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DETERMINATION ANALYSIS OF WORLD COAL PRICE FLUCTUATIONS USING THE VECTOR ERROR CORRECTION MODEL (VECM) METHOD

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ABSTRACT

This study aims to analyze the fluctuations of global coal prices from Q1 2007 to Q4 2023 using the Vector Error Correction Model (VECM). The research focuses on identifying the factors that influence coal price movements, such as China's GDP growth, currency exchange rates (IDR/USD, AUD/USD), and global oil and gas prices. The results of the Johansen Cointegration Test reveal that these variables exhibit long-term equilibrium relationships, while the VECM estimation helps to examine both short-term and long-term dynamics. The Granger Causality test shows that coal price movements are significantly influenced by China's GDP growth, as well as fluctuations in the IDR/USD and AUD/USD exchange rates. The Impulse Response Function (IRF) analysis indicates that coal prices respond to shocks in these predictor variables for up to 8 periods, after which the effect weakens. The findings have significant implications for stakeholders in the coal industry, offering insights into how coal prices are driven by macroeconomic factors, and providing tools for more informed decision-making regarding coal production, pricing, and investment strategies. This research also highlights the importance of understanding the broader economic and geopolitical factors that shape the coal market and offers valuable input for policy formulation and risk management in the energy sector.

KEYWORDS *Coal, Forecasting, Fluctuations, Commodities, Energies show that at 1% alpha*

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INTRODUCTION

Coal is a rock formed through the processes of sedimentation and compaction of plant remains over millions of years, ultimately producing carbon-rich material. Coal can be divided into two main categories: Thermal Coal and Metallurgical Coal (also known as Coking Coal). This research focuses exclusively on Thermal Coal. Currently, coal is used directly by various industries for different purposes,

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including as fuel and for power plants. Globally, coal is widely used to produce heat, especially in developing countries, with coal consumption increasing to more than 30% in 2011. Coal used as fuel supports both small-scale home industries and large industrial operations. Additionally, coal is extensively utilized in Steam Coal Power Plants, where it is burned to produce steam that drives turbine engines. These power plants primarily rely on coal as their main fuel source. In South Africa, approximately 93% of power plants are coal-fired, and many countries in the Asia-Pacific region also depend heavily on coal for electricity generation. Globally, about 68% of coal consumption is dedicated to power generation.

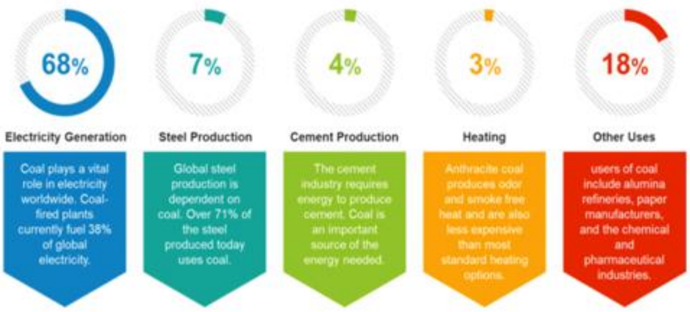

Figure 1. Percentage of coal use by industrial sector. Source: Journal of Material Science

As explained above, of the world's total coal consumption, coal is used most in power plants (68%), and for Coal Fired Plants where coal feedstock is used as its energy source, it has a population of 38% of the world's power generation population at the moment.

Coking Coal is a crucial material in the steel industry, where it is used to smelt iron ore and purify it from impurities to produce steel. Many major steel-producing countries, such as the United States, China, Russia, India, and Japan, are among the largest importers of this type of coal. In addition to its role in steel processing, coal can also be utilized to produce various synthetic products for industrial use. For example, coal is used to produce syngas, a combination of hydrogen and carbon monoxide, which can serve as a fuel similar to petroleum or diesel. Coal tar is another derivative, widely used in the medical and cosmetic industries. Furthermore, fly ash from coal is utilized as a raw material in cement production, and coal also serves as a filler material in the manufacture of polymers for the plastic and chemical industries, among other applications.

Historical growth of world coal prices

Based on Baffes et al. (2024), Commodity Market, the historical growth of coal prices from the period 1970 to 2022 can be explained as follows:

a. Period 1970-1980

The coal commodity market began to take shape when the price of petroleum experienced a high rise in the 1970s, which made coal more competitive with crude oil as a fuel for power generation.

The increase in the use of coal for power generation was facilitated by the International Energy Agency's (IEA) decision to prohibit their member states from building new power plants that use oil fuel (IEA 1979). This caused coal consumption to increase by about 20% from 1970 to 1980, which led to an increase in coal prices, as explained in the chart below.

b. Period 1980-2000

In addition, several countries are expanding their coal reserves and becoming coal exporters, including Australia, Canada, and South Africa. This resulted in the quantity of coal traded between 1970 and 1990 doubling.

