Commodity Price Volatility and Jakarta Composite Index Volatility: Evidence from the Indonesia Stock Exchange

Fitri Noprita Sari[1*], Fitri Santi[2]

[1,2] Faculty of Economics and Business, University of Bengkulu, Bengkulu, Indonesia

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****Corresponding Author:***
nopie353@gmail.com

A B S T R A C T

This study aims to analyze the impact of crude oil, coal, and gold price volatility on the volatility of the Jakarta Composite Index (JCI) on the Indonesia Stock Exchange during 2018-2025. While numerous prior studies have examined the relationship between commodity prices and the JCI, most have focused on price changes and employed linear regression approaches. Research regarding the simultaneous volatility transmission from multiple global commodities to the JCI remains limited and has yielded inconsistent results. This study addresses this gap by analyzing the volatility of crude oil, coal, and gold using an ARCH-family approach over a period characterized by various episodes of global uncertainty. The study uses daily secondary data on WTI crude oil, Newcastle coal, the London Gold Fixing, and the JCI, sourced from Investing.com and Yahoo Finance. GARCH, TARCH, IGARCH, and EGARCH models were tested, with TARCH selected as the best-fitting model based on AIC, SIC, and log-likelihood criteria. The results indicate that the volatility of crude oil and gold has a positive and significant impact on JCI volatility, whereas coal volatility does not have a significant effect. Theoretically, this study enriches the volatility spillover literature by demonstrating that volatility transmission varies across commodities. From a practical perspective, the volatility of oil and gold can serve as indicators for monitoring risk in the Indonesian stock market. Keywords: Coal, JCI, Oil, TARCH, Volatility

A B S T R A K

Penelitian ini bertujuan untuk menganalisis pengaruh volatilitas harga minyak bumi, batu bara, dan emas terhadap volatilitas Indeks Harga Saham Gabungan (IHSG) di Bursa Efek Indonesia pada periode 2018-2025. Meskipun berbagai penelitian terdahulu telah mengkaji hubungan antara komoditas dan IHSG, sebagian besar penelitian tersebut berfokus pada perubahan harga dan menggunakan pendekatan regresi linier. Sementara itu, penelitian mengenai volatilitas berbagai komoditas global terhadap IHSG masih terbatas dan hasilnya tidak konsisten. Penelitian ini mengisi kesenjangan tersebut dengan menganalisis volatilitas harga minyak bumi, batu bara, dan emas menggunakan pendekatan ARCH-family selama periode yang ditandai oleh berbagai episode ketidakpastian global. Penelitian ini menggunakan data sekunder harian WTI, batu bara Newcastle, London Gold Fixing, dan IHSG yang diperoleh dari Investing.com dan Yahoo Finance. Model GARCH, TARCH, IGARCH, dan EGARCH diuji, dan TARCH dipilih sebagai model terbaik berdasarkan kriteria AIC, SIC, dan log-likelihood. Hasil penelitian menunjukkan bahwa volatilitas minyak bumi dan emas berpengaruh positif dan signifikan terhadap volatilitas IHSG, sedangkan volatilitas batu bara tidak berpengaruh signifikan. Secara teoritis, penelitian ini memperkaya literatur mengenai volatilitas spillover dengan menunjukkan bahwa transmisi volatilitas berbeda antar komoditas. Sedangkan secara praktis, volatilitas minyak bumi dan emas dapat digunakan sebagai salah satu indikator dalam memantau risiko di pasar saham Indonesia.

1. INTRODUCTION

Fluctuations in global commodity prices over the past few years have been a significant source of uncertainty for the economy and financial markets. The 2018-2025 period was marked by global economic and geopolitical events, including the US-China trade war, the COVID-19 pandemic, and the Russia-Ukraine conflict, which disrupted economic activity, supply chains, and global commodity markets. These conditions were reflected in the price movements of crude oil, coal, and gold, which experienced sharp declines, rapid surges, and correlations within relatively short timeframes (World Bank, 2025). Such changes demonstrate that issues within commodity markets relate not only to shifts in price levels but also to heightened price uncertainty or volatility. For an open economy like Indonesia, global commodity volatility is critical, as changes in external conditions can be transmitted to domestic financial markets and influence investment conditions.

The relationship between commodity markets and the Indonesian stock market warrants examination, given the strong ties between Indonesia's economic activity and commodity-based sectors. The Jakarta Composite Index (JCI), serving as an aggregate indicator of the Indonesian stock market, can respond to changes in global commodity conditions through shifts in corporate profitability, production costs, inflationary pressures, investor sentiment, and investment allocation decisions. Crude oil, coal, and gold each possess distinct transmission mechanisms that affect the stock market. Rising crude oil prices can increase production and transportation costs and exert inflationary pressure, potentially dampening stock market performance (Adiningtyas, 2018; Sopiyah et al., 2025). Conversely, rising coal prices boost mining companies' profitability and positively affect the stock market (Wardani & Budiwitjaksono, 2021; Nu'man et al., 2024). Meanwhile, gold exhibits different characteristics, as it is frequently utilized as a hedging asset. Amidst rising uncertainty, investors may shift their investments from the stock market to gold, potentially creating an inverse relationship between gold prices and the Jakarta Composite Index (JCI) (Handika et al., 2021; Oktariansyah, 2023). These differing mechanisms indicate that changes in commodity market conditions do not always yield the same impact on the Indonesian stock market.

