Interactions among International Commodities, Macroeconomic Variables, Foreign Capital Market, and Mining Sector Index in Indonesia

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Abstract

Indonesia has the most mineral resources in the world. However, Indonesia's mining sector's stock index has been trending downward for over a decade. This study aims to determine the factors that influence Mining Sector Index in Indonesia. Using the Vector Error Correction Model (VECM), we try to find short- and long-term effects and causal relationships between international commodities (crude oil and nickel), macroeconomic (exchange rate), foreign capital market (Shanghai Composite Index), and Mining Sector Index. The VECM indicates that the mining sector is sensitive to global commodity price fluctuations. Additionally, changes in mining stock prices can cause changes in the Chinese Yuan/Indonesian Rupiah exchange rate. This study also found that changes in crude oil, nickel, exchange rate, and the Shanghai Composite Stock Index have significant short-term and long-term effects on Indonesia's Mining Sector Stock Index. This study has implications for policymakers and investors that should pay attention to the commodity prices, especially the mining sector's performance, to ensure currency stability.

Keywords: International Commodities, Macroeconomic, Capital Market, Mining Sector Index

JEL Classifications: Q02, F21, F31, F32

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1. Introduction

Liberalization of cross-border capital movements and financial system reform increased linkages between world financial markets. In addition, the development of information technology that facilitates the spread of information worldwide can reduce domestic market segmentation and increase the likelihood of being affected by shocks from world financial markets (Ng et al., 2017).

The global financial crisis in 2007 experienced by many countries, especially developing countries, including Indonesia, could directly affect the economy, in this case, the performance of the capital market. The capital market is part of the financial system and is an important part that can describe the condition of a country's economic and financial health. In addition, the capital market can also act as a vehicle for investors who want to channel funds for investment and for traders who want to take short-term profits from buying and selling transactions. To find out the performance of the capital market easily, we can use a market index that provides a performance measure for some stocks (Antono et al., 2019; Tripathi et al., 2014).

After the global financial crisis, there has been a significant increase in interest in risk diversification by exploring several alternative financial assets that can be used (Rizvi & Arshad, 2018). However, the fundamental question that must be considered is whether financial assets are predictable (Charles et al., 2017). Fama (1965) developed a hypothesis about the efficient market hypothesis (EMH), which states that asset prices as a whole immediately reflect all relevant variables and information. Therefore, discussions about the capital market and other factors influencing each other are still interesting.

This study examines world oil prices and nickel prices as international commodities, Chinese Yuan/Indonesian Rupiah as macroeconomic, the Shanghai Composite Index as foreign capital market, and the stock index of the mining sector in Indonesia. We will discuss several variables closely related to the capital market by looking at short- and long-term effects and causal relationships.

We chose sectoral indices, especially the mining sector, for several reasons. (1) Each sector's response to events beyond control may differ (Dharani et al., 2022). Therefore, sectoral differences will likely have different responses from several factors that can affect the stock index. (2) Indonesia has the most mineral resources globally and is committed to increasing investment in the mining sector in the following years (OCallaghan, 2010). (3) Indonesia's mining sector's stock index has been trending downward for over a decade. So, if investment in the mining sector does not increase, it can affect economic growth in Indonesia (Antono et al., 2019).

Crude oil is a vital energy source that is needed by industry, especially in developing countries (Sakaki, 2019). The oil price is closely related to the company's operational activities and the stock price. Several different research results exist on the relationship between oil and stock prices. Several studies have found an asymmetry effect between oil and stock prices (Herrera et al., 2019;

Sim & Zhou, 2015; Wei & Guo, 2017; Zhang et al., 2020). Oil prices can positively influence stock prices (Phan et al., 2015). On the other hand, oil prices can also negatively influence stock prices (Diaz et al., 2016; Smyth & Narayan, 2018).

Previous research on nickel prices focused on types of nickel prices, such as future, spot, and trade prices. In addition, factors that affect nickel prices such as supply, demand, and other factors such as country (Chen et al., 2016; Gustafsson et al., 2022; Lee et al., 2022; Ozdemir et al., 2022; Sun et al., 2021). To the author's best knowledge, there is still little research linking nickel prices and stock prices or stock returns.

In addition to using oil and nickel prices to see their effect on stock prices, we also use the exchange rate because there is little previous research that focuses on the analysis of oil prices, exchange rates, and stock prices (Delgado et al., 2018). Like research between oil and stock prices, previous research on exchange rates and stock prices has mixed results. Starting from asymmetry relationships, positive relationships, and negative relationships (Afshan et al., 2018; Cao, 2012; Dahir et al., 2018; Delgado et al., 2018; Li et al., 2018; Liu & Wan, 2012; Mroua & Trabelsi, 2020; Nusair & Al-Khasawneh, 2022; Rutledge et al., 2014; Zhao, 2010).

We also use stock price indexes from other countries, such as China, namely the Shanghai Composite Index, to see the effect on stock prices in Indonesia. Financial market conditions in one country often affect other countries' financial markets. Likewise, the condition of the capital market of a country will affect the capital market of other countries (Chien et al., 2015; Hung et al., 2022; Ichsani et al., 2019; Mensi et al., 2021; Shan et al., 2022; Shi, 2022; Zhong & Liu, 2021). We use the Renminbi or Chinese Yuan exchange rate against the Indonesian Rupiah and the Shanghai Composite Index because China is one of the countries that have the most significant investment in Indonesia. So, it is essential to see the effect of the exchange rate of the Renminbi or Chinese Yuan on the Indonesian Rupiah and the Shanghai Composite Index on the stock prices of companies in Indonesia.

The primary research question seeks to delve into the dynamics of the Mining Sector Index in Indonesia by identifying the key factors that exert influence. Despite the nation's possession of abundant mineral resources, the persistent downward trend in the mining sector's stock index over the past decade prompts an investigation into the underlying causes. This question sets the stage for a comprehensive exploration of the multifaceted variables influencing the mining sector's performance.

A subsequent set of research questions addresses the role of international commodities, specifically crude oil, and nickel, in shaping the short-term and long-term effect of the Mining Sector Index. By scrutinizing the short-term and long-term effects of these commodities, the study aims to unravel the nuanced relationships between global commodity markets and Indonesia's mining sector. These questions underscore the importance of understanding how fluctuations in international commodities can influence the day-to-day operations as well as the sustained growth or decline of the mining sector in the Indonesian context.

Macro-economic factors are also brought into focus through another research question, aiming to unravel the connection between the exchange rate and the Mining Sector Index. This exploration recognizes the role of broader economic conditions in shaping the performance of the mining sector, adding a layer of complexity to the investigation. Additionally, the study delves into the impact of the foreign capital market, represented by the Shanghai Composite Index, on the Mining Sector Index. This question highlights the interconnectedness of global financial markets and their potential repercussions on the mining industry within Indonesia.

The research questions collectively guide the study towards employing the Vector Error Correction Model (VECM) to uncover causal relationships among international commodities, macroeconomic factors, foreign capital market indicators, and the Mining Sector Index. This analytical approach is chosen to provide a nuanced understanding of the intricate interplay between these variables, capturing both short-term fluctuations and long-term trends. Ultimately, the research questions culminate in an exploration of the implications of the study's findings for policymakers and investors, emphasizing the practical significance of the research in informing decision-making processes related to currency stability and strategic investments in the Indonesian mining sector.