Coal prices began to decline since the 1980s, and in 1990 they remained relatively flat despite an increase in demand for coal. The decline was caused by the supply side, and the emergence of new exporters in 1980, including China, Colombia, and Indonesia, as well as technological developments, especially in the United States, which caused the cost of coal mining to decline sharply (Ellerman 1995). Between 1985 and 1995, the productivity of workers in coal mining became more effective from 2.7 tons per hour to 5.4 tons per hour per employee (EIA 2021).

c. Period 2000-2008

The coal market changed significantly from 2000 as a result of growth from developing countries, especially China, which made coal demand soar (Baffes, Kabundi, and Nagle 2022; World Bank 2018). Coal consumption increased by almost 50% during the period 2000 – 2008, where China as a country has demand up to 2/3 of the world's total coal consumption. Although China has coal mines and increases their coal production, it cannot meet their demand for coal. To meet this coal demand deficit, China has become the largest importing country in the world, and at the same time as a controller of coal price fluctuations in the global market.

d. Period 2009 – 2013

As a result of the global crisis, coal prices fell far between 2008 – 2009, although they rose again in the period 2010 – 2014 where China was the most demanded country.

e. Period 2014 - 2019

Coal demand in 2014 experienced a slight decline, this is due to the decline in economic growth in China, so investors also diverted their investments. In line with that, it will make coal consumption and demand decline (World Bank 2019a).

Coal demand has been slightly affected by the revolution in the exploitation of Coal Bed Methane Gas, which is a new technology that produces methane gas trapped in thin layers of coal lamination. Where this finding produces gas that is cheaper to produce, and replaces the use of coal with gas fuel for power plants (EIA 2020).

Concern about global warming (climate change) and efforts to reduce carbon emissions, the growth of power generation technology with solar panels and windmills, also have an impact on decreasing demand for coal for the power generation industry (Kementerian Energi dan Sumber Daya Mineral, 2017; Kementerian ESDM, 2017; KESDM, 2017; Kuswardini & Suprapto, 2018; Mariana, 2023).

Reflecting on these developments, coal for power generation has declined in Europe and the United States in recent years, but in China and India the demand for coal has increased. After all, coal consumption in energy commodities is up to 30% worldwide, or 40% as a source of raw materials for power plants in the world.

f. Period 2020

In this period, coal prices have again decreased when compared to 2019, and throughout the year there has been no growth, the main contributing factor is the global recession due to the Covid-19 pandemic that spreads around the world, thus having an impact on the decline in coal demand in various regions/countries around the world.

g. Period 2021-2022

Coal prices in Q1 2021 still did not experience a significant increase, but in mid-2021 (Q2-2021) coal prices increased significantly. This is caused by the increasing demand for coal in line with the recovery from the global economy. Coal is further corrected upwards due to the decline in other energy sources, including hydropower plants due to heat waves and droughts in North America, South America, and China (World Bank 2021).

Due to concerns about a shortage of energy resources, China increased its coal production at the end of 2021, and this increase in production caused coal prices to decline again in Q4 2021.

In the Q1 2022 period, caused by the war between Ukraine and Russia, the Russian state took a policy to stop gas sales throughout Europe, this resulted in an increase in world gas prices, so countries in Europe are looking for coal as a substitute for natural gas. This high demand for coal has resulted in a very significant increase in world coal prices, and the highest increase in world history (World Bank 2022).

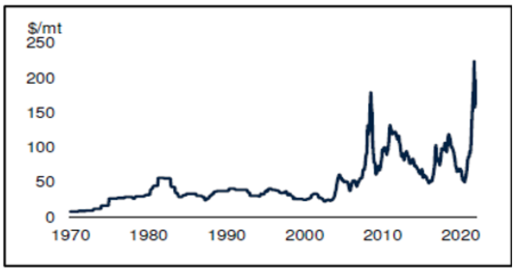

Figure 2. Graph of world coal price fluctuations from 1970-2020. Sources: BP Statistical Review; Energy Information Administration; Global Energy Monitor; International Energy Agency; World Bank.

h. Period 2023

These fluctuations in coal prices can be attributed to several sources from global economic events, which are currently occurring. In this period, coal prices have decreased, due to the improvement of the gas supply chain in the European region, and the decline in world gas prices, so that the alternative use of gas as a source of energy for power plants is one of the good choices by various countries.

Based on the explanations above, we can see:

1) Coal prices are very risky to change depending on the turmoil that occurs in the global market.

2) Coal is an important commodity as an energy fuel, in addition to oil and natural gas,
3) Coal is an important product in the power generation industry,
4) Coal consumption is very high in the world,
5) Coal can be a supporter of industrial/economic growth in a country/region.