Numerous prior studies have examined the relationship between crude oil, coal, gold, and the JCI; however, the findings remain inconsistent. Some studies have identified the influence of crude oil prices on the Indonesian stock market, while others have reported contrasting results. Similar inconsistencies appear in research concerning coal and gold prices (Sopiyah et al., 2025; Nu'man et al., 2024; Oktariansyah, 2023). These divergent findings suggest that the relationship between commodity markets and the JCI cannot be fully explained by changes in price levels alone. Furthermore, most previous studies have focused primarily on commodity price levels or changes in them, employing linear regression. Such approaches fail to adequately capture the dynamic volatility characteristics of financial markets, such as volatility clustering and time-varying risk levels. Consequently, measuring volatility is crucial for determining whether uncertainty in commodity markets transmits to uncertainty in the Indonesian stock market.

Although prior research has explored the relationship between commodities and stock markets, as well as studies on volatility, the empirical evidence currently available remains limited and fragmented, particularly concerning the scope of commodities, measurement methodologies, and research contexts. While some investigations have examined the impact of commodity volatility on the Indonesian stock market, with specific focus on commodities such as crude oil and gold, there is a notable scarcity of studies that analyze the simultaneous volatility of crude oil, coal, and gold to elucidate JCI volatility. Furthermore, existing studies have not offered a comprehensive understanding of whether the transmission of volatility from various global commodities to the Indonesian stock market is uniform or varies across different commodities. This issue has gained increased significance during the period of 2018-2025, as the timeframe encompasses several episodes of global uncertainty that could potentially amplify volatility and strengthen inter-market linkages. To address this gap, the present study analyzes the impact of volatility in crude oil, coal, and gold prices on the volatility of the Jakarta Composite Index (JCI) during the period of 2018-2025. The ARCH family of models is employed to analyze volatility by considering the influence of past variances on current conditions (Bollerslev, 1986).

2. THEORETICAL FRAMEWORK AND HYPOTHESES

Theoretical Framework

This investigation utilizes the concept of volatility spillover, which posits that uncertainty or shocks in one market can propagate to other markets (Brooks, 2008). Volatility spillover elucidates how shocks or fluctuations in volatility within a single market can be transmitted to other markets or asset classes through mechanisms such as information dissemination, economic conditions, investor expectations, risk perceptions, and portfolio allocation strategies. Diebold and Yilmaz (2012) articulate that volatility can be transmitted across markets and asset classes, with the intensity of spillover fluctuating over time and magnifying during periods of economic and financial turmoil. In this research, volatility spillover is employed to elucidate the potential transmission of volatility from global commodity markets to the Indonesian stock market. An escalation in volatility of crude oil, coal, and gold prices may augment uncertainty concerning economic conditions, corporate expenditures, profitability, and investment risks. Such variations can influence investor expectations and decision-making, thereby affecting the volatility of the Jakarta Composite Index (JCI). Accordingly, this study concentrates on the relationship between commodity volatility and JCI volatility rather than on the correlation between variations in commodity price levels and the JCI. Transmission mechanisms may differ, considering that crude oil is associated with energy costs and economic activities, coal pertains to the mining and export sectors, and gold fulfills a more defensive investment role.

The attributes of gold as a defensive asset are best elucidated through the concept of a safe-haven asset. Baur and Lucey (2010) differentiate between a hedge and a safe haven; a safe haven is an asset that tends to sustain a negative correlation or no correlation with risky assets during episodes of extreme market stress. They concluded that gold can function as a hedge against stocks and as a safe haven during such periods. The safe-haven concept complements volatility spillover theory by elucidating the mechanisms of investor behavior, particularly in times of heightened uncertainty. Under these circumstances, investors may diminish their holdings of risky assets, such as stocks, and reallocate a portion of their funds into assets perceived as more defensive, including gold. These reallocations can intensify volatility linkages between gold and stock markets. Research by Dura et al. (2024), employing TGARCH and DCC-GARCH models, identified volatility spillovers between stock markets and precious metals, as well as shifts in these relationships during periods of market distress.

Therefore, although volatility spillover functions as the fundamental framework for elucidating the transmission of uncertainty across financial markets, the safe haven concept offers a supplementary explanation of investor behavior concerning the relationship between gold and stock markets. The integration of these concepts establishes a theoretical foundation for understanding how volatility in crude oil, coal, and gold may be transmitted to the volatility of the Jakarta Composite Index (JCI) through variations in information, economic conditions, risk perception, and investment decisions. Nevertheless, due to the distinct characteristics inherent to these three commodities, the patterns of volatility transmission to the Indonesian stock market may also exhibit variability.

Previous Studies

Previous studies, as presented in Table 2.1, show differences in the findings regarding the impact of global commodities, particularly crude oil, coal, and gold, on the JCI. Most prior research has generally used linear regression methods, which are less capable of capturing the uncertainty and volatility dynamics. Therefore, this study employs volatility modeling methods that are more appropriate for representing uncertainty in financial time-series data.

