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FLUCTUATING COMMODITY PRICES' EFFECT ON INDONESIAN COAL AND PALM OIL

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ABSTRAK

Studi ini mengkaji dampak fluktuasi harga komoditas terhadap volatilitas saham dan kinerja keuangan perusahaan batubara dan kelapa sawit Indonesia antara tahun 2011 dan 2022. Selama pandemi COVID-19, sektor-sektor ini sangat dipengaruhi oleh fluktuasi harga komoditas. Dengan menggunakan pendekatan Vector Error Correction Model (VECM) dan Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC GARCH), serta regresi panel, penelitian ini menganalisis volatilitas harga dan pengaruhnya terhadap kinerja keuangan. Temuan mengungkapkan pola volatilitas yang berbeda dalam industri kelapa sawit dan batubara, memberikan wawasan berharga bagi investor untuk memahami risiko yang terkait dengan fluktuasi harga dan untuk mengidentifikasi perusahaan yang secara signifikan dipengaruhi oleh volatilitas tersebut. Penelitian ini memberikan kontribusi untuk memahami hubungan antara fluktuasi harga komoditas dan harga saham perusahaan kelapa sawit dan batubara, serta kinerja keuangannya, dalam konteks perekonomian Indonesia yang sangat bergantung pada kedua komoditas tersebut. Dengan menekankan pentingnya memahami dinamika harga komoditas, kajian ini memberikan informasi berharga bagi investor dalam pengambilan keputusan dan manajemen risiko dalam menghadapi gejolak harga komoditas.

Kata kunci: harga komoditas, volatilitas saham, kinerja keuangan.

ABSTRACT

This study examines the impact of fluctuating commodity prices on the stock volatility and financial performance of Indonesian coal and palm oil companies between 2011 and 2022. During the COVID-19 pandemic, commodity price fluctuations have significantly influenced these sectors. Using Vector Error Correction Model (VECM) and Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC GARCH) approaches, as well as panel regression, this study analyzes price volatility and its effect on financial performance. The findings reveal distinct volatility patterns in the palm oil and coal industries, providing valuable insights for investors to understand the risks associated with price fluctuations and identify companies significantly affected by such volatility. This research contributes to understanding the relationship between fluctuations in commodity prices and stock prices of palm oil and coal companies, as well as their financial performance, in the context of the Indonesian economy, which relies heavily on these two commodities. By emphasizing the importance of understanding commodity price dynamics, this study provides valuable information for investor decision-making and risk management in the face of commodity price volatility.

Key words: commodity prices, stock volatility, financial performance.

INTRODUCTION

The Indonesian economy relies heavily on two primary commodities: palm oil and coal. These industries substantially contribute to the country's Gross Domestic Product (GDP), both directly and indirectly, by creating income by selling raw or partially processed goods. The plantation sub-sector alone accounted for 3.94% of the GDP in 2021. Palm product exports were valued at USD 35.79 billion, showing a 56.63% growth from 2020 (Badan Pusat Statistik, 2022). This industry, including the small and medium-sized enterprises engaged, has employed up to 16 million persons. In 2021, coal made up 2.35% of the national economy's GDP, while coal exports were valued at USD 26.53 billion, showing an increase of 82.56% compared to 2020.

Palm oil is a major agricultural commodity used for various uses, including food, cosmetics, and biofuels. However, the coal industry is a primary global energy provider for generating electricity and meeting other industrial needs. These industries undergo price variations because of different variables, like shifts in supply and demand, geopolitical events, and economic situations. The prices of palm oil and coal commodities varied from their lowest points in 2013 to 2017 and increased in 2020. These changes can have a substantial effect on enterprises engaged in the manufacture and sale of these goods and on the whole economy because the money earned by the sectors that deal with these goods relies significantly on the prices at which these products are sold, making them vulnerable to market swings.

The COVID-19 pandemic significantly impacted commodity prices, with a decrease in demand and disruption in supply chains leading to a drop in prices in 2020. Lockdowns implemented by various countries to control the virus spread also disruptted commodity supplies, affecting raw material supply for industries. However, from mid-2020, commodity prices began to recover and have been relatively stable. Some analysts predict that this rise in commodity prices may mark the beginning of a commodity supercycle, a period of significant and sustained price increases above average increases caused by surging demand not matched by supply.

Historically, these cycles have occurred several times, around 1904, 1947, 1978, and from 2002 to 2011, mainly due to industrialization in China, leading to a significant increase in the demand for raw materials and commodities (Buyuksahin et al., 2016). These fluctuations can significantly impact businesses, especially those involved in production and sales. According to Camacho and Perez-Quiros (2014), the impact of commodity price shocks on output growth depends on economic conditions, the size of the shock, and its characteristics.

The risk of commodity price fluctuations affects companies that rely on commodities as input factors in their production processes. Therefore, a priori, commodity price risk is a more critical source of risk for companies. Commodity price changes are expected to impact a company's value due to its relevance as an input or output factor in its production process. In addition, there may be significant indirect effects on a company's value for its shareholders due to the impact of commodity price changes on customers, suppliers, or competitors, and thus the company's competitive position. If they hedge effectively, companies exposed to volatile commodity prices may only show small net exposure.

In the past decade, commodity price volatility has taken centre stage for investors and company managers. These price fluctuations can significantly impact a company's financial performance, especially for palm oil and coal companies. Both sectors are highly vulnerable to fluctuations in global commodity prices, which can affect the performance of companies and the entire economy (Damodaran, 2014).

Damodaran (2014) suggests that if companies can design their debt structure with debt cash flow increasing and decreasing as operating cash flow, companies can borrow more with a lower risk of default. Commodity companies, such as those in the palm oil and coal sectors, tend to have operating cash flows that fluctuate with commodity prices. Therefore, company management must choose a capital structure that they believe will provide the highest value for the company because that capital structure will provide the most significant benefit to its shareholders.

Companies in this sector often use a variety of risk management strategies to mitigate the impact of commodity price fluctuations on financial performance. One popular strategy is to use derivative contracts to hedge a company's natural exposure to commodities (Wang and Zhou, 2022). Wang and Zhou's (2022) study found that commodity hedging effects are heterogeneous across sectors, and companies with smaller sizes, higher valuations, and better profitability benefit more from commodity hedging.

Changes in commodity prices can also affect a company's stock performance. Studies by Wen et al. (2021) show that the Chinese stock market has a strong dependence on commodity markets and varying degrees of impact on the stock market. Therefore, companies must hedge to anticipate commodity price fluctuations and execute dynamic investment strategies considering the potential for risk transmission between market assets during major economic events.