In the study of the movement of coal price fluctuations in the world, the author will limit the formulation of the problem to several focus of discussion. As discussed in the previous subchapter where Coal is divided into 2 (two) categories, namely: Thermal Coal, and Metallurgical Coal (Coking Coal). However, in this writing, the author conducted research on the type of Thermal Coal only. The hypotheses that will be tested in this study are:

a) The movement of coal prices is positively and significantly influenced by the price movements of petroleum and natural gas as its substituent products.
b) Coal price movements are positively and significantly influenced by the growth of Global GDP and China's GDP
c) Coal price movements are significantly influenced by currency exchange rate fluctuations in the world's largest coal exporters and importers

The volatility of global coal prices poses a significant challenge for stakeholders in the energy sector, including governments, mining companies, and market brokers. Fluctuating coal prices can affect state revenues from the non-oil and gas sector, complicate financial planning for mining companies, and make it difficult for brokers to forecast price trends accurately (Cao et al., 2023; Nguyen et al., 2020; Putra et al., 2021; Sianturi, 2024; Yuani et al., 2023). For the Indonesian coal industry, price volatility also impacts export volumes, tax royalties, and the overall economic stability of the region. The inability to predict these fluctuations can lead to substantial financial losses, affect business growth, and create difficulty in managing contractual obligations related to coal prices (Arintoko et al., 2023; Han et al., 2023; Pandiyan et al., 2019; Plakitkin et al., 2019; TOMITA & OKABE, 2018).

Furthermore, various macroeconomic factors influence coal prices, including the economic growth of major coal-consuming countries like China, currency exchange rates of key coal exporters and importers, and the global price trends of oil and natural gas. Understanding the relationship between these factors and coal price fluctuations is critical for formulating effective policies and business strategies. This study aims to model the factors influencing coal price volatility using the Vector Error Correction Model (VECM), a technique that can examine both short-term and long-term relationships between these key variables.

This research is urgent due to the significant economic and environmental implications of coal price fluctuations. As coal remains a primary energy source for power generation worldwide, particularly in developing countries like Indonesia, understanding the factors driving these price changes is essential for mitigating the risks associated with price volatility. The study also addresses the challenge of forecasting coal prices, which has become increasingly difficult in the face of global economic uncertainties, geopolitical tensions, and environmental concerns. By providing a deeper understanding of the macroeconomic variables affecting coal prices, this research can help stakeholders make more informed decisions in an increasingly unpredictable market.

Previous studies have explored various factors influencing commodity price fluctuations, with a focus on energy resources like oil and coal. For example, research by Baffes et al. (2024) analyzed the correlation between global economic indicators, such as GDP growth in major coal-consuming countries like China, and coal price movements. Their study emphasized the role of economic growth in driving demand for coal, thus influencing price trends. Similarly, research by Rehal (2022) examined the impact of currency fluctuations on coal prices, noting that changes in exchange rates can affect the purchasing power of coal-importing countries and, consequently, the global price of coal (Wu et al., 2020).

In addition, studies such as those by Duan & Meng (2020) have focused on the influence of supply-side factors, including coal production levels and technological advancements in mining, on price fluctuations. These studies highlighted the critical role of supply disruptions, such as those caused by natural disasters or geopolitical events, in shaping the price dynamics of coal. However, there is a limited focus on the combined impact of both demand-side and supply-side factors in modeling coal price fluctuations, particularly through the use of VECM, which can capture the short-term and long-term dynamics of these relationships.

Moreover, research by the World Bank (2023) has identified that global energy prices, including oil and gas, have a direct impact on coal prices due to the competitive nature of the energy market. As energy prices increase, coal becomes a more competitive alternative, driving up demand and coal prices. However, few studies have utilized econometric models like VECM to quantify the long-term equilibrium relationships between these factors and coal prices, which is a key aspect of this research (Kusumah et al., 2020; Mahor & Banerji, 2023; Setyowati, 2019; Sri Anggeny Marta Fiona & Trenggana, 2020; Tippe, 2013; Umiyati et al., 2021).

Despite existing research on the individual factors influencing coal price fluctuations, there is a lack of studies that comprehensively analyze the relationships between various macroeconomic variables, such as GDP growth, exchange rates, and energy prices, in the context of coal price movements. Additionally, while some studies have explored these relationships, there is limited use of advanced econometric models like the Vector Error Correction Model (VECM) that can account for both short-term dynamics and long-term equilibrium. This research aims to fill this gap by applying VECM to model the interactions between key economic variables and coal prices, providing a more nuanced understanding of the factors driving price volatility.

This study introduces a novel approach by applying the Vector Error Correction Model (VECM) to analyze the relationship between coal prices and key macroeconomic variables such as GDP growth, exchange rates, and energy prices. Unlike previous studies that have relied on simpler models or focused on individual factors, this research uses VECM to capture both the short-term dynamics and long-term equilibrium relationships between these variables. This methodology allows for a more comprehensive understanding of how global economic and energy market factors influence coal price movements, making it a valuable contribution to the field of energy economics.