Hypothesis

This study is based on two theories: volatility spillover and the safe haven asset theory. Additionally, many earlier studies back up and support this research as well. So, the main ideas we're testing in this study are:

Crude Oil Price Volatility and Jakarta Composite Index (JCI) Volatility

Based on volatility spillover theory, changes in volatility in one market can be transmitted to another through shifts in information, expectations, and investor risk perceptions. In the context of oil and shock markets, heightened uncertainty in the oil market can influence investor assessments of economic conditions and corporate risk, potentially triggering volatility changes in the stock market. Ewing & Malik (2016) identified volatility spillovers between oil and stock markets using a GARCH model.

Table 2.1. Previous Studies

No.	Author	Research Methodology	Variables	Findings
1	Yohanes	TARCH	Harga Minyak Dunia (X1), Nilai Tukar USD IDR (X2), BI Rate (X3), IHSG (Y)	Global oil prices, measured by West Texas Intermediate, have a positive and significant effect on the JCI. The rupiah exchange rate against the US dollar has a negative and significant effect on JCI. The BI rate, measured by the BI 7-Day Rate, has a positive and significant effect on the JCI.
2	Desy Trishardiyanti Adiningtyas	Error Correction Model	Indonesian inflation (X1), exchange rate of rupiah against US dollar (X2), world crude oil price (X3), world gold price (X4), Jakarta Islamic Index (Y)	In the long run, Indonesian inflation, exchange rate, world crude oil price, and world gold price affect the Jakarta Islamic Index. In the short term, changes in Indonesian inflation, global crude oil prices, and global gold prices don't influence the Jakarta Islamic Index, but the exchange rate does impact the Jakarta Islamic Index.
3	Siti Sopiyah, Lia Safitri,Ainur Rodiyah, Endang Noer Anisah, Hari Sundana, Akhmad Afandi, Sriyono	Multiple linear regression	World gold price (X1), world oil price (X2), Dow Jones Index (X3)	World gold price and the Dow Jones Index have a significant positive effect on the JCI, while the world oil price has a significant negative effect on the JCI.
4	Abdul Hayyi Nu'man, Yusron Aliansyah & Abdul Haris	Multiple linear regression and residual test for moderating variable	World gold price (X1), world oil price (X2), coal price (X3), exchange rate (X4), Composite Stock Price Index (Y), Geopolitical Risk Index (M)	Simultaneously, X variables affect the composite stock price index. Partially, world gold, world oil, coal, and exchange rates affect the composite stock price index.
5	Hangga Handika, Anita Damajanti, Rosyati	Multiple linear regression	IDR/USD exchange rate (X1), world gold price (X2), Dow Jones Index (X3), SBI interest rate (X4), inflation (X5), world oil price (X6), JCI (Y)	The IDR/USD exchange rate, world gold price, and Dow Jones Index have a significant effect on the JCI, while the SBI interest rate, inflation, and world oil price have no significant effect on the JCI.
6	Oktariansyah, Andri Eko Putra, Vera Sari, Benny Usman, Yeyen Sundari	Multiple linear regression	Inflation (X1), interest rate (X2), gold price (X3), world oil price (X4), JCI (Y)	Some factors, such as inflation, interest rates, and gold prices, do not influence the composite stock price index, but global oil prices do have an impact on it. At the same time, inflation, interest rates, gold prices, and global oil prices have a positive impact on the composite stock price index.
7	Maria Magdalena Marwanti, Robiyanto	GARCH (1,1)	Gold price volatility, crude oil price volatility, JCI	The ups and downs in crude oil and gold prices did not have an effect on stock returns either before or during the Covid-19 pandemic.
8	Abdul Basit	Multiple linear regression	Gold price (X1), world oil price (X2), JCI (Y)	The gold price has a negative and insignificant effect on the JCI during 2016–2019. Meanwhile, world oil price has a positive and significant effect on the JCI during the same period.
9	Surya Darmawan, Muhammad Shani Saiful Haq	ARDL	Inflation (X1), IDR/USD exchange rate (X2), Nikkei 225 Index (X3), SSE Index (X4), world gold price (X5), world oil price (X6), JCI (Y)	In the short run, inflation, exchange rate, and world oil price have a negative effect on the JCI, while the Nikkei 225, SSE Index, and gold price have a positive effect. In the long run, inflation, exchange rate, SSE Index and oil prices have a negative impact, the Nikkei 225 has a positive impact, and the gold price does not affect the JCI.
10	AnakAgung Ngurah Ramacandra Purwantara	Multiple linear regression	Coal price (X1), palm oil (CPO) price (X2), JCI (Y)	Coal price has a significant positive effect on the JCI. CPO price also has a significant positive effect on JCI.

Similarly, Bastianin & Manera (2017) demonstrated that stock market volatility responds to oil price shocks, and Bagchi (2017) found a linkage between crude oil markets and the stock markets of BRIC nations using an APARCH model. Lin volatility: when oil price volatility rises, uncertainty regarding economic conditions and corporate prospects may also increase. Such conditions can prompt investors to adjust their expectations and investment decisions in response to heightened risk. These adjustments in investment decisions can intensify trading activity and lead to greater stock price fluctuations. Conversely, when oil volatility is lower, the uncertainty faced by investors tends to diminish, potentially leading to greater stock market stability. Thus, changes in oil price volatility can theoretically be transmitted to the volatility of the Jakarta Composite Index (JCI) through shifts in investor risk perceptions and investment decisions.