Based on this background, this study aims to understand how changes in global commodity prices, particularly in the palm oil and coal sectors, affect the volatility of share prices of companies that produce these commodities. In addition, this study also seeks to understand how fluctuations in commodity prices affect the financial performance of companies in both sectors.

This study seeks to fill gaps in the current literature by focusing on two essential sectors in Indonesia: palm oil and coal. Although various studies have explained the relationship between commodity prices and stock market volatility (Kang et al., 2020; Akkoc and Civcir, 2019) and their impact on corporate financial performance (Wang and Zhou, 2022; Wen et al., 2021), however, there is still a lack of research that specifically analyzes the impact of commodity price fluctuations in the palm oil and coal sectors on stock price volatility and corporate financial performance.

To achieve this research objective, we use empirical data analysis methods, including relevant literature studies, historical data on commodity prices and corporate financial data, and VECM and DCC GARCH models to understand the relationship between commodity prices and corporate financial performance. The research hopes to provide essential insights and information for investors, company managers, and policymakers on how commodity price fluctuations affect share price volatility and the financial performance of companies in the palm oil and coal sectors.

THEORETICAL REVIEW

Commodity Prices Volatility and Stock Return

Stock price volatility is an essential measure of risk that helps investors predict future fluctuations. Stock price volatility results from new information being introduced into the market rather than a systematic pattern. A market is efficient if all public and private information is reflected in the market price, so even investors with the correct insider information cannot beat the market. The market is divided into three levels of efficiency by Eugene Fama, namely weak form, semi-strong, and strong, depending on what information is reflected in the price. However, Market efficiency is not always equal for all investors, and transaction costs and tax rates can give some investors an advantage (Damodaran, 2012). The correlation between commodity prices and stock returns has been examined in several studies. Kang et al. (2020) and Enilov et al. (2021) found that the relationship between global stock markets and commodity prices is complex and dynamic, with effects varying across nations and time.

Atif et al. (2022) found that the interdependence between oil and stock price changes increased after the COVID-19 pandemic-induced oil price crash, affecting both oil-exporting and importing countries. Osah and Mollick (2023) analyzed monthly data from 1990 to 2020 for 12 major economies to examine how stock returns respond to oil prices. The study found varying effects of oil price returns in the short term, while increases in volatility had adverse effects on stock markets. In the long run, oil prices positively affected stock markets for oil exporters and relatively weaker adverse effects for oil importers. Degiannakis (2018) reviewed research on the relationship between oil prices and stock markets and found that the causal effects between oil and stock markets depend on various factors.

The study by Cagli et al. (2023) emphasizes two gaps in previous research on commodities; first, too few studies have considered agricultural commodities despite their significance, and second, most previous studies have focused on aggregate stock market data rather than firm-level data. In their research, Cagli et al. (2023) analyzed the volatility relationship between the stock prices of ten major agribusiness companies and the prices of various agricultural commodities from 2005 to 2022. They found that the stock prices of agricultural companies were the net senders of shocks, while agricultural commodities were the net recipients of volatility. These findings underscore the increased connectivity between these asset classes, especially during periods of crisis, such as the global financial crisis and the COVID-19 pandemic.

Maitra (2019) discovered unidirectional return spillover from non-agro commodities to stock indices and exchange rates, with equity markets having a return spillover on agro commodities during the post-crisis period. There were volatility spillover effects on each asset market, with commodity indices having more spillover effects on stocks. Zhang et al. (2021) analyzed the impact of COVID-19 on spillover effects and asset allocations between energy and stock markets. They found significant spillover effects between energy and stock markets, with natural gas being the highest net recipient among the three energy markets.

Wen et al. (2021) found a strong relationship between the Chinese stock market and commodity markets, with the stock market being the net recipient of spillover. Chemical and non-ferrous metal industries have a significant impact on the stock market. They also analyzed optimal portfolio weights and hedge ratios for risk management and found that CRFI is the most effective in hedging against risk. Akkoc and Civcir (2019) studied the relationship between oil, gold, and stock market returns in Turkey. They found a time-varying co-movement and volatility spillover from gold and oil to the Turkish stock market.

Adams and Glück (2015) found that stock market shocks were not transmitted to commodity markets before the financial crisis, but significant risk spillover occurred after September 2008. Mensi et al. (2013) reported significant volatility spillovers between oil prices and equity markets. The study by Mensi et al. (2021) examines volatility spillovers between developed and emerging stock markets and commodity futures markets. The results indicate that volatility spillovers are time-varying and intensified during significant events. The short-term spillovers contribute the most to total connectedness, and a mixed portfolio of commodity and stock assets provides better risk reduction than an individual stock portfolio.

The results of Atif et al. (2022) and Osah and Mollick (2023) highlight the importance of examining this relationship separately for different types of countries and periods. The present study will add to this literature by examining the relationship between global commodity prices, specifically in the palm oil and coal sectors, and the volatility of the share prices of companies that produce these commodities.

This literature review shows that the relationship between commodity prices and stock returns is complex and varies across nations and periods. The present study aims to add to this literature by examining the relationship between global commodity prices, specifically in the palm oil and coal sectors, and the volatility of the share prices of companies that produce these commodeties in Indonesia.

H_1: There is a relationship between global commodity prices, especially in the palm oil and coal sectors, and the volatility of the share prices of companies that produce these commodities in Indonesia.

Price Uncertainty and Firm Performance

This literature review aims to examine the impact of commodity price fluctuations, specifically in the palm oil and coal sectors, on the financial performance of companies. This review will present empirical evidence on the relationship between commodity prices and firm performance, including the effects of price uncertainty and risk management strategies. The review will also explore the determinants of corporate default risk and the effects of global crises on the financial performance of commodity-producing companies. Finally, this review will discuss the implications of volatility spillover among exchange rates, crude palm oil prices, coal prices, and inflation and the role of risk management strategies in mitigating the impact of commodity price fluctuations.

Donders et al. (2018) discuss how a decline in commodity prices impacts the substantial debt held by commodity-producing companies. The study's results indicate that debt financing only partially dries during commodity price decreases. This research found that bonds are far more sensitive to price declines than price increases, and the type of commodity price change is significant. Temporary changes affect short-term bonds and companies with high leverage. Donders et al. (2018) conclude that hedging derivatives can reduce bond sensitivity to price changes. Additionally, bond sensitivity to commodities is more significant in smaller companies with substantial leverage and lower profitability.

Previous studies have examined the relationship between commodity prices and firm performance. Carter et al. (2017) highlights that the uncertainty of commodity prices can affect the value of oil-producing companies, and risk management can increase shareholder value by reducing the expected costs of financial distress and underinvestment. However, commodity price movements are less than other financial risks, with few cash flows being affected. They highlight the importance of risk management strategies such as hedging, which can help reduce sensitivity to price fluctuations (Wang and Zhou, 2022).

