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THE IMPACT OF COAL AND NICKEL SHOCKS ON STOCK VOLATILITY THROUGHOUT THE DYNAMIC ERA

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Abstrak: Numerous scholars have examined the relationship between stock returns and metal commodities, but there has been less emphasis on specific metal commodities such as coal and nickel. This study sought to investigate the correlation between coal and nickel price fluctuations and their impact on stock market volatility. The researchers employed the GARCH and EGARCH models for analysis. This study utilized data on coal price, nickel price, and two stock market indices in Indonesia, specifically LQ45 and IDX30, spanning from January 2020 to December 2023. The results indicate that there was no substantial correlation between coal shock and nickel shock on stock market volatility. The EGARCH model would be more suitable for prediction. The significance of this research lies in its discovery of the relationship between coal shock and nickel shock on stock return throughout a dynamic period.

INTRODUCTION

Although coal generates carbon emissions, it remains necessary due to its cost-effectiveness as a fuel source for energy and electricity (Lin & Raza, 2020). Several power plants in Europe and the US rely on coal as their primary fuel source. Examples include the Belchatow Power Station in Poland, the Neurath Power Station in Germany (which is the largest operational coal power plant in the European Union as of 2021 in terms of capacity), and the James H. Miller Power Station in Alabama, US. Coal is a necessary source of energy and electricity until a suitable alternative is invented. Despite the impact of the Covid-19 era, coal usage remains elevated and has further increased due to the Ukraine-Russia war. According to the EIA [10], coal use is projected to increase to 28% by 2030 (Lin & Raza, 2020). Nickel is a crucial primary resource for several products, including stainless steel and batteries. Consequently, nickel holds significant importance as a raw material in the manufacturing of electric cars.

Indonesia ranks as the fifth largest coal producer globally, following China, the US, India, and Australia. Its annual coal production exceeds 500 billion tons, making it a significant player in the global coal industry. Indonesia has several prominent mining companies listed on the Indonesia Stock Index (IDX), including PT Bumi Resources, Tbk and PT Adaro Indonesia, Tbk. These stocks are also included in the LQ45 and IDX30, which are major stock indices in the IDX. According to GlobalData, the primary countries dominating the nickel mining market include Indonesia, the Philippines, Russia, New Caledonia, and Australia, among others. Indonesia exerted significant control over the nickel mining business in 2023.

The commodity market has garnered significant interest from traders and speculators for trading and hedging purposes in recent years. The recent attention lies in the association between the fluctuation of metal prices and the financial market (Choi & Hammoudeh, 2010; Peng et al., 2014). Several studies indicate that the volatility of commodities has had a reinforcing effect on the financial market. This is because any increase in the commodity market would have an impact on the sales of mining firms, and vice versa (Wen et al., 2021). A significant number of scholars have examined the relationship between metal commodities and stock returns, with a predominant focus on gold and less attention given to other metals like nickel and coal (Woode et al., 2024). It is crucial to comprehend the correlation between various assets in order to effectively manage portfolios and assess risks in financial markets (Junttila et al., 2018).

Indonesia possesses significant coal reserves, ranking as the 7th largest globally, following the United States, Russia, Australia, China, India, and Germany. Indonesia's annual coal production exceeds 200 million tons, making it a significant contributor to the country's economy (bps.go.id). Indonesia holds the title of being the largest producer of nickel globally, with a production volume of 1.8 million tons. Additionally, it is home to the world's largest nickel factory (Mutia Annur, n.d.). Hence, it is crucial to closely monitor the prices of coal and nickel in this study.

The significance of this research lies in its discovery of the relationship between coal shock and nickel shock on stock returns throughout a dynamic period. The paper is divided into the following sections. Section 2 presents the theoretical framework and hypothesis. Section 3 consists of both a procedure and data. Section 4 provides an overview of the findings and includes a detailed discussion. Section 5 presents the final findings, constraints, and recommendations for future investigations.