H1: Crude oil price volatility affects the volatility of the Jakarta Composite Index on the Indonesia Stock Exchange during the 2018–2025 period.

Coal Price Volatility and Jakarta Composite Index (JCI) Volatility

Coal is one of Indonesia's main coal price volatility can influence stock market volatility through cross-market risk transmission mechanisms. Increased coal volatility reflects rising uncertainty in the commodity market, which can affect investors' expectations and risk perceptions, thereby prompting portfolio adjustments and heightening stock market volatility. Asadi et al. (2022) demonstrated the existence of volatility linkages among coal, stock, and currency markets in the United States and China. Their study found that the coal market acts as a net giver within the volatility linkage system, indicating that it transmits more volatility shocks to other markets than it receives from them. Similar findings were reported by Zolfaghari et al. (2020), who identified volatility spillovers between energy and stock markets, including a significant covolatility relationship involving the coal market. Furthermore, Feng et al. (2023) discovered dynamic spillovers between energy markets, including coal and stock markets, demonstrating that risk changes in energy markets can be transmitted to stock markets. When coal price volatility rises, increased uncertainty and shifts in investor risk perception can drive portfolio adjustments, ultimately leading to higher stock market volatility.

H2: Coal price volatility affects the volatility of the Jakarta Composite Index on the Indonesia Stock Exchange during the 2018–2025 period.

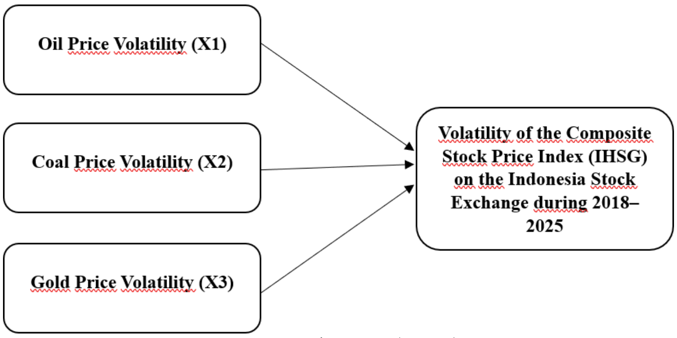
Gold price volatility and Jakarta Composite Index (JCI) Volatility

Gold price volatility can heighten stock market volatility through the transmission of risk across financial markets. From the perspective of the safe-haven asset theory, gold is viewed as a relatively secure asset during periods of financial market stress or uncertainty; consequently, investors tend to increase their allocation to gold while adjusting their holdings of riskier assets, such as stocks. Gold price volatility often reflects conditions in global financial markets, where an increase in volatility indicates rising risk and uncertainty. An increase in gold prices typically signals heightened uncertainty in financial markets (Handika et al., 2021). In these situations, investors usually move their money from stocks to gold because gold is seen as a more secure investment (Marwanti & Robiyanto, 2021). When gold volatility rises alongside increasing market uncertainty, shifts in risk perception and investor portfolio adjustments can amplify stock market fluctuations. Celik et al. (2018) identified a volatility spillover from the gold market to the stock market of emerging economies. Similarly, Xie et al. (2020) demonstrated the existence of a volatility spillover between the gold and stock markets. These findings support the existence of a risk linkage between the gold and stock markets. Although gold's role as a safe haven primarily manifests during conditions of market stress, indicating that heightened uncertainty in the gold market can influence investor behavior, an increase in gold price volatility is expected to heighten the volatility of the Jakarta Composite Index through changes in risk perception and investor portfolio adjustments.

H3: Gold price volatility affects the volatility of the Composite Stock Price Index on the Indonesian Stock Exchange during the 2018–2025 period.

Conceptual Framework

This conceptual framework delineates the relationship between the price volatility of crude oil, coal, and gold, serving as independent variables, and the volatility of the Jakarta Composite Index (JCI), which functions as the dependent variable. This relationship is rooted in the concept of volatility spillover, which pertains to the transmission of volatility changes from commodity markets to equity markets, as well as the role of gold as a safe haven and an alternative investment sought during periods of uncertainty. Crude oil price volatility is anticipated to be correlated with JCI volatility because changes in uncertainty within the oil market can influence investor expectations and risk perceptions. Similarly, variations in coal price volatility can impact JCI volatility owing to the commodity's connection with economic activity and enterprises operating within the energy and mining sectors. Furthermore, gold price volatility is expected to be associated with JCI volatility, considering gold's status as an asset to which investors turn during times of heightened uncertainty. Consequently, this conceptual framework posits that the price volatilities of oil (X1), coal (X2), and gold (X3) are related to JCI volatility (Y) over the period 2018–2025.



Source: Yohanes (2023)
Figure 2.1 Conceptual Framework

3. RESEARCH METHOD

Data and Variables

This study employs a quantitative approach with a confirmatory design to examine the impact of variations in global commodity prices on fluctuations in the Indonesian stock market. The data utilized are secondary time series data gathered on a daily basis from 2018 to 2025. The data set includes prices for West Texas Intermediate crude oil, Newcastle coal, London Gold Fixing, and the Composite Stock Price Index. The data are gathered from official websites like Investing.com and Yahoo Finance through documentation methods, which involve collecting and downloading the available historical data.