Bagirov and Mateus (2020) examined the relationship between oil prices, stock markets, and the financial performance of oil and gas firms over the past decade. The results suggest that crude oil prices significantly and positively impact the performance of listed firms in Western Europe. At the same time, the recent geopolitical and global financial crises negatively affected unlisted firms' financial performance, which addresses the importance of examining the effects of external factors on the financial performance of commodity-producing companies.

Abubakar et al. (2021) examined the determinants of corporate default risk in Indonesia's palm oil and coal sectors, finding that CPO price fluctuations are insignificant in explaining CDR. Internal factors such as excess stock market returns and return on assets are better at explaining default risk than external factors such as oil prices. In other words, other factors may be more critical in determining corporate default risk in these sectors.

Chandrarin et al. (2022) found that volatility spillover among exchange rate, crude palm oil price, coal price, and inflation is significant, with coal price being the highest volatility contributor. Palm oil price is a net volatility contributor, but marginally, while inflation and exchange rate are net volatility receivers. These findings have important policy implications for Indonesia, as the country is a significant exporter of crude palm oil and coal. So, there is a need for effective risk management strategies to mitigate the impact of commodity price fluctuations on the financial performance of companies in these sectors.

Overall, this literature review supports the hypothesis that commodity price fluctuations significantly impact the financial performance of companies in sectors such as palm oil and coal. While risk management strategies such as hedging can reduce sensitivity to price fluctuations, other factors, such as internal factors, maybe more critical in determining corporate default risk. Global crises can also significantly impact the financial performance of commodity-producing companies. Companies can engage in risk management strategies such as hedging to mitigate the impact of commodity price fluctuations on their financial performance. These findings have important policy implycations, particularly for countries such as Indonesia, which export palm oil and coal commodities.

H_2: Commodity price fluctuations, such as those of palm oil and coal, significantly impact the financial performance of companies in these sectors.

RESEARCH METHOD

The Relationship between the Volatility of Commodity Prices and the Stock Prices of Companies that Produce these Commodities

This research aims to analyze the relationship between the volatility of palm oil and coal commodity prices and the stock prices of companies producing these commodities listed on the Indonesia Stock Exchange (IDX) from January 2011 to December 2021. The study employs a quantitative research design with a time-series analysis approach. The population comprises palm oil and coal-producing companies listed on the IDX during the research period, with a sample of 22 coal-producing companies and 12 palm oil-producing companies.

The volume and value of transactions can provide information on the liquidity of shares, which is an essential factor in assessing the dynamics of changes in the share price of such producers. The company's shares are filtered based on daily transaction volume and value for each stock for the subsequent analysis of VECM and DCC GARCH with the following criteria: 1) Daily transaction volume of 0 or no transactions < 250 transaction days, 2) Daily transaction value in 2020-2022 > IDR 1 billion. Based on these criteria, the stock data studied are 22 coal-producing companies and 12 palm oil-producing companies.

The testing process employs several stages of analytical methods. The first stage involves a Unit Root Test using the Augmented Dickey-Fuller (ADF) to identify stationarity in the time series data. Following this, the Granger Causality test establishes causal relationships between variables. Subsequently, the Vector Error Correction Model (VECM) is applied to investigate both the short-term and long-term relationships between the variables. Lastly, the Dynamic Conditional Correlation GARCH (DCC GARCH) method analyses volatility. These processing methods are the basis for analyzing the issues raised in the first hypothesis.

Vector Error Correction Model (VECM)

The Vector Error Correction Model (VECM) is a Vector Autoregressive (VAR) designed for use on non-stationary data known to have a cointegration relationship. The presence of cointegration in the VECM model makes the VECM referred to as a restricted VAR.

VECM is an analysis technique designed to handle non-stationary multivariate time series data and reveal the long-term relationships between these variables. In this research context, VECM can be used to model the long-term relationship between global commodity price changes and the volatility of commodity producers' stock prices.

The assumption that must be met in VECM analysis is that all variables must be stationary in the same order or degree indicated by all residuals being white noise, having zero mean, constant variance, and no correlation among dependent variables.

If the variables are not cointegrated, a standard VAR can be applied, and the results will be identical to OLS (Ordinary et al.). However, if the test proves a cointegration vector, VECM can be applied.

Implementing the VECM method involves several testing stages, including stationary testing, determining the optimal lag (lag length), cointegration testing, causality testing, VAR/VECM model estimation, Impulse Response, and Variance Decoposition.

The Vector Error Correction Model (VECM) for two variables (return of commodity price, denoted as Cp, and return of stock price, denoted as Sp) can be formulated as follows:

The VECM model in the first difference could be written as:

$$\Delta C_{p,t} = \alpha_1\left(C_{p,t-1} - \beta_1 S_{p,t-1} - \mu_1\right) + \gamma_{11}\Delta C_{p,t-1} + \gamma_{12}\Delta S_{p,t-1} + \epsilon_{1,t}$$

$$\Delta S_{p,t} = \alpha_2\left(C_{p,t-1} - \beta_2 S_{p,t-1} - \mu_2\right) + \gamma_{21}\Delta C_{p,t-1} + \gamma_{22}\Delta S_{p,t-1} + \epsilon_{2,t}$$

Where:

ΔCp,t and ΔSp,t represent the first difference of the return of commodity price and stock price, respectively, at time t.

α1 and α2 are the speed of adjustment parameters for the return of commodity and stock prices, respectively.

Cp,t−1 and Sp,t−1 represent the return of commodity and stock prices, respectively, at time t−1.

β1 and β2 are the cointegrating parameters for the return of commodity and stock prices, respectively.

μ1 and μ2 are the constants in the cointegrating equation for the return of commodity price and stock price, respectively.

γ11, γ12, γ21, and γ22 are the short-term parameters.

ϵ1,t and ϵ2,t are the error terms at time t for the return of commodity and stock prices, respectively.

This model captures short-term and long-term dynamics between the return of commodity price and stock price. The first term in each equation (with the α's) represents the long-run relationship (Error Correction), which corrects any imbalance between Cp and Sp from their long-term equilibrium relationship. The other terms (with the γ's) represent the short-run dynamics.

DCC-GARCH METHOD

To understand the relationship between the variables 'return of commodity price' and 'return of stock price', we can use the DCC GARCH model. The DCC part of the model can be used to estimate the dynamic correlation between the return of commodity prices and stock prices over time.

