilon_{1t}, \epsilon_{2t}, \dots, \epsilon_{qt}\right)$ is a $q \times 1$ white noise error vector, and it is assumed that $E(\epsilon_t) = 0$, $E(\epsilon_t \epsilon_t') = \Sigma_\epsilon$, and $E(\epsilon_t \epsilon_s') = 0$ for $t \neq s$.

2.2 Stationarity Test

Stationarity is a fundamental requirement in VAR modeling. A time series is considered stationary when its statistical properties, such as the mean, variance, and autocorrelation, remain stable over time. If the data are non-stationary, it may result in misleading or spurious regression outcomes, thereby emphasizing the importance of conducting stationarity tests prior to estimating a VAR model [16].

$$\Delta \boldsymbol{y_t} = \alpha + \beta t + \gamma \boldsymbol{y_t} + \sum_{i=1}^{p} \delta_i \Delta \boldsymbol{y_{t-i}} + \varepsilon_t \,. \tag{2}$$

Hypotheses null $H_0: \gamma = 0$ (unit root exists or non-stationary) versus alternative $H_1: \gamma < 0$ (stationary). If the p-value < significance level (e.g., 0.05), then reject H_0 (stationary). Otherwise, the series is non-stationary.

2.3 Johansen Cointegration Test

The Johansen cointegration test is a statistical technique employed to detect the presence of long-term equilibrium relationships among several non-stationary time series variables. Unlike the Engle-Granger test, which only detects one cointegration relationship, the Johansen test can find multiple cointegrating vectors. The test is based on a Vector Error Correction Model (VECM) derived from a VAR model. The key equation is $\Delta \boldsymbol{y_t} = \mu + \Pi \boldsymbol{y_{t-1}} - \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_j \Delta \boldsymbol{y_{t-i}} + \boldsymbol{C x_t} + \boldsymbol{\epsilon_t}$, where $\Pi = \sum_{i=1}^{p} \boldsymbol{A_i} - \boldsymbol{I}$ represents the long-run relationship matrix and $\boldsymbol{\Gamma_j} = \sum_{j=i+1}^{p} \boldsymbol{A_j}$ captures short-term dynamics. The rank of Π determines the number of cointegrating relationships: if the rank is zero, no cointegration exists; if the rank equals the number of variables, all are stationary. The test uses two statistics - the trace test and the maximum eigenvalue test - to determine the cointegration rank. Before applying the Johansen test, variables must be non-stationary (1), and the appropriate lag length should be selected using information criteria. This method is particularly useful in econometrics for analyzing macroeconomic and financial data where multiple variables may share long-term equilibrium relationships.

2.4 Optimal Lag Determination

Selecting the optimal lag length (p) is crucial in VAR models to balance model fit and parsimony. Using too few lags may miss important dynamics, while too many lags can overfit the data. The most common approach uses information criteria, which penalize model complexity. Key Equations for Lag Selection [12]:

1. Akaike Information Criterion (AIC):

$$AIC(p) = \ln\left|\tilde{\Sigma}_p\right| + \frac{2pq^2}{n}. \tag{3}$$

2. Schwarz Criterion (SC):

$$SC(p) = \ln\left|\tilde{\Sigma}_p\right| + \frac{\ln n}{n} pq^2. \tag{4}$$

3. Hannan-Quinn Criterion (HQ):

$$HQ(p) = \ln\left|\tilde{\Sigma}_p\right| + \frac{2\ln(\ln n)}{n} pq^2. \tag{5}$$

2.5 Determination of Model Stability

In VAR models, stability ensures that the system returns to equilibrium after shocks. A stable VAR(p) model has all its roots lying inside the unit circle (modulus < 1). If any root lies on or outside the unit circle, the process is non-stationary or explosive.

2.6 Impulse Response Function

The Impulse Response Function (IRF) is a tool used in the analysis of VAR models to track how endogenous variables respond over time to shocks or disturbances in other variables within the system. The primary purpose of the IRF is to understand how a shock impacts other variables over a certain time horizon. These shocks are measured in standard deviation units and may produce positive, negative, or negligible effects. The IRF helps isolate and clarify the impact of specific shocks, allowing for a more detailed explanation of their influence. Through IRF analysis, the interactions and reactions among variables in the system are revealed, offering insights into the dynamic relationships within the VAR model [17].

2.7 Variance Decomposition

Variance Decomposition is a method used to break down the total variance of a variable into several components, allowing us to assess the extent to which each variable contributes to that variance. By applying this method, we can determine how much influence a particular variable has on the fluctuations of other variables. In the context of VAR and VECM models, variance decomposition is employed to analyze how different components contribute to the forecasted changes in the variables within the system [12].

2.8 Multiresponse Regression

Multiresponse regression is an extension of multiple linear regression used when there is more than one response variable observed simultaneously and suspected to be influenced by the same set of predictor variables. In other words, this model is used when the observed responses are multivariate and mutually correlated. In general, the multi-regression model can be written in matrix:

$$\boldsymbol{Y} = \boldsymbol{X}\boldsymbol{B} + \boldsymbol{\epsilon} \tag{6}$$

with $\boldsymbol{Y}$ is a matrix of size $n \times q$ containing q response variables for n observations; $\boldsymbol{X}$ is a matrix of size $n \times (r+1)$ containing the predictor variables (including the intercept); $\boldsymbol{B}$ is a regression coefficient matrix of size $(r+1) \times p$; $\boldsymbol{\epsilon}$ is an error matrix of size $n \times q$ assumed to have a mean of zero and covariance Σ.