THEORETICAL FRAMEWORK AND HYPOTHESES

The Indonesia Stock Exchange Index 30 (IDX30) was introduced on April 23, 2012, with an initial value of 100. It is a stock market index in Indonesia that comprises the top 30 stocks in the country's stock market. The IDX30 is primarily composed of the infrastructure and banking industries. The IDX30 stock index assesses a company's performance by considering three key factors: substantial market value, significant liquidity, and robust performance. The selection of these companies will be determined on many criteria, such as their financial performance, free float market capitalization, transaction volume, value, and other considerations (idx.co.id). This research focuses on discussing the significance of this stock index, which comprises the 30 largest market capitalization stocks.

The LQ45 Index measures the performance of the 45 most liquid businesses listed on the Indonesia Stock Exchange (IDX), including at least 70% of their capitalization and transaction value. A stock included in the LQ45 index must possess robust financial stability, exhibit potential for growth, and experience significant trading volume. Every half-year, an evaluation will be conducted on those stocks; if any of them fail to meet the established criteria, they will be substituted in the subsequent stock selection cycle (idx.co.id). The LQ45 index was first introduced in February 1997, making it a suitable candidate for examination in this research.

Zhu et al (2021) examined the impact of non-ferrous metal prices on the stock market. The Chicago Board of Exchange (CBOE) Volatility Index (VIX) was utilized to represent stock market uncertainty, while the London Metal Exchange base metal index (LME index) was employed as a substitute for non-ferrous metal prices. The researchers conducted an analysis on how changes in pricing of non-ferrous metals affect the stock market by employing Quantile Regression (QREQ) methodology. Consequently, the stock market gains advantages from the pricing of non-ferrous metals.

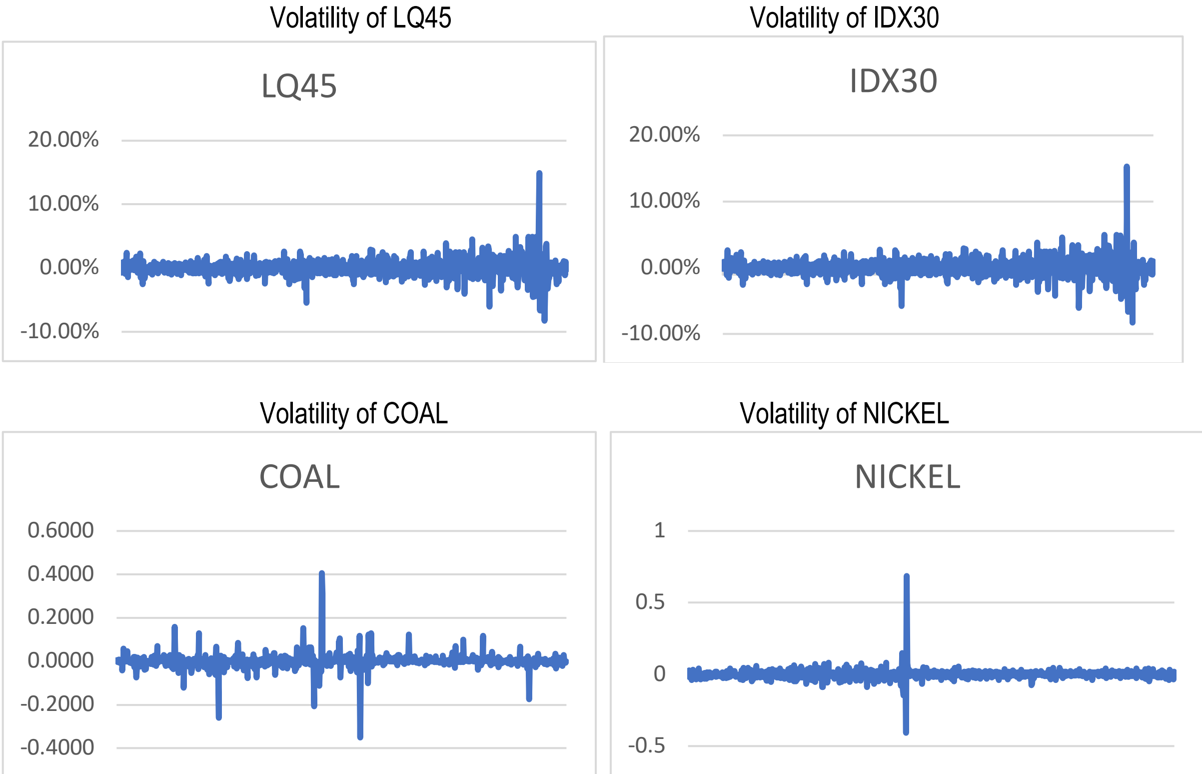
Iyke & Ho (2021) conducted a study to examine the influence of several commodity prices, including nickel, on stock prices in three countries. The countries in question were the Netherlands, United Kingdom, and USA. Data from the Netherlands was collected from 1629 to 1812, data from the UK was collected from 1629 to 1870, and data from the US was collected from 1871 to 2015. The researchers employed the out-of-sample R-squared (OOS) and Theil's U ratio as evaluation metrics to test the approach. They discovered that the commodities accurately predicted stock returns. In their study, Gorton & Rouwenhorst (2006) analyzed the impact of commodities on US stock returns throughout the period from July 1959 to December 2004. They discovered a negative association between commodities and stock returns.