The equation used for calculating the volatility of the stock prices of the commodity-producing company is:

The DCC GARCH model equation used for calculating stock price volatility is as follows:

$$\sigma_t^2 = \omega + \alpha_1 r_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1(\sigma_{t-1}^2 \times r_{t-1}^2)$$

Where:

σ_t^2 is the stock price volatility at period t

ω is the constant term

α_1 measures the influence of stock price volatility history on current volatility

β_1 measures the influence of stock price volatility history on current volatility

γ_1 measures the influence of the correlation between stock price volatility history and stock return history on current volatility

Changes in Global Commodity Prices Affect the Company's Financial Performance

This study employs a panel data regression model to examine the impact of global commodity price changes on the financial performance of palm oil and coal companies in Indonesia. The model is adopted by Bagirov and Mateus (2019), who studied the impact of oil price changes on European oil and gas companies' performance.

The panel data regression analysis involves dependent variable ROE and independent variables exchange rate, interest rate, GEAR ratio, asset size, commodity price, and a dummy variable for the COVID-19 pandemic year multiplied by the commodity price. The steps are as follows: gather data for all variables in a panel format (cross-sectional and time-series dimensions); estimate the panel regression model using Ordinary Least Squares (OLS), Fixed Effects

(FE), and Random Effects (RE) models; test for regression coefficient variations among individuals using the Chow test; and compare the FE and RE models using the Hausman test.

Adopting this panel data regression model is expected to measure how global commodity price changes affect the financial performance of companies in Indonesia's palm oil and coal sectors. The model can be specified as follows:

$$Y_{i,t} = \alpha + \beta_1 \text{Size}_{i,t} + \beta_2 \text{GEAR}_{i,t} + \beta_{3\text{Commodity}} \text{ Price}_{i,t} + \beta_4 D_1 \times \text{Commodity rice} + \epsilon_{i,t}$$

Where:

Yi,t = financial performance of company i at time t (ROE)

Size i,t = Size of company i at time t (logarithm value of assets)

GEAR I,t = gearing ratio i at time t (debt/equity)

Commodity Price i,t = global commodity price at time t for company I (average price)

D1 i,t = Dummy variable for COVID-19 pandemic year 2020-2021 (1 or 0)

α = constant term

β1 – β4 = coefficients to be estimated

εi,t = error term

The equation above represents a panel regression with fixed effects, where the intercept α_i is included to control for time-invariant company characteristics. The regression coefficients of β1, β2, β3, β4, and β5 reflect the effect of independent variables on the dependent variable. The panel regression equation can be estimated using Ordinary Least Squares (OLS) or other methods, such as the Fixed Effects Model (FEM) or Random Effects Model (REM), depending on the data characteristics and research objectives.

ANALYSIS AND DISCUSSION

Descriptive Statistics

Data Table 1 presents each stock's daily transaction volume and value from 2020-2022. Transaction volume and value can provide information regarding the liquidity of a stock, which is a crucial factor in assessing the dynamics of these commodity producers' stock price changes. For further analysis with the Vector Error Correction Model (VECM) and Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC GARCH), stock selection was based on Daily transaction value in 2020-2022 exceeding Rp. 1 Billion and daily transactions that are less than 250 trading days but greater than zero.

The total number of stocks from coal and palm oil commodity producers that meet these criteria is as follows.

Table 1
Company Stock Filtering

Company Type	Before	After
Coal	22 companies	12 companies
Palm Oil	13 companies	8 companies

Source: Data Processed (2023)

Descriptive analysis was conducted on the stock returns of coal and palm oil producers, including the mean return, standard deviation, skewness, and Augmented Dickey-Fuller (ADF). Variations between firms are found in mean return and volatility (measured by standard deviation).

Skewness indicates a distribution of returns, with some stocks having a positive skewness, indicating a distribution skewed to the left and the right tail longer. All stocks show data stationarity based on ADF tests, essential for advanced statistical analysis.

Table 2 shows that coal producers such as BYAN, ADRO, and UNTR have positive mean returns, while BUMI and PTBA show negative returns. Positive skewness is indicated by stocks such as BUMI and HRUM. Palm oil producers such as SSMS and DSNG showed positive mean returns, while AALI and LSIP showed negative returns. Stocks such as SSMS and DSNG also showed positive skewness.

Table 2
Descriptive Analysis of Stock Return of Coal & Palm Oil Producers

Saham	Mean Return	Standard Deviation	Skewness	Augmented Dickey-Fuller
Coal				
BYAN	0.0004	0.0256	0.3181	-12***
ADRO	0.0003	0.0295	0.2202	-13***
UNTR	0.0001	0.0249	0.2958	-14***
BUMI	-0.0010	0.0425	1.8060	-13***
PTBA	-0.0001	0.0277	0.1442	-13***
ITMG	-0.0003	0.0278	0.3817	-13***
HRUM	0.0003	0.0294	1.3005	-11***
INDY	0.0000	0.0372	1.1567	-12***
PTRO	0.0002	0.0297	1.2599	-13***
TOBA	0.0005	0.0291	1.2892	-13***
DOID	0.0001	0.0396	1.5755	-13***
KKGI	-0.0003	0.0321	0.8983	-13***
Palm Oil				
AALI	-0.0004	0.0237	0.2670	-13***
SSMS	0.0002	0.0227	0.7825	-13***
LSIP	-0.0003	0.0264	0.5059	-13***
DSNG	0.0001	0.0261	0.8159	-12***
SIMP	-0.0003	0.0223	0.8800	-11***
SGRO	0.0000	0.0180	0.6182	-12***
TBLA	0.0002	0.0219	0.0615	-12***

Source: Data Processed (2023)

Panel unit Root Test

This study conducted a Panel Unit Root Test to determine variable stationarity (coal return, coal company stock return, CPO return, and CPO company stock return) before being applied in the VAR or VECM model. As shown in Table 3.

Table 3
Unit root test output

Description	Statistic	Prob.**
Coal		
Coal return	-216.677	0.0000
Coal company's stock return	-234.223	0.0000
Palm Oil		
CPO return	-158.849	0.0000
Palm Oil Company's stock return	-186.296	0.0000

Source: Data Processed (2023)

The test results show highly negative statistical values and probabilities close to zero for all variables, which allows the null hypothesis about the presence of root units to be rejected. The finding indicates that all-time series is stationary, making them suitable for linear regression models and other time series analysis techniques.

Determination of Optimum Lag

This study used optimal lag selection as an initial PVAR/VECM estimation stage. Using Final Prediction Error (FPE), Akaike Information (AIC), Schwarz Criterion (SC), and Hanna-Quinn (HQ) information criteria, optimal lag was identified for endogenous variables. From Table 4, lag order three was selected as the best for variable coal based on AIC and HQ criteria. Meanwhile, lag order 4 is the best for palm oil variables based on AIC criteria. This result shows a long-term relationship between commodity returns (coal or CPO) and stock returns of companies engaged in the industry, indicating a significant effect of changes in commodity returns on companies engaged in the industry.