The results of this study have important implications for investors in the mining sector in Indonesia. First, the study found that changes in WTI and nickel prices can cause changes in mining stock prices in Indonesia, suggesting that the mining sector is sensitive to global commodity price fluctuations. Therefore, investors in the mining sector should closely monitor changes in these commodity prices to make informed investment decisions. Second, changes in mining stock prices can cause changes in the Chinese yuan/Indonesian rupiah exchange rate, implying that the mining sector's performance in Indonesia could potentially impact the stability of the Indonesian currency exchange rate with China. Thus, policymakers and investors should pay attention to Indonesia's mining sector's performance to ensure currency stability. Finally, the study found that changes in World Oil, Nickel, Yuan Exchange Rate, and the Shanghai Composite Stock Index have significant short-term and long-term effects on Indonesia's Mining Sector Stock Index. Therefore, investors in the mining sector should also closely monitor changes in these variables to make informed investment decisions.

2. Literature Review

2.1. International Commodities

This study uses crude oil and nickel as variables in international commodities. Crude oil is a vital energy source industry needs, especially in developing countries (Sakaki, 2019), while nickel is essential for some industries. In addition, Indonesia is also known as a nickel-producing country.

Several studies have examined the relationship between oil prices and the stock market, and many have found evidence of an asymmetric relationship (Herrera et al., 2019; Sim & Zhou, 2015; Wei & Guo, 2017; Zhang et al., 2020). Specifically, adverse changes in oil prices tend to impact stock returns substantially more than positive ones. The impact has been observed in developed and developing countries and across industries and sectors (Narayan & Gupta, 2015). The impact of oil prices on stock returns can vary depending on whether a company is a producer or consumer of oil. Companies that produce oil tend to see positive stock returns when oil prices change, regardless of whether prices increase or decrease. In contrast, companies that consume oil tend to see negative stock returns when oil prices increase but may not see a significant impact when prices decrease (Phan et al., 2015).

The impact of oil prices on stock returns also can vary depending on whether a company is a producer or consumer of oil. Companies that produce oil tend to see positive stock returns when oil prices change, regardless of whether prices increase or decrease. In contrast, companies that consume oil tend to see negative stock returns when oil prices increase but may not see a significant impact when prices decrease (Salisu & Isah, 2017). Oil prices can also affect companies' stock prices in countries exporting or importing oil. However, the impact tends to be more pronounced in countries that export oil, which is more vulnerable to changes in oil prices. Adverse changes in oil prices have been found to have a more significant impact on equity values in oil-exporting countries. In contrast, positive changes significantly impact oil-importing countries (Siddiqui et al., 2020).

Based on previous studies, the relationship between oil prices and the stock market is intricate and influenced by several factors. However, some studies have identified a positive correlation between crude oil prices and stock prices, the asymmetry in the impact of negative and positive oil price changes on stock returns. Suggests that companies and investors approach the interpretation of oil price changes' impact on stock market performance cautiously.

Nickel is essential for making stainless steel, alloys, and rechargeable electric vehicle batteries. The rise in demand for eco-friendly electric cars and nickel in battery manufacturing will impact nickel prices, mining investment decisions, mine planning, and the economic development of nickel companies and countries that depend on nickel resources (Ozdemir et al., 2022). However, based on the authors' knowledge, no research has examined the relationship between nickel prices and stock returns.

Research on nickel prices has focused on supply, demand, and country of origin, significantly affecting exporting countries' economies. Price volatility is the primary factor influencing metal prices and can impact the performance of metal processing companies. Although nickel is not a haven for renewable energy stocks, it does affect the profitability of electric vehicle battery manufacturers. Short- and long-term estimations suggest a significant and positive correlation between rare metals, electrical conductors, and solar energy stocks, subject to market conditions. (Chen et al., 2016; Gustafsson et al., 2022; Lee et al., 2022; Sun et al., 2021).

2.2. Macroeconomic

This study uses exchange rates as macroeconomic variable. Little previous research that focuses on the analysis of oil prices, exchange rates, and stock prices (Delgado et al., 2018). Furthermore, we use the Renminbi or Chinese Yuan exchange rate against the Indonesian Rupiah because China is one of the countries that have the most significant investment in Indonesia.

There is a complex and multifaceted relationship between exchange rates and stock markets. Previous studies show cross-correlations between exchange rates and stock market liquidity. The short-term effect of changes in exchange rates on stock returns is sensitive to exchange rate flexibility reforms. The exchange rate markets play an essential role in influencing stock markets, and exchange rate changes have a significant effect on the past and current volatility of stock indices (Cao, 2012; Delgado et al., 2018; Gustafsson et al., 2022; Li et al., 2018; Mroua & Trabelsi, 2020).

Moreover, there is a relationship between stock prices and exchange rates in the long term, meaning that changes in exchange rates could potentially influence the stock market. However, the strength of this relationship varies over time, and there is no consistent correlation pattern. Additionally, there are some countries where exchange rates have a significant impact on stock returns in the medium to long term. While in other countries, this relationship is not as pronounced (Afshan et al., 2018; Dahir et al., 2018; Nusair & Al-Khasawneh, 2022; Sugiharti et al., 2020).

There is a bidirectional effect between foreign exchange and stock markets regarding volatility spillover effects. Changes in one market can significantly impact future volatility in the other market. Moreover, evidence suggests that exchange rates can influence stock prices, but the relationship is not always stable. During the most volatile periods, there is a long-term co-integration between exchange rates and stock prices. However, the causal relationship is unidirectional, from exchange rates to stock indices, after the recent financial crisis. The relationship between the two markets can change over time and is influenced by various factors (Liu & Wan, 2012; Rutledge et al., 2014; Zhao, 2010).

2.3. Foreign Capital Market

This study uses Shanghai Composite Index as variable in foreign capital market. Same as in Chinese Yuan exchange rate, we use Shanghai Composite Index because China is one of the countries that have the most significant investment in Indonesia.

The interdependence of financial markets and the increasing global financial integration underscore the significance of investigating the spillover effect of risk in various financial markets. The stock market gauges a country or region's economic fluctuations, making it a critical factor in promoting economic development. Hence, monitoring and averting the propagation of risks across financial markets is crucial to ensure the stable functioning of financial systems and promote sustainable economic growth. By examining the spillover effect of risk between financial markets, researchers can gain insights into how market changes in one domain can affect other markets and make well-informed decisions regarding investment and economic policies. Therefore, a thorough understanding of the risk spillover effect in different financial markets is essential for policymakers, economists, and investors to enhance financial stability and promote sustainable economic growth (Ichsani et al., 2019; Mensi et al., 2021; Zhong & Liu, 2021).

The level of financial integration between China and ASEAN-5 countries has risen in recent years. The empirical analysis indicates that China and Indonesia stock markets bear the burden of adjustment for the identified co-integration (Chien et al., 2015). The study's findings indicate that there has been a rise in the incidence of contagion among the stock markets of China and its trading partners, including Indonesia. Besides that, the capital market liberalization reforms implemented in China have significantly intensified the risk linkages between China and external stock markets. Therefore, monitoring and assessment of the risk spillover effects in stock markets are important to avoid the potential negative consequences for global financial stability and economic growth (Shi, 2022; Sun et al., 2023).

The research findings also indicate that China's monetary policy substantially impacts the stock market indices of the Non-Developed and Emerging Economies (NDEE) group. As such, it is recommended that policymakers in the capital market maintain flexibility when making decisions, considering the influence of China's monetary policy-related factors when developing asset market policies in NDEE economies. Therefore, financial interdependence among countries and the need for careful consideration of global economic factors in formulating effective policies are essential (Hung et al., 2022).

