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Volatility Modeling of LQ45 Energy Stocks Using GARCH: Evidence from 2022–2025

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ABSTRACT

Purpose – This study aims to model the volatility of energy sector stocks listed in the LQ45 Index of the Indonesia Stock Exchange from January 2022 to March 2025. As the energy sector plays a vital role in the national economy and is sensitive to global commodity prices and the energy transition, understanding volatility patterns is essential for effective risk management. **Methodology/approach –** A quantitative approach was employed by transforming daily closing prices into stock returns as the main variable. Data from seven energy stocks were analyzed using descriptive statistics, stationarity tests, ARCH effect testing, and volatility estimation via the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The model's performance was validated through volatility prediction for April 2025. **Findings –** The results demonstrate that each stock exhibits distinct volatility characteristics. ARMA(1,1)-GARCH(1,1) was the best-fit model for ADMR, while AR(1)-GARCH(1,1) suited ADRO, and MA(2)-GARCH(1,1) was optimal for AKRA. ITMG and PTBA also yielded accurate and robust estimations. However, no heteroskedasticity effects were detected for MEDC and PGAS, making GARCH modeling inapplicable. Long-term volatility estimations generally indicated that risk remained manageable despite price fluctuations.

INTRODUCTION

Energy sector stocks are crucial to Indonesia's economy, as energy is a fundamental resource supporting industrial activities and daily life (Frensidy, 2024). This sector includes companies involved in energy processing, such as oil, gas, and renewable energy (Frensidy, 2024). According to data from the Indonesia Stock Exchange (IDX), the energy sector holds a significant portion of the market capitalization in Indonesia, with several large energy companies listed in the LQ45 index (IDX, 2024). In 2024, energy sector stocks accounted for approximately 9.40% of the total listed stocks in the Indonesian market, with a market capitalization of IDR 1.772 trillion, contributing 14.37% to the total market capitalization. The sector also exhibited high trading activity, with a transaction value of IDR 488 trillion, contributing 16.03% to the total transaction value. The sector's trading volume reached 732 billion shares, making up 16.90% of the total market trading volume. These figures demonstrate that the energy sector is not only active but also an important and liquid part of Indonesia's stock market.

Stock volatility, which reflects the risk of investments, is defined as the fluctuations in stock prices over time (Firmansyah, 2016). Understanding stock volatility is crucial for investors as it helps minimize investment risk and optimize decision-making (Anggriani, Pratiwi, & Erfiansyah, 2023). From a financial management perspective, volatility analysis also plays a role in designing more efficient investment portfolios by balancing risk and return potential. By analyzing volatility, investors can identify price movement patterns, assess company stability, and develop appropriate investment strategies (Nurhakim, 2017). The volatility of energy sector stocks is of particular concern due to their high sensitivity to commodity price changes, geopolitical policies, and the global energy transition dynamics. Studies have shown that oil price shocks significantly impact the volatility of energy stocks, often more than in other sectors (Kang & Ratti, 2015). Furthermore, the volatility of energy stocks has been found to be asymmetric and persistent, necessitating models capable of capturing these characteristics, such as GARCH models (Bouri et al., 2018). The external factors influencing energy stock volatility, such as exchange rate fluctuations and global market dynamics, have been highlighted in studies focusing on emerging economies (Tiwari et al., 2019). These findings underscore the importance of accurate volatility modeling for investment decision-making.

Recent years have witnessed significant fluctuations in energy sector stocks due to global factors, particularly oil prices and international energy policies (Bouri et al., 2021). In 2019, global energy sector indices decreased by 6.4% due to oil prices hitting their lowest point in two decades (Statista, 2020). However, in 2020, the sector showed a significant recovery with a 4.5% increase despite the global stock market being under pressure from the COVID-19 pandemic (Bloomberg, 2021). The sector experienced a 55.3% price increase in 2021, driven by the improving economic conditions (Reuters, 2022). In contrast, 2022 saw a 3.1% decline, but investor interest shifted toward renewable energy stocks, which saw a 23% market growth that year (IEA, 2023). Given these dynamics, understanding the volatility of energy stocks in Indonesia, particularly those in the LQ45 index, is essential for gaining deeper insights into the risks and investment opportunities in this sector. This research aims to analyze the volatility of energy stocks listed in the LQ45 index, which is considered representative of the Indonesian stock market. The LQ45 index includes only highly liquid stocks with large market capitalizations, ensuring stability and reliability in reflecting the overall performance of the market (IDX, 2024). The stocks included in the index meet strict criteria for performance and company fundamentals, making it an ideal representative of high-quality companies in the market. Furthermore, the LQ45 index is dynamic, with its composition evaluated and updated semi-annually to remain relevant to market changes (IDX, 2024).