Cointegration Test

The cointegration test results in Table 5 show a long-term relationship between commodity returns (coal or CPO) and stock returns of commodity-producing companies. Statistics indicate one cointegration relationship in each sample period. Trace statistical values for the hypotheses "None" and "At most 1" are much greater than the critical values at the significance level of 5%, with a probability close to 0, indicating rejection of the null hypothesis without a cointegration relationship. Therefore, at least one cointegration relationship confirms a long-term relationship between commodity returns and stock returns of companies engaged in the industry. The relationship supports the use of VECM models in analysis.

Dynamics and Volatility: Returns of Commodity Prices and Stock of These Commodity Producers

Table 6 of the Granger Causality test results indicates a two-way causal relationship between commodity returns (coal and palm oil) and related company returns. The table shows that commodity return data can be used to predict a company's return and vice versa.

Table 4
Optimal Lag Test Results

Lag	LogL	LR	FPE	AIC	SC	HQ
Coal						
0	-167904.8	NA	46.105	9.507	9.507	9.507
1	-167370.1	1,069.37	44.740	9.477	9.478*	9.477
2	-167365.1	9.998	44.738	9.477	9.479	9.477
3	-167333.7	62.736*	44.668*	9.475*	9.478	9.476*
4	-167330.2	7.003	44.669	9.475	9.479	9.476
Palm Oil						
0	-100801.4	NA	28.226	9.016	9.017	9.016
1	-100307.7	987.266	27.017	8.972	8.974	8.973
2	-100189.2	237.040	26.741	8.962	8.965*	8.963
3	-100177.8	22.761	26.724	8.961	8.966	8.962*
4	-100172.3	10.994*	26.719*	8.961*	8.968	8.963

Source: Data Processed (2023)

Table 5
Cointegration Test Results

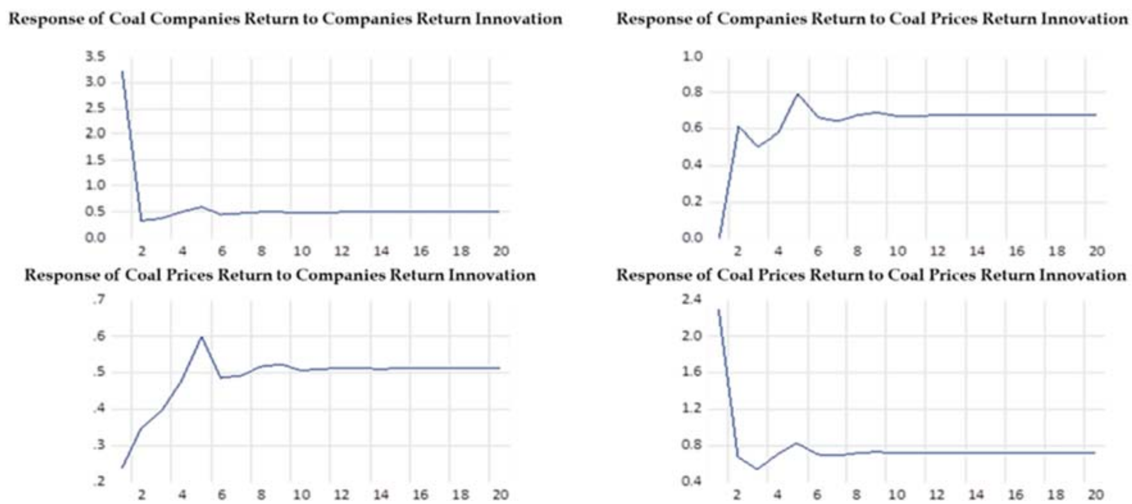
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
Coal				
None *	0.19	14405.04	12.32	0.000
At most 1 *	0.18	6845.89	4.13	0.000
CPO				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.30	14178.62	12.32	0.000
At most 1 *	0.25	6323.62	4.13	0.000

Source: Data Processed (2023)

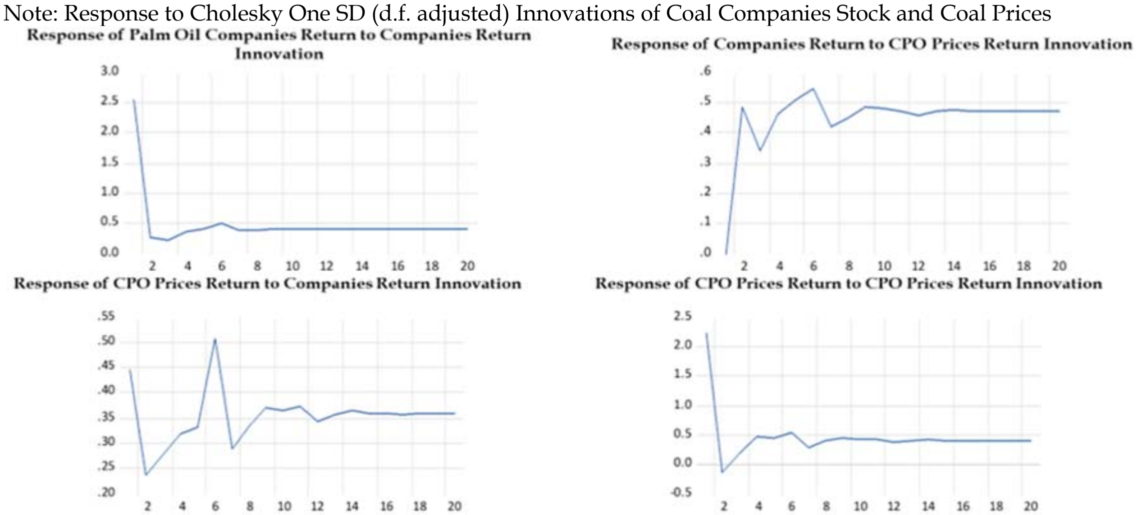
Table 6
Granger Causality Test Results

Null Hypothesis:	Obs	F-Statistic	Prob.
Coal			
Coal Price Return is not Granger Cause Coal Companies Stock Return	35360	285.968	0.0000
Coal Companies Stock Return is not Granger Cause Coal Price Return		25.472	0.0000
Palm Oil			
CPO Price Return does not Granger Cause Palm Oil Companies Stock Return	22385	165.163	0.0000
Palm Oil Companies Stock Return does not Granger Cause CPO Price Return		12.940	0.0003

Source: Data Processed (2023)



Note: Response to Cholesky One SD (d.f. adjusted) Innovations of Coal Companies Stock and Coal Prices



Note: Response to Cholesky One SD (d.f. adjusted) Innovations of Palm Oil Companies Stock and CPO Prices

Figure 1
Impulse Response Function (IRF)

Source: Data Processed (2023

The Impulse Response Function (IRF) in VECM analysis (Figure 1) provides insight into how certain variables react to 'surprises' or 'impulses' in other variables. In this context, IRF is used to visualize the response of the following 20 periods caused by a shock equal to one standard deviation, either from the variable itself or another variable.

