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Forecasting the Stock Price of Coal and Coal Commodity Companies using the ARIMA and ARCH/GARCH Models for 2011-2022

Prediksi Harga Saham Perusahaan Batubara dan Komoditas Batubara menggunakan Model ARIMA dan ARCH/GARCH Periode 2011-2022

Didi Nuryadin*), Ida Bagus Putu Cesario Putra Sarayuda, Dewi Qutrun Nada
Faculty of Economic and Business, UPN Veteran Yogyakarta, Indonesia
**correspondence e-mail: didinuryadin@upnyk.ac.id*

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Abstract

This study focuses on coal companies in Indonesia, a key sector in the mining industry. It explores how ARIMA and ARCH/GARCH models can predict the share prices of these companies. The results indicate that these models are effective, with Mean Absolute Percentage Error (MAPE) values ranging from 6 to 20 percent. The movement of stock prices is directly proportional to changes in the benchmark price. Additionally, it emphasizes the significant impact of geopolitical events, like the Russia-Ukraine conflict, and post-pandemic economic conditions on the coal industry. These factors have influenced coal company stock prices, highlighting the value of forecasting models in adapting to market fluctuations. The research provides important insights for investors, suggesting that advanced econometric models can help make informed investment decisions and enhance strategies in the volatile coal market by accounting for external events and model accuracy.

Keywords: ARCH/GARCH, ARIMA, Coal, Forecasting, Stock Price.

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Abstrak

Studi ini berfokus pada perusahaan batu bara batubara di Indonesia, sebuah sektor utama dalam industri pertambangan. Penelitian ini mengeksplorasi bagaimana Model ARIMA dan ARCH/GARCH dapat memprediksi harga saham perusahaan-perusahaan ini. Hasilnya menunjukkan bahwa model-model ini efektif, dengan nilai Mean Absolute Absolute Percentage Error (MAPE) yang berkisar antara 6 hingga 20 persen. Studi ini menemukan bahwa pergerakan harga saham berbanding lurus dengan perubahan harga. Selain itu, studi ini menekankan dampak signifikan dari peristiwa geopolitik, seperti konflik Rusia-Ukraina, dan kondisi ekonomi pasca pandemi terhadap industri batu bara. Faktor-faktor ini telah mempengaruhi harga saham perusahaan batu bara, menyoroti nilai dari model peramalan dalam beradaptasi dengan fluktuasi pasar. Penelitian ini memberikan wawasan penting bagi para investor, menunjukkan model ekonometrik yang canggih dapat membantu membuat investasi yang tepat dan meningkatkan strategi di pasar batubara yang bergejolak dengan memperhitungkan peristiwa eksternal dan akurasi model.

Keywords: *ARCH/GARCH, ARIMA, Batubara, Prediksi, Harga Saham.*

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INTRODUCTION

Indonesia's mining sector contributed part of the state revenue in 2020 and 2021; this is because Indonesia is a country that has abundant natural resources, especially non-oil and gas coal energy sources. Meyliawati *et al*. (2022) stated that mining is among the most significant contributors to national exports. Indonesia is a strategic archipelagic country with great potential as a coal exporter whose use is a source of steam power generation. Electric power is the primary commodity consumed by the world community and is used in the industrial sector and households. Considering its utility, coal supports the mining industry's growth and encourages economic growth in line with the rapid demand for coal exports abroad (Junaid *et al*., 2020; Meyliawati *et al*., 2022; Wibowo, 2020).

After easing the COVID-19 pandemic, the dynamics and geopolitical developments brought a new paradigm to investors to consider collecting coal sector issuers. This is because Indonesia's demand for coal commodities has increased significantly due to international coal trade sanctions on Russia. In response to this, several regulatory changes impacted decreasing investor enthusiasm; the regulatory changes were contained in Law No. 4 of 2009 Article 10 paragraph (1) to meet the Domestic Market Obligation (DMO) to reduce the deadline for stopping coal exports. The condemnation of several NATO-allied countries preceded the halt of domestic coal exports to Russia to stop conducting trade contracts. This has resulted in systematic risks worldwide after the Covid-19 pandemic towards an energy crisis. Macroeconomically, the crisis has a spillover effect on several countries that previously had cooperation with the Russian state towards a global shock economy, reinforced by the fact that Russia is the third largest coal exporter country in the world (Costola & Lorusso, 2022; Qureshi *et al*., 2022).

The Russia-Ukraine conflict impacts the high demand for domestic coal for export to several countries that depend on coal energy. Since the strong sentiment caused by the Russian-Ukrainian conflict and the economic recovery following the COVID-19 outbreak, coal commodity prices have risen. According to Setiawan *et al*. (2020), the demand for the coal mining sector causes over-demand while the supply owned cannot meet domestic needs, so a production and export control policy is needed as stated in Law No. 4 of 2009 Article 5 - concerning the priority of domestic minerals and coal. The policy of controlling domestic supply and increasing demand for foreign coal imports impacts the high fluctuations in the share prices of several coal issuers