A few studies have focused on modeling volatility in energy stocks, particularly using the GARCH model. Despite the success of the GARCH model in predicting financial data volatility, certain limitations remain. These include assumptions of normal distribution for residuals, which do not always hold true in financial data, as well as the inability of traditional GARCH models to capture asymmetry effects such as the leverage effect (Nelson, 1991). Thus, the need to reassess the effectiveness of the GARCH model in modeling volatility in dynamic and complex data, such as the energy sector, has become evident. This research seeks to address these gaps by examining the relevance and effectiveness of the GARCH model in modeling the volatility of energy stocks in the LQ45 index from 2022 to March 2025. The objective of this research is to provide a comprehensive understanding of how the GARCH model can be applied to energy sector stock volatility, taking into account both global and domestic factors that influence the market.

LITERATURE REVIEW

Capital Market

The capital market is a financial mechanism that connects those in need of funds (issuers) with investors possessing surplus capital through the trading of securities such as stocks, bonds, and other financial instruments. According to Law No. 8 of 1995, it encompasses activities related to public offerings, securities trading, public companies, and related institutions and professions. Tandelilin (2017) defines the capital market as a venue for issuers and investors to engage in securities transactions, while Fahmi (2015) emphasizes its role as a long-term financing tool for investors and institutions. Husnan (2015) highlights the capital market's function in facilitating the trade of financial instruments in an organized environment, with Jogiyanto (2010) noting that it mobilizes funds for economic activities through the trade of long-term financial instruments such as equities and bonds. The capital market plays a crucial role in a country's economy by providing funding for companies, investment opportunities for the public, improving resource allocation efficiency, and serving as an economic health indicator. It also offers liquidity, enabling investors to buy and sell financial instruments at any time, thus supporting economic growth (Fahmi, 2015).

Investment

Investment refers to the allocation of current resources with the goal of generating future returns. It can take the form of real assets (e.g., land, gold, buildings) or financial assets (e.g., stocks, bonds, deposits). Tandelilin (2001) defines investment as a commitment of funds today with expectations of future benefits, while Jogiyanto (2010) views it as deferring current consumption for productive use. Investment plays a crucial role in economic development by increasing aggregate demand, production capacity, and technological advancement (Nizar et al., 2013). Financial investments can be made directly through tradable instruments or indirectly via mutual funds (Achsien, 2003), and they may be classified by time horizon into short-, medium-, or long-term, each with varying risk-return profiles (Tandelilin, 2001).

Investment Risk

Investment risk refers to the uncertainty or potential for undesirable outcomes resulting from an investment. It is generally categorized into two types: systematic and unsystematic risks. Systematic risk, which cannot be avoided through diversification, affects the entire market or economic sector and includes factors like inflation, interest rate changes, economic crises, or global recessions, significantly impacting most assets (Sharpe, 1964). On the other hand, unsystematic risk is specific to individual companies or industries and can be minimized through diversification, such as risks arising from poor company performance or managerial issues (Fama & French, 1993). Additionally, the risk-return tradeoff describes the relationship between risk and potential return in investments: higher risk typically yields higher returns, and vice versa. This concept is central to investment decision-making, helping investors align their risk tolerance with their investment goals (Bodie, Kane, & Marcus, 2021).

Stocks

Stocks are securities that represent ownership in a company and are issued to raise capital (Bodie, Kane, & Marcus, 2021). The two main types are common stock, which provides voting rights and potential dividends, and preferred stock, which offers fixed dividends and priority in bankruptcy but no voting rights (Ross, Westerfield, & Jaffe, 2016). Stocks are traded on exchanges such as the Indonesia Stock Exchange (BEI), with prices fluctuating based on factors like company performance, economic conditions, and market sentiment (Malkiel, 2016). While offering potential gains, stock investments carry the risk of capital loss due to price volatility (Ross et al., 2016).

Stock Return

Stock return refers to the level of profit earned by shareholders from changes in stock prices and dividends received over a specific period. It serves as a measure of investment performance and is used to compare the performance of one stock to others (Bodie et al., 2021). Stock returns are typically calculated as a percentage and can be classified into two types: nominal return and real return. Nominal return is calculated based on changes in stock prices without considering inflation. It reflects the extent of the change in the value of the investment over a given period (Bodie, Kane, & Marcus, 2021). Real return, on the other hand, accounts for the effects of inflation by subtracting the inflation rate from the nominal return, thereby indicating the actual gain or loss in purchasing power (Madura, 2018).

Stock Volatility Theory

Stock volatility refers to the degree of fluctuation in stock prices over a specific period, reflecting how much stock prices rise or fall over time. It is a key indicator used to measure the risk faced by investors in a particular stock or the stock market as a whole (Black, 1976). Volatility is a statistical measure of how much an asset's price changes over time. The greater the price fluctuation, the higher the volatility. It can be measured by calculating the standard deviation of price changes over a given period, known as historical volatility (Hull, 2017). There are two main types of volatility: historical volatility, which measures price fluctuations based on past data and gives insight into past market behavior (Andersen, 1997), and implied volatility, which reflects the projected future volatility embedded in option prices, helping investors estimate future market risk (Black, 1976). High volatility indicates significant price fluctuations, meaning investors face higher risk, while low volatility suggests a more stable market with less risk. Determining volatility is crucial for assessing investment risk and managing portfolios (Bodie et al., 2021). Low-risk investors may avoid high-volatility stocks, while risk-tolerant investors may see high volatility as an opportunity for greater returns. High volatility can create opportunities for traders to buy low and sell high in short time frames (Merton, 1980). Volatility is often considered a measure of risk, and stocks with high volatility are deemed riskier, so investors must consider volatility in their investment strategies to manage risk effectively (Fama & French, 1992).