Commodities returns differ from other financial assets, such as stocks, bonds, and other financial assets. Commodities are financial assets that are derived from other securities. As a result, commodities are not considered to be long-lasting investments. Additionally, many commodities exhibit significant fluctuations in volatility that are influenced by seasonal patterns (Gorton & Rouwenhorst, 2006). Commodity investors seek to mitigate risk or generate profits by capitalizing on short-term fluctuations in commodity prices. Commodity prices are influenced by the actions of commodity traders and speculators (Junttila et al., 2018).

The following hypothesis can be derived from the aforementioned information:

Hypothesis 1: The occurrence of a coal shock has a significant effect on the level of fluctuation in stock prices.

Hypothesis 2: The occurrence of a nickel shock has a significant effect on the degree of fluctuation in stock prices.



Source : investing.com, processed

Figure 1. The Variables Fluctuation From January 2020 to December 2023

RESEARCH METHODS

The research focuses on analyzing the volatility of LQ45 and IDX30 as the dependent variables. The independent factors included are Coal shock and Nickel shock, which are derived from the daily fluctuations observed between January 2020 and December 2023. The information originated from investing.com. The computation of the return for those variables is performed using:

$$Rt = \frac{Pt - Pt\text{-}1}{Pt-1} \quad (1)$$

Note :

Rt = return of variables

Pt = the price or value of variables in t period

Pt-1 = the price or value of variables in t-1 period

This study examines the correlation between dependent and independent variables using Generalized Auto Regression Conditional Heteroskedasticity (GARCH) models, specifically GARCH (1,1) and Exponential GARCH (EGARCH). Prior to applying the GARCH approach, it is imperative to conduct tests on the stationary variables. Time series data necessitate a stationary test due to the presence of a root or non-stationary data, which might result in erroneous or dubious regression outcomes. Hence, doing a stationary test is important. One way to assess the stationarity of these variables is by use the Augmented Dickey-Fuller (ADF) test (Setiawan et al., 2021). This study performed a stationary test utilizing the Augmented Dickey-Fuller (ADF) test. The GARCH series is considered the most effective approach for explaining time series data, as stated by Jalbert in 2013. The subsequent are the exemplar of GARCH methodologies:

$$Rt = \alpha + \beta t\,(X) + \varepsilon t \quad (2)$$

$$\varepsilon t = \Phi\varepsilon_{t-1} + \ldots + \Phi\varepsilon_{t-n} + \dot{\eta}_t \sim N(0,1) \quad (3)$$

$$\dot{\eta}_t = \sigma\varepsilon_t \quad (4)$$

$$\sigma\varepsilon_t = \alpha 0 + \alpha_1\dot{\eta}_{t-1} + \ldots + \alpha_n\dot{\eta}_{t-n} + \beta_1\sigma\varepsilon_{t-1} + \ldots + \beta_n\sigma\varepsilon_{t-n} \quad (5)$$

Notes :

Rt = return of dependent variables (LQ45 and IDX30)

α = constant

β = regression coefficient of independent variables (Coal and Nickel)
εt = residual of regression

The symbol εt represents a discrete time stochastic process with real values that follows an identical and independent distribution with mean 0 and standard deviation 1 (N(0,1)). This process is not influenced by any historical data. The total body of knowledge at a given moment t is denoted as X (Bollerslev, 1986; Yunita & Robiyanto, 2018).