This study utilizes two categories of variables: dependent and independent variables. The independent variables include crude oil price volatility (X1), coal price volatility (X2), and gold price volatility (X3), whereas the dependent variable is the volatility of the composite stock price index (Y).

Data Analysis Technique

This study uses a time series econometric method based on ARCH family models, including GARCH, TARCH, IGARCH, and EGARCH. These models were tested, and the one that worked best was chosen to analyze the data. The analysis began by calculating the daily data of the JCI, WTI crude oil, Newcastle coal, and gold. Subsequently, stationarity testing was performed on the return data using the Augmented Dickey-Fuller (ADF) test. The ADF test utilizes a constant without a tren, with the lag length automatically selected based on the Akaike Information Criterion (AIC) up to a maximum of 24 lags. The test results indicate that all data series were stationary.

Once the data are confirmed to be stationary, the ARCH-LM test is conducted to determine the presence of time-varying volatility. The results reveal significant ARCH effects, justifying the use of ARCH-family models to analyze volatility. Next, the GARCH, TARCH, EGARCH, and IGARCH

The models were estimated and compared to identify the most suitable model. The GARCH model was used to observe volatility patterns over time, while TARCH and EGARCH were employed to examine potential asymmetries in volatility responses to positive and negative shocks. The IGARCH model was used to assess whether volatility exhibits a very high level of persistence, indicated when the sum of the ARCH and GARCH parameters equals one. All models utilized the Student-t distribution. The selection of the best model was conducted by comparing the AIC, SIC, and log-likelihood values. The model with the lowest AIC and SIC values and the highest log-likelihood was selected as the best model. Based on the comparison reslts, TARCH was chosen as the best model, exhibiting an AIC of 2.546583, an SIC of 2.573169, and log likelihood of -2,377.148. Following the selection of the TARCH model, an ARCH-LM test was performed to verify that the model successfully captured the ARCH effects present in the data. Subsequently, hypothesis testing was conducted by examining the coefficient and probability values at a 5% level.

Table 3.1. Operational Definition of Variables

Variable	Operational Definition	Operational Definition	Data Source
Crude Oil Price Volatility (X1)	The level of fluctuation in West Texas Intermediate (WTI) crude oil prices was measured using daily returns and then modeled using GARCH (1,1).	The return of crude oil prices is calculated as follows: $R_{WTI,t} = 100\ x\ log\left(\frac{WTI_t}{WTI_{t-1}}\right)$ .... (1) Subsequently, the return series is modeled for volatility using the TARCH model.	Investing.com
Coal Price Volatility (X2)	The level of fluctuation in Newcastle coal prices was measured using daily returns and then modeled using GARCH (1,1).	The return of coal prices is calculated as follows: $R_{Coal,t} = 100\ x\ log\left(\frac{Coal_t}{Coal_{t-1}}\right)$... (2) Subsequently, the return series is modeled for volatility using the TARCH model.	Investing.com
Gold Price Volatility (X3)	The level of fluctuation in gold futures prices was measured using daily returns and then modeled using GARCH (1,1).	The return of gold prices is calculated using: $R_{Gold,t} = 100\ x\ log\left(\frac{Gold_t}{Gold_{t-1}}\right)$...(3) Subsequently, the return series is modeled for volatility using the TARCH model.	Investing.com
Composite Stock Price Index (Y)	The daily return or loss of the composite stock price index calculated from changes in the daily closing price of the Composite Stock Price Index.	The return of gold prices is calculated using: $R_{Gold,t} = 100\ x\ log\left(\frac{Gold_t}{Gold_{t-1}}\right)$......(4) Subsequently, the return series is modeled for volatility using the TARCH model.	Yahoo finance

4. DATA ANALYSIS

Augmented Dickey-Fuller (ADF) Stationarity Test

The Augmented Dickey-Fuller test checks whether the data has a unit root and is not stationary. This test is also performed to check whether the estimates of ARCH-family volatility models are accurate. The ADF test utilizes a constant without a trend, with the lag length automatically selected based on the Akaike Information Criterion (AIC) up to a maximum of 24 lags. The test results indicate that all data series are stationary.

Table 4.1. Results of the Augmented Dickey-Fuller (ADF) Stationarity Test

Variable	ADF *Statistic*	*Critical Value* (5%)	Probability	Remark
JCI	-13.51271	-2.862889	0.0000	Stationary
Crude Oil	-8.970390	-2.862896	0.0000	Stationary
Coal	-10.23391	-2.862895	0.0000	Stationary
Gold	-25.15257	-2.862882	0.0000	Stationary

As indicated by the ADF stationarity test results in Table 4.1, all variables in the study exhibit ADF test statistics below the critical values at the 5% significance level, with p-values all under 0.05. These findings lead to the rejection of the null hypothesis, which posits the presence of unit roots in the data. Consequently, all the research variables were deemed stationary.

Normality Test (Jarque-Bera)

The Jarque–Bera test checks whether the residuals from the returns are normally distributed. This test checks whether the assumption about how errors are spread out in the ARCH-family model is correct.