ARIMA Model

ARIMA (AutoRegressive Integrated Moving Average) is a statistical model used for forecasting time series data, incorporating autoregressive (AR), moving average (MA), and integration (I) components. The model is expressed as ARIMA(p, d, q), where p is the order of the AR model, d represents the number of differencing steps to make the data stationary, and q is the order of the MA model. For ARIMA to be applied, the data must first be stationary, meaning its statistical properties like mean and variance remain constant over time. The Augmented Dickey-Fuller (ADF) test is often used to check for stationarity. If the data is non-stationary, differencing is applied to remove trends or autocorrelation, and the process is repeated until stationarity is achieved (Gujarati & Porter, 2009). Proper differencing is crucial for valid and unbiased time series modeling (Box et al., 2015).

ARCH and GARCH Models

The ARCH (Autoregressive Conditional Heteroskedasticity) model, introduced by Robert Engle in 1982, addresses heteroskedasticity, where the variance of errors (residuals) is not constant over time. This often occurs in economic and financial data, such as fluctuating volatility during certain periods (Engle, 1982; Bollerslev, 1986). The Breusch-Pagan test is commonly used to detect heteroskedasticity, indicating whether the variance of errors changes with predictors. If heteroskedasticity is present (p-value < 0.05), more complex models like ARCH or GARCH are needed, as ARIMA assumes constant error variance (homoskedasticity). ARCH models assume that the error variance depends on past information, allowing for more accurate volatility forecasting. However, ARCH can become computationally complex as the number of lags increases. To address this, Bollerslev developed the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model in 1986, which improves efficiency by incorporating both past errors and past volatility lags (Bollerslev, 1986). The GARCH model is widely used to model volatility in financial markets, including sectors like energy, which are impacted by commodity price fluctuations. Parameter estimation in both ARCH and GARCH models is typically done using Maximum Likelihood Estimation (MLE), which finds optimal parameters based on the assumed distribution, often normal. Unlike Ordinary Least Squares (OLS), MLE is better suited for heteroskedastic conditions (Engle, 1982; Bollerslev, 1986). The GARCH(p, q) model is expressed as
$y_t = \mu + \varepsilon_t, \varepsilon_t \sim N(0, h_t)$ and $h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$, where h_t represents the conditional variance at time t. GARCH models also measure volatility persistence, indicating how long

shocks affect volatility. Persistence is calculated $\alpha + \beta$, and if the sum is close to 1, volatility is persistent, showing long-term effects of shocks (Merton, 1980). Additionally, GARCH models calculate long-term volatility with unconditional variance, given by $V_L = \frac{\omega}{1-\alpha-\beta}$, which is crucial for investment risk assessment. Thus, GARCH modeling not only predicts short-term volatility but also uncovers long-term volatility patterns, essential for risk analysis and portfolio strategies.

METHOD

Research Design

This study utilizes a quantitative research approach, focusing on the modeling of stock volatility using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. The research aims to analyze the volatility patterns of energy sector stocks listed in the LQ45 index as of February 2025. The data analyzed in this study consists of daily stock prices of energy companies included in the LQ45 index from January 2022 to March 2025. This research is classified as descriptive-comparative, as it compares the volatility across several energy companies listed in the LQ45 index, identifying patterns and factors affecting stock price movements within the specified period.

Population and Sample

The population for this study comprises all energy sector stocks listed on the Indonesia Stock Exchange (IDX), categorized under the IDX Industrial Classification, amounting to a total of 90 stocks. For sample selection, the study uses purposive sampling, a non-probability sampling technique, where specific units are chosen based on predefined criteria. The selection criteria include: (1) the stock must belong to the energy sector according to the IDX classification, (2) the stock must be listed in the LQ45 index as of February 2025, and (3) the stock must have complete daily price data from January 2022 to March 2025. Based on these criteria, 7 energy sector stocks were selected to serve as the sample for this study.

Data Collection Techniques

The data collection method employed in this research is time series analysis. Secondary data on daily stock prices of energy sector companies listed in the LQ45 index is gathered for the period from January 2022 to March 2025. The stock price data is sourced from the Indonesia Stock Exchange (IDX) and Yahoo Finance. The study involves two distinct periods: the in-sample period from January 2022 to March 2025 for volatility modeling and the out-of-sample period from April 2025 for forecasting and testing the accuracy of the GARCH model.