3. Method

3.1. Data

The type of data in this study is time series data with daily data from January 4, 2009, to December 31, 2021. The data source in this study can be seen in the following table:

Table 1. Data Source

Variable Code	Variable Name	Variable Measurement	Data Source
MINING	Mining Sector Stock Index	$Ret.Mining = \frac{Index_{(t)} - Index_{(t-1)}}{Index_{(t-1)}}$	Investing.com
WTI	Crude Oil WTI Futures	$Ln.WTI = Ln(WTI\ Price)$	Investing.com
NICKEL	Nickel Futures	$Ln.NICKEL = Ln(Nickel\ Price)$	Investing.com
CNY/IDR	Yuan/Rupiah	$Ret.CNY/IDR = \frac{CNY/IDR_{(t)} - CNY/IDR_{(t-1)}}{CNY/IDR_{(t-1)}}$	Investing.com
SSEC	Exchange Rate Shanghai Composite Index	$Ret.SSEC = \frac{SSEC_{(t)} - SSEC_{(t-1)}}{SSEC_{(t-1)}}$	Investing.com

Source: investing.com

The data for this study was meticulously gathered from Investing.com, a financial information website widely recognized for its comprehensive coverage of various financial instruments. This study focuses on a time series dataset spanning from January 4, 2009, to December 31, 2021, ensuring a detailed daily record of key variables influencing the Indonesian mining sector. The chosen variables include MINING (Mining Sector Stock Index), WTI (Crude Oil WTI Futures), NICKEL (Nickel Futures), CNY/IDR (Yuan/Rupiah Exchange Rate), and SSEC (Shanghai Composite Index).

The process of data collection involved accessing the historical data sections on Investing.com dedicated to each specific variable. Each variable's dataset is structured in tabular form, with rows representing daily observations and columns containing the corresponding values for the given date. Investing.com's accuracy and real-time updates enhance the reliability of the dataset. We are following quality control measures, scrutinizing the data for any missing values, outliers, or discrepancies that could impact the integrity of the dataset.

Furthermore, specific mathematical transformations were applied to certain variables to facilitate robust analysis. Variables MINING, SSEC, and CNY/IDR utilized a return formula, capturing the relative changes in the Mining Sector Stock Index, Shanghai Composite Index, and Chinese Yuan/Indonesian Rupiah Exchange Rate, respectively. On the other hand, WTI and NICKEL underwent a natural logarithm transformation, providing a stabilized representation of their values and aiding in the interpretation of percentage changes.

The choice of a daily frequency for the dataset enables the study to capture both short-term fluctuations and long-term trends, providing a comprehensive perspective on the dynamics of the Indonesian mining sector. The extensive time frame, spanning over a decade, allows us to analyze economic cycles, trends, and potential structural changes within the chosen variables. Ultimately, the diligent data collection process from Investing.com, coupled with thoughtful transformations, forms the foundation for robust analyses that aim to uncover the intricate relationships within the Indonesian mining sector.

3.2. Unit Root Test

The Dickey-Fuller (DF) test, introduced by Dickey and Fuller (1979), is a well-known and widely used unit root test. The Augmented Dickey-Fuller test (ADF test) is a modification of the DF, as proposed by Dickey and Fuller (1981). The ADF test is beneficial for analyzing time series models that are more complex and extensive than those that can be handled by the DF test alone. The test statistic used in the ADF test is negative, which assumes the presence of a unit root is determined by its negativity (Shao et al., 2019). If the test statistic is more negative than critical values from statistical tables, the null hypothesis of a unit root is rejected, indicating stationarity. On the other hand, if the test statistic is less negative than critical values, the null hypothesis of a unit root is not rejected, suggesting non-stationarity.

We apply the unit root test to assess the stationarity of the time series data used in the Vector Error Correction Model (VECM) analysis. Stationarity is a critical concept in time series analysis, and unit root tests help determine whether a variable exhibits a unit root, indicating a non-stationary process. The goal is to determine the order of integration of each variable, which indicates whether differencing is needed to make the data stationary. Differencing involves subtracting the previous observation from the current one, aiming to remove the trend and make the data stationary. Stationary data are crucial for accurate time series analysis, as non-stationary data can lead to spurious regression results and inaccurate conclusions.

3.3. Optimal Lag

The optimal lags are typically determined using model selection criteria such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which aim to balance model fit and complexity (Enders, 2004; Lütkepohl, 2005). These criteria are essential for selecting the optimal lag order as they help ensure the model is not overfit or underfit (Enders, 2004). The optimal lag order is also essential for testing co-integration among variables using methods such as the Johansen procedure, which requires selecting the appropriate lag order (Si et al., 2021). Determining the optimal lag length is a crucial step in time series analysis as it directly influences the accuracy and effectiveness of models such as the Vector Error Correction Model (VECM). The lag length signifies the number of past observations considered when predicting the current value of a dependent variable. Striking the right balance between capturing relevant dynamics and avoiding unnecessary complexity is essential for constructing robust models.

This study chooses Akaike Information Criterion (AIC) because of its ability to assess the relative quality of statistical models by weighing the trade-off between model fit and complexity. When all the evaluated models exhibit inadequate fit with a specific set of data or observations, the AIC will identify the model that offers a slightly superior fit compared to the others (Profillidis & Botzoris, 2018). Besides that, several studies use AIC to determine the optimal lag length (Ada et al., 2014; Asumadu-Sarkodie & Owusu, 2016; Obayelu & Salau, 2010).

3.4. Co-integration Test

Co-integration is a statistical method commonly used in econometrics to detect long-term relationships between economic variables. The term was coined initially by Granger (1980) and implied that if two or more variables have a stable and persistent equilibrium relationship, they are considered co-integrated.

Engle and Granger (1987) proposed a two-step co-integration test that involves estimating a regression equation and then using the residuals to test for the presence of a unit root. Regression model is estimated using the time series variables, accommodating for any non-stationarity by differencing the variables if necessary. The regression model captures short-term relationships between the variables. The residuals of the regression, representing the differences between observed and predicted values, are examined for the presence of a unit root using appropriate statistical tests. If the residuals exhibit stationarity, it suggests the existence of a long-term relationship among the variables.

However, this test has limitations in handling situations with more than one co-integrating relationship. To address this limitation, Johansen (1988) developed a likelihood ratio test that can identify up to r linearly independent co-integrating vectors or ranks of co-integration. The Johansen test involves estimating a vector error correction model (VECM) and conducting likelihood ratio tests on the eigenvalues and eigenvectors of the estimated matrix. The outcomes of these tests help determine the number of co-integrating relationships, providing a more nuanced understanding of the long-term associations among the variables. Johansen's test is more powerful and flexible than the Engle-Granger test and has become a widely used method in empirical studies of co-integration.

3.5. Granger Causality Test

Establishing a co-integrating relationship between variables is the first step in understanding the underlying causal relationships. While co-integration suggests the presence of long-run equilibrium relationships among the variables, it is insufficient to determine the causality direction between them. Therefore, it is necessary also to investigate Granger causality, which can indicate the presence of causality in at least one direction among the variables. This additional analysis is crucial in accurately identifying the underlying relationships and dynamics between variables (Engle & Granger, 1987).

This test aims to investigate whether one time series variable can be considered a predictor of another based on past information. The underlying principle is rooted in the concept of Granger causality, which suggests that if the past values of one variable offer valuable information in predicting another variable beyond what can be predicted using only the past values of the second variable, then the first variable is said to Granger-cause the second. The hypothesis testing phase employs statistical tests, often based on F-statistics, to evaluate whether the inclusion of lagged values from one variable significantly improves the prediction of the other variable. If the inclusion of past values from one variable enhances the accuracy of predicting the other variable, Granger causality is indicated (Engle & Granger, 1987).