The results of the analysis show that the coal and palm oil industries react to 'shocks' on their variables and reach an equilibrium point in the 20th period. This variable response shows how companies in both industries are highly responsive to changes in commodity returns and the company's returns.

More specifically, the response of coal and palm oil companies to 'shocks' in commodity returns or the company's returns shows fluctuations over time. However, this instability began to diminish and reached a point of equilibrium after the 12th period.

The Variance Decomposition (Figure 2) analysis highlights the impact of 'shocks' on various variables within the system and how they influence the fluctuations of the variables under investigation.

For coal and palm oil company returns and their corresponding commodity prices, the early periods showed that most of the variation was driven by 'shocks' in their variables (coal: 100% and 98.9%; palm oil: 100% and 96.1%). However, by the 60th period for coal and the 77th period for palm oil, 'shocks' in other variables explained over half of the variation in company returns and 30.5% (coal) and 36.1% (palm oil) of the variation in commodity prices. A significant interplay between corporate returns and commodity prices affects commodity producers' stock returns. The variations seen in a company's stock price are not solely driven by 'shocks' in the variables themselves but also by 'shocks' in the associated commodity price variables.

The DCC model in this analysis requires α and β values to meet the $\alpha + \beta < 1$ requirement to ensure model stability (persistence coefficient requirement). α refers to the impact of recent 'shocks' on dynamic correlation, while β represents the impact of dynamic correlations in previous periods on current correlations.

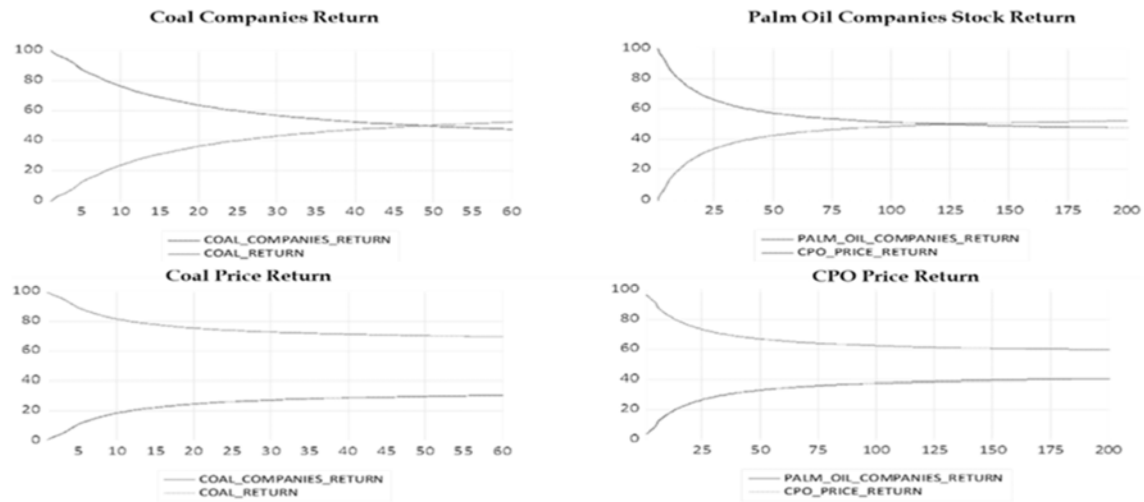
Volatility and correlation change all the time. Low α parameters in Coal, HRUM &; AALI, and LSIP indicate a relatively low impact of 'shocks' on volatility. Meanwhile, high β parameters in ADRO, UNTR, AALI, and LSIP indicate the impact of high volatility persistence.

Table 7 shows for DCC parameters of coal (α=0.0072, β=0.9804) and CPO (α=0.0047, β=0.9917), the historical effect of correlation has a more substantial influence on the current correlation compared to sudden changes from previous periods.

Volatility and correlations that change over time affect the value of an investment. For example, investors in INDY, PTRO/ DSNG, and SSMS stocks may face higher volatility due to 'shocks' than other stocks (with higher α).

Hypothesis 1 in this study argues that there is a relationship between global commodity prices, particularly in the palm oil and coal sectors, and the volatility of share prices of companies producing these commodities. This finding supports this claim, which is demonstrated through various analytical techniques and shows that fluctuations in commodity prices affect the volatility and return of shares of companies in the same industry (Kang et al., 2020; Akkoc and Civcir, 2019).

During the 2011-2022 research period, it was proven that there was a long-term relationship between commodity returns (coal and CPO) and company stock returns in the same industry. The Granger Causality test shows a two-way relationship between commodity returns and company returns. In addition, through the Impulse Response Function, it is known that company stocks are responsive to changes in commodity returns and their returns when there is a 'surprise' or 'unexpected return'.



Note: Variance Decomposition using Cholesky (d.f. adjusted) Factors

Figure 2
Variance Decomposition

Source: Data Processed (2023

Table 7
DCC GARCH Result

Coal					**Palm Oil**				
Variabel	**Coefficient**				**Variabel**	**Coefficient**			
	μ	**ω**	**α**	**β**		**μ**	**ω**	**α**	**β**
Coal	-0,0500	0.0114	0.0241	0.9749***	CPO	0,0000	0.0858*	0.0925***	0.8965***
ADRO	0.0258	0.6145*	0.087**	0.8414***	AALI	-0.0433	0.1062**	0.0886***	0.8945***
BUMI	0.0091	0.0137	0.0699***	0.9291***	SSMS	-0.0057	0.2555**	0.0952***	0.8578***
BYAN	-0.0521	0.4996**	0.1619***	0.7832***	LSIP	-0.0124	0.1278	0.057**	0.9231***
DOID	-0.1011	1.6998*	0.1704**	0.7373***	DSNG	0.0672	1.4846**	0.3***	0.5287***
HRUM	-0.0732	0.0635*	0.0416***	0.9531***	SIMP	-0.0389	0.2021	0.0872	0.8706***
INDY	-0.0582	1.1099	0.1364**	0.7891***	SGRO	0.0072	0.0853	0.0976	0.8821***
ITMG	0.0021	0.7367	0.0702***	0.8305***	TBLA	0.0154	0.1227	0.0941	0.8806***
KKGI	-0.1329**	0.2354	0.0771**	0.906***	BWPT	-0,0800	0.2178	0.0685***	0.9208***
PTBA	0.0025	0.3896***	0.0961***	0.8516***	**DCC parameters**				
PTRO	-0.0607	0.1849**	0.1246***	0.8697***	α	0,0047***			
TOBA	0.0814	0.2792	0.122	0.8745***	β	0,9917***			
UNTR	0.0183	0.4025***	0.065***	0.8656***	α+β	0,9964			
DCC parameters									
α	0,0072***								
β	0,9804***								
α+β	0,9876								

Source: Data Processed (2023).