RESULT AND DISCUSSION

Descriptive Statistics

After obtaining the closing stock prices of seven issuers listed on the LQ45 index, the next step is to transform the closing stock prices into daily stock returns. Stock returns are calculated using the following formula:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) = \ln(P_t) - \ln\,(P_{t-1}) \tag{1}$$

Once the transformation of the closing prices into stock returns is complete, descriptive statistics are calculated to analyze the characteristics of the returns. The descriptive statistics calculated include the mean, median, standard deviation, as well as the minimum and maximum values, which are then presented in the following table.

Table 1. Descriptive Statistics of Stock Returns

	ADMR	ADRO	AKRA	ITMG	MEDC	PGAS	PTBA
Mean	0.0024	0.0008	0.0005	0.0010	0.0012	0.0005	0.0008
Median	-0.0029	0.0000	0.0000	0.0008	0.0000	0.0000	0.0000

Maximum	0.2987	0.1772	0.0919	0.1179	0.1870	0.1076	0.1896
Minimum	-0.1138	-0.2829	-0.1049	-0.0722	-0.1195	-0.0704	-0.1616
Std. Dev.	0.0422	0.0277	0.0242	0.0208	0.0318	0.0195	0.0219
Observations	779	779	779	779	779	779	779

Source: Processed data

The sample size used in this study consists of 779 observations for each stock, with a consistent analysis period spanning over two years, from January 1, 2022, to March 31, 2025. The daily returns of the seven stocks analyzed show varying levels of growth and volatility. ADMR has the highest volatility, with a mean return of 0.0024 and a standard deviation of 0.0422, indicating significant potential for both profit and loss. ADRO's return of 0.08% reflects moderate growth but with high fluctuations, as seen in its maximum return of 17.72% and minimum of -28.29%. AKRA, with a mean return of 0.0005 and moderate volatility (standard deviation of 0.0242), exhibits more stable price movements. ITMG shows the lowest volatility (0.0208), with a balanced return distribution and a daily return mean of 0.0010. MEDC, with a mean return of 0.0012 and a standard deviation of 0.0318, is an aggressive stock offering positive returns but with higher risk. PGAS shows low volatility and a symmetric distribution, with a mean return of 0.0005. PTBA, with moderate volatility (0.0219) and a mean return of 0.0008, presents a balanced option between return and risk.

Stationarity Test

The stationarity test in time series analysis is conducted to determine whether the data exhibits stationarity, meaning its statistical properties (such as mean, variance, and covariance) do not depend on time. In this study, the Augmented Dickey-Fuller (ADF) test is used to check whether the stock return variables for each energy sector issuer have a unit root, indicating non-stationarity. The ADF test is performed using EViews12 software, and the hypotheses tested are as follows: Null Hypothesis (H_0): The stock return variable has a unit root (data is non-stationary), and Alternative Hypothesis (H_1): The stock return variable does not have a unit root (data is stationary).

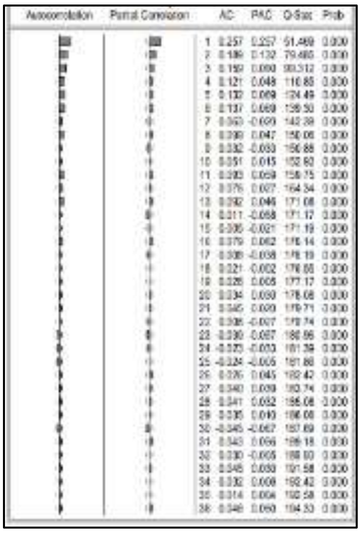
Table 2. Results of Stock Return Data Stationarity Testing

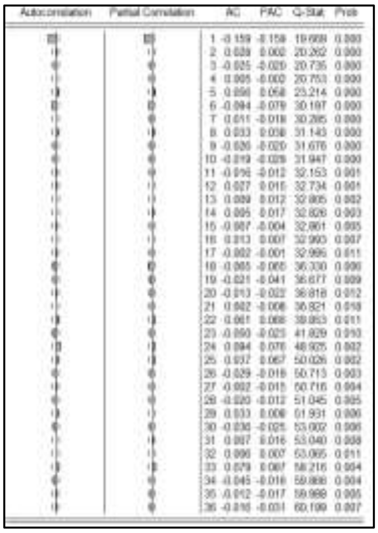
Kode Emiten Saham	pvalue
ADMR	0.000
ADRO	0.000
AKRA	0.000
ITMG	0.000
MEDC	0.000
PGAS	0.000
PTBA	0.000

The ADF test is conducted by selecting the automatic lag length using the Schwarz Information Criterion (SIC) criteria. Based on the test results shown in Table 2, the p-value for each stock issuer is 0.000. Because the p-value obtained is smaller than the significance level $\alpha = 5\%$, the null hypothesis is rejected, indicating that all stock returns on the tested issuers are stationary at the level. Thus, there is no need to differencing the data.