Table 4.2. Descriptive Statistics of Returns

Variable	Mean	Std.Dev	Maximum	Minimum	*Skewness*	Curtosis
JCI	0.016566	1.032091	9.704184	-8.231876	-0.352884	12.86507
Crude Oil	-0.002192	3.329629	58.12350	-56.85889	-0.496582	104.7828
Coal	0.002040	2.534551	34.05715	-43.24539	-2.108224	91.87076
Gold	0.064410	0.929430	6.789938	-5.400950	0.114588	6.737655

As shown in Table 4.2, the returns of the JCI, crude oil, coal, and gold exhibit varying levels of volatility. Crude oil and coal display the highest volatility and the most extreme movements, while gold is relatively more stable. In addition, skewness values that differ from zero and curtosis values significantly greater than three for all variables indicate that the return distributions are non-symmetric and leptokurtic. This reflects the characteristics of financial data, which are inherently unstable and prone to shocks. These conditions confirm that the use of return data, along with the application of ARCH-family volatility models, is necessary to analyze the impact of crude oil, coal, and gold on JCI volatility.

Table 4.3. Results of the Jarque-Bera Normality Test

Variable	*Jarque-Bera*	Probability	Remark
JCI	7637.939	0.000000	Not Normally
Crude Oil	809000.0	0.000000	Not Normally
Coal	618091.3	0.000000	Not Normally
Gold	1094.930	0.000000	Not Normally

Table 4.3 presents the outcomes of the Jarque-Bera normality test. The JCI variable yields a Jarque-Bera (JB) statistic of 7637.939 and a probability value of 0.000000, which is below 0.05, signifying that the data do not follow a normal distribution. For the crude oil variable, the JB statistic is 809000.0 with a probability of 0.000000, also under 0.05, indicating non-normality. Likewise, the coal variable shows a JB statistic of 618091.3 and a probability of 0.000000, verifying non-normal distribution. Lastly, the gold variable has a JB statistic of 1094.930 and a probability of 0.000000, less than 0.05, confirming that the data are not normally distributed.

ARCH-LM Test

The ARCH-LM test is used to check for heteroscedasticity in the residuals from the mean model, which is the starting point for using ARCH-family models.

Table 4.4. Results of the ARCH-LM Test

Test Statistics	Value	Probability
F-Statistic	79.98613	0.0000
*Obs*R-squared*	330.3108	0.0000

According to the ARCH-LM test results in Table 4.4, the F-statistic was 79.98613 and the Obs* R-squared was 330.3108, with a p-value of 0.0000. Since the p-value is below 0.05, the null hypothesis H_0 is rejected. This indicates that the residuals from the mean model exhibit conditional heteroscedasticity, commonly referred to as an ARCH effect. Therefore, employing ARCH-family models in this study proves to be the appropriate and necessary approach.

Selection of Volatility Models: GARCH, TARCH, IGARCH, and EGARCH

The selection of volatility models is conducted to determine the most appropriate model for analyzing data that typically exhibit time-varying volatility, extreme shocks, and potential asymmetric market responses that cannot be captured by conventional linear models. The GARCH model is used as the main model to understand volatility clustering, which means that times of high market swings are often followed by more swings, and calm periods are usually followed by calm periods. The TARCH and EGARCH models can handle asymmetric effects, also known as leverage effects, where negative surprises or bad news tend to have a larger effect on volatility compared to positive surprises.

The IGARCH model is used to detect long-term volatility persistence, which refers to a situation in which the effect of shocks on volatility lingers and fades gradually over time.

The best model was selected based on three key criteria: the lowest Akaike Information Criterion (AIC), the lowest Schwarz Information Criterion (SIC), and the highest (most positive) log likelihood value.

Table 4.5. Results of Volatility Model Selection

Model	AIC	SIC	*Log Likelihood*
GARCH	2.561130	2.584762	-2391.779
TARCH	2.546583	2.573169	-2377.148
IGARCH	2.654045	2.668815	-2481.840
EGARCH	2.547724	2.574310	-2378.217

The results from the volatility model selection in Table 4.5 show that the TARCH model performs best. It has the smallest AIC and SIC values, which are 2.546583 and 2.573169, respectively. Additionally, it has a higher Log-Likelihood value of -2377.148 compared to the other models.

The results show that the TARCH model explains volatility best because it can account for both how volatility depends on past values and the different effects of negative and positive shocks.

Model Adequacy Test

This stage is conducted to ensure that the selected model—namely, the one with the lowest AIC and SIC values and the highest (most positive) log likelihood—is appropriate for modeling volatility. The model adequacy test is performed by reapplying the ARCH-LM test to the model residuals. If the results indicate that ARCH effects are still present in the residuals, the model is considered inadequate. Conversely, if no ARCH effects are detected, the model is deemed appropriate for capturing volatility.

Table 4.6. Results of Model Adequacy Test

Test Statistics	Value	Probability
F-Statistic	0.187669	0.9673
*Obs*R-squared*	0.940892	0.9672

Based on the model adequacy test results using the ARCH-LM test, the F-statistic is 0.187669 and the Obs*R-squared is 0.940892, with corresponding probabilities of 0.9673 and 0.9672. The probability numbers are all higher than 0.05, which means that there are no more ARCH effects left in the residuals. Therefore, the TARCH model is a good choice and works well for modeling volatility.