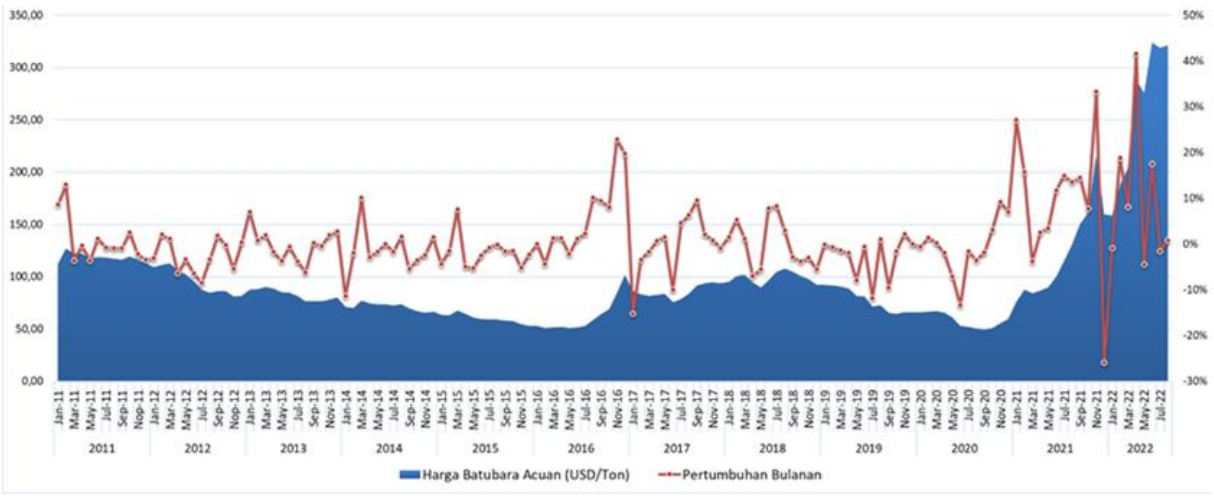


Figure 1. Indonesia Reference Coal Price Trend, January 2011 - August 2022
Source: Ministry of Energy and Mineral Resources of Indonesia (processed), 2024.

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Figure 1 illustrates the trend of coal prices in Indonesia over the specified period. The figure highlights the business prospects of several domestic coal issuers, which appear favorable based on various indicators and sentiments. Indonesia is a significant player in the coal market, attracting attention from large countries needing coal. This relevance to global coal demand is valuable information for investors and financial managers, especially those looking into the performance of Initial Public Offering (IPO) companies in the mining sector or those dealing with coal commodities. Economic observers and investors use statistical analysis tools for forecasting stock prices, employing techniques that integrate to identify volatility clustering and market capitalization behavior. The figure supports the understanding that positive sentiment in the coal market can lead to significant fluctuations in stock prices, characterized by sharp increases followed by drastic declines, a phenomenon known as heteroskedasticity in time series data.

Several domestic coal issuers have good business prospects, as seen from several indicators and sentiments. Indonesia plays a significant role in being the target of several large countries that need coal. According to Junaid *et al*. (2020), this can be used as a consideration for investors and financial management to expose the performance of Initial Public Offering (IPO) companies in the mining sector or coal commodities. Economic observers and investors speculate using statistical analysis tools in forecasting stock prices. The forecasting method is carried out by integrating several techniques to identify volatility clustering and market capitalization behavior. The integration efforts are carried out following stock behavior. Positive sentiment can stimulate a significant increase in stock prices followed by a drastic decline in several cycles or heteroskedasticity in the time series data (Junaid *et al*., 2020; Susanti *et al*., 2018).

Several strategies can be used to forecast stock and commodity prices in the financial sector if there is random data with high volatility. One of them is the Autoregressive Integrated Moving Average (ARIMA) method. This method is used to predict random or random data conditions. Then, the following method is Autoregressive Conditional Heteroskedasticity (ARCH), which identifies and overcomes heteroskedasticity conditions in data behavior error variance. Studies related to stock price forecasting with ARIMA and GARCH, among others, were conducted by Junaid *et al*. (2020) and Kasim (2022). Another study by Azmi & Syaifudin (2020) concluded that the prediction model provided the highest and best accuracy for determining the price of gold, copper, and oil commodities.

The accuracy of using the best models to predict stock and commodity prices is fascinating. This is because the behavior of financial time series data is dynamic, so there are several different perceptions between observers. Forecasting using the ARIMA and ARCH methods can answer parameters to consider a policy by accurate and relevant information regarding projections of coal export issuers and coal commodity prices. Moreover, the approach is based on the principle of the *efficient market hypothesis*, where the selected companies must avoid the assumption of market anomalies (Bodie *et al*., 2004; Jones, 2014). This study will discuss how the projected share prices of issuers opened for coal exports are compared to the projected coal reference price. Some of the issuers that will be projected are ADRO, INDY, ITMG, PTBA, and HRUM, which have a large portion of coal exports from 2018 to 2022 with daily stock closing data.

LITERATURE REVIEW

The theoretical foundation is presented in complete, concise sentences and is relevant to writing scientific articles. The introduction's theoretical framework can be divided into smaller chapters to distinguish different sections.

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Forecasting and Volatility

Forecasting is the process of making predictions (Alfarisi, 2017). In economics, one of the practical tools is forecasting using historical data from a variable and projecting its value in the future (Purba, 2015; Rusydiana, 2019; Rusyida & Pratama, 2020). Forecasting is essential for managers when making investment decisions. In investing, information related to stock prices is needed for decision-making because of its volatile and stochastic nature. Forecasting is performed to determine the proper stock price modeling, so that the forecast is close to the actual stock price. The best results from the model projections can be used to determine the price movement direction according to the stakeholders' point of view (Fitria *et al*., 2017; Lubis *et al*., 2021).