Best Arima Model Estimation

The determination of the most appropriate ARIMA model aims to model the deterministic components in the data, specifically the linear relationship between current and past values (autocorrelation). This estimation process is carried out separately for each stock by following several analytical stages. The first step involves identifying the model order through the examination of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, which are used to determine the parameters p (autoregressive order), d (differencing degree), and q (moving average order). To identify whether values in ACF or PACF are significant, the significance threshold is calculated using the formula in Equation (3.4), resulting in a threshold of ±0.0702. Therefore, ACF or PACF values greater than 0.0702 or less than -0.0702 are considered statistically significant at the 5% level, while values between -0.0702 and 0.0702 are deemed insignificant. Based on previous stationarity tests, it is found that all stock return data are stationary at the level, so the value of d is set to 0. After determining the model order, the ARIMA model parameters are estimated using EViews 12 software, followed by performance evaluation using statistical criteria such as AIC, SIC, and error values. The model with the best performance is then selected as the optimal ARIMA representation for each stock.


(a)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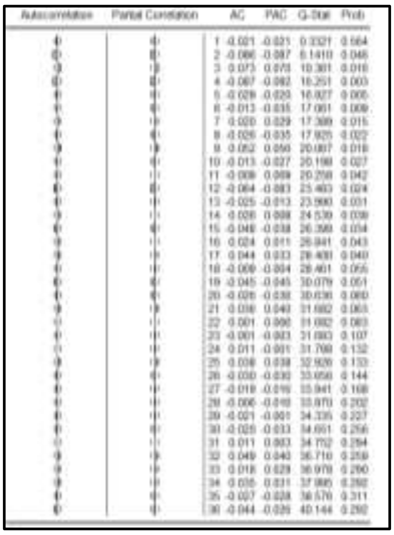
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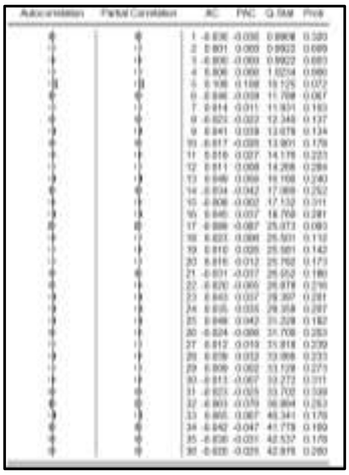
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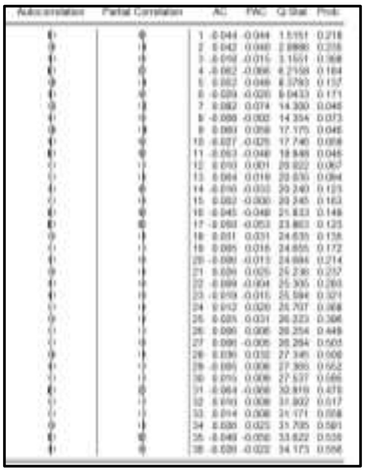
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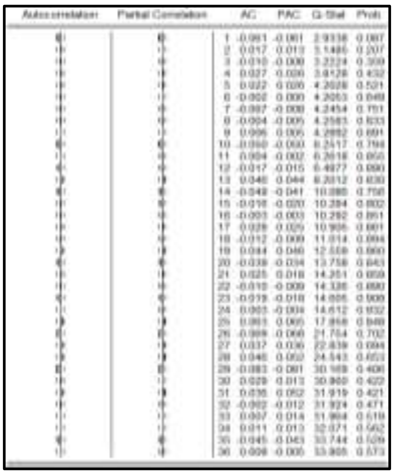
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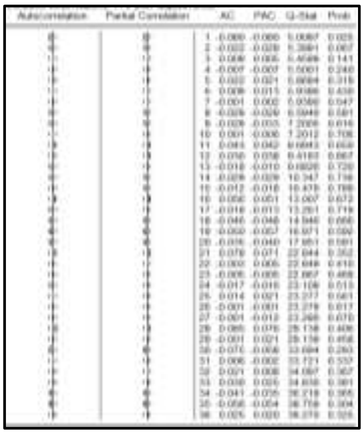


(g)

Figure 1. Correlogram Return Saham (a) ADMR; (b) ADRO; (c) AKRA; (d) ITMG; (e) MEDC; (f) PGAS; (g) PTBA

Based on the ACF and PACF analysis for various models, some common patterns can be identified. For ADMR and ADRO, the ACF shows significant decay, supporting the selection of ARMA(1,1) and ARMA(1,2) models. Meanwhile, for AKRA, the PACF pattern that does not show a sharp cut-off and the ACF being significant up to lag 17 suggest a model with low order, such as ARIMA(1,2). For ITMG, the positive autocorrelation at lag 5 indicates the potential presence of AR or MA components at that lag. For MEDC, the absence of significant peaks in both the PACF and ACF points to ARIMA(0,0,0) or models with low order. PGAS, with its insignificant ACF pattern and small PACF values, requires an ARIMA model with low order, such as ARIMA(0,0,0) or ARIMA(1,0,1). For PTBA, the ACF and PACF are significant at the first lag, but after that, the p-value increases, indiscating that ARIMA(1,0,0), ARIMA(0,0,1), or ARIMA(1,0,1) are more suitable. Overall, the proposed ARIMA models focus on selecting low-order models based on the ACF and PACF patterns, with some models considering AR and MA components at the first or higher lags, depending on the characteristics of each dataset.