$$\boldsymbol{Y} = \begin{pmatrix} y_{11} & y_{12} & \cdots & y_{1q} \\ y_{21} & y_{22} & \cdots & y_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ y_{n1} & y_{n2} & \cdots & y_{nq} \end{pmatrix} = \begin{pmatrix} y_1' \\ y_2' \\ \vdots \\ y_n' \end{pmatrix},$$

$$\boldsymbol{X} = \begin{pmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1r} \\ 1 & x_{21} & x_{22} & \cdots & x_{2r} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nr} \end{pmatrix},$$

$$\boldsymbol{B} = (\beta_1, \beta_2, \dots, \beta_q)\,.$$

The regression coefficient parameters in the multivariate response model are estimated using the Ordinary Least Squares (OLS) method, which aims to minimize the sum of squared errors. The estimator of the parameter $\boldsymbol{B}$ is given by:

$$\widehat{\boldsymbol{B}} = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{Y}. \tag{7}$$

Each column of the matrix $\widehat{\boldsymbol{B}}$ represents the regression results for each response variable. For example, the first column represents the coefficients for the model Y_1, the second column for Y_2, and so on. Once $\widehat{\boldsymbol{B}}$ is obtained, the predicted response values can be calculated as:

$$\widehat{\boldsymbol{Y}} = \boldsymbol{X}\widehat{\boldsymbol{B}}. \tag{8}$$

The multivariate response regression model assumes that: $E(\boldsymbol{\epsilon}) = 0$, meaning the error term has a mean of zero; $\mathrm{cov}(y_i) = \Sigma$ for all $i = 1,2,\dots,n$ where y_i' is the i-th row of $\boldsymbol{Y}$; $\mathrm{cov}(y_i, y_j) = 0$ for all $i \neq j$.

2.9 Selection of The Best Method Based on Model Evaluation

The selection of the best method between MRR and VAR is based on the evaluation criteria of R^2, Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). A model with a higher R^2 value and lower MSE and MAPE values is considered to provide better predictive performance.

1. R^2 (Coefficient of Determination):

   Indicates the proportion of variation in the response variable that can be explained by the predictor variables. A higher R^2 value implies that the model explains a greater portion of the data variability. It is calculated as:

$$R^2 = \frac{\sum_{i=1}^{n}\left(\hat{y}_i - \underline{y}\right)^2}{\sum_{i=1}^{n}\left(y_i - \underline{y}\right)^2}. \tag{9}$$

2. Mean Squared Error (MSE):

   Measures the average squared difference between the observed and predicted values. A lower MSE value indicates that the predicted values are closer to the actual observations, reflecting a more accurate model. It is calculated as:

$$MSE = \frac{1}{n-k}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{10}$$

where k is the number of parameters in the model.

3. Mean Absolute Percentage Error (MAPE):

   Measures the average percentage difference between the observed and predicted values. The smaller the MAPE value, the more accurate the model's prediction performance, and it is defined as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\%. \tag{11}$$

3. RESULTS AND DISCUSSION

3.1 Research Variables

The data used is secondary data obtained from the World Bank website and FRED economic data [18], [19]. This study uses 60 data points as the source. In this study, there are three response variables and three predictor variables. Table 1 provides the variables used in the study.

Table 1. Research Variables

Variable	Information	Units	Scale
Y_1	Nickel Price	USD per metric ton (USD/MT)	Ratio
Y_2	Gold Price	USD per troy ounce (USD/oz)	Ratio
Y_3	Tin Price	USD per metric ton (USD/MT)	Ratio
X_1	World Crude Oil Prices	USD per barrel (USD/barrel)	Ratio
X_2	USD Exchange Rate	IDR/USD	Ratio
X_3	Silver Price	USD per troy ounce (USD/oz)	Ratio

The data used in this study consisted of 60 observations from the time period January 2020 to December 2024. The research variables used are divided into two, namely, response variables (Y) and predictor variables (X), each of which consists of 3 variables, with details in Table 1.

3.2 Descriptive Statistics of Research Variables

Descriptive statistics are used to understand the characteristics of the samples in the study based on each variable analyzed. Descriptive statistics for research variables are presented in Table 2.

Table 2. Descriptive Statistics

Variable	Minimum	Maximum	Average
Y_1	11804.01	33924.18	19284.21
Y_2	1560.67	2690.08	1940.17
Y_3	14952.80	43983.35	27269.71
X_1	23.34	120.08	75.18
X_2	11.23	127.81	119.04
X_3	14.88	32.42	23.83

Based on Table 2, it can be seen that each research variable has a different minimum, maximum, and average value range. These values describe the level of variation and central tendency of each variable in the observation period. A more detailed explanation of the characteristics of each variable is presented as follows:

1. Nickel prices (Y_1) experienced significant fluctuations, with a low of USD 11,804.01 in April 2020 due to the COVID-19 pandemic that reduced demand and disrupted supply chains, as well as overproduction from Indonesia and the Philippines. The highest price was USD 33,924.18 in March 2022, triggered by the Russia-Ukraine conflict disrupting global supply, and trading anomalies on the London Metal Exchange (LME) caused a 250% price spike two days before trading was suspended. The average price was USD 19,284.21.
2. Gold prices (Y_2) experienced significant fluctuations, with the lowest price of USD 1,560.67 in January 2020 due to the strengthening of the US dollar, which suppressed demand. In contrast, the highest price of USD 2,690.08 occurred in October 2024, driven by increased demand as a hedging asset and a 40% surge in trading volume. This rise was also influenced by geopolitical uncertainties, such as conflicts in the Middle East and Russia-Ukraine, as well as the Federal Reserve's monetary policy. The average gold price is USD 1,940.17.
3. Tin prices (Y_3) experienced sharp fluctuations, with the lowest price of USD 14,952.80 in April 2020 due to the COVID-19 pandemic, which reduced demand and led to oversupply. In contrast, the highest price of USD 43,983.35 occurred in February 2022 due to declining production from China and Indonesia, where China's production fell 7.7%, and Indonesia's fell 25.4% (yoy). This condition caused tin prices to rise 91% throughout 2021 and jumped 13.74% in early 2022. The average price during the observation period was USD 27,269.71.
4. Crude Oil prices (X_1) have fluctuated. The lowest price of 23.34 USD in April 2020 occurred due to concerns of near-full global storage capacity and falling demand due to the COVID-19 pandemic. In contrast, the highest price was 120.08 USD in June 2022, driven by geopolitical tensions, particularly the Russia-Ukraine conflict, which triggered fears of global energy supply disruptions. The average price is 75.18 USD.
5. The USD Exchange rate (X_2) fluctuated with a low of 11.23 in May 2021 due to the Federal Reserve's policy of keeping interest rates low and increasing dollar liquidity in the global market. In contrast, the highest value of 127.81 occurred in December 2024 due to capital outflows from developing countries as a result of tight monetary policy in the US, which prompted investors to switch to dollar-denominated assets. The average exchange rate was 119.04.
6. Silver prices (X_3) fluctuated, with a low of 14.88 USD in March 2020 due to economic uncertainty caused by COVID-19, which prompted investors to sell risky assets to increase liquidity. In contrast, the highest price of 32.42 USD occurred in October 2024, driven by rising gold prices and global economic uncertainty that increased demand for silver as a hedging asset. The average price of silver is 23.83 USD.

3.3 Stationarity Test

The data stationarity test can be done by the graph method and the ADF test method. A time series data is said to be stationary if its average and variance tend to be constant over time [20]. If the absolute t statistical value is greater than the critical value in the MacKinnon table at the 1%, 5%, and 10% significance levels, then this indicates that the data is stationary. In addition, data can be said to be stationary if the probability value is smaller than 0.05 [21]. The following are the results of stationarity testing.

Table 3. Stationarity Test

Variable	DF	Prob	Conclusion
World Crude Oil Prices (X_1)	-1.347885	0.6015	Non-stationary
USD Exchange Rate (X_2)	-1.502364	0.5254	Non-stationary
Silver Price (X_3)	-1.514391	0.5195	Non-stationary
Nickel Price (Y_1)	-2.252700	0.1096	Non-stationary
Gold Price (Y_2)	0.637805	0.9897	Non-stationary
Tin Price (Y_3)	-2.233355	0.1971	Non-stationary

Based on Table 3, it can be seen that none of the variables are stationary. Therefore, it is necessary to do differencing one on all variables. The following are the results of the data stationarity test after differencing by one.

Table 4. Stationarity Test After Differencing by One

Variable	DF	Prob	Conclusion
World Crude Oil Prices (X_1)	-5.937117	0.0000	Stationary
USD Exchange Rate (X_2)	-5.183381	0.0000	Stationary
Silver Price (X_3)	-6.168290	0.0000	Stationary
Nickel Price (Y_1)	-5.811677	0.0000	Stationary
Gold Price (Y_2)	-5.774405	0.0000	Stationary
Tin Price (Y_3)	-4.493043	0.0000	Stationary

Based on Table 4, it can be seen that all research variables used are stationary after differencing by one, so the analysis can be continued to determine the optimal lag.

3.4 Optimal Lag Determination

Choosing the optimal lag length in a VAR model is essential for obtaining reliable and efficient estimates. An underspecified lag (too short) might overlook important dynamics among the variables, whereas an overly long lag can reduce degrees of freedom, particularly in smaller samples, potentially compromising the model's performance. Hence, determining the appropriate lag length is a critical component of the VAR modeling process [22]. Optimal lag also plays an important role in cointegration analysis. The determination of the optimal lag is based on certain recommended criteria, such as LR, FPE, AIC, SC, and HQ [23] [24]**.** The optimal lag value is indicated by criteria that have an asterisk (*) as presented in Table 5.

Table 5. Optimal Lag Determination

Lag	LR	FPE ($\times 10^{16}$)	AIC	SC	HQ
0	NA	4.88	46.94078	47.05128*	46.98340
1	23.85054*	4.23*	46.79711*	47.23910	46.96757*
2	11.34340	4.66	46.88909	47.66258	47.18740
3	4.618269	5.90	47.11746	48.22245	47.54362
4	8.388438	6.82	47.24620	48.68269	47.80020
5	5.314362	8.50	47.43968	49.20767	48.12153

Determining the optimal lag length is done by selecting the lag that has the highest number of asterisks (*). In Table 5, it can be seen that there are four stars, namely from the LR, FPE, AIC, and HQ criteria, on the first lag, so the optimal lag is one.

3.5 Johansen Cointegration Test

The cointegration test in this study aims to assess whether variables that become stationary at the same differencing level form an integrated process and share a long-term relationship. If no cointegration is found, the VAR model is appropriate; however, if cointegration exists, the VECM model is more suitable. The decision is based on the trace statistic: when its value is lower than the 5% critical value, it suggests that there is no cointegration, or long-term relationship, among the variables [25].