Volatility is a statistical method used to measure fluctuations in stock prices over a certain period (Satriawan *et al*., 2017). According to Harsi *et al*. (2017), volatility can also be interpreted as a measure of the rapid rise and fall of stock prices over a certain period. This measure can explain the increase and decrease in stock prices in the short term and see variations from one period to the next. Volatility is considered by investors while making investing decisions. Despite the potential for significant profits, many investors remain apprehensive about entering the stock market due to its inherent volatility (Edeh *et al*., 2021). This is due to the volatility of measuring a company's risks and profits (returns) (Rosyida *et al*., 2020). According to Wang (2001), volatility is generally deterministic or more definitive in measurement parameters, and data input and output are time-invariant.

Investment

Investment is a commitment to place a certain amount of funds or other resources during a specific period to obtain profits or returns in the future through risk considerations. Investments can be made in tangible assets such as gold, real estate, buildings, machinery, etc. In addition, investments can be made in financial assets, including deposits, equities, mutual funds, and bonds (Muharam, 2018). Understanding the basics of investment is essential for managers when making investment decisions. Understanding the relationship between profit or return and the risk of an investment is essential. Investors will always face high profits or returns from investment activities, but investors are also faced with significant risks due to high returns. The greater the profit or return generated from the investment, the greater the possibility of risk faced by the investor (Bodie *et al*., 2001; Brigham & Ehrhardt, 2019).

Stock Price

Stock prices exist in the stock exchange market at a given time, are established by market participants, and are influenced by the demand and supply of the shares involved in the capital market (Puspitaningtyas, 2017). Profitable companies provide dividends to shareholders. Moreover, if the selling price of shares is higher than the buying price, shareholders will benefit, namely capital gains (Bodie *et al*., 2001; Brigham & Ehrhardt, 2019; Susanti *et al*., 2018). The higher the company's profit, the more likely dividends will be distributed to shareholders (Linda & Yosevin, 2019).

The stock price is formed by sellers and buyers of shares, who are motivated by their expectations for the company's profit (Najib & Triyonowati, 2017). Stock prices can fluctuate as the demand and supply for stock changes and various off-market factors. Investors need information about stock price formation when deciding to sell or buy shares. The financial statement can present information relevant to investors' decision models to buy, hold, or sell shares (Novitasari, 2015). In

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the financial statements, stock prices consist of three categories, namely the highest price, the lowest price, and the closing price. The most significant or lowest price occurs on a particular trading day. The closing price is the price at the end of the exchange hour that occurs last.

The hypothesis of this study refers to the univariate approach, which is in line with research conducted by Lu *et al*. (2023) and Muhammad *et al*. (2024) that inference can be made by comparing industry sectors and commodity prices. Therefore, the hypothesis in this study will test whether coal commodity prices in Indonesia will have the same forecasting direction as the coal industry sector in Indonesia. Determining the forecasting direction will provide a comprehensive explanation of how the behavior of investors or buyers in response to rising commodity prices will affect capital expansion in the industrial sector.

METHOD

The data used in this study is in the form of closing prices of shares of coal companies that have a portion of coal exports abroad and coal reference prices during 2018-2022. Data was obtained through the Yahoo Finance (www.finance.yahoo.com) website and the Ministry of Energy and Mineral Resources (www.minerba.esdm.go.id). The reference coal price at issue is the coal price utilized as an index by the Indonesian Coal Index/Argus Coal Indo, New Castle Export Index, Platts, and Global Coal New Castle Index. The stock prices of issuers taken as samples in the study included PT. Bukit Asam Tbk. (PTBA), PT. Adaro Energy Tbk. (ADRO), PT. Harum Energy Tbk. (HRUM), PT. Indika Energy Tbk. (INDY), and PT. Indo Tambangraya Megah Tbk. (ITMG)

Autoregressive Moving Average (ARIMA)

ARIMA is one of the research methods used to forecast. This method can identify random data that does not have stationariness resistance so that an integration process is carried out between autoregressive (AR) and moving average (MA) using difference so that non-stationary data can be transformed into stationary data. The analysis process is carried out using the Box-Jenkins methodology (Alam *et al*., 2023; Desvina, 2016; Gujarati, 2015; Rusyida & Pratama, 2020; Wooldridge, 2016). The first process required is to identify the behavior of the data by looking at the correlogram and partial correlogram to identify the maximum order of ARIMA. Second, estimating the parameters utilized during the iterative process requires selecting the model with the highest significance value. Third, the best model projection is based on literacy findings and calculations to derive the projection results from the processed data (Gujarati, 2015). Based on the approach of (Ziegel & Enders, 1995), the ARMA method in the absence of an integration process is written as follows:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, y_{t-i} + X_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

The equation represents the data at time period *t*; y_t as a function of the autoregressive parameters α_i up to lag *p*, where y_{t-i} denotes the autoregressive error values at time t; and X_t represents the error term. The integration process can be implemented for the ARMA model with a difference in the model so that it is modified into ARIMA with the following formula:

$$\mathrm{y_t} = \alpha_0 + \sum_{i=l}^{p} \alpha_i y_{t-i} + \sum_{i=l}^{p} \beta_i \varepsilon_{t-k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

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The data at time period *t*; y_t is influenced by the autoregressive parameters α_i up to lag *p*, where y_{t-i} represents the autoregressive error values at time *t*; and ε_{t-k} denotes the moving average error values at time *t-k*.