The TARCH regression model is specified as follows:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma D_{t-1}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (5)$$

Where:
σ_t^2= current level of volatility
ω= long term volatility level in the absence of shocks
$\alpha\varepsilon_{t-1}^2$= sensitivity of volatility to past shocks
$\gamma D_{t-1}\varepsilon_{t-1}^2$= asymmetric (leverage) effect
$\beta\sigma_{t-1}^2$= effect of past volatility on current volatility

Hypothesis Testing

The Effect of Crude Oil, Coal, and Gold Price Volatility on JCI Volatility

Table 4.7. The Effect of Crude Oil, Coal, and Gold Return Volatility on JCI Volatility

Variable	Coefficient	Probability	Remark
VOL_WTI	0.009253	0.0000	Significant
VOL_COAL	-0.000000385	0.0930	Insignificant
VOL_GOLD	0.034114	0.0000	Significant

According to Table 4.7, the coefficient for the crude oil volatility variable is 0.009253, which means that when crude oil volatility increases, it also causes JCI volatility to rise. The probability value for crude oil volatility is 0.0000, which is below 0.05, indicating that this variable is statistically significant. The coal volatility variable has a coefficient of -0.000000385, meaning that when coal volatility increases, it usually leads to lower JCI volatility. Nevertheless, this variable lacks statistical significance, given its probability value exceeds 0.05, specifically 0.0930. The gold volatility variable carries a coefficient of 0.034114, indicating that an increase in gold volatility leads to a rise in JCI volatility. This variable is statistically significant, given its very low probability value below 0.05, namely 0.0000.

5. DISCUSSION

The Effect of Crude Oil Price Volatility on JCI Volatility

Data analysis reveals that volatility in crude oil prices significantly affects JCI volatility. This is evidenced by the hypothesis testing results in Table 4.7, derived from Equation (5), which display a coefficient of 0.009253 and a probability value of 0.0000, below 0.05. The results indicate that crude oil price changes exert a substantial influence on the variance component of the TARCH model. Substantial shifts in crude oil prices lead to greater frequency and unpredictability in JCI movements.

The findings indicate the presence of volatility spillover from the crude oil market to the Indonesian stock market. In this study, volatility spillover means the way volatility moves in onirection from the commodity to the stock market. Volatility spillover occurs when uncertainty or shocks in one market spread and affect the risk level in another market. In this context, fluctuations in crude oil prices generate broader economic uncertainty because of the critical role of oil in production costs, inflation, and industrial activities.

These findings align with those of various prior studies that have identified a significant link between crude oil volatility and JCI volatility. For instance, Marwanti and Robiyanto (2021) demonstrated that WTI oil volatility positively and significantly impacted JCI volatility both prior to and during the COVID-19 period. Likewise, Alpiansyah et al. (2025) reveal that oil price fluctuations exert a positive and substantial effect on the Indonesian stock market from both short- and long-term perspectives.

Crude oil is one of the most important commodities in both national and global economies as it is closely linked to business activities and production costs. It plays a crucial role in various industrial sectors, including transportation, manufacturing, mining, energy, and logistics industries. When WTI oil prices experience extreme fluctuations, production and operational costs in these sectors become uncertain, making it difficult to predict corporate earnings. This uncertainty leads to instability in stock prices. As crude oil affects many sectors simultaneously, its volatility contributes significantly to fluctuations in the JCI.

Furthermore, WTI crude oil prices are often regarded as a benchmark or indicator of global economic conditions, as almost all industrial and non-industrial activities depend on energy, with oil being a primary source. When oil prices increase or decrease quickly, global investors usually see it as a sign that there might be concerns about the economy or political situations around the world, because oil prices are very responsive to global risks. This situation makes the world more uncertain, so foreign investors are cutting back on risky investments, such as stocks in emerging markets, such as Indonesia. The capital leaving the country causes more instability in the JCI. In short, the ups and downs in crude oil prices have a significant impact on the volatility of the JCI. This means that when there is more uncertainty in the crude oil market, it can make the stock market more risky and unstable.

The Effect of Coal Price Volatility on JCI Volatility

Volatility in coal prices does not substantially drive fluctuations in the JCI. This is evident from the hypothesis testing results in Table 4.7, derived from Equation (5), which report a coefficient of - 0.000000385 and a probability value of 0.0930. As the probability exceeds 0.05, it is concluded that coal price volatility has no significant impact on JCI volatility. This implies that shifts in coal prices do not transmit sufficient risk to the broader Indonesian stock market. This also means that not every change in commodity prices causes fluctuations in other areas. For volatility spillover to occur, volatility shocks need to have wide effects and influence many different areas of the economy.

The findings of this study do not match those of earlier research conducted by Nu'man et al. (2024) and Agung (2023), which found that coal prices significantly affect the JCI. These differences may be attributed to variations in methodology, data characteristics, research periods, and analytical approaches. In addition, the impact of coal prices tends to be sector-specific, making their overall effect on the broader market relatively limited.

Indonesia is one of the largest countries that produces and sells a large amount of coal worldwide; however, changes in the price of coal do not seem to have a significant effect on the movement of the JCI index. Changes in coal prices could mainly impact businesses involved in coal mining. These stocks might go up or down significantly when coal prices change; however, the JCI is an overall index that shows how all the different sectors on the Indonesia Stock Exchange are doing, such as telecom, healthcare, banking, and consumer industries. This spread-out approach might be the reason why changes in coal prices do not have a significant impact on JCI changes.