Table 6. Johansen Cointegration Test

Cointegration	Trace Statistics	Critical T-value	p-value
None	17.58830	29.79707	0.5966
At Most 1	6.001185	15.49471	0.6954
At Most 2	0.461185	3.841465	0.4971

The following hypothesis is used in the Johansen cointegration test: H_0: There is no cointegration (no long-run relationship) between the variables in the system; H_1: There is at least one cointegrating relationship between the variables in the system. H_0 is rejected if the p-value is less than $\alpha = 5\% = 0.05$.

Based on Table 6, the probability values in the rows labeled None, At Most 1, and At Most 2 all exceed 0.05, indicating the absence of a cointegration equation. This suggests that there is no long-term equilibrium relationship among crude oil prices, the USD exchange rate, and the prices of silver, nickel, gold, and tin. In other words, these variables do not exhibit a mutual adjustment toward long-run equilibrium. Since the data are stationary at the first difference and no cointegration is found, the analysis proceeds with a VAR model to explore the short-term relationships between the variables.

3.6 VAR Model Estimation

The model estimation aims to determine whether the lag of a variable has a significant influence by assessing the absolute value of the t-statistic. Significance is evaluated by comparing the t-statistic value with the predetermined critical value. In this study, the following hypotheses are used: H_0 = The response variable is not significantly influenced by the predictor variable; H_1 = The response variable is significantly influenced by the predictor variable. H_0 is rejected if the t-statistic > t critical or < $-t$ critical.

The interpretation of the VAR model estimation results is as follows. After estimating the variables, a VAR model that includes significant variables is obtained. The estimated VAR model can be expressed as follows.

$$D(Nickel) = \ 501.7216\, D(Silver). \tag{12}$$

Based on the model above, an increase in the price of silver by one USD per troy ounce causes a change in the price of nickel by 501.7216 USD per metric ton.

$$D(Gold) = \ 27.74111\, D(Silver). \tag{13}$$

Based on the model above, an increase in the price of silver by one USD per troy ounce causes a change in the price of gold by 27.74111 USD per troy ounce.

$$D(Tin) = \ 0.436142\, D\big(Tin(-1)\big). \tag{14}$$

Based on the model above, an increase in the price of tin one month ago by one USD per metric ton causes a change in the price of tin by 0.436142 USD per metric ton.

$$D(Tin) = -436.3142\, D(Exchange_{rate}). \tag{15}$$

Based on the model above, a one-point decrease in the exchange rate index causes a change in the price of tin by 436.3142 USD per metric ton.

$$D(Tin) = \ 443.5582\, D(Silver) \tag{16}$$

Based on the model above, an increase in the price of silver by one USD per troy ounce causes a change in the price of tin by 443.5582 USD per metric ton.

3.7 Determination of Model Stability

In the VAR method, it is necessary to conduct a model stability test because if the estimated VAR model is not stable, then the IRF and VDC analyses become invalid. Based on this test, a VAR system is considered stable if all its roots have a modulus of less than one [26] [27].

Table 7. Model Stability Test

Root	Modulus
0.481805	0.481805
0.105154	0.105154
0.097639	0.097639

Based on the stability test results in Table 7, the model's stability can be assessed from the modulus values in the roots table. If the largest modulus value is less than 1 and at the optimal point, the VAR model is considered stable. According to the stability test results in Table 7, the model is confirmed to be stable. This is evident from the modulus values, which remain below one. Additionally, the plot of the inverse roots of the AR characteristic polynomial is presented to further illustrate the stability analysis results.

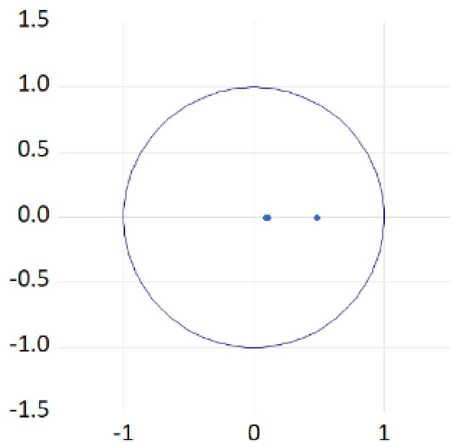
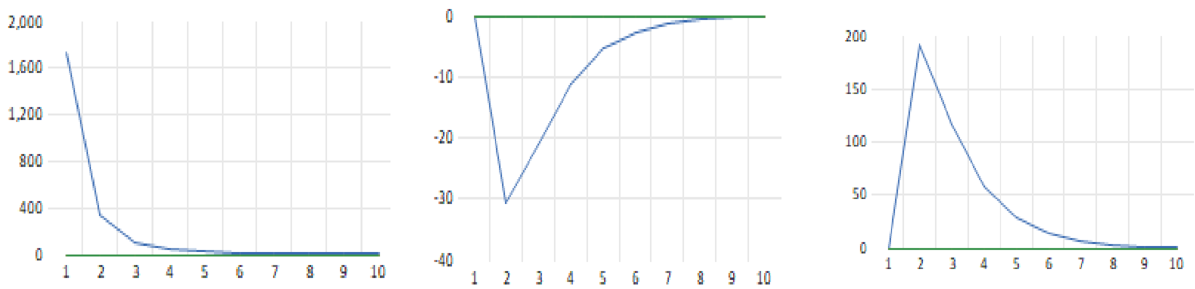