The situation is associated with the efficient market theory, where the stock market is related to commodities that are positive in the short term to shock/impulse/ unexpected returns that show weak market efficiency but stable returns in the long run, which indicates that efficient markets are stronger applicable to the long-term period.

Variance Decomposition also reveals that variations in a company's stock returns are influenced by 'surprises' in its variables and commodity price return variables, with different contributions from both groups of commodity companies. DCC GARCH analysis shows that volatility and correlation between stock returns and commodity prices change over time. A coefficient of β greater than α indicates that the historical correlation effect substantially influences the current correlation more than sudden changes from previous periods.

This dynamic affects (Figure 3) volatility and the correlation between stock returns and commodity prices, influenced by market conditions and macroeconomic variables such as the global financial crisis and the COVID-19 pandemic (Enilov et al., 2021; Wen et al., 2021; Cagli et al., 2023). According to Cagli et al. (2023), the standard share price of agricultural companies is a net emitter of shocks, whereas agricultural futures are net recipients of volatility.

The findings also demonstrate the importance of a deep understanding of the relationship between commodity and stock markets, particularly in risk management and investment decision-making. Thus, both this study and the study by Cagli et al. (2023), although focusing on different sectors and markets, complement each other in providing a better understanding of these market dynamics.

Examining the Effect of Commodity Prices on the Financial Performance of Commodity Producers

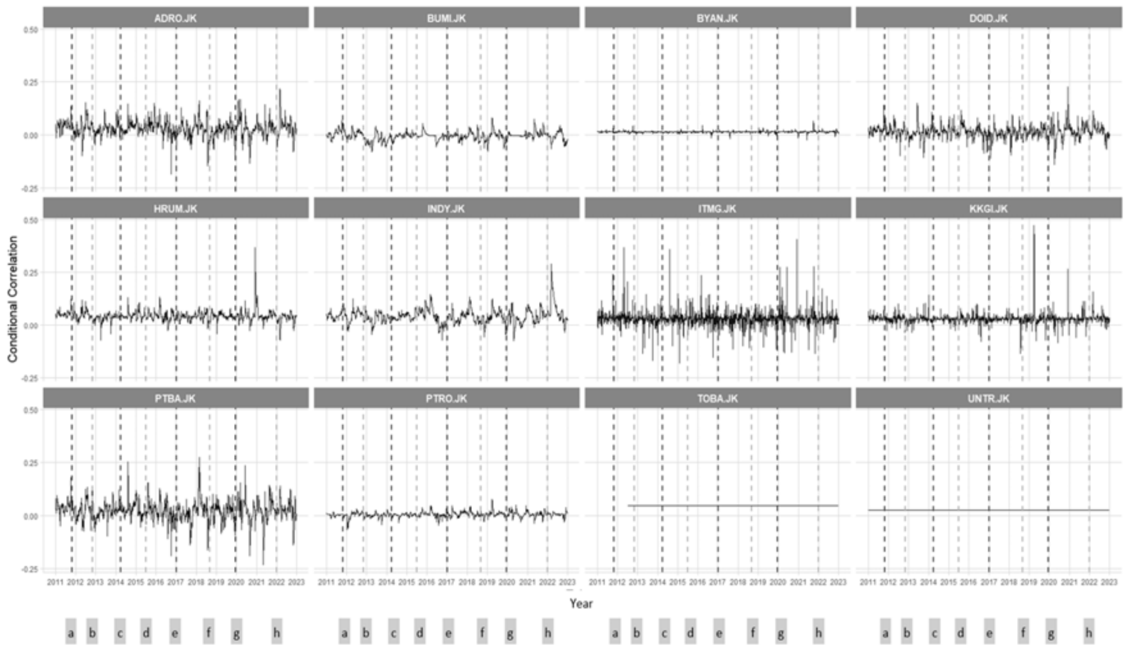
This analysis is based on financial report data per year from 2011 to 2021. In the coal sector, panel regression analysis (table 8) through the Random Effect method reveals a significant influence of debt ratio (GEAR) and stock price (PRICE) on the Return on Equity (ROE) of a company. According to studies conducted by Bagirov and Mateues (2019), the company's leverage increases, and the ROE decreases. Conversely, if stock price increases, ROE also increases. Other variables, such as total asset size and price period variables during COVID-19 (D1XPRICE), did not significantly affect ROE.

In the palm oil sector, panel regression analysis using the Fixed Effect method shows the negative influence of total assets (LOG (ASSETS)) and GEAR on ROE, while PRICE has a positive influence. The variable D1XPRICE showed adverse effects during COVID-19, but these effects were less significant at 5% but significant at 10%.