Table 3. Best ARIMA Model Identification Results

Stock Code	**ARIMA (p,d,q)**	**AIC**	**SIC**	R^2	**SSE**	**Significance Of Parameters**
ADMR	ARIMA (1,0,1)	-3.63387	-3.60995	0.14300	1.18969	Significant
ADRO	ARIMA (1,0,0)	-4.3544	-4.3365	0.0252	0.5816	Significant
AKRA	ARIMA (0,0,2)	-4.6077	-4.5898	0.0092	0.4514	Significant
ITMG	ARIMA (5,0,0)	-4.91260	-4.89466	0.01224	0.33279	Significant
MEDC	ARIMA (0,0,0)	-4.0536	-4.0477	0.0000	0.7897	Not Significant
PGAS	ARIMA (0,0,0)	-5.0294	-5.0235	0.0000	0.2976	Not Significant
PTBA	ARIMA (0,0,1)	-4.8053	-4.7874	0.0067	0.3705	Significant

Table 3 presents the best ARIMA model identification results for several stocks. For each stock, the ARIMA model is specified along with its AIC, SIC, R², SSE values, and the significance of its parameters. Stocks such as ADMR, ADRO, AKRA, ITMG, and PTBA show significant parameters, indicating a good fit for the ARIMA models. However, for MEDC and PGAS, the chosen ARIMA(0,0,0) models indicate that ARIMA may not be suitable for these stocks, as this model does not provide meaningful results for them, suggesting the need for further exploration or the application of alternative modeling techniques.

Heteroscedasticity Test

The residual heteroscedasticity test in the ARIMA model is carried out to ensure that the residual variance (error) is not constant over time. This inconstancy, or known as heteroscedasticity, is one of the main requirements before proceeding to the GARCH modeling stage.

Table 4. ARIMA Residual Heteroscedasticity Test Results

Stock Code	Residuals of the ARIMA Model tested	$pvalue$
ADMR	ARIMA (1,0,1)	0.00000
ADRO	ARIMA (1,0,0)	0.00000
AKRA	ARIMA (0,0,2)	0.00005
ITMG	ARIMA (5,0,0)	0.00820
MEDC	ARIMA (0,0,0)	0.31230
PGAS	ARIMA (0,0,0)	0.20470
PTBA	ARIMA (0,0,1)	0.00000

Based on Table 4.12, the p-values for ADMR, ADRO, AKRA, ITMG, and PTBA are smaller than the 5% significance level, indicating that H_0 is rejected. This suggests that the residuals of these stocks exhibit ARCH effects, making them suitable for GARCH modeling. In contrast, MEDC and PGAS have p-values greater than 0.05, so H_0 is not rejected, implying no significant heteroskedasticity in the residuals, and thus, GARCH modeling is not applicable for these stocks.

GARCH Model Estimation

The GARCH model has two main parameters: p, representing the order of past conditional variances (GARCH component), and q, representing the order of past squared residuals (ARCH component). Several combinations of p and q values, ranging from 1 to 3 (e.g., GARCH(1,1), GARCH(1,2), GARCH(2,1), GARCH(3,3)), are tested to find the most appropriate model. The selection of p and q is limited to lag 3 for model efficiency and based on empirical findings from previous literature, as higher orders may lead to increased model complexity, reduced estimation stability, and a higher risk of overfitting. Each estimated model is evaluated and the best model is selected based on the lowest AIC and SIC values, small SSE, high R^2, and statistically significant positive parameters. The modeling is conducted on the stocks ADMR, ADRO, AKRA, ITMG, and PTBA using EViews12 software.

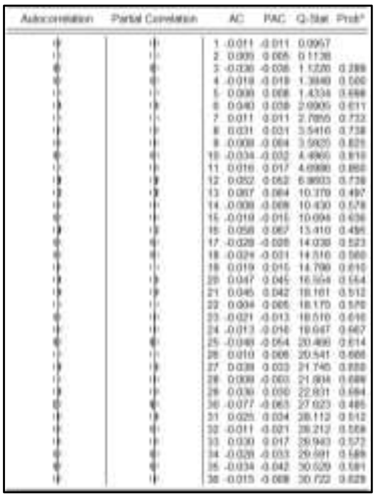
Table 5. Best GARCH Model Identification Results