3.6. Impulse Responses Test

The impulse response function (IRF) is a statistical technique widely used in time series analysis to examine the dynamic relationship between variables over time. It provides a way to visualize the effects of a shock on a particular variable and can be used to determine how quickly the shock dissipates over time. The IRF is estimated by simulating the impact of a one-time shock on one variable on the behavior of other variables in the system. The magnitude and duration of the shock can be specified in advance, and the model is used to forecast how the system will respond over time. The IRF shows how each variable's response changes over time due to the shock (Lütkepohl, 2005).

3.7. Model

The study utilizes a restricted vector autoregressive (VAR) model to investigate the causality between variables. A vector error correction model (VECM), a multivariate model derived from the restricted VAR, is also used to analyze the relationships among the variables (Si et al., 2021). VECM models consider short-term and long-term dynamics and are particularly useful for analyzing economic time series data that exhibit co-integration. The VECM framework enables the estimation of the speed of adjustment toward the long-run equilibrium and the short-run dynamics that lead to deviations from the long-run equilibrium. Several studies use VECM to capture short-term and long-term effect in the context of finance (Gunasekarage et al., 2004; Kwon & Shin, 1999; Maysami & Koh, 2000; Mukherjee & Naka, 1995).

This study uses a vector error correction model (VECM) instead of vector autoregressive (VAR) due to VECM's inclusion of an error correction mechanism. VAR is deemed more suitable for analyses with a short-term focus, emphasizing the immediate responses of variables to shocks without explicitly modeling long-term equilibrium relationships. This makes it a pragmatic choice for scenarios where researchers are primarily interested in understanding contemporaneous dynamics within a system. Here are the VECM models:

$$\Delta MINING_{it} = \theta_{1i} + \sum_{k=1}^{n} \theta_{11ik} \Delta WTI_{it-k} + \sum_{k=1}^{n} \theta_{12ik} \Delta NICKEL_{it-k} + \sum_{k=1}^{n} \theta_{13ik} \Delta CNY/IDR_{it-k} + \sum_{k=1}^{n} \theta_{14ik} \Delta SSEC_{it-k} + \lambda_{1i} ECT_{it-1} + \varepsilon_{it} \quad (1)$$

Where Δ shows the first difference data level, k is the length of the lag that is the object of observation in this study, and n is the optimal lag length.

The Vector Error Correction Model (VECM) formula presented encapsulates the dynamic relationships between the Mining Sector Stock Index (ΔMINING) and several key variables, employing the first differences of these variables and their lagged values. Each component of the formula contributes to capturing the short-term and lagged effects of various factors on the Mining Sector Stock Index.

The intercept term (θ1i) represents the constant baseline for the change in MINING when all other explanatory variables are zero. The subsequent terms involve summations over lagged differences (ΔWTI, ΔNICKEL, ΔCNY/IDR, and ΔSSEC), each multiplied by corresponding coefficients (θ11ik, θ12ik, θ13ik, θ14ik). These terms capture the influence of changes in Crude Oil WTI Futures, Nickel Futures, Yuan/Rupiah Exchange Rate, and the Shanghai Composite Index on the Mining Sector Stock Index at various lag orders (up to "n").

The Error Correction Term (ECT) is incorporated into the model, representing the speed at which the system corrects deviations from the long-term equilibrium relationship among the variables. This term is multiplied by a coefficient (λ1i) and the lagged value of the ECT at time "t-1." The ECT plays a crucial role in adjusting the model towards its equilibrium state. The error term (εit) accounts for unobserved and unexplained factors influencing the change in MINING at time "t." It captures the residuals of the model—deviations that are not accounted for by the specified explanatory variables.

4. Result and Discussion

4.1. Descriptive Statistics

Table 2. Descriptive Statistics

	MINING	WTI	NICKEL	SSEC	CNY/IDR
Mean	6.76E-05	4.167992	9.585695	0.000221	0.000134
Median	-0.000200	4.142976	9.575053	0.000236	0.000510
Maximum	0.109618	4.726148	10.27946	0.041177	0.065766
Minimum	-0.125307	2.303585	9.001469	-0.052870	-0.084907
Std. Dev.	0.015927	0.358190	0.280148	0.004461	0.014752
Skewness	-0.110048	-0.529460	0.091870	-0.200342	-0.625391
Kurtosis	7.692990	3.352854	2.501531	21.59592	7.967354

Source: Processed Data in E-views (2023)

Based on table 2, the descriptions suggest that the five variables have different distribution characteristics. MINING, SSEC, and CNY/IDR have relatively higher degrees of variability and are highly peaked, indicating a concentration of values around the mean. WTI and NICKEL have a moderately high degree of variability and a highly peaked distribution. The skewness values suggest that MINING, WTI, SSEC, and CNY/IDR are moderately negatively skewed, while NICKEL slightly positively skewed.

4.2 Unit Root Test

The unit root test is performed to determine the level of data for each variable in the study in achieving stationarity. The results of the unit root test at the level are presented as follows:

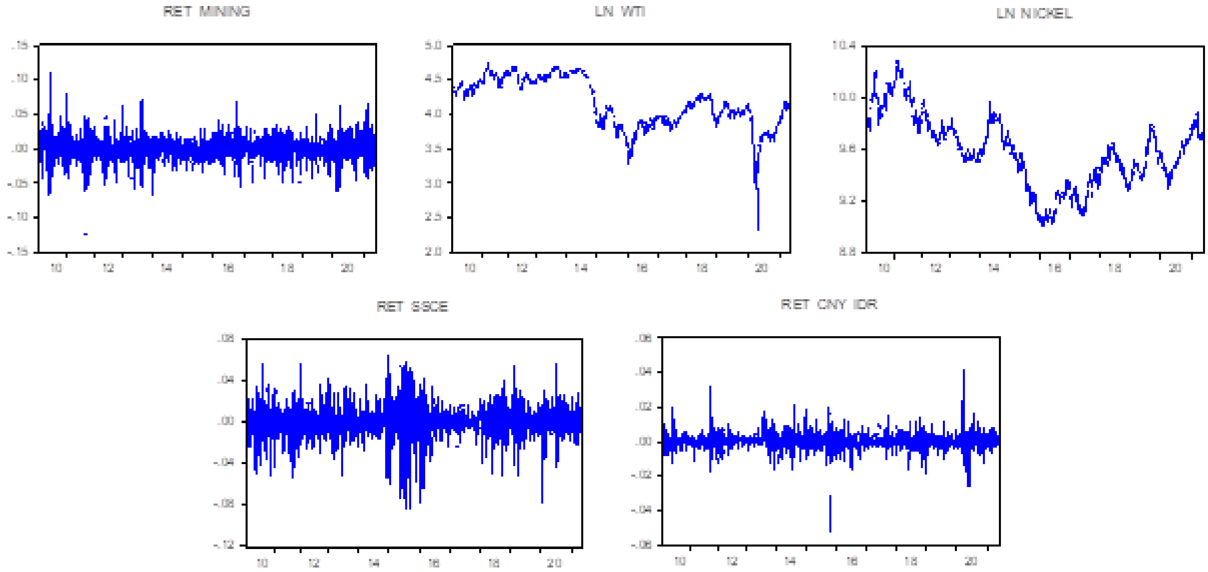
Table 3. Unit Root Test Results at the Level and First Difference Data

Variable	Level	Variable	First Difference
	ADF t-Statistic		ADF t-Statistic
MINING	-45.21111***	ΔMINING	-21.13778***
WTI	-2.799172*	ΔWTI	-48.75743***
NICKEL	-1.788103	ΔNICKEL	-49.58282***
SSEC	-47.22696***	ΔCNY/IDR	-20.02540***
CNY/IDR	-44.10139***	ΔSSEC	-20.29509***

Source: Processed Data in E-views (2023)
Note: ***, **, * indicate significance at the α levels of 1%, 5% and 10%

Based on the unit root test results at the level data level, as shown in Table 3 above. The ADF t-Statistic value for MINING, SSEC, and CNY/IDR are greater than the Critical Value with probability value significant at $\alpha = 0.01$. The ADF t-Statistic value for WTI is greater than the Critical Value with probability value significant at $\alpha = 0.1$. The ADF t-Statistic value for NICKEL is less than the Critical Value with probability value not significant at $\alpha = 0.01$, 0.05 or 0.1.