Autoregressive Conditional Heteroscedasticity (ARCH)

The Autoregressive Conditional Heteroscedasticity (ARCH) model is an autoregressive model with non-constant variance (Bilondatu *et al*., 2019). The ARCH model is also one of the techniques used to forecast, and it is known as the time series forecasting model. According to Engle (2001), the ARCH model is a technique used to measure volatility. Volatility is a statistical method used to measure stock price fluctuations over time (Satriawan *et al*., 2017). If price fluctuations continue to occur over some time, it causes high price volatility so that variants are not constant and heteroskedasticity. Therefore, the ARCH model can test whether, in a regression model, there is a difference in variance from the residual of one observation to another. The equation of the ARCH model can be written as follows (Wang, 2001):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 \quad \text{..... (3)}$$

The data variance at time period *t*; σ_t^2 is modeled as a function of the coefficient α_0; the ARCH parameter α_1; and the squared error term from the previous period, ε_{t-1}^2. The criteria used in this test compare the level of signification obtained from the alpha level used. The data is said to be normally distributed if the signification value is more than alpha. This study used a signification rate of 0.05 (α = 5 percent), where the assessment criteria for this test were: (1) If the significance of the *F* and Chi-Square values calculated Chi-Square is > 0.05, then the distributed data is standard; (2) If the significance of the *F* and Chi-Square values calculated Chi-Square is < 0.05, then the data is not normally distributed (Gujarati, 2009; Kenett & Newbold, 2013; Wooldridge, 2016).

RESULTS

Prose's identification is carried out using the ARIMA model. Then, a residual value scale of the ARIMA order will be analyzed to see the heteroskedasticity in the obtained model; if heteroskedasticity is identified in the obtained model, then continue modeling using ARCH. Before carrying out the ARIMA modeling process, it is necessary to look at the time series of each variable to identify the stationarity data.

Descriptive Statistics

Table 1 presents the descriptive statistics of the coal reference price and the stock index price of coal companies, encompassing 139 observations for each variable. The coal reference price, measured in USD per ton, has a mean of 93.14 with a standard deviation of 46.40, indicating a wide variation in prices ranging from a minimum of 49.42 to a maximum of 323.9. The stock prices of coal companies show a broad range of average values. ITMG has the highest average stock price index at 22,984 per share, indicating its high market valuation compared to other companies in the study. In contrast, HRUM has the lowest average stock price index at 748.9 per share, reflecting its lower market valuation. The data highlights the variance in company sizes and valuations within the coal industry, which could influence forecasting models for coal reference and company-specific stock prices.

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Table 1. Descriptive Statistics of Coal Reference Price and Stock Index Price of Coal Companies

Variables	(1) N	(2) Mean	(3) sd	(4) min	(5) max
Coal Reference Price (USDTon)	139	93.14	46.40	49.42	323.9
ADRO	139	1.458	572.4	515	3.340
HRUM	139	748.9	597.6	124	2.455
INDY	139	1.521	1,084	110	4.470
ITMG	139	22.984	11,703	4.810	50.500
PTBA	139	2,717	886.0	890	4.530

Source: Data analysis, 2023.

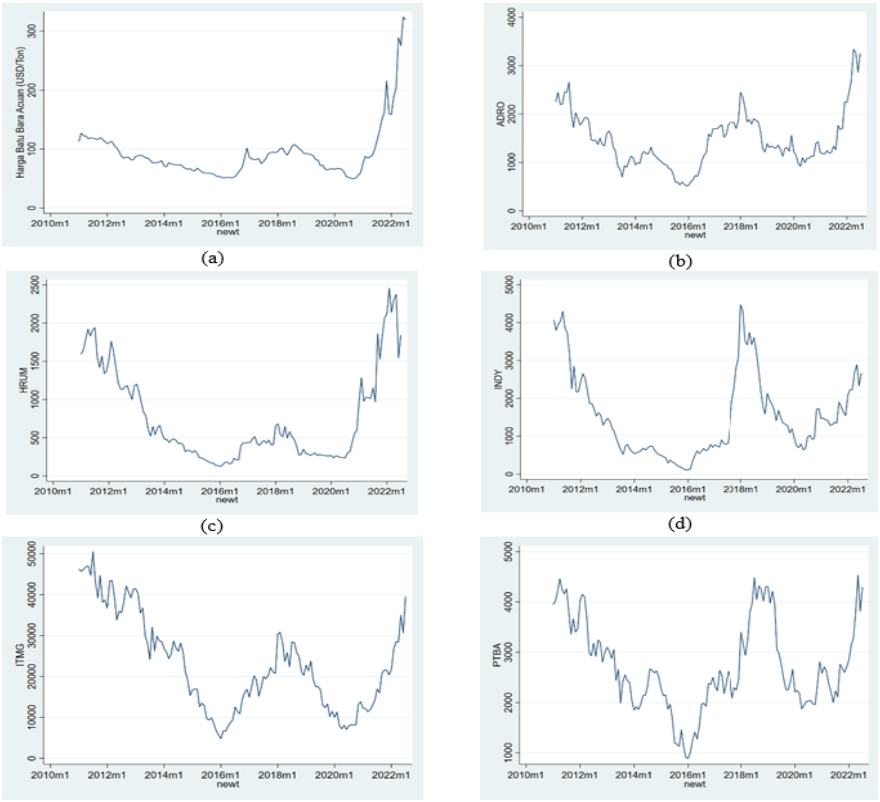


Figure 2. Coal Reference Price (a) and Coal Company Stock Index Price (b)
Source: Data analysis, 2023.