Figure 1. Plot Inverse Roots of AR Characteristic Polynomial

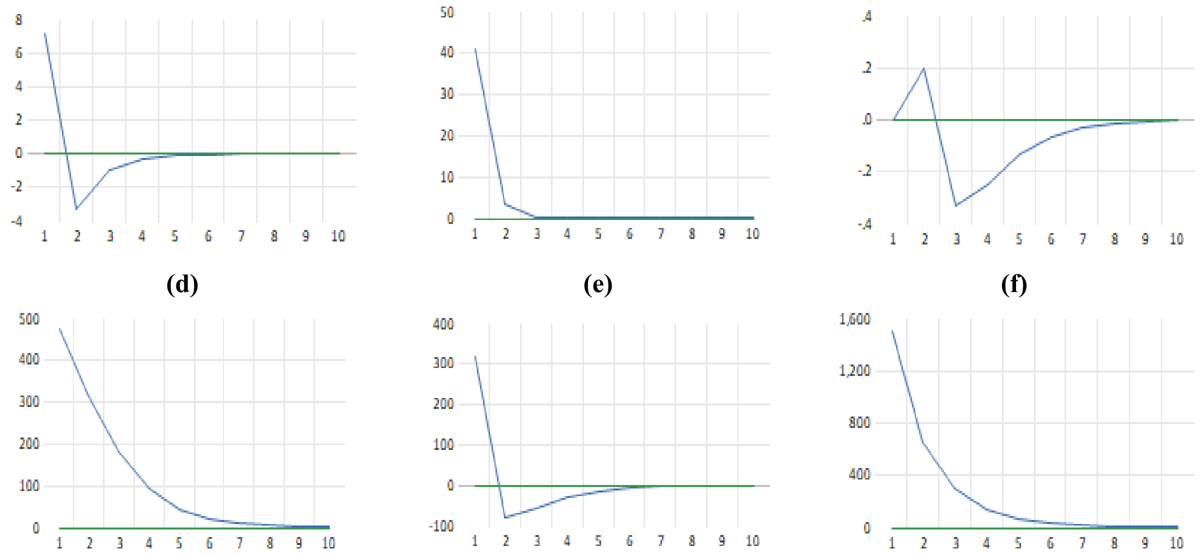
Based on Fig. 1, it can be observed that the distribution of root values and modulus points lies within the circle, meaning their values are less than one. Therefore, it can be concluded that the model used is stable, which indicates that the IRF and VDC analysis results are valid.

3.8 Analysis of Impulse Response Function

IRF (Impulse Response Function) shows how changes in an endogenous variable are influenced by shocks to other endogenous variables [28]. The IRF (Impulse Response Function) graph illustrates the response of a variable to a shock over time, with the horizontal axis representing the time period and the vertical axis indicating the response value. The response can be positive or negative, with significant fluctuations in the short term and a tendency to stabilize in the long term. If the response line is above zero, the impact is positive; if it is below zero, the impact is negative [25]. The results of the IRF analysis are presented in Fig. 2.



(a) **(b)** **(c)**



(d) (e) (f)

(g) (h) (i)

Figure 2. IRF Analysis Result Chart (a) Response of D(Nickel) to D(Nickel), (b) Response of D(Nickel) to D(Gold), (c) Response of D(Nickel) to D(Tin), (d) Response of D(Gold) to D(Nickel), (e) Response of D(Gold) to D(Gold), (f) Response of D(Gold) to D(Tin), (g) Response of D(Tin) to D(Nickel), (h) Response of D(Tin) to D(Gold), and (i) Response of D(Tin) to D(Tin)

Based on Fig. 2, it can be explained that IRF analysis can also be conducted by examining the IRF values for each period or cumulatively. This approach provides insight into the development of variable responses after a shock over a certain time frame. The IRF value per period indicates the response of a variable at each point in time, while the cumulative value represents the total impact of the shock over time. Through this approach, it can be observed whether the effect of the shock increases, decreases, or returns to its initial condition. The IRF values for each period over 10 periods are presented in Table 8 below.

Table 8. Results of IRF Analysis of Nickel, Gold, and Tin Price Variables

Period	IRF Nickel Price			IRF Gold Price			IRF Tin Price		
	Nickel	Gold	Tin	Nickel	Gold	Tin	Nickel	Gold	Tin
1	1726.209	0.000000	0.00000	7.140056	41.15505	0.000000	477.0459	317.8882	1500.260
2	340.1639	-30.46665	192.3996	-3.265671	3.321481	0.199570	313.3602	-79.29493	654.3272
3	103.2509	-21.06022	116.0408	-0.986663	0.322903	-0.331525	182.1645	-54.69885	300.2738
4	42.49566	-11.12819	58.66719	-0.287540	0.066010	-0.248510	93.23459	-27.31243	142.3381
5	19.62677	-5.495094	28.58583	-0.106470	0.026756	-0.133346	45.70934	-13.18425	68.25947
6	9.358785	-2.664557	13.80931	-0.046723	0.012787	-0.066096	22.12675	-6.347465	32.84690
7	4.498045	-1.285873	6.657517	-0.021913	0.006191	-0.032081	10.67373	-3.057016	15.82080
8	2.165938	-0.619787	3.208087	-0.010483	0.002990	-0.015485	5.144218	-1.472687	7.621945
9	1.043421	-0.298645	1.545724	-0.005042	0.001442	-0.007464	2.478694	-0.709520	3.672223
10	0.502710	-0.143892	0.744743	-0.002428	0.000695	-0.003597	1.194268	-0.341847	1.769288

From Table 8, the following observations can be made:

1. Nickel Price Responses

   Nickel prices exhibit a strong and immediate response to shocks in their own prices, followed by a gradual decline toward equilibrium within several periods. This pattern indicates that nickel price dynamics are largely driven by commodity-specific factors. Shocks originating from gold and tin prices generate only temporary effects on nickel prices, with gold price shocks producing a short-lived negative response and tin price shocks inducing a brief positive response. These cross-commodity effects quickly dissipate, suggesting limited and non-persistent spillover influences on nickel prices.