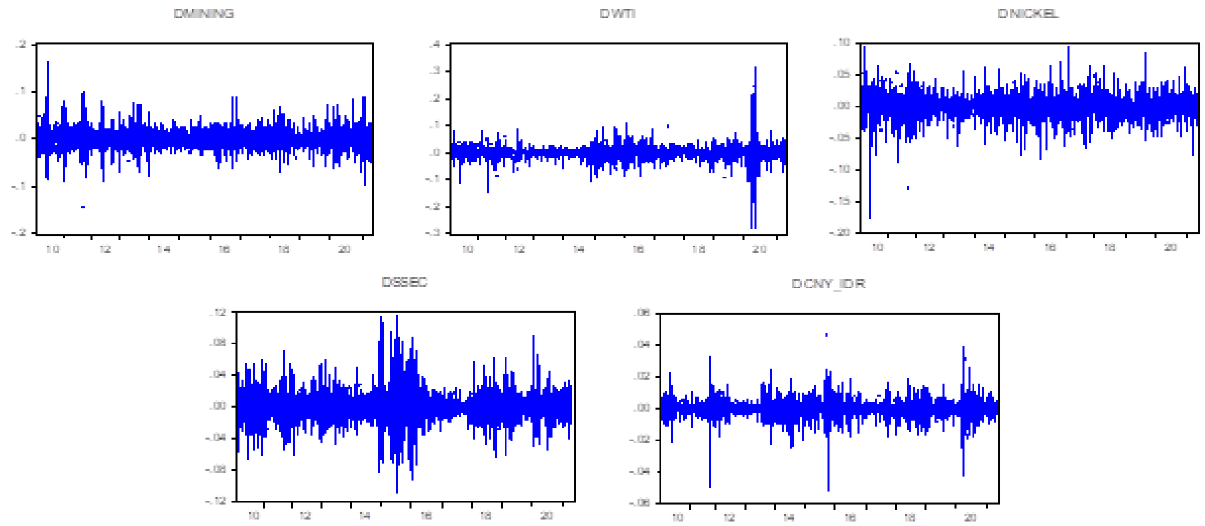
However, not all variables in this study achieve stationarity at the level data. Therefore, the time series data is non-stationary and requires further analysis using appropriate time series methods such as differencing or transformations to ensure the reliability of the analysis.



Source: Processed Data in E-views (2023)

Figure 1. Graph of the movement of variable research values at the level of data

Based on the unit root test results at the first difference level, as shown in Table 3 above, the ADF t-statistic values for each variable are less than the Critical Value with probability values significant at $\alpha = 0.01$, 0.05, and 0.1. Thus, it can be concluded that the first difference level of the data in this study has achieved stationarity. Figures 1 and 2 also show the time series plots of the variables before and after differences. The plots for the first difference series indicate that the data have become stationary, with less apparent trends and fluctuations over time. ADF test is a critical step in time series analysis as non-stationary data can lead to inaccurate modeling and forecasting results. Therefore, the stationarity of the data at the first difference level provides a more reliable basis for further analysis in this study.



Source: Processed Data in E-views (2023)

Figure 2. Graph of the movement of variable research values at the first difference data

4.3. Optimal Lag

After achieving stationarity in the data, the next step is to conduct a co-integration test. However, before conducting the co-integration test, it is necessary to determine the optimal lag length of the research data as follows:

Table 4. Optimal Lag

Lag	FPE	AIC	SC	HQ
0	4.67e-15	-18.80779	-18.79531	-18.80324
1	2.33e-19	-28.71569	-28.64084*	-28.68840
2	2.21e-19*	-28.76869*	-28.63146	-28.71866*
3	2.22e-19	-28.76111	-28.56151	-28.68834
4	2.25e-19	-28.74822	-28.48624	-28.65271
5	2.27e-19	-28.74167	-28.41732	-28.62342
6	2.29e-19	-28.73125	-28.34452	-28.59026
7	2.30e-19	-28.72699	-28.27788	-28.56326
8	2.26e-19	-28.74562	-28.23413	-28.55914

Source: Processed Data in E-views (2023)

Based on the results of determining the optimal lag length, which can be seen in Table 4 above. According to the Akaike Information Criterion (AIC), the optimal lag length for the research data is 2. However, according to the Schwarz Information Criterion (SC) the optimal lag length for the research data is 1. Nevertheless, this study chose the optimal lag length based on the Akaike Information Criterion (AIC) because it has advantages over other optimal lag length determination criteria. Therefore, it can be concluded that the optimal lag length for the data in this research is 2.

4.4. Co-integration Test

The co-integration test was performed to determine the long-run effect of the independent variables on the dependent variable in this study. The results of the co-integration test are presented in the following table:

Table 5. Co-integration Test Result

No. of CE(s)	None			
	No Intercept and No Trend		Intercept and No Trend	
	Trace Statistic	Max-Eigen Statistic	Trace Statistic	Max-Eigen Statistic
r = 0	1309.835	511.1220***	1317.242	511.2601***
r ≤ 1	798.7127***	406.4575***	805.9820***	406.5814***
r ≤ 2	392.2552***	377.5598***	399.4006***	377.7123***
r ≤ 3	14.69543**	14.68890**	21.68831**	18.89234**
r ≤ 4	0.006529	0.006529	2.795967	2.795967
No. of CE(s)	**Linear**			
	Intercept and No Trend		**Intercept and Trend**	
	Trace Statistic	**Max-Eigen Statistic**	**Trace Statistic**	**Max-Eigen Statistic**
r = 0	1317.227	511.2589***	1320.912	511.2827***
r ≤ 1	805.9680***	406.5805***	809.6295***	407.1815***
r ≤ 2	399.3875***	377.7123***	402.4479***	377.9884***
r ≤ 3	21.67521***	18.87927***	24.45951*	21.56889**
r ≤ 4	2.795934	2.795934*	2.890615	2.890615

Source: Processed Data in E-views (2023)
Note: ***, **, * indicate significance at the α levels of 1%, 5% and 10%

Based on the co-integration test results shown in Table 5 above, with several assumptions of deterministic trends, the values of trace statistic and max-eigen statistic are greater than the 5% critical value at the number of CE (S) none (r = 0), at most 1 (r ≤ 1), at most 2 (r ≤ 2), at most 3 (r ≤ 3), and at most 4 (r ≤ 4). It can be concluded that there is evidence of co-integration relationships or long-term effects among the specified variables. Specifically, the World Oil Prices, Nickel Prices, the Yuan Exchange Rate, and the Shanghai Composite Stock Index have a co-integration relationship with the Mining Sector Stock Index in Indonesia. This implies that these variables are not independent in the long run, and any short-term deviations from their equilibrium relationship will eventually be corrected over time.

This result suggests that the Mining Sector Stock Index in Indonesia is influenced by the long-term movements and interdependencies of World Oil Prices, Nickel Prices, the Yuan Exchange Rate, and the Shanghai Composite Stock Index. Investors, policymakers, and analysts can use this information to better understand the underlying dynamics of the mining sector and make more informed decisions, considering the sustained relationships among these key variables. Additionally, the acknowledgment of co-integration implies a certain degree of predictability and stability in the long-term behavior of these economic indicators.