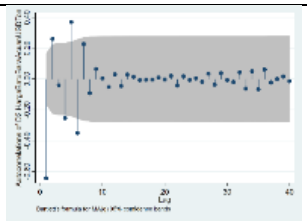
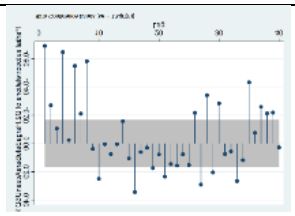
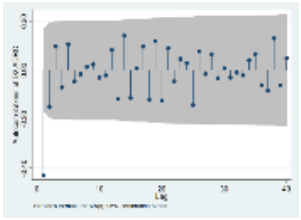
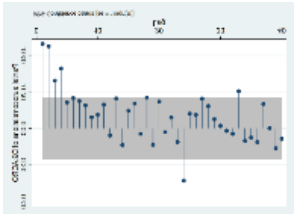
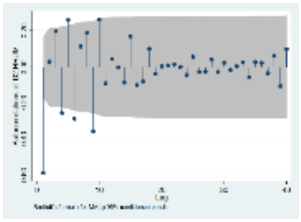
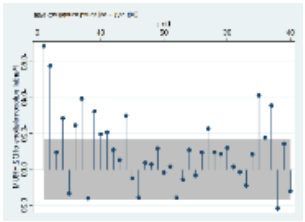
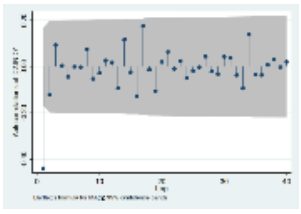
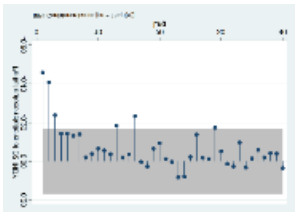
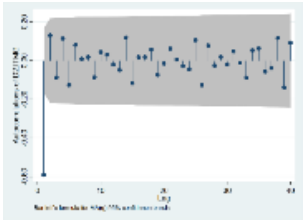
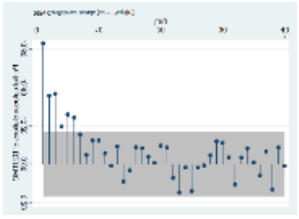
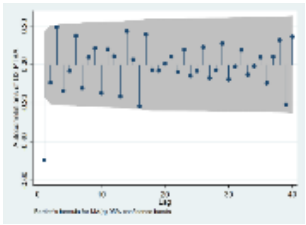
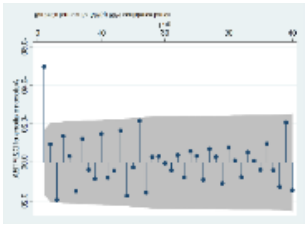
The average stock price index disparity among the companies (ADRO, HRUM, INDY, ITMG, and PTBA) underscores the heterogeneity within the coal sector, suggesting that while some companies may be thriving and expanding, others might face challenges. This variance is crucial for investors and analysts as it highlights the importance of conducting a detailed assessment of individual companies within the sector rather than making generalized investment decisions based on sector-wide trends alone. The data in Table 1 serves as a foundational element for further analysis of these coal companies' financial health and market positioning.

Stationarity Test

The visualization in Figure 2 shows the reference price of coal experienced price fluctuations from January 2016 to January 2020, experiencing a price decrease. However, in March 2020, there was an increase in the benchmark coal price and the price of the coal company's stock index.

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Table 2. Determination of Fit Model and Order ARIMA

Variable	Fit Model	ACF	PACF
Coal Reference Price	ARIMA (1,2,1) ARCH (1)		
ADRO	ARIMA (0,2,1)		
HRUM	ARIMA (1,2,1)		
INDY	ARIMA (0,2,1)		
ITMG	ARIMA (1,2,1)		
PTBA	ARIMA (1,2,1)		

Source: Data analysis, 2023.

Figure 2 illustrates the relationship between the coal reference price (a) and the stock index prices of several coal exporting companies (b), highlighting a direct proportional fluctuation and increase between these two variables. This relationship suggests that movements in the benchmark coal price can significantly influence the stock index prices of coal mining companies, indicating a strong correlation between commodity prices and stock market performance within this sector. The

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figure further demonstrates that the coal reference price can be a critical consideration for investors and financial managers, as it drives positive sentiment towards the value of coal export companies.

The time-series pattern depicted in Figure 2, showing periodic fluctuations in both the coal reference price and the share prices of the five issuers (ADRO, HRUM, INDY, ITMG, and PTBA), suggests that these variables are not stationary at levels. This necessitates using ARIMA and ARCH models for accurate forecasting after appropriate differencing. This visual representation underscores the interconnectedness of commodity prices and stock market valuations, offering valuable insights for investment strategies in the coal sector.