2. Gold Price Responses

   Gold prices respond sharply to shocks in their own prices, reflecting gold's sensitivity to global economic uncertainty and its role as a safe-haven asset. In contrast, shocks from nickel and tin prices result in relatively small and short-lived responses that fade within a few periods. This finding suggests that gold price movements are primarily influenced by broader macroeconomic and financial conditions rather than by fluctuations in industrial metal prices.

3. Tin Price Responses

   Tin prices show a pronounced immediate response to shocks in their own prices, followed by a rapid convergence toward stability. Shocks from nickel and gold prices initially generate positive responses in tin prices; however, these effects weaken and reverse over time before disappearing. This indicates that although tin prices may react to movements in other metals in the short term, such interactions are not sustained and do not exert long-term influence on tin price dynamics.

Overall, the IRF results indicate that nickel, gold, and tin prices are predominantly driven by their own shocks, while cross-commodity effects remain temporary and limited in magnitude. This highlights the dominance of commodity-specific dynamics over prolonged interdependence among metal prices during the study period.

3.9 Analysis of Variance Decomposition

Variance Analysis aims to measure the extent to which the movement of a variable is influenced by shocks from the variable itself and compare it with the impact exerted by other variables in an equation. VDC separates the total variance based on the variance of other variables, allowing the identification of the extent to which a particular variable contributes to the overall variance [29]. The VDC results are presented in the following table.

Table 9. Results of VDC Analysis of Nickel, Gold, and Tin Price Variables

Period	IRF Nickel Price			IRF Gold Price			IRF Tin Price		
	Nickel	Gold	Tin	Nickel	Gold	Tin	Nickel	Gold	Tin
1	100.0000	0.000000	0.000000	2.921985	97.07801	0.000000	8.822680	3.917679	87.25964
2	98.78901	0.029623	1.181367	3.489759	96.50799	0.002255	10.46799	3.449210	86.08280
3	98.35800	0.043437	1.598565	3.542487	96.44904	0.008471	11.08431	3.407035	85.50865
4	98.24807	0.047278	1.704653	3.546866	96.44117	0.011964	11.24957	3.398900	85.35153
5	98.22198	0.048214	1.729810	3.547448	96.43958	0.012969	11.28959	3.397023	85.31339
6	98.21589	0.048434	1.735680	3.547558	96.43923	0.013216	11.29899	3.396585	85.30443
7	98.21447	0.048485	1.737044	3.547582	96.43914	0.013275	11.30117	3.396483	85.30234
8	98.21414	0.048497	1.737360	3.547587	96.43912	0.013288	11.30168	3.396459	85.30186
9	98.21407	0.048499	1.737434	3.547588	96.43912	0.013291	11.30180	3.396453	85.30175

In Table 9, the VDC analysis shows that Nickel Prices in the first period are entirely determined by themselves, accounting for 100%. In the second period, Nickel Prices are explained by themselves at 98.79%, while the remaining variance is explained by Gold Prices and Tin Prices at 0.03% and 1.18%, respectively. By the tenth period, Nickel Prices explained by their own past values amount to 98.21%. This indicates that fluctuations in Nickel Prices are largely influenced by their own movements rather than the relatively small influence of Gold Prices and Tin Prices. Additionally, the VDC analysis shows that in the first period, Gold Prices are determined by themselves at 97.08%, while the remaining 2.92% is influenced by Nickel Prices, with Tin Prices having no effect. In the second period, the influence of Gold Prices on themselves decreases to 96.51%, while the influence of Nickel Prices increases to 3.49%, and Tin Prices start to contribute at 0.002%. Over time, the proportion of Gold Prices explaining their own variance slightly declines, reaching 96.44% in the fourth period. By the end of the period, Gold Prices explain themselves by 96.439%, while Nickel Prices account for 3.548% and Tin Prices around 0.013%. This indicates that fluctuations in Gold Prices are primarily influenced by their own movements, though the impact diminishes slightly over time, while the influence of Nickel and Tin Prices increases but remains relatively small. Meanwhile, the VDC analysis shows that in the first period, Tin Prices are determined by themselves at 87.26%, while the remaining 8.82% is influenced by Nickel Prices and 3.92% by Gold Prices. In the second period, the influence of Tin Prices on themselves decreases to 86.08%, while the influence of Nickel Prices increases to 10.47%, and the influence of Gold Prices decreases to 3.45%. Over time, the proportion of Tin Prices explaining their own variance slightly declines, reaching 85.35% in the fourth period. By the end of the period, Tin Prices explain themselves at 85.30%, while Nickel Prices contribute 11.30%, and Gold Prices around 3.40%. This suggests that fluctuations in Tin Prices are largely influenced by their own past values, although the impact decreases slightly over time. Meanwhile, the influence of Nickel Prices increases, and the influence of Gold Prices decreases, though both remain relatively small. This finding is consistent with previous studies such as [2]-[5], which also showed that fluctuations in nickel, gold, and tin prices are predominantly influenced by their own past values, while the effects of other commodities remain relatively small.

3.10 Multiresponse Regression

Multiresponse regression analysis was used to determine the effect of predictor variables, namely oil, USD, and silver, on three response variables, namely nickel, gold, and tin prices. The test was conducted by considering the simultaneous relationship between response variables to avoid model bias arising from correlations between responses.