The main objective of this study is to analyze the factors influencing coal price fluctuations using the Vector Error Correction Model (VECM). Specifically, the research aims to identify the long-term and short-term relationships between coal prices and macroeconomic variables such as GDP growth in major coal-consuming countries, exchange rates of coal-exporting countries, and global oil and gas prices. The study also seeks to assess how these variables interact and contribute to coal price volatility, providing insights into potential forecasting methods for stakeholders in the coal industry.

The findings of this study will provide valuable insights for policymakers, business leaders, and market analysts involved in the coal industry. By identifying the key macroeconomic drivers of coal price fluctuations, this research will help stakeholders anticipate market trends and make more informed decisions regarding coal production, pricing, and investment. Additionally, the study's use of VECM provides a more robust framework for understanding the long-term relationships between variables, offering a better tool for forecasting and risk management in the energy sector. The implications of this research extend to governments seeking to stabilize coal-related revenues and mitigate the economic impacts of price volatility.

RESEARCH METHOD

The method used in this study is a Vector Error Correction Model (VECM), which is applied to examine the relationship between coal prices and several macroeconomic variables, including China's GDP, exchange rates, and oil and gas prices. The VECM is a statistical method designed to model and analyze the short-term and long-term dynamics of multiple time series variables that are cointegrated. This method is suitable for this study as it can account for both the long-run equilibrium relationships and the short-term dynamics between the variables. The analysis process involves several key steps, such as verifying data consistency, checking for stationarity using the Augmented Dickey-Fuller (ADF) test, performing cointegration tests, determining the optimal lag, and conducting Granger causality tests. Additionally, the model includes Impulse Response Function (IRF) analysis and Variance Decomposition to assess the dynamic responses and the influence of shocks on the variables over time.

The study begins by collecting secondary data, including quarterly coal prices and various macroeconomic indicators from 2007 to 2023. After data validation and verification, the study explores the correlations and fluctuations in the data to understand the impact of specific events on coal price changes. The VECM method is then used to analyze these variables' interactions and assess the long-term equilibrium relationships, as well as the short-term dynamics. This approach helps to identify significant causal relationships and the impact of external shocks, providing insights into how coal prices are influenced by factors like exchange rates, GDP growth, and oil and gas prices.

RESULT AND DISCUSSION

Data Characteristics

1) Coal price time series data plot

The time series data plot of the coal price quarterly data from the first quarter of 2007 to the fourth quarter of 2023 can be shown in the figure below:

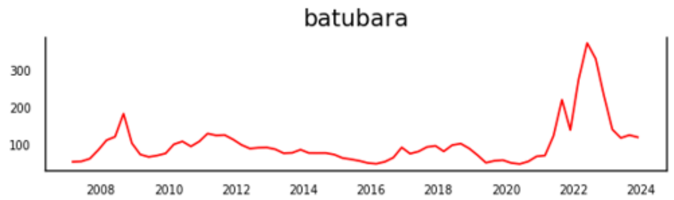

Figure 4. Time Series world coal prices 2007 – 2023

Based on the image above, we can see the pattern of coal price movements during the analysis period.

a. The period when coal prices increased: 2007-2008, 2010–2011, 2016–2018, 2021-2022.
b. Coal price period decreased: 2009, 2012–2015, 2019–2020, 2023.
c. Stable/stagnant coal price period: 2014-2015, 2020

The explanation of the factors that cause coal price fluctuations, based on studies from several sources, as explained in the previous subchapters, is as follows:

1. Period 2007-2008 (increase in coal prices)
   This period the increase in coal prices is due to the high sea freight rates of coal carriers. Australia restricts coal shipping to various countries, while the world depends on this country where Australia is one of the largest coal exporters in the world.
2. Period 2009 (decrease in coal prices)
   In this period, there was a global economic crisis, and world GDP grew negatively (-1.67%).
3. Period 2010-2011 (increase in coal prices)
   There are several factors that caused the increase in coal prices in the 2010-2011 period, such as: high rainfall in coal exporting countries such as Australia, Indonesia, and Columbia, which caused disruption in their mining productivity. Extreme winter weather in Europe caused the paralysis of several roads and ports in the European region. The existence of security turmoil in the Middle East and North Africa region, which has led to a correction in the price of fossil fuels such as oil and gas, has also affected coal prices. There was a mining accident at the Raspadskaya mine - Russia, so that the inspections carried out

made several mining companies delayed and temporarily stopped their production. And finally the earthquake in Japan that caused the rupture of their nuclear reactor (Fukushima), the Japanese government took a policy to use coal-fired power plants. This was also followed by European countries, which shut down their nuclear power plants and replaced them with coal.