Table 2 outlines the determination of the fit model and order for the ARIMA model for the coal reference price and the stock prices of several coal companies, including ADRO, HRUM, INDY, ITMG, and PTBA. For the coal reference price, the ARIMA (1,2,1) model combined with ARCH (1) was selected as the best fit, indicating that this model adequately captures the time series characteristics of the coal reference price, including its trend and volatility. The use of ARCH (1) suggests volatility clustering in the coal reference price data, where significant changes tend to be followed by large changes, and small changes tend to be followed by small changes of either sign.

For the stock prices of the coal companies, different ARIMA models were identified as the best fit for each company, reflecting the unique time series properties of each company's stock price data. ADRO and INDY were best modeled by ARIMA (0,2,1), suggesting that their stock prices are best described by a model that emphasizes the moving average component without the need for autoregressive terms. In contrast, HRUM, ITMG, and PTBA were best modeled by ARIMA (1,2,1), indicating that autoregressive and moving average components are essential for capturing the dynamics of their stock prices.

These findings imply that while there are commonalities in the time series behavior of these companies' stock prices, as indicated by the necessity of differencing to achieve stationarity (the '2' in the ARIMA models), there are also significant differences that necessitate the use of different ARIMA models to capture best the individual characteristics of each company's stock price time series. This tailored approach to model selection underscores the complexity of financial time series analysis and the importance of considering each time series on its own merits when developing forecasting models.

ARIMA Estimation

After determining the ARIMA order, it is required to identify the orders with the lowest Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. The selection of the fit model for each variable was based on these values, aiming to minimize information loss while accounting for the complexity of the model. The ARIMA models chosen for the coal reference price and the companies' stock prices reflect a careful balance between model simplicity and the ability to capture the essential dynamics of the time series data. This approach aligns with the methodology recommended for identifying the most appropriate ARIMA model for time series forecasting, emphasizing the importance of AIC and BIC in guiding the selection process. The selection of the best model can be identified based on several parameters that have been significant, namely the reference price of coal with ARIMA (1,2,1), ADRO with ARIMA (0,2,1), HRUM ARIMA (1,2,1), INDY ARIMA (0,2,1), ITMG ARIMA (1,2,1), and PTBA ARIMA (1,2,1).

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Table 3. AIC and BIC Tests to Determine the Best Model

Akaike's Information Criterion and Bayesian Information Criterion	AIC	BIC
Coal Reference Price	1060.956	1063.876
ADRO	1821.812	1827.652
HRUM	1774.538	1783.298
INDY	1944.879	1953.639
ITMG	2580.693	2589.453
PTBA	1960.313	1971.993

Source: Data analysis, 2023.

Table 4. ARIMA Model Estimation Results of Coal Company Stock Index Price

ARIMA FIT MODEL	ARIMA (0,2,1) ADRO	ARIMA (1,2,1) HRUM	ARIMA (0,2,1) INDY	ARIMA (1,2,1) ITMG	ARIMA (1,2,1) PTBA
L,ar		-0.262***		-0.239***	-0.0516
		(0.0742)		(0.0801)	(0.0840)
L,ma	-1.000***	-1.000***	-1.000	-1.000***	-1.000
	(0.0891)	(0.0476)	(356.4)	(0.116)	(470.5)
Constant	0.820**	0.605***	1.175*	12.19**	0.889
	(0.354)	(0.187)	(0.650)	(5.483)	(0.571)
Observations	137	137	137	137	137

Note. Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1
Source: Data analysis, 2023.

Table 3 provides the Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) values for the coal reference price and the stock prices of various coal companies. These values are instrumental in determining the best model for forecasting purposes. Each number in Table 3 is a key indicator of the model's performance for the respective stock price data. Beginning with the Coal Reference Price, the AIC value stands at 1060.956, accompanied by a BIC value of 1063.876. These figures provide insight into the model's fit for the coal reference price data, with lower values generally indicating a better fit and less information loss. Moving on to ADRO, the AIC value is 1821.812, with a corresponding BIC value of 1827.652, which assesses the model's capability to capture the dynamics of ADRO's stock price.

Similarly, HRUM's AIC value of 1774.538 and BIC value of 1783.298 aid in evaluating the adequacy of the model for HRUM's stock price data. For INDY, the AIC value is 1944.879, complemented by a BIC value of 1953.639, facilitating an evaluation of the model's suitability for forecasting INDY's stock price. Conversely, ITMG exhibits the highest AIC value among the listed companies, at 2580.693, along with a BIC value of 2589.453, indicating the model's fit for ITMG's stock price data. Finally, PTBA's AIC value of 1960.313 and BIC value of 1971.993 provide insights into the model's performance concerning PTBA's stock price data.

The AIC and BIC values are critical for model selection, aim to minimize information loss while accounting for the complexity of the model. The best model for each variable, including the coal reference price and the companies' stock prices, was based on these values. The estimates of the ARIMA model based on the unit root test and the determination of the best order are presented in Table 4. Based on the fit model through the approaches, it can be interpreted that the best model for ADRO and INDY companies is in order (0,2,1), then the model with the best order (1,2,1) is obtained in HRUM, ITMG, and PTBA companies. The selected ARIMA model uses two non-seasonal

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differences in conjunction with the MA term. The second difference of a Y series is not the difference between Y and itself delayed by two periods, but the first difference of the changes in Y in period t.