Table 10. Multivariate Test

Variable	F	Sig.	Partial Eta Squared	Interpretation
World Crude Oil Prices	48.731	0.000	0.730	Significant multivariate effect
USD Exchange Rate	73.619	0.000	0.804	Significant multivariate effect
Silver Prices	125.100	0.000	0.874	Strongest joint influence

Based on Table 10 can be explained that the multivariate test indicates that changes in oil, USD, and silver significantly affect the overall pattern of movement among the three metal prices. The strong effect of silver highlights its interconnectedness with both industrial and precious metal markets, consistent with global commodity co-movement theories. The Between-Subjects Effects test decomposes the overall multivariate significance into the impact of each predictor variable on each response variable separately. Results summarized in Table 10 show that all models are statistically significant across the three response variables (Sig. = 0.000). Oil significantly affects nickel and tin, but its influence on gold is relatively weaker. The USD variable significantly influences all three metals, with the strongest effect observed on gold prices. Meanwhile, silver has a very strong impact on gold and tin, but not on nickel (Sig. = 0.132).

Table 11. Test Between-Subjects Effects

Response Variable	Predictor Variable	F Value	Sig.	Partial Eta Squared	Interpretation
Nickel	World Crude Oil Prices	86.513	0.000	0.607	Significant positive effect
	USD Exchange Rate	4.919	0.031	0.079	Significant negative effect
	Silver Prices	2.335	0.132	0.048	Not Significant
Gold	World Crude Oil Prices	5.892	0.016	0.099	Weak significant effect
	USD Exchange Rate	126.623	0.000	0.693	Strong significant effect
	Silver Prices	356.691	0.000	0.864	Strongest effect
Tin	World Crude Oil Prices	68.463	0.000	0.550	Strong positive effect
	USD Exchange Rate	21.721	0.000	0.267	Significant negative effect
	Silver Prices	17.271	0.000	0.236	Significant positive effect

Based on Table 11 can be explained that the results indicate that oil price fluctuations primarily affect industrial metals such as nickel and tin, while their impact on precious metals like gold is relatively limited. This suggests that energy market dynamics are more closely tied to the sector's response to industrial production and manufacturing demand. Furthermore, the USD exchange rate demonstrates a broad and significant influence across all metal categories, underscoring its pivotal role as the world's primary trade and reserve currency that affects commodity pricing globally. Lastly, silver exhibits the highest explanatory power for gold, reaffirming the strong historical co-movement between these two precious metals as safe-haven assets that investors tend to favor during periods of financial instability or economic uncertainty.

Table 12. Parameter Estimation

Response Variable	Predictor Variable	B	t	Sig.	Effect Direction
Nickel	World Crude Oil Prices	192.989	9.301	0.000	Positive
	USD Exchange rate	-216.498	-2.217	0.031	Negative
	Silver Prices	-168.192	-1.529	0.132	None
Gold	World Crude Oil Prices	-1.461	-2.477	0.016	Negative
	USD Exchange rate	31.226	11.253	0.000	Positive
	Silver Prices	59.056	18.886	0.000	Positive
Tin	World Crude Oil Prices	243.216	8.274	0.000	Positive
	USD Exchange rate	-644.689	-4.661	0.000	Negative
	Silver Prices	647.780	4.156	0.000	Positive

Based on Table 12 can be explained that the parameter estimates reveal distinct directional relationships among the examined variables. Oil prices exhibit a positive influence on industrial metals such as nickel and tin, but a negative effect on gold, suggesting that rising energy costs tend to boost industrial activity and demand for base metals while reducing investment interest in non-industrial commodities like gold. The U.S. dollar (USD) shows a negative relationship with base metals yet a positive relationship with gold, reflecting the tendency of gold to serve as a hedge against currency depreciation, whereas stronger dollar conditions often suppress demand for industrial commodities. Meanwhile, silver demonstrates a strong positive association with both gold and tin, but its relationship with nickel is statistically insignificant. This finding is consistent with economic theory: industrial metals are closely linked to production and energy costs, precious metals are sensitive to exchange rate movements, and silver often co-moves with gold due to their shared role as safe-haven assets in times of market uncertainty.

3.11 Comparison of VAR and MRR Methods

The selection between VAR and MRR methods fundamentally depends on the nature of the data, research objectives, and the interdependence structure among variables. Although both techniques handle multiple variables simultaneously, their conceptual foundations, analytical objectives, and interpretation scopes differ substantially. The VAR model is primarily designed for time series analysis, emphasizing the dynamic interrelationship among variables over time. Each variable in a VAR system is treated as an endogenous variable, explained by its own past values and those of other variables. This allows researchers to explore causality, temporal responses, and shock propagation through mechanisms such as IRF and VD. In contrast, the MRR approach focuses on the simultaneous estimation of multiple response variables as functions of one or more predictors. It assumes that the predictor variables influence all response variables, which may themselves be correlated. The method does not model time dynamics but rather seeks to uncover structural and cross-sectional relationships between predictors and responses within a given period.

Table 13. Quantitative Comparison Between VAR and MRR

Model	Predictor Variable	Rsquare (R^2)	MSE	MAPE(%)
MRR	Nickel	0.608	9335133.085	11.7795
	Gold	0.891	7539.9194	3.4712
	Tin	0.667	18735555	14.3242
VAR	Nickel	0.338864	44790328.15	22.41839
	Gold	0.583771	40145.74097	9.350347
	Tin	0.529091	39537390.94	14.02012

Based on Table 13, the MRR model demonstrates superior overall performance compared to the VAR model in terms of explanatory power and predictive accuracy. The higher coefficient of determination obtained from the MRR model indicates that global factors, namely world crude oil prices, the USD exchange rate, and silver prices, play a substantial role in jointly explaining variations in nickel, gold, and tin prices. This finding suggests that simultaneous modeling is effective in capturing the common influence of global economic drivers across multiple commodities.