4.5. Vector Error Correction Model

Table 6. Vector Error Correction Estimates

Error Correction	ΔMINING	ΔWTI	ΔNICKEL	ΔSSEC	ΔCNY/IDR
ECT_{t-1}	-0.552707 [-22.8281]***	0.047680 [1.12457]	0.063862 [2.11856]	-0.376664 [-15.5818]***	0.080888 [11.0393]***
ΔMINING (-1)	-0.296246 [-12.4950]***	-0.027358 [-0.65894]	-0.011795 [-0.39959]	0.252142 [10.6516]***	-0.064542 [-8.99518]***
ΔMINING (-2)	-0.163678 [-8.21374]***	0.011142 [0.31930]	-0.025946 [-1.04579]	0.117320 [5.89676]***	-0.029951 [-4.96654]***
ΔWTI (-1)	0.086266 [7.02525]***	-0.016487 [-0.76675]	0.005417 [0.35434]	0.041464 [3.38209]**	-0.020982 [-5.64632]***
ΔWTI (-2)	-0.003864 [-0.31903]	0.002091 [0.09860]	-0.026982 [-1.78955]	-0.005335 [-0.44125]	0.008480 [2.31384]
ΔNICKEL (-1)	0.108649 [6.03026]***	-0.034154 [-1.08249]	-0.038730 [-1.72655]	0.012866 [0.71522]	-0.009641 [-1.76821]
ΔNICKEL (-2)	0.011724 [0.64790]	-0.013051 [-0.41186]	-0.022347 [-0.99194]	0.023649 [1.30899]	-0.008649 [-1.57944]
ΔCNY/IDR (-1)	0.267397 [11.3748]***	-0.032398 [-0.78702]	-0.067321 [-2.30019]	-0.455232 [-19.3959]***	-0.033294 [-4.67992]***
ΔCNY/IDR (-2)	0.116986 [5.74421]***	-0.014105 [-0.39549]	-0.009811 [-0.38692]	-0.232847 [-11.4513]***	-0.017222 [-2.79417]*
ΔSSEC (-1)	-0.515120 [-7.30791]***	-0.166095 [-1.34561]	0.064808 [0.73848]	-0.412095 [-5.85560]***	-0.534272 [-25.0457]***
ΔSSEC (-2)	-0.318140 [-4.77184]***	-0.068010 [-0.58253]	-0.043568 [-0.52488]	-0.290701 [-4.36720]***	-0.257667 [-12.7706]***
C	9.49E-06 [0.02827]	-7.09E-05 [-0.12060]	-2.01E-05 [-0.04807]	1.28E-05 [0.03827]	-5.07E-06 [-0.04995]
R^2	0.455248	0.003395	0.006372	0.395990	0.347104
Adj. R^2	0.452642	-0.001373	0.001617	0.393100	0.343980
F-statistic	174.6609	0.712044	1.340202	137.0207	111.1121

Source: Processed Data in E-views (2023)
Note: ***, **, * indicate significance at the α levels of 1%, 5% and 10%

The coefficient of ΔWTI (-1) and ΔNICKEL (-1) is positive and statistically significant at the 1% level, indicating a positive relationship between oil prices and nickel prices to mining stock prices in the previous period. Higher oil prices and nickel prices would likely lead to higher profits for mining companies and hence higher stock prices.

The coefficient of ΔSSEC (-1) and ΔSSEC (-2) are positive and statistically significant at the 1% level. Suggests that there are positive spillover effects from the Chinese stock market to the Indonesian mining stock price.

The coefficient of ΔCNY/IDR (-1) and ΔCNY/IDR (-2) are positive and statistically significant at the 1% level. Suggests that there is some short-term and long-term relationship between the exchange rate and mining stock prices.

The vector error correction model suggests a long-term relationship between the variables. Mining stock prices are influenced by their past values, changes in oil and nickel prices, and to some extent, changes in the Chinese yuan/Indonesian rupiah exchange rate and the Shanghai Stock Exchange Composite Index. The model also suggests that there may be some short-term overshooting and spillover effects in the relationship between these variables.

4.6. Granger Causality Test

The Granger Causality Test determines the causality relationship between independent and dependent variables. The results of the Granger Causality Test can be seen in the table below:

Table 7. VEC Granger Causality/Block Exogeneity Wald Tests

Independent Variables	**Dependent Variables**				
	ΔMINING	**ΔWTI**	**ΔNICKEL**	**ΔSSEC**	**ΔCNY/IDR**
ΔMINING	-	1.133739	1.146597	113.4743***	80.92938***
ΔWTI	49.46491***	-	3.330538	11.63917***	37.28624***
ΔNICKEL	36.44744***	1.292847	-	2.120867	5.306980*
ΔSSEC	129.7410***	0.621303	6.387431**	-	21.97465***
ΔCNY/IDR	54.89341***	1.824959	1.641544	36.87729***	-

Source: Processed Data in E-views (2023)
Note: ***, **, * indicate significance at the α levels of 1%, 5% and 10%

The analysis based on Table 7 reveals significant insights into the causal relationships among key economic variables, providing valuable implications for investors and policymakers. Specifically, the results of the Vector Error Correction (VEC) Granger causality/block exogeneity Wald tests highlight distinct patterns of causation within the economic system under consideration.

The result suggests a unidirectional causal relationship from changes in World Oil Prices (ΔWTI) and changes in Nickel Prices (ΔNICKEL) to changes in the Mining Sector Stock Index (ΔMINING). This implies that fluctuations in oil prices and nickel prices can influence and potentially cause changes in the stock prices of the mining sector. The sensitivity of the mining sector to global commodity price changes underscores the importance for investors to closely monitor and respond to variations in WTI oil prices and nickel prices.

Moreover, the analysis identifies a two-way causal relationship between changes in the Shanghai Composite Stock Index (ΔSSEC), changes in the Yuan/Indonesian Rupiah Exchange Rate (ΔCNY/IDR), and changes in the Mining Sector Stock Index (ΔMINING). This suggests that alterations in the Shanghai Stock Exchange and the CNY/IDR exchange rate can cause changes in mining stock prices. Conversely, changes in mining stock prices can also impact on the Shanghai Stock Exchange and the CNY/IDR exchange rate. This dynamic relationship indicates a noteworthy influence of China's macroeconomics on the performance of Indonesia's mining sector. Furthermore, it implies that fluctuations in the mining sector's performance may have repercussions on the stability of the Indonesian currency exchange rate with China.

These results hold significant implications for stakeholders. Investors in the mining sector are advised to consider the potential impact of global commodity price changes, particularly in WTI oil and nickel, on the mining stock prices. Additionally, policymakers need to be mindful of the interconnectedness between China's macroeconomic indicators, the mining sector's performance in Indonesia, and the stability of the exchange rate between the Indonesian Rupiah and the Chinese Yuan. This understanding of causal relationships facilitates more informed decision-making in the context of economic stability and investment strategies.