Stock Code	GARCH Model	AIC	SIC	R^2	SSE	Coefficient	Significance Of Parameters
ADMR	GARCH (1,1)	-3.9419	-3.9060	0.2393	0.9892	s	Significant
						0.1441	Significant
						0.8008	Significant
ADRO	GARCH (1,1)	-4.5175	-4.4876	0.0164	0.5859	0.0001	Significant
						0.1433	Significant
						0.6868	Significant
AKRA	GARCH (1,1)	-4.6733	-4.6434	0.0088	0.4516	0.0000	Not Significant
						0.0251	Significant
						0.9701	Significant
ITMG	GARCH (1,1)	-5.0308	-5.0007	0.0069	0.3335	0.0000	Significant
						0.0501	Significant
						0.9444	Significant
PTBA	GARCH (1,1)	-4.9024	-4.8725	0.0058	0.3709	0.0000	Significant
						0.0998	Significant
						0.8331	Significant

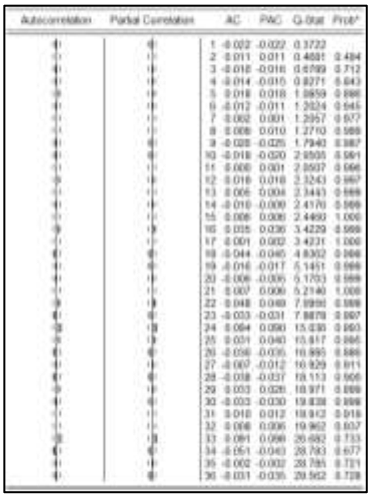
Based on the estimation results of the GARCH(1,1) models for five stocks, all exhibit high levels of volatility persistence. AKRA and ITMG show the highest persistence, at 0.9952 and 0.9945 respectively, indicating that past volatility shocks continue to have a strong influence on current volatility. ADMR and PTBA also show relatively high persistence levels, at 0.9449 and 0.9329, while ADRO has the lowest persistence at 0.8300. In terms of long-term volatility, ADMR records the highest value at 0.0013, followed by ADRO at 0.0007, whereas AKRA, ITMG, and PTBA show relatively lower long-term volatility values of 0.0006, 0.0006, and 0.0005, respectively. These findings suggest that, overall, the price movements of these stocks remain significantly influenced by past volatility, although the degree of influence varies across stocks.

Best GARCH Model Diagnostic Evaluation

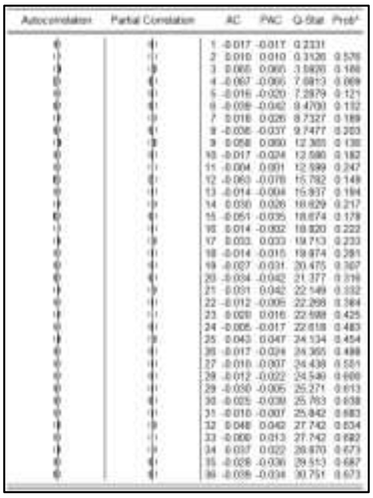
A diagnostic evaluation was then conducted on the best GARCH model selected for each stock to ensure model adequacy and reliability. This evaluation involved two main tests: the autocorrelation test on residuals and the ARCH effect test. The first step was to examine residual autocorrelation to identify any remaining structured patterns, which would indicate model misspecification. This is typically visualized using a correlogram, showing correlations at various lags. To statistically assess autocorrelation, the Ljung-Box test was applied, evaluating the p-values under the null hypothesis of no autocorrelation.



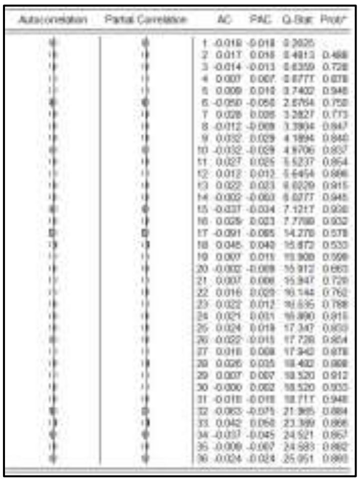
(a)



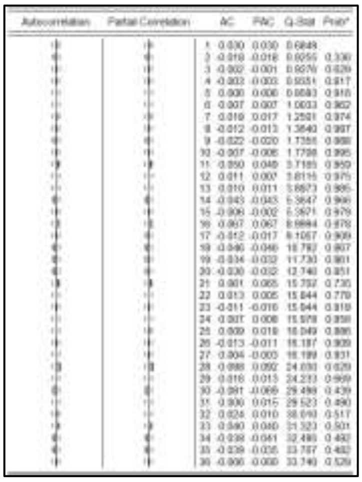
(b)



(c)



(d)



(e)

Figure 2. Correlogram: (a) Residual model ARMA(1,1)-GARCH(1,1) On ADMR Stock; (b) Residual model AR(1)-GARCH(1,1) On ADRO Stock; (c) Residual model MA(2)-GARCH(1,1) On AKRA Stock; (d) Residual model AR(5)-GARCH(1,1) On ITMG Stock; (e) Residual model MA(1)-GARCH(1,1) On PTBA Stock

Based on Figure 2, all Prob* values from lag 1 to lag 35 for the GARCH model residuals of ADMR, ADRO, AKRA, ITMG, and PTBA are above the 0.05 significance threshold. Therefore, the null hypothesis cannot be rejected, indicating no significant autocorrelation in the residuals. Additionally, the Autocorrelation (AC) and Partial Autocorrelation (PAC) patterns at each lag show relatively small values with no significant spikes, suggesting there are no residual correlation patterns requiring further modeling. These results confirm that the residuals meet the white noise assumption, indicating that the GARCH model has passed the autocorrelation diagnostic test and effectively captured the data dynamics without leaving unexplained patterns in the residuals.