The Akaike Information Criterion (AIC) is a commonly employed statistical metric for the purpose of selecting models. It is beneficial to determine the model that provides the most accurate explanation of the data while minimizing complexity, taking into account both the quality of fit and simplicity. AIC values are used to compare different models; the model with the lowest AIC is preferred. By comparing AIC values across models, one can objectively choose the model that achieves the best trade-off between goodness of fit and simplicity. The computation of AIC can be performed by:

$$AIC = 2k - 2\ln(L) \quad (6)$$

Note :
k is the number of parameters in the model.
L is the maximum likelihood of the model.
The lower AIC value indicates a better model fit relative to the other models being compared. This research uses AIC to examine a better model fit between GARCH and EGARCH.

RESULTS AND DISCUSSION

The descriptive statistics for all variables are shown in table 1.

Table 1. Descriptive Statistic of All Variables

	LQ45	IDX30	Coal	Nickel
Mean	5.62E-05	-1.05E-05	0.001318	0.000910
Median	0.000175	9.72E-05	0.000574	0.000687
Maximum	0.149216	0.152847	0.405751	0.685833
Minimum	-0.082613	-0.082803	-0.351085	-0.407192
Std. Dev.	0.014100	0.014322	0.032389	0.041441
Skewness	0.694699	0.761077	1.088251	7.773722
Kurtosis	20.12371	20.35611	58.72113	154.7652
Observations	972	972	972	972

Source : investing.com, processed

The mean of LQ45 volatility, IDX30 volatility, Coal shock, and Nickel shock are 5.62E-05, -1.05E-05, 0.001098, and 0.00091 respectively. The mean value of all variables is positive, except IDX30 volatility. It means the portfolio still remain loss even the member of IDX30 index are the blue chip stock. The maximum, minimum, standard deviation, skewness, and kurtosis of LQ45 volatility and IDX30 volatility almost the same, it is because some stock in LQ45 and IDX30 are the same. The maximum, minimum, standard deviation, skewness, and kurtosis value of Coal shock and Nickel shock are shown at table 1 indicate the volatility are higher than LQ45 volatility and IDX30 volatility. The total number of observations is 972 data.

Table 2. Correlation of Variables

	LQ45	IDX30	Coal	Nickel
LQ45	1.000000	0.997661	0.005244	0.079555
IDX30	0.997661	1.000000	0.003434	0.077383
Coal	0.005244	0.003434	1.000000	-0.023617
Nickel	0.079555	0.077383	-0.023617	1.000000

Source : investing.com, processed

Table 2 shown there are no perfect correlation between all variables, hence, those variables might be scrutinized by GARCH methods.

Table 3. Unit Root Test

Variable	t-Statistic	Probability	Result
LQ45	-16.31760	0.0000*	Stationary
IDX30	-16.40037	0.0000*	Stationary
Coal	-26.61206	0.0000*	Stationary
Nickel	-23.94539	0.0000*	Stationary

Note : * indicate significance at the 0.01
Source: investing.com, processed

Table 3 uses the Augmented Dickey-Fuller (ADF) test to describe the unit root test of all variables. The result of that test is all variables significant at 0.01, hence, GARCH methods might be used to scrutinize the stationary data of all variables.

Table 4. GARCH Result

Variables		Result				
Y	X	Coefficient	Probability	RESID(-1)^2	GARCH(-1)	AIC
LQ45	Coal	0.004951	0.5794	0.0000	0.0000	-6.194911
LQ45	Nickel	0.009999	0.2311	0.0000	0.0000	-6.197410
IDX30	Coal	0.005280	0.5656	0.0000	0.0000	-6.143187
IDX30	Nickel	0.009974	0.2438	0.0000	0.0000	-6.145446

Note: *,**,*** are significant at 0.01, 0.05, and 0.1 level of significance, respectively
Source : investing.com, processed

The impact of Coal shock on LQ45 volatility and IDX30 volatility was described in table 4. The coefficient of those impact are 0.009244 and 0.009025 respectively, hence, there is a positive relationship between those variables. It means the variable LQ45 and Coal changes as well, and vice versa. The probability value of those impact are 0.3167 and 0.3526, those value are more than 0.1, indicate there is insignificant impact the shock of Coal on the LQ45 volatility and IDX30 volatility.