4. Period 2012-2015 (coal price decrease)
   In this period, the global economy is declining again, where the global GDP growth is less than 3% per year.
5. Period 2016-2018 (increase in coal prices)
   The decline in coal production from mining has led to an increase in coal prices. High geothermal temperatures cause an increase in coal demand as well. The Chinese government's policy to increase domestic coal prices has led to an increase in coal imports as well. Another factor is the presence of storm La Lina accompanied by rain that occurred in Indonesia and Australia. As a result of the nuclear reactor leak in Fukushima, Japan uses conventional power plants such as coal, oil, and gas. Since 2017, World GDP has also grown well above 3% per year.
6. Period 2019-2020 (coal price decrease)
   The trade war between China and the United States has led to a decline in coal consumption, an increase in coal stocks in Europe, an increase in renewable energy power plants, and an oversupply of natural gas. At the end of December 2019, there was an outbreak of the COVID-19 pandemic around the world, this caused a global crisis, where world GDP growth was negative (-3.9%).
7. Period 2021 – 2022 (increase in coal prices)
   The increase in coal was caused by two factors, the first was due to the improvement in the world economy due to the recovery of the Covid-19 pandemic outbreak, the second was started in the Q1 2022 period, this was caused by the war between Ukraine and Russia, where the Russian state took a policy to stop gas sales throughout Europe, this resulted in an increase in world gas prices, so that countries in Europe were looking for coal as a substitute for natural gas. This high demand for coal has resulted in a very significant increase in world coal prices (>300%), this increase is the highest increase in the history of coal trade (World Bank 2022).
8. Period 2023 (decrease in coal prices)
   During this period, coal prices decreased, due to the improvement of the gas supply chain in the European region, and the decline in world gas prices.