The lower MSE and MAPE values produced by the MRR model further indicate more stable and accurate predictions, particularly for gold prices, which are strongly influenced by global financial conditions. These results imply that the MRR approach is well suited for identifying dominant external determinants and for comparative forecasting purposes across related commodities. Nevertheless, the VAR model retains important advantages despite its relatively lower predictive performance. The VAR framework explicitly incorporates lagged dynamics and feedback effects, enabling the analysis of short-term adjustments and shock transmission mechanisms through tools such as Impulse Response Functions and Variance Decomposition. Consequently, VAR is more appropriate for examining dynamic responses to economic shocks, whereas MRR is preferable when the research objective focuses on simultaneous relationships and overall explanatory strength. Therefore, rather than serving as competing approaches, VAR and MRR provide complementary insights. The combined use of both methods enhances the robustness of the analysis by capturing both dynamic temporal interactions and contemporaneous structural relationships among nickel, gold, and tin prices. Building on the comparison between VAR and MRR methods, the following subsection discusses how the findings relate to and extend existing studies on multi-metal price dynamics.

3.12 Discussion in Relation to Existing Literature

The findings of this study are generally in line with previous research on metal price dynamics, which highlights the existence of interdependencies and adjustment processes among commodity prices. Earlier studies have shown that metal prices tend to move together and respond to both market-specific and broader economic shocks. The results obtained from the VAR analysis support this view by confirming that gold, tin, and nickel prices are dynamically connected and influence one another over time.

Despite this consistency, the present study offers several extensions to the existing literature. Most prior research concentrates on a single metal, particularly gold, or examines relationships between two commodities at a time. By modeling gold, tin, and nickel prices simultaneously, this study provides a more comprehensive view of cross-metal interactions. The results suggest that shocks in industrial metals such as tin and nickel lead to response patterns that differ from those associated with gold. This distinction reflects the different economic roles of precious and industrial metals and emphasizes the importance of analyzing them within a joint framework.

This study also contributes by combining vector autoregression and multiresponse regression approaches. Previous studies often apply these methods separately, focusing either on dynamic interactions over time or on contemporaneous relationships across variables. The integration of VAR and MRR in this study allows both aspects to be examined together. The VAR model captures how price shocks propagate across metals over time, while the MRR model highlights differences in the magnitude of simultaneous price responses. Together, these approaches provide a more complete picture of metal price behavior than either method alone.

The comparison between the two modeling approaches further reveals that certain cross-metal effects are more clearly identified in the multiresponse regression results. While the VAR model emphasizes dynamic feedback mechanisms, the MRR framework uncovers heterogeneous response patterns across metals that may be less visible in a purely time series setting. This finding suggests that important differences in price behavior can be overlooked when relying on a single econometric approach, particularly in markets characterized by diverse demand structures and industrial applications. In summary, this study not only confirms existing empirical evidence on metal price interactions but also extends the literature by offering a joint analysis of gold, tin, and nickel prices using complementary econometric methods. The results provide new insights into asymmetric cross-metal relationships and varying adjustment processes, contributing to a deeper understanding of multi-metal price dynamics. These findings have practical relevance for investors, analysts, and policymakers who seek to better understand risk transmission and diversification opportunities in commodity markets.

4. CONCLUSION

Descriptive statistics show significant fluctuations in nickel, gold, and tin prices, with average values of 19,284.21; 1,940.17; and 27,269.71, respectively. The predictor variables, global crude oil prices, the USD exchange rate, and silver prices, also exhibit notable variability, indicating potential external influences on metal price dynamics. The VAR model estimation identifies several significant relationships, where silver prices strongly affect nickel and gold prices, while both silver and the exchange rate significantly influence tin prices. The IRF confirms model stability, with all roots lying within the unit circle. The VDC analysis shows that nickel, gold, and tin prices are primarily driven by their own past values, with relatively small cross-commodity effects. Based on model evaluation using three statistical criteria, coefficient of determination (R^2), MSE, and MAPE, the MRR model outperforms the VAR model, achieving higher R^2 (0.608–0.891), lower MSE, and smaller MAPE (3.47%–14.32%). This indicates that MRR provides better explanatory power and predictive accuracy in modeling metal price behavior. Overall, these findings enhance understanding of commodity price dynamics and their determining factors, offering valuable insights for investors, industry stakeholders, and policymakers in managing price volatility and designing effective investment strategies. Future research is encouraged to include additional macroeconomic variables, extend the observation period, and apply alternative models for broader comparative analysis.

Author Contributions

Suliyanto: Conceptualization, Methodology, Formal Analysis, Writing – Review and Editing. Dita Amelia: Supervision, Data Curation, Investigation, Writing – Review and Editing. Gabriella Agnes Budijono: Formal Analysis, Validation, Visualization, Writing – Review and Editing. Rere Fetri Damanik: Software, Data Curation, Project Administration, Visualization. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare that has no conflicts of interest to report.

Declaration of Generative AI and AI-assisted Technologies

Generative AI tools (e.g., ChatGPT) were used solely for language refinement, including grammar, spelling, and clarity. The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. All final text was reviewed and approved by the authors.

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