4.7. Impulse Responses Test

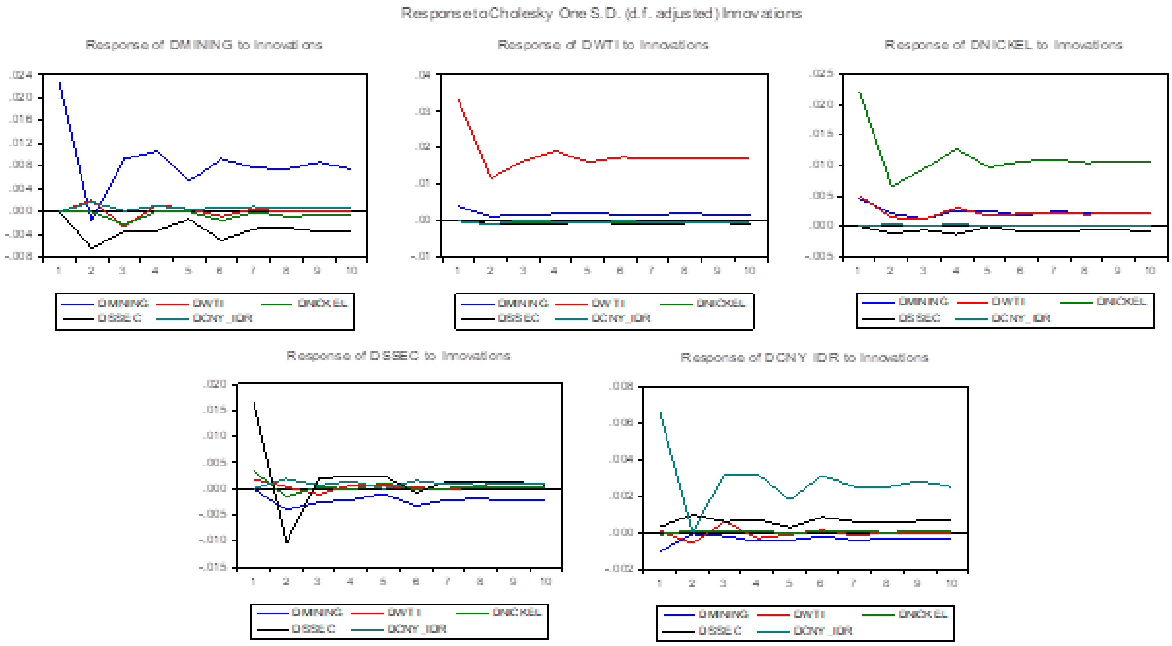
The Impulse Response Function (IRF) test was conducted to determine each independent variable's short-term and long-term effects on the dependent variable in this study. The IRF test was also performed to investigate the response of each variable to shocks from other variables over several observation periods. The results of the IRF test are presented in the table below:

Table 8. The Impulse Response Function (IRF)

Response of ΔMINING					
Period	**ΔMINING**	**ΔWTI**	**ΔNICKEL**	**ΔSSEC**	**ΔCNY/IDR**
1	0.022633	0.000000	0.000000	0.000000	0.000000
2	-0.001629	0.002011	3.51E-05	-0.006337	0.001736
3	0.009261	-0.002582	-0.002251	-0.003540	0.000181
4	0.010614	0.001202	6.28E-05	-0.003335	0.001040
5	0.005309	0.000478	-1.24E-05	-0.001280	0.000460
6	0.009255	-0.000785	-0.001526	-0.005026	0.000719
7	0.007699	0.000531	-7.87E-05	-0.002992	0.000899
8	0.007440	-8.15E-05	-0.000794	-0.002836	0.000597
9	0.008647	-2.73E-05	-0.000652	-0.003449	0.000651
10	0.007453	0.000222	-0.000474	-0.003311	0.000846
Response of ΔWTI					
Period	**ΔMINING**	**ΔWTI**	**ΔNICKEL**	**ΔSSEC**	**ΔCNY/IDR**
1	0.003969	0.033128	0.000000	0.000000	0.000000
2	0.001283	0.011648	-0.000718	-0.000733	-0.000983
3	0.001679	0.016450	-0.000577	-0.000937	0.000301
4	0.001931	0.019082	-0.000256	-0.000885	-0.000200
5	0.002043	0.016129	-0.000544	-0.000154	-0.000607
6	0.001808	0.017433	-0.000412	-0.000799	7.58E-05
7	0.001828	0.017281	-0.000412	-0.000760	-0.000360
8	0.001935	0.017035	-0.000521	-0.000604	-0.000256
9	0.001878	0.017268	-0.000385	-0.000567	-0.000171
10	0.001869	0.017173	-0.000453	-0.000706	-0.000302
Response of ΔNICKEL					
Period	**ΔMINING**	**ΔWTI**	**ΔNICKEL**	**ΔSSEC**	**ΔCNY/IDR**
1	0.004510	0.004977	0.022101	0.000000	0.000000
2	0.002066	0.001433	0.006577	-0.001200	0.000282
3	0.001240	0.001119	0.009436	-0.000621	8.94E-06
4	0.002592	0.003055	0.012696	-0.001330	0.000342
5	0.002506	0.001747	0.009677	-9.00E-05	-2.67E-05
6	0.001765	0.002037	0.010590	-0.000876	0.000177
7	0.002373	0.002239	0.010979	-0.000970	0.000184
8	0.002197	0.001990	0.010374	-0.000652	0.000110
9	0.002113	0.002113	0.010690	-0.000647	0.000139
10	0.002264	0.002119	0.010676	-0.000857	0.000149

Response of ΔSSEC					
Period	**ΔMINING**	**ΔWTI**	**ΔNICKEL**	**ΔSSEC**	**ΔCNY/IDR**
1	-4.72E-07	0.001787	0.003481	0.016708	0.000000
2	-0.004062	0.000385	-0.001619	-0.010439	0.001866
3	-0.002560	-0.001093	0.000394	0.001988	0.000660
4	-0.002113	0.000715	-0.000165	0.002442	0.001484
5	-0.000996	0.000550	0.001139	0.002486	-8.99E-06
6	-0.003210	0.000209	-0.000143	-0.000727	0.001562
7	-0.002072	-0.000148	7.85E-05	0.001423	0.000865
8	-0.001944	0.000492	0.000411	0.001331	0.000785
9	-0.002228	0.000279	0.000343	0.001329	0.001009
10	-0.002260	0.000123	0.000117	0.000716	0.000933
Response of ΔCNY/IDR					
Period	**ΔMINING**	**ΔWTI**	**ΔNICKEL**	**ΔSSEC**	**ΔCNY/IDR**
1	-0.001052	0.000106	-9.65E-05	0.000324	0.006605
2	-6.00E-05	-0.000599	0.000105	0.000973	3.36E-05
3	-0.000190	0.000600	5.15E-05	0.000601	0.003210
4	-0.000481	-0.000298	0.000124	0.000727	0.003215
5	-0.000415	-0.000110	-8.04E-05	0.000286	0.001798
6	-0.000210	0.000150	0.000104	0.000846	0.003132
7	-0.000415	-0.000143	6.61E-05	0.000608	0.002502
8	-0.000339	1.92E-06	1.13E-05	0.000546	0.002477
9	-0.000328	-1.22E-05	5.74E-05	0.000631	0.002817
10	-0.000368	-6.38E-05	5.10E-05	0.000635	0.002492

Source: Processed Data in E-views (2023)



Source: Processed Data in E-views (2023)

Figure 3. Impulse Responses Graph

The impulse response test assesses how each variable responds to shocks originating from other variables, providing valuable insights into the short-term and long-term effects within the economic system. Based on the impulse responses test results, which can be seen in table 8 and figure 3 above, each variable of this study responds to shocks from other variables for ten predetermined periods. Indonesia's Mining Sector Stock Index variable responds to any shocks from the World Oil, Nickel, Yuan Exchange Rate, and Shanghai Composite Stock Index variables from period 1 to period 10. The responsiveness of the Mining Sector Stock Index in Indonesia indicates that any abrupt changes in World Oil Prices, Nickel Prices, the Yuan/Indonesian Rupiah Exchange Rate, and the Shanghai Composite Stock Index impact the index's trajectory. This responsiveness is observed over the short term, suggesting immediate reactions to external shocks, as well as over the long term, signifying a sustained influence that persists beyond immediate fluctuations. For instance, if there is a sudden increase in World Oil Prices (WTI), a corresponding response in Indonesia's Mining Sector Stock Index is observed, and this effect is not confined to an isolated time frame. The same applies to shocks in Nickel Prices, changes in the Yuan/Indonesian Rupiah Exchange Rate, and fluctuations in the Shanghai Composite Stock Index. This dynamic relationship underscores the interconnectedness between the mining sector in Indonesia and these external economic variables.