2) Plot data time series GDP China

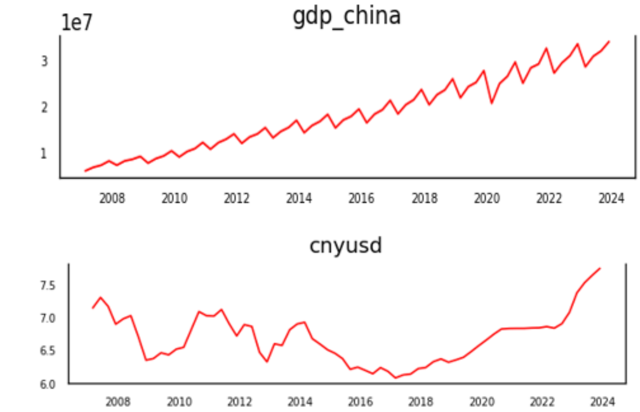

Figure 4. Plot Time Series China's Exchange Rate Against USD

3) Plot data time series IDR-USD

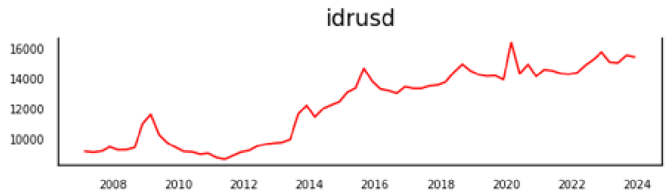

Figure 5. Plot Time Series Rupiah Exchange Rate Against USD

4) Plot data time series AUS-USD

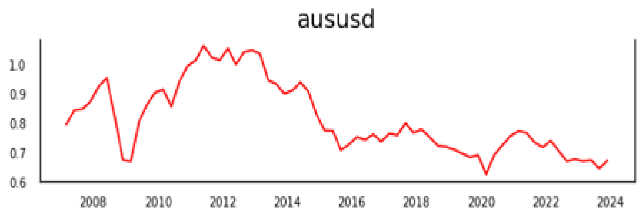

Figure 6. Plot Time Series AUD to USD exchange rate

5) Plot data time series RUB-USD

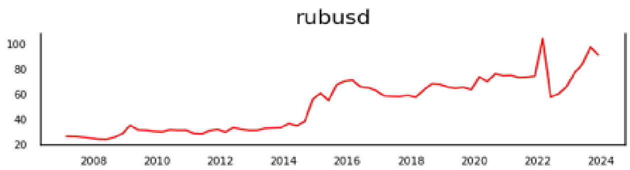

Figure 7. Plot Time Series RUB against USD

6) Plot data time series EURO-USD

Figure 8. Plot Time Series EUR against USD

7) Crude oil time series data plot

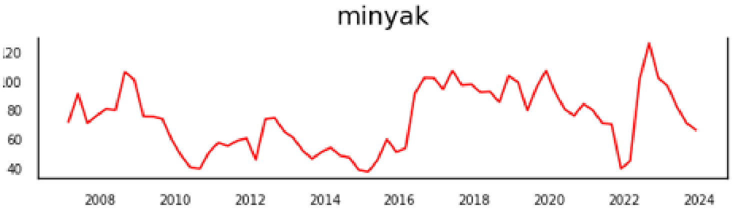

Figure 9. Oil Time Series Plot

8) Plot data time series gas alam

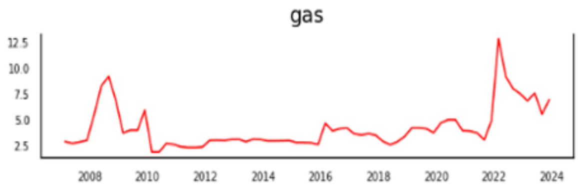

Figure 10. Natural Gas Price Plot

Pemodelan Vector Error Correction Model

1) Data Stationary Testing

Time series economic data is generally stochastic (has a trend that is not stationary / the data has a unit root). If the data has a unit root, then the value will tend to fluctuate not around the average value, making it difficult to estimate a model. Unit Root Test is one of the concepts that has recently become increasingly popular to test the stationarity of time series data. This test was developed by Dickey and Fuller, using the Augmented Dickey Fuller Test (ADF). The stationarity test that will be used is the ADF (Augmented Dickey Fuller) test using a real level of 5%.

From the results of modeling using Eviews, the results of the stationery test of 9 research variables were obtained:

BATUBARA
Null Hypothesis: BATUBARA has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.538686	0.1111
Test critical values:	1% level	-3.531592	
	5% level	-2.905519	
	10% level	-2.590262	

AUSUSD
Null Hypothesis: AUSUSD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.471655	0.3409
Test critical values:	1% level	-4.100935	
	5% level	-3.478305	
	10% level	-3.166788	

CNYUSD
Null Hypothesis: CNYUSD has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.504233	0.5254
Test critical values:	1% level	-3.533204	
	5% level	-2.906210	
	10% level	-2.590628	

EUROUSD
Null Hypothesis: EUROUSD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.222147	0.0889
Test critical values:	1% level	-4.100935	
	5% level	-3.478305	
	10% level	-3.166788	

IDRUSD
Null Hypothesis: IDRUSD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.893606	0.1712
Test critical values:	1% level	-4.100935	
	5% level	-3.478305	
	10% level	-3.166788	

RUBUSD
Null Hypothesis: RUBUSD has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.614215	0.8597
Test critical values:	1% level	-3.533204	
	5% level	-2.906210	
	10% level	-2.590628	

GAS
Null Hypothesis: GAS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.363134	0.0652
Test critical values:	1% level	-4.100935	
	5% level	-3.478305	
	10% level	-3.166788	

GDP_CHINA
Null Hypothesis: GDP_CHINA has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.834785	0.6759
Test critical values:	1% level	-4.110440	
	5% level	-3.482763	
	10% level	-3.169372	

The tie of the test results using the ADF test procedure showed that all research variables were root/random walk/non-stationary units at the level.

Cointegration Testing

As stated by Engle-Granger, the existence of non-stationary variables makes it more likely that there will be long-term relationships between variables in the system. The cointegration test was carried out to determine the existence of relationships between variables, especially in the long term. If there is a cointegration of the variables used in the model, then it can be ensured that there is a long-term relationship between the variables. The method that can be used in testing the existence of this cointegration is the Johansen Cointegration method. The following are the results of the cointegration test:

Cointegration Test Results

Date: 02/06/24 Time: 08:29
Sample (adjusted): 2007Q4 2023Q4
Included observations: 65 after adjustments
Trend assumption: Linear deterministic trend
Series: BATUBARA AUSUSD CNYUSD EUROUSD IDRUSD RUBUSD GAS GDP_CHINA MINYAK
Lags interval (in first differences): 1 to 2

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.684520	242.4237	197.3709	0.0000
At most 1 *	0.556041	167.4358	159.5297	0.0172
At most 2	0.391921	114.6543	125.6154	0.1915
At most 3	0.328144	82.32002	95.75366	0.2913
At most 4	0.295426	56.46878	69.81889	0.3594
At most 5	0.217963	33.70830	47.85613	0.5178
At most 6	0.143527	17.72781	29.79707	0.5862
At most 7	0.107747	7.657161	15.49471	0.5028
At most 8	0.003789	0.246784	3.841465	0.6193

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.684520	74.98788	58.43354	0.0006
At most 1 *	0.556041	52.78154	52.36261	0.0453
At most 2	0.391921	32.33427	46.23142	0.6356
At most 3	0.328144	25.85124	40.07757	0.7124
At most 4	0.295426	22.76048	33.87687	0.5488
At most 5	0.217963	15.98049	27.58434	0.6674
At most 6	0.143527	10.07065	21.13162	0.7380
At most 7	0.107747	7.410376	14.26460	0.4418
At most 8	0.003789	0.246784	3.841465	0.6193

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

The results of the cointegration test using the Johansen Cointegration Test procedure show that all the variables that are random walks above, have a cointegration relationship (equilibrium relationship in the long term), so that the relationship between the variables of this study will be analyzed through VECM estimation.