ARCH Estimation

Based on the ARCH-LM test in Table 5, the reference price of coal rejects H0 with a probability level of 0.016 < p value. It can be interpreted that the reference price of coal indicates heteroskedasticity or error of non-constant variance to the element ARCH. The ARCH model can precisely test variables with non-constant variance values.

The results of the ARCH model estimate on the coal reference price variable are presented in Table 6. The table presents the estimation results of the ARCH model for the coal reference price, expressed in USD per ton. The ARCH fit model includes an ARCH (1) term for the coal reference price. The specific numerical data or coefficients related to the ARCH model, such as the coefficients for lagged variables or the constant term, are not detailed in the provided information. The table is part of an analysis aiming to understand the volatility and predictability of coal prices using the ARCH model, which is particularly suited for financial time series data that exhibit time-varying volatility or heteroskedasticity.

Forecasting

Forecasting is the final stage in testing the model. The following are the results of forecasting the benchmark coal price and the company's stock index price. The forecasting results of Coal Reference Price (CRP), Stock of ADRO, HRUM, ITMG, and PTBA are presented in Figure 3. The figure illustrates the forecasting projection results based on the best model of Coal Reference Price (a) and Coal Company Stock Price Index (b, c, d, e, f). This figure is part of a study that aims to forecast the stock price of coal and coal commodity companies using the ARIMA and ARCH/GARCH models for 2011 - 2022. As we know, forecasting using these models provides a positive direction in the coal industry in Indonesia.

The next stage in forecasting is to look at the direction of projection by the ARIMA – ARCH model that has been estimated in the previous equation. The forecasting results show that the price trend of the coal company stock index is directly proportional to the coal reference price. The mood of economic recovery affected the simultaneous increase in index and benchmark prices following the COVID-19 pandemic and the Russia – Ukraine war, where the average electrical energy consumption in big countries relies on coal as the principal energy source.

The indicator means absolute percentage error (MAPE) was used to determine the percentage deviation of the predicted results. In ARCH forecasting in Table 7, the reference price of coal MAPE value of 6 < 10 percent shows that the model made is very accurate. The MAPE value of the ADRO and PTBA stock price indices of 9 < 10 percent can be interpreted to mean that the ARIMA model built is accurate, as for HRUM, INDY, and ITMG shares in the range of 10 – 20 percent, it can be interpreted that the ARIMA model is quite good in predicting the value of the company's shares.

Table 5. ARCH LM Test to Identify the ARCH Effect

LM test for Autoregressive Conditional Heteroskedasticity (ARCH) chi2	df	Prob > Chi2
5.796	1	0.016

H0: No ARCH effects vs. H1: ARCH(p) disturbance.
Source: Data analysis, 2023.

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Table 6. Coal Reference Price ARCH Model Estimation Results

ARCH FIT MODEL	ARCH (1) Coal Reference Price (USDTon)
L.ar	-0.610***
	(0.0581)
L.ma	-0.278***
	(0.0637)
L.arch	1.348***
	(0.261)
Constant	20.36***
	(4.073)
Observations	137

Note. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Data analysis, 2023.

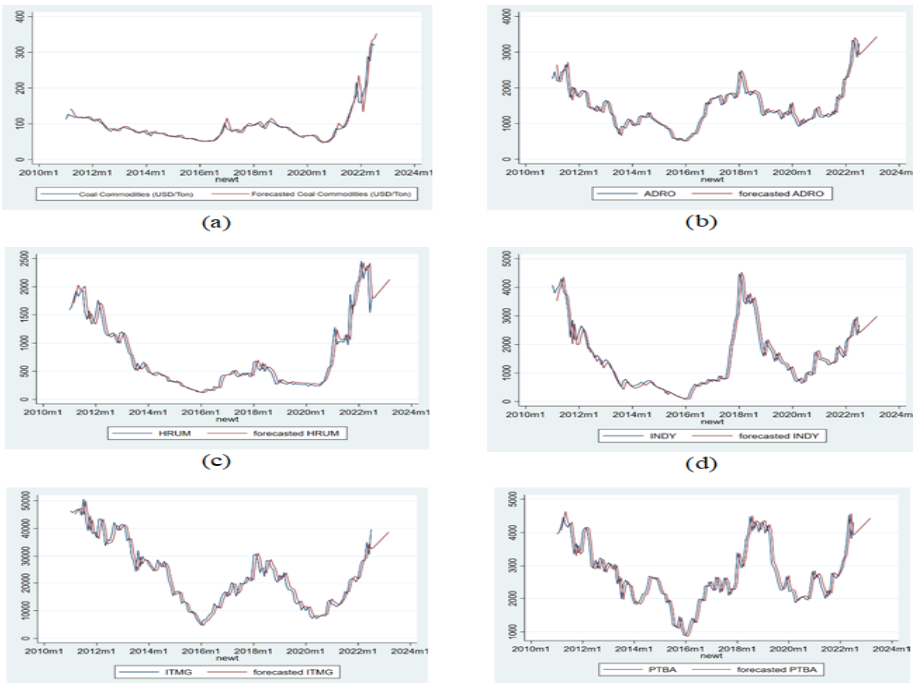


Figure 3. Forecasting Projection Results Based on the Best Model of Coal Reference Price (a) and Coal Company Stock Price Index (b, c, d, e, f)
Source: Data analysis, 2023.