The variables of the Mining Sector Index in Indonesia, World Oil, Nickel, Yuan Exchange Rate, and the Shanghai Composite Stock Index at the beginning of each period responded with considerable shocks from other variables, then stabilized until the end of the observation period. So, it can be concluded that there are short-term and long-term effects of World Oil, Nickel, Yuan Exchange Rate, and the Shanghai Composite Stock Index on Indonesia's Mining Sector Stock Index. The short-term effects observed in the impulse responses indicate immediate reactions of

Indonesia's Mining Sector Stock Index to shocks in World Oil Prices, Nickel Prices, Yuan Exchange Rate, and the Shanghai Composite Stock Index. These immediate responses showcase the sensitivity of the mining sector to rapid changes in global commodity prices, exchange rates, and international stock market movements. On the other hand, the confirmation of long-term effects suggests that the influence of these external factors endures over an extended period. This sustained impact emphasizes that fluctuations in World Oil Prices, Nickel Prices, Yuan Exchange Rate, and the Shanghai Composite Stock Index have enduring consequences for Indonesia's Mining Sector Stock Index. This aligns seamlessly with the co-integration test results, which indicated a stable and persistent relationship between these variables over the long run.

5. Conclusion

The unit root test was conducted to determine the level of research data in achieving stationarity. Based on the unit root test results, it can be concluded that the research data at the level data did not reach stationarities for all variables. So, testing was carried out at the first difference data level, and the result was that the research data reached stationarity. The optimal lag length from the research data is two, obtained based on the Akaike Information Criterion (AIC). The results of the co-integration test found that world oil prices, nickel, the Yuan exchange rate, and the Shanghai Composite Stock Index have a long-term influence on the Mining Sector Stock Index in Indonesia.

The vector error correction model indicates higher oil prices and nickel prices would likely lead to higher profits for mining companies and hence higher stock prices. There are positive spillover effects from the Chinese stock market to the Indonesian mining stock price. Furthermore, there is a long-term relationship between the variables, with mining stock prices being influenced by their past values, changes in oil and nickel prices, and to some extent, changes in the Chinese yuan/Indonesian rupiah exchange rate and the Shanghai Stock Exchange Composite Index. The model also suggests that there are short-term overshooting and spillover effects in the relationship between these variables.

The results of the VEC Granger causality/block exogeneity Wald tests indicate that the mining sector in Indonesia is sensitive to changes in global commodity prices, and investors in the mining sector should closely monitor changes in the prices of WTI and nickel prices. Furthermore, China macroeconomics has impact to the mining sector's performance in Indonesia. Besides that, the mining sector's performance in Indonesia also could potentially impact the stability of the Indonesian currency exchange rate with China.

The results of the impulse responses test suggest that changes in World Oil, Nickel, Yuan Exchange Rate, and the Shanghai Composite Stock Index have significant short-term and long-term effects on Indonesia's Mining Sector Stock Index. The response of the Mining Sector Stock Index to shocks from these variables lasts for ten predetermined periods, indicating that the effects are not short-lived. Moreover, the variables responded to considerable shocks from other variables at the beginning of each period and then stabilized until the end of the observation period. These findings are consistent with the results of the co-integration test, which revealed a long-term effect of the variables on the Mining Sector Stock Index in Indonesia.

This study findings present a multifaceted set of implications for both policymakers and investors engaged in Indonesia's mining sector. One of the key takeaways is the sector's heightened sensitivity to global commodity price fluctuations, particularly evident in the responses to changes in West Texas Intermediate (WTI) and nickel prices. For policymakers, this underscores the need for proactive measures to mitigate the potential risks associated with volatile commodity markets. Strategies could include establishing strategic reserves, implementing risk management mechanisms, and fostering diversification within the mining sector to reduce vulnerability to specific commodities. Policymakers should stay attuned to global commodity trends and tailor interventions that enhance the sector's resilience to external shocks.

The identified link between changes in mining stock prices and the Chinese yuan/Indonesian rupiah exchange rate holds crucial implications for currency stability. Policymakers must recognize the impact of the mining sector on bilateral currency dynamics with China. Strategies to ensure exchange rate stability may involve diplomatic negotiations, collaboration with international financial institutions, and the development of hedging mechanisms. A stable exchange rate is fundamental for attracting foreign investment and maintaining economic stability, making it imperative for policymakers to integrate insights from the mining sector into broader economic policy frameworks.

This study's revelation of significant short-term and long-term effects on Indonesia's Mining Sector Stock Index emphasizes the need for nuanced investment strategies. Investors should adopt a dual perspective, considering both immediate market reactions and enduring effects. Policymakers may play a role in fostering investor education initiatives to enhance market literacy, ensuring investors understand the intricate relationships within the mining sector. Encouraging long-term investment strategies aligned with sustainable development goals could contribute to stability and resilience in the sector. The government may explore incentives to promote such investment behaviors.

The findings also underscore the importance of economic diversification and risk management. Policymakers may consider strategies to diversify the economy, reducing dependence on a specific industry. This diversification could involve promoting the development of alternative sectors, such as technology or renewable energy. Simultaneously, investors should diversify portfolios to spread risks across different industries and asset classes, mitigating the inherent volatility associated with the mining sector.

Collaboration and information sharing emerge as critical components for effective decision-making. Establishing platforms for regular dialogue between the government, mining companies, and investors can facilitate the exchange of insights, market intelligence, and risk assessments. This collaborative approach promotes a shared understanding of challenges and opportunities within the sector, contributing to more informed policymaking and investment decision-making processes. Overall, by addressing these implications, stakeholders can contribute to the development of a resilient and dynamic mining sector aligned with broader economic goals in Indonesia.

This study on Indonesia's mining sector provides important insights into the relationships between key variables, including World Oil Prices, Nickel Prices, Yuan/Indonesian Rupiah Exchange Rate, and the Shanghai Composite Stock Index, and the Mining Sector Stock Index. However, it is essential to critically assess the limitations of the study. Endogeneity, or the potential bidirectional causality between variables, could be a concern. For instance, there might be feedback loops where changes in the Mining Sector Stock Index influence other variables, creating a complex web of relationships. Endogeneity can lead to biased parameter estimates and affect the accuracy of causal inferences. Future studies might consider employing advanced econometric techniques, such as instrumental variable approaches, to address endogeneity concerns and enhance the credibility of causal relationships. Additionally, this study's exclusive focus on specific variables, such as World Oil Prices, Nickel Prices, Yuan/Indonesian Rupiah Exchange Rate, and the Shanghai Composite Stock Index, might overlook other relevant factors influencing the mining sector. For instance, government policies, regulatory changes, or technological advancements could play a substantial role. The omission of such variables could limit the study's comprehensiveness, and future research should strive to incorporate a broader set of determinants. Furthermore, this study's concentration on the mining sector in Indonesia implies that the findings may not be readily generalizable to other countries or industries. Each economic context is unique, and the specific factors influencing the mining sector in Indonesia may not apply universally. Future studies should consider conducting comparative analyses across multiple countries and industries to enhance the external validity of the findings.

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