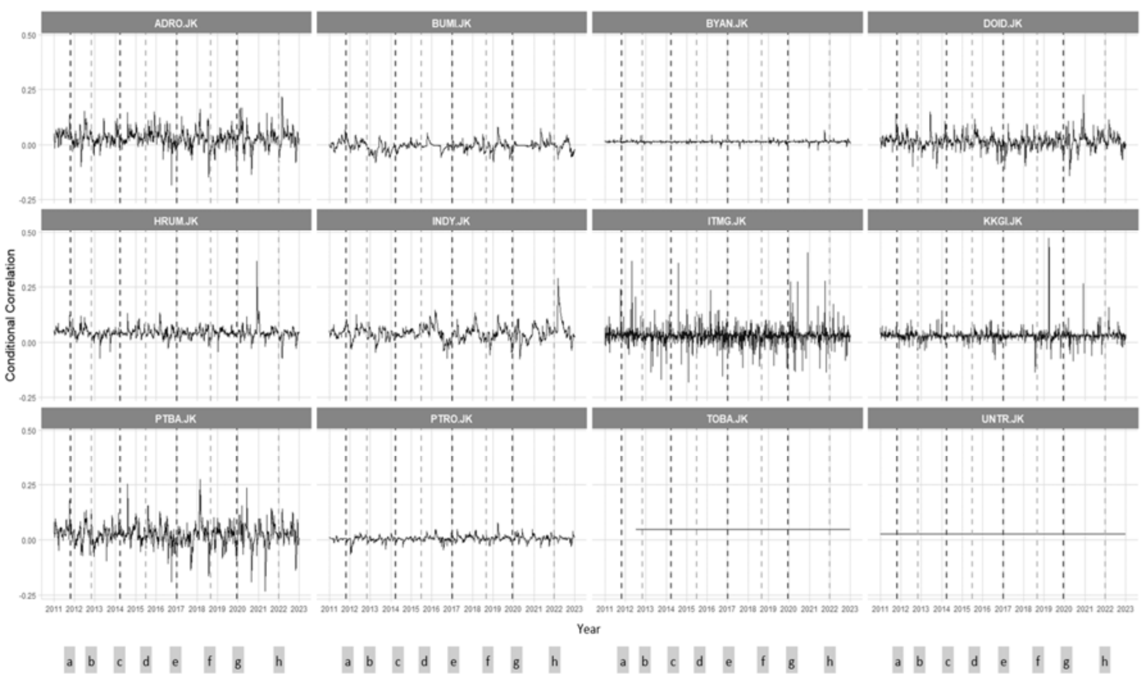
From a technical perspective, the analysis shows significant coefficients for GEAR and PRICE are -0.0318 and 0.3622, with probabilities of 2.48E-11 and 3.39E-06, respectively, which signify a significant influence on ROE. Meanwhile, LOG(ASSETS) and D1XPRICE appear to have no significant effect on ROE, with probabilities of 0.659 and 0.785, respectively, above the significance threshold of 0.05. This model was able to explain a 22.21% variation in ROE.

For the palm oil sector, the coefficients for LOG(ASSETS), GEAR, and PRICE are -1.51E+01, -0.0552, and 0.0362, with probabilities of 0.0074, 0.0002, and 0.0037, respectively, indicating that these three variables have a significant influence on ROE. The variable D1XPRICE has a probability of 0.0693, slightly above the significance threshold of 0.05, but can still be considered significant at 10%.

The study confirms that debt management and stock prices play an important role in determining the financial performance of companies in the coal and palm oil sectors. In addition, other variables, such as total asset size and external factors, such as the COVID-19 pandemic, can also affect performance, although the effect may only sometimes be significant.



Note: The blue line represents coal producers and the returns on coal prices from 2011 to 2022.



Note: The blue line represents palm oil producers and the returns on palm oil prices from 2011 to 2022.

a. October 28 2011: Eurozone (debt) crisis (Zhang et al., 2022).	b. November (2012). Due to the "Penetrating effect" of the European debt crisis, many countries are now on anti-austerity strikes (Zhang et al., 2022).	c. April (2014). Oil market prices show a downward trend—oil prices downward – Oversupply from OPEC countries and production (Zhang et al., 2022).	d. June 29–August 28, 2015: Turmoil in China's financial markets led to a sharp decline in global stock market indices (Zhang et al., 2022).	e. January 4 2017: OPEC and non-OPEC (Russia) cut oil production.	f. September (2018). China–United States trade war: US announces 10% tariffs on USD 200 billion of Chinese goods (Zhang et al., 2022).	g. December 2019: COVID-19 pandemic.	h. January 1, 2022: Start of Russia-Ukraine War.

Figure 3

Dynamic Conditional Correlation Return of Stock and Commodity Prices

Source: Data Processed (2023)

Table 8
Panel Regression Result

Coal					
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	
C	-35.1013	44.1588	-0.7949	0.4274	
LOG(ASSETS)	0.8297	1.8760	0.4422	0.6587	
GEAR	-0.0318	0.0046	-6.9821	0.0000	***
PRICE	0.3622	0.0763	4.7496	0.0000	***
D1XPRICE	0.0135	0.0494	0.2735	0.7847	
R-squared		0.2221			
Adjusted R-squared		0.2100			
SE of regression		25.6309			
F-statistic		18.3473			
Prob(F-statistic)		0.0000			
Palm Oil					
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	
C	331.0595	132.2691	2.5029	0.0135	**
LOG(ASSETS)	-15.0698	5.5421	-2.7191	0.0074	***
GEAR	-0.0552	0.0147	-3.7666	0.0002	***
PRICE	0.0362	0.0123	2.9511	0.0037	***
D1XPRICE	-0.0123	0.0067	-1.8314	0.0693	*
R-squared		0.543			
Adjusted R-squared		0.487			
Log-likelihood		-647.559			
F-statistic		9.787			
Prob(F-statistic)		0.000			

Source: Data Processed (2023

The results of this study provide important insights for investors and managers in making investment and managerial decisions, especially in the context of commodity price fluctuations and high market volatility.

CONCLUSIONS AND SUGGESTIONS

The research showed a lasting connection between the profits from commodities, particularly coal and Crude Palm Oil (CPO), and the stock profits of corporations in these industries for 2011-2022. The Granger Causality study showed a two-way relationship between commodity returns and firm returns, which the Impulse Response Function further supported. This function describes how company stocks react to changes in both commodities returns and their returns during unexpected events or shocks. Following a significant shock, the market encountered temporary inefficiencies. Nevertheless, it bounced back and eventually achieved sustained effectiveness by the Efficient Market Hypothesis (EMH). This study discovered that these sectors respond quickly to changes in commodity prices and corporate returns, confirming the market's overall efficiency.

A variance decomposition analysis reveals variations in a company's stock returns, which are influenced by shocks in its variables and commodity price return variables with different contributions from both groups of commodity companies. DCC GARCH analysis shows volatility and correlation between stock returns and commodity prices change over time, with correlation historical effects having a more substantial influence on current correlations compared to sudden changes from previous periods.

This study proves that fluctuations in commodity prices significantly impact companies' returns and financial performance. Variables such as leverage (GEAR), stock price (PRICE), and logarithm of total assets (LOG(ASSETS)) play an essential role in determining Return on Equity (ROE), with increased leverage negatively associated with ROE. In contrast, increased commodity prices are positively related. In the palm oil sector, an increase in total assets is negatively related to ROE.

However, the study had some limitations. The effect of commodity price fluctuations may be more complex and influenced by many other factors not considered in this study. The analysis method used may also have limitations in capturing all the nuances of relationships between variables. In addition, this study focuses on two commodity sectors in Indonesia, and the results may not apply to other sectors or countries.

This research provides a better understanding of the impact of commodity price fluctuations on company performance, which is very important for investors and company management. With this knowledge, they can make better investment and managerial decisions and manage the risks of commodity price fluctuations.

For further research, consider more variables and sectors and apply other analysis methods that are more accurate and complete in describing the relationship between commodity price fluctuations and company performance.

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