Next, the second step, the ARCH effect test is conducted to detect the presence of remaining heteroscedasticity in the residual model. This test is crucial because the GARCH model is designed to capture volatility that varies over time.

Table 6. GARCH Residual Heteroscedasticity Test Results

Stock Code	The GARCH model residuals tested	$pvalue$
ADMR	GARCH (1,1)	0.8369
ADRO	GARCH (1,1)	0.0702
AKRA	GARCH (1,1)	0.1445
ITMG	GARCH (1,1)	0.2291
PTBA	GARCH (1,1)	0.6650

Based on Table 6, the p-values for the stocks ADMR, ADRO, AKRA, ITMG, and PTBA are above the 5% significance level. Therefore, the null hypothesis (H_0) cannot be rejected, indicating no significant ARCH effects in the residuals of the GARCH model for these stocks. This result suggests that the GARCH model effectively addresses heteroskedasticity and captures all volatility dynamics, making it suitable for future forecasting.

Volatility Forecasting

The stock return forecasting for the energy sector is performed using the best-selected GARCH model from the previous stage. The goal is to estimate stock returns and volatility for April 2025 based on historical data up to March 2025. The forecasting process uses seven stock return observations reflecting past price movements. To evaluate the forecasting results, the Mean Squared Error (MSE) is calculated to measure the average squared difference between actual and predicted values. Additionally, the Average Mean Squared Error (AMSE) is computed as the mean of all MSE values for each stock, where a lower AMSE indicates better overall model performance.

Table 7. Volatility Forecasting of ADMR, ADRO, AKRA, ITMG, PTBA Stock Returns for the Next 7 Days

Stock Code	Day Number	Stock Return Prediction Value	MSE Value	Volatility Prediction Value
ADMR	1	-0.00138	0.01664	0.000656
	2	-0.00136	0.00000	0.000600
	3	-0.00135	0.00257	0.000556
	4	-0.00133	0.00002	0.000520
	5	-0.00132	0.00434	0.000492
	6	-0.00131	0.00005	0.000469
	7	-0.00130	0.00056	0.000451

ADRO	1	0.00108	0.01341	0.000702
	2	0.00119	0.00000	0.000601
	3	0.00118	0.00082	0.000531
	4	0.00118	0.00006	0.000483
	5	0.00118	0.00076	0.000450
	6	0.00118	0.00034	0.000428
	7	0.00118	0.00000	0.000412
AKRA	1	0.00284	0.01539	0.000915
	2	0.00108	0.00577	0.000890
	3	0.00052	0.04006	0.000867
	4	0.00052	0.00221	0.000844
	5	0.00052	0.00053	0.000822
	6	0.00052	0.00058	0.000800
	7	0.00052	0.00003	0.000779
ITMG	1	-0.00053	0.00247	0.00031
	2	-0.00090	0.00189	0.00030
	3	0.00148	0.00041	0.00029
	4	0.00131	0.00002	0.00027
	5	0.00031	0.00334	0.00026
	6	0.00029	0.00002	0.00025
	7	0.00027	0.00002	0.00024
PTBA	1	0.00048	0.00168	0.000641
	2	0.00072	0.00025	0.000568
	3	0.00072	0.00721	0.000508
	4	0.00072	0.00000	0.000458
	5	0.00072	0.00046	0.000416
	6	0.00072	0.00004	0.000382
	7	0.00072	0.00036	0.000353

Table 7 reports the seven-day-ahead forecasts of daily returns and conditional volatilities for five LQ45 energy-sector stocks: ADMR, ADRO, AKRA, ITMG, and PTBA. Across all stocks, the predicted conditional volatility exhibits a consistently declining trend over the forecast horizon, indicating a mean-reverting pattern of volatility as captured by the ARMA–GARCH models. For example, the conditional variance for ADMR decreases from 0.000656 on Day 1 to 0.000451 on Day 7, while ADRO declines from 0.000702 to 0.000412, and PTBA from 0.000641 to 0.000353. Similar trends are observed for AKRA and ITMG, reflecting the effectiveness of the fitted models in capturing short-term volatility dynamics. Forecasted returns tend to be low in magnitude and relatively stable, with stocks such as ADRO and PTBA maintaining nearly constant positive return values