Optimum Lag Testing

VECM modeling estimation requires researchers to determine the optimal lag in selecting the model specifications. The existence of data limitations causes the determination of the optimum lag in this study can only be done until the 4th lag. The test results using the VEC Lag Exclusion Wald Tests procedure, are shown in the following Table.

VEC Lag Exclusion Wald Tests
Date: 02/06/24 Time: 10:29
Sample (adjusted): 2008Q2 2023Q4
Included observations: 63 after adjustments

Chi-squared test statistics for lag exclusion:
Numbers in [ ] are p-values

	D(BATUBARA)	D(AUSUSD)	D(CNYUSD)	D(EUROUSD)	D(IDRUSD)	D(RUBUSD)	D(GAS)	D(GDP_CHINA)	D(MINYAK)	Joint
DLag 1	26.66234 [0.0016]	5.701017 [0.7694]	12.40401 [0.1915]	8.338551 [0.5004]	5.362422 [0.8016]	26.19702 [0.0019]	48.60210 [0.0000]	16.05811 [0.0657]	87.48391 [0.0000]	578.2068 [0.0000]
DLag 2	21.28741 [0.0114]	13.09559 [0.1583]	3.525454 [0.9398]	11.20529 [0.2619]	4.686047 [0.8608]	5.860875 [0.7538]	44.67638 [0.0000]	17.14705 [0.0465]	101.4871 [0.0000]	468.9772 [0.0000]
DLag 3	30.39244 [0.0004]	11.84654 [0.2221]	4.537764 [0.8726]	25.85597 [0.0022]	7.289323 [0.6070]	7.283684 [0.6076]	58.91919 [0.0000]	20.08463 [0.0174]	68.93542 [0.0000]	553.1076 [0.0000]
DLag 4	19.22004 [0.0234]	8.124279 [0.5217]	2.125535 [0.9893]	17.20577 [0.0456]	6.455149 [0.6936]	6.200354 [0.7197]	43.13792 [0.0000]	14.32292 [0.1113]	31.92016 [0.0002]	397.6468 [0.0000]
df	9	9	9	9	9	9	9	9	9	81

The joint hypothesis tested with this procedure requires the researcher to include 4 lags in the VEC model to be estimated. This is shown from the prob value (p-value) for the joint hypothesis until lag 4 which is statistically significant at alpha 5%.

Interpretasi hasil estimasi VECM (Vector Error Correction Model)

The interpretation of the VECM (vector error correction model) estimation results in this study will be carried out with 3 forms of analysis, namely Granger Causality Test, Impulse Response Function (IRF), and Variance Decomposition.

1) Granger Causality Testing

The causality test was carried out to determine the important determinants of coal price movements. Other directions of causality between variables in this study based on the results of the Granger Causality test are shown in Appendix 2.

VEC Granger Causality/Block Exogeneity Wald Tests
Date: 02/06/24 Time: 10:24
Sample: 2007Q1 2023Q4
Included observations: 63

Dependent variable: D(BATUBARA)

Excluded	Chi-sq	df	Prob.
D(AUSUSD)	17.04325	4	0.0019
D(CNYUSD)	0.741258	4	0.9461
D(EUROUSD)	2.831269	4	0.5864
D(IDRUSD)	16.12239	4	0.0029
D(RUBUSD)	6.490637	4	0.1654
D(GAS)	2.834405	4	0.5859
D(GDP_CHINA)	19.43280	4	0.0006
D(MINYAK)	1.393811	4	0.8453
All	90.67222	32	0.0000

The results of the Granger Causality test show that the movement of coal prices is positively and significantly influenced by the movement of GDP_China, the movement of IDRUSD, and the movement of AUSUSD. The observation of the important role of China's GDP in coal price movements is due to the fact that China is the largest coal importing country in the world with coal consumption of around 30% - 35% of the world's total coal consumption. Therefore, China's GDP growth, which is an indicator of their economic growth, will certainly affect the growth of industrial and manufacturing sectors that require energy, and energy will require power plants (coal-fueled). Therefore, China's GDP growth will also affect coal prices.

Regarding the role of IDR-USD as an important predictor of coal prices is because Indonesia is the world's largest coal exporter, even in 2022 Indonesia is the highest country above Australia in exporting coal, with an export range of 26% - 28% of the world's total coal. Therefore, fluctuations in the value of the Indonesian currency will be able to affect coal prices. Similarly, Australia is also the world's coal exporting country, with the number of exports almost the same as Indonesia's exports, with an export range of 26% - 28% of the world's total coal. Therefore, fluctuations in the value of the Australian currency will also affect the price of coal.