The impact of Nickel shock on LQ45 volatility and IDX30 volatility was described in table 4. The coefficient of those impact are 0.009999 and 0.009974 respectively, hence, there is a positive relationship between those variables. It means the variable volatility of LQ45 and volatility of Nickel shock as well, and vice versa. The probability value of those impact are 0.2311 and 0.2438, those value are more than 0.1, indicate there is insignificant impact the shock of Nickel and IDX30 volatility.

Table 5. EGARCH Result

Variables		Result				
Y	X	Coefficient	Probability	RESID(-1)^2	GARCH(-1)	AIC
LQ45	Coal	0.007774	0.3402	0.0000	0.0000	-6.211336
LQ45	Nickel	0.007891	0.4052	0.0000	0.0000	-6.212424
IDX30	Coal	0.005942	0.4744	0.0000	0.0000	-6.150054
IDX30	Nickel	0.008929	0.2902	0.0000	0.0000	-6.151795

Note: *,**,*** are significant at 0.01, 0.05, and 0.1 level of significance, respectively
Source : investing.com, processed

The impact of Coal shock on LQ45 volatility and IDX30 volatility was described in table 5. The coefficient of those impact are 0.007889 and 0.008629 respectively, hence, there is a positive relationship between those variables. It means the variable LQ45 and Coal changes as well, and vice versa. The probability value of those impact are 0.4631 and 0.3909, those value are more than 0.1, indicate there is insignificant impact the shock of coal on the LQ45 volatility and IDX30 volatility.

The impact of Nickel shock on LQ45 volatility and IDX30 volatility was described in table 5. The coefficient of those impact are 0.007891 and 0.008929 respectively, hence, there is a positive relationship between those variables. It means the variable LQ45 and Nickel changes as well, and vice versa. The probability value of those impact are 0.4052 and 0.2902, those value are more than 0.1, indicate there is insignificant impact the shock of Nickel on the LQ45 volatility and IDX30 volatility.

Table 4 and table 5 described the impact of Coal and Nickel on volatility of LQ45 and volatility of IDX30, the proxy of stock market volatility. Table 4 uses GARCH method and table 5 uses EGARCH methods. Both of table 4 and table 5 indicate there is insignificant implication of Coal return on stock market (LQ45 and IDX30), hence hypothesis 1 is to be rejected. Both of table 4 and table 5 indicate there is insignificant implication of Nickel return on stock market (LQ45 and IDX30), hence hypothesis 2 is to be rejected.

The Akaike Info Criterion (AIC) value in table 4, that uses GARCH method are -6.197002, -6.197410, -6144982, and -6.145446 respectively and table 5 that uses EGARCH method are -6.212200, -6.212424, -6.151463, and -6.151795. The lower AIC values indicates a better model than another as the aforementioned. The comparisons indicate that the AIC values of EGARCH is lower than the AIC values of GARCH, hence, EGARCH methods are better to use for predicting the future value.

CONCLUSION

The empirical evidence demonstrates that the coal shock and nickel shock have a negligible impact on stock returns during the dynamic age of the Covid-19 pandemic. The coal and nickel mining firm has been anticipating these shocks and implementing a hedging plan, resulting in a little impact on the company's performance and stock due to the coal and nickel shocks. Another possible explanation is that these mining companies have established long-term contracts with their buyers, resulting in the coal and nickel shocks having a negligible effect on stock returns. The portfolio manager, stock trader, and stock investor should take into account the empirical evidence. The limitations of this research include the utilization of data from the COVID-19 era and the reliance on data from a single country. Further research is investigating the effects of coal shock and nickel shock at different periods, such as financial crises. Additionally, it is examining the influence of another commodity shock, specifically natural gas, on stock returns.

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