Furthermore, the dependence of domestic industries on coal is relatively limited. Although coal plays an important role in exports and government revenue, its use is more concentrated in specific sectors, such as industrial energy, power generation, and transportation, rather than as a primary input for household consumption. According to data from the Ministry of Energy and Mineral Resources, the largest users of coal are coal-fired power plants (PLTU), followed by smelters. Consequently, coal price volatility does not directly affect consumer purchasing power or overall domestic economic activity.

The Effect of Gold Price Volatility on JCI Volatility

Gold price volatility significantly influences JCI volatility. This is supported by the hypothesis testing results in Table 4.7, based on Equation (5), which displays a coefficient of 0.034114. The probability value was 0.0000. With a probability below 0.05, the effect was statistically significant. These results point to a unidirectional volatility spillover from the gold market to the Indonesian stock market. This outcome aligns with earlier research. For instance, Hadi and Robiyanto (2025) observed that amid the Russia–Ukraine war and the Israel conflict, gold positively and significantly affected JCI volatility. Likewise, Marwanti and Robiyanto (2021) found that prior to the COVID-19 period, gold exerted a positive and significant impact on JCI volatility, while during the COVID-19 period, gold price volatility had a negative and significant effect on JCI volatility.

Gold functions as a safe haven asset. When the economy is stable, people usually invest their money in riskier options, such as stocks, because they have the chance to earn more money. However, during periods of global uncertainty—such as economic crises, geopolitical conflicts, or financial market turbulence—investors tend to shift their funds to safer and more stable assets, such as gold. This reallocation of funds can lead to sharp increases and decreases in the stock market, thereby increasing JCI volatility. In this context, gold can be viewed as an indicator of investors' concern regarding stock market risk. These findings indicate that gold price volatility influences JCI volatility. An increase in gold volatility reflects heightened global uncertainty, which encourages more cautious investor behavior and leads to greater fluctuations and risk in the Indonesian stock market.

In summary, changes in coal prices do not significantly impact the movement of the JCI. This shows that changes in coal prices are not a consistent risk that affects the performance of the Indonesian stock market. This study did not find any evidence that changes in the coal market affect the Indonesian stock market.

6. CONCLUSION, IMPLICATION, SUGGESTION, AND LIMITATIONS

The research findings demonstrate that volatility in crude oil and gold prices markedly influences the volatility of the Jakarta Composite Index (JCI), whereas fluctuations in coal prices do not have a significant effect. The pronounced impact of oil price volatility suggests that alterations in uncertainty within the global oil market are correlated with variations in the volatility of the Indonesian stock market. Oil market volatility can influence market uncertainty by modifying production costs, inflation expectations, and corporate performance. Furthermore, the notable effect of gold price volatility indicates that shifts in uncertainty within the gold market are linked to changes in JCI volatility. These results are consistent with gold's function as a safe-haven asset during times of market uncertainty. Nonetheless, the study does not explicitly demonstrate that investors reallocated funds from equities to gold, as the actual investment decision-making processes were not directly observed.

Conversely, the lack of significance regarding coal price volatility suggests that changes in uncertainty within the coal market did not exert a substantial influence on JCI volatility during the study period. Therefore, the impact of commodity volatility on the Indonesian stock market is not uniform but varies according to the specific characteristics and economic roles of each commodity. Overall, this study provides evidence of volatility transmission from global commodity markets to the Indonesian stock market, particularly through crude oil and gold price volatility. These findings have several implications for investors. The price volatility of crude oil and gold can serve as additional information for monitoring changes in market risk. Increased oil volatility may indicate rising uncertainty in the global energy market, while increased gold volatility may reflect changing levels of uncertainty in financial markets. Consequently, information regarding the volatility of these two commodities can be incorporated into risk assessments and investment decision-making, especially during periods of heightened global uncertainty.

This study has several limitations. First, it relies exclusively on Indonesian stock market data; consequently, the findings may not be generalizable to other countries with different economic structures and varying degrees of commodity dependence. Second, the study does not incorporate other macroeconomic and financial variables that could influence JCI volatility, such as interest rates, exchange rates, inflation, and global financial market conditions. Therefore, the observed relationship must be interpreted within the context of the variables included in the research model. Third, although the study period (2018–2025) encompasses major global events, including the US-China trade war, the COVID-19 pandemic, and the Russia-Ukraine conflict, it does not analyze these events individually. Thus, the study captures the aggregate impact of these events over the observation period but does not determine whether volatility transmission patterns differ across specific crisis periods.

Future research can expand on this study by utilizing data from multiple countries, enabling a comparison of how commodity volatility transmits to stock markets in developing versus developed economies. Subsequent studies can also incorporate global macroeconomic and financial variables, such as interest rates, exchange rates, inflation, and global stock market indices, to provide a more comprehensive picture of the factors influencing JCI volatility. Additionally, future research can segment the observation period based on specific events or crises, such as the COVID-19 pandemic and the Russia-

Ukraine conflict. Such an approach would offer deeper insights into whether the transmission of oil and gold volatility to the Indonesian stock market intensifies or weakens under varying conditions of global uncertainty.

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