2) Hasil Estimasi Impulse Response Function (IRF)

The results of the Impulse Response Function (IRF) analysis are shown in the following graph:

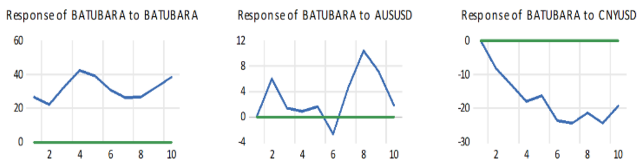

Figure 11: Chart of Coal's Impulse Response Function (IRF) to Coal, AUSUSD, CNYUSD

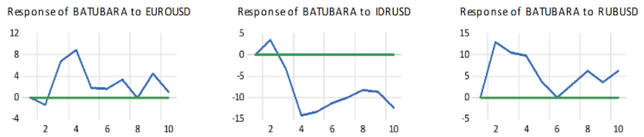

Figure 12: Chart of Coal's Impulse Response Function (IRF) against EUROUSD, IDRUSD, RUBUSD

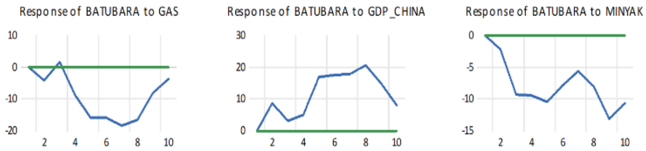

Figure 13: Coal Impulse Response Function (IRF) graph against GAS, CHINA'S GDP, OIL

VEC Granger Causality from VECM modeling shows that the significant predictors affecting the movement of coal prices are the movement of the IDR-USD and AUS-USD currencies as well as the GDP of China. The response of coal prices to shocks that occurred in the three predictor variables generally increased to 8 periods after the shock occurred and the response began to weaken afterwards.

3) Hasil Estimasi Variance Decomposition

Meanwhile, the results of the Variance Decomposition estimate for coal price movements are shown in the following table.

Variance Decomposition of BATUBARA: Period	S.E.	BATUBARA	AUSUSD	CNYUSD	EUROUSD	IDRUSD	RUBUSD	GAS	GDP_CHINA	MINYAK
1	26.38964	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	39.58975	75.72601	2.303549	4.286260	0.131518	0.741712	10.62034	1.085589	4.795909	0.309120
3	55.63571	73.62194	1.226343	7.675184	1.514747	0.733671	8.890840	0.633820	2.754031	2.949428
4	76.03777	70.50401	0.669634	9.696897	2.175738	3.878444	6.397593	1.648659	1.902853	3.126171
5	91.74728	66.48363	0.489973	9.827575	1.530573	4.789576	4.556150	4.162107	4.712043	3.448373
6	103.4032	61.21074	0.455231	12.98380	1.228246	4.986587	3.586928	5.656513	6.603220	3.288739
7	113.1494	56.45091	0.542678	15.52083	1.110457	4.951581	3.064881	7.367932	7.994409	2.996320
8	122.3169	53.13157	1.183539	16.34934	0.950301	4.703371	2.874722	8.120166	9.683286	3.003711
9	131.2430	52.22313	1.321820	17.66033	0.941663	4.530712	2.569566	7.443830	9.697476	3.611471
10	139.4824	53.78020	1.186831	17.55908	0.839199	4.799865	2.469974	6.662359	8.917446	3.785044

The Variance Decomposition table above describes how much variation occurs in the current coal price, which can be explained by the shock that occurs in the coal price itself and the shock of other predictor variables at 1, 2, 3,.. up to the previous 10 periods. The table shows that the variation in the current coal price is largely explained by the shocks that occurred in the previous 1 to 10 periods of the coal price itself, followed by the shocks that occurred in the CNYUSD and the GDP of China and Gas.

CONCLUSION

Based on the analysis results, the conclusion drawn from the study reveals significant trends and relationships between coal prices and various macroeconomic variables from Q1 2007 to Q4 2023. The historical data shows periods of coal price increases, such as in 2007-2008, 2010-2011, 2016-2018, and 2021-2022, while coal prices decreased during 2009, 2012-2015, 2019-2020, and 2023. There were also periods of stable or stagnant coal prices, particularly in 2014-2015 and 2020. The Johansen Cointegration Test confirmed that the variables under study, which include GDP_China, IDRUSD, and AUSUSD, exhibit a long-term cointegration relationship, indicating that these variables move together in the long run. The Granger Causality test further indicated that coal prices are positively and significantly influenced by the movement of China's GDP, the IDR/USD exchange rate, and the AUD/USD exchange rate. The Impulse Response Function (IRF) estimates revealed that coal prices respond to shocks from these predictor variables with an increase for up to 8 periods after the shock, after which the response starts to weaken. This suggests that the impact of these variables on coal prices is more pronounced in the short term before stabilizing.

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