Table 7. MAPE Value Coal Reference Price and Stock Index Price Coal Company

Variable	MAPE Value
Coal Reference Price	0.0613
ADRO	0.0900
HRUM	0.1225
INDY	0.1341
ITMG	0.1102
PTBA	0.0912

Source: Data analysis, 2023.

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Discussion

This study confirms the findings of Lu *et al*. (2023) and Muhammad *et al*. (2024) on the importance of monitoring and communication between monetary authorities and market participants. It can comprehensively load investment decision-makers if the forecast shows an upward trend in coal prices; it might be a signal to buy shares of coal companies and vice versa. Companies in the coal industry can use this forecasting to plan their business strategies. For example, if coal prices are expected to fall, companies can take measures such as hedging or diversification to reduce the negative impact on corporate profits to plan their long-term strategies, such as investment in new technology, production expansion, or even diversification into other sectors (Alam *et al*., 2023; Babu & Reddy, 2015; Xiang, 2022).

Geopolitical conditions and post-pandemic economic conditions COVID-19 influence the condition of coal companies. The Russian and Ukrainian wars played a significant role in the increase in world coal prices (Stala-Szlugaj & Grudziński, 2022). According to Wicaksana *et al*. (2022), this is the embargo's impact on Russian gas and coal to Europe as a source of power generation, so it must switch to coal. This situation forced European countries to import coal more precisely to Indonesia. Indonesian coal companies are the main targets of coal exports, so it is necessary to observe the government's policy in fulfilling domestic market obligations (DMO).

In the findings section, our analysis reveals a significant relationship between the coal reference price and the stock prices of coal companies, echoing the insights from previous studies exploring the dynamics between commodity prices and stock market performance. The ARIMA and ARCH/GARCH models employed in this study have demonstrated their efficacy in forecasting stock prices within the volatile coal sector, aligning with the methodologies advocated by Zainal *et al*. (2023) and the foundational principles of time series analysis as outlined by Ziegel & Enders (1995). This research contributes to the existing body of knowledge by applying these models specifically to the context of Indonesian coal companies, thereby offering a nuanced understanding of the sector's behavior in response to local and global economic shifts.

From a policy perspective, the findings highlight the need for regulatory frameworks to accommodate the dynamic nature of coal markets, especially considering geopolitical tensions and global economic shifts. Policymakers could use these insights to devise strategies that stabilize the market, protect domestic interests, and ensure a sustainable energy supply chain (Alam *et al*., 2023; Gumikar *et al*., 2020; Setiawan *et al*., 2020). This research suggests that the coal industry more closely examines market trends and external factors affecting coal prices, such as international sanctions and trade policies. By understanding these dynamics, companies can better position themselves in the global market, optimizing production and export strategies to mitigate risks associated with price fluctuations (Brigham & Ehrhardt, 2019).

The implications of this research are multifaceted, offering valuable insights for investors, policymakers, and the coal industry. Firstly, the study underscores the importance of employing sophisticated forecasting models like ARIMA and ARCH/GARCH to navigate the volatile landscape of coal prices and stock valuations (Fufa & Zeleke, 2018). For investors, these models provide a quantitative basis for making informed decisions, potentially enhancing portfolio returns in the energy sector in short term (Fauziah & Pratomo, 2014).

The overall value of this research lies in its contribution to the existing literature on financial econometrics and its application to the coal sector. It bridges the gap between theoretical models and practical applications, offering a comprehensive analysis that various stakeholders can leverage to

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make data-driven decisions in a complex and ever-changing market environment (Deaton, 2015; Wooldridge, 2016; Ziegel & Enders, 1995). In conclusion, this research not only corroborates the findings of previous studies regarding the interplay between commodity prices and stock market performance but also extends the application of sophisticated forecasting models to the Indonesian coal market. The insights derived from this study are expected to aid investors, financial analysts, and policymakers in making more informed decisions in the face of market volatility and economic uncertainties.

CONCLUSION

Based on the results of these predictions and the phenomenon that catalyzes the increase in the reference price of coal and the stock index of coal companies, it can be proven using the ARIMA and ARCH methods. The best model produced is ARIMA (1,2,1) – ARCH (1) for the coal reference price. Meanwhile, the coal company's stock price index model includes ADRO ARIMA (0,2,1); HRUM ARIMA (1,2,1); INDY ARIMA (0,2,1); ITMG ARIMA (1,2,1) and PTBA ARIMA (1,2,1). Model ARCH can more accurately predict the volatility of the benchmark coal price. The ARIMA model has the best level of accuracy in terms of the stock index price of ADRO and PTBA companies. Hence, INDY and ITMG are good enough to forecast.

This study advances our understanding of the relationship between coal prices and stock market performance and provides a methodological framework for future research. The suggestions for investors, implications for policymakers, and insights for the coal industry collectively underscore the significance of this research in informing strategic decisions and fostering a more resilient and sustainable energy sector.

Univariate analysis does not consider how variability in one variable might be related to another. In contrast, multivariate analysis can explore how variability between variables is related, which can be very important in many research contexts. When only one variable is analyzed, it is difficult to control or separate the effects of other variables that might influence the results. Multivariate analysis allows for more effective control of other variables, providing more valid and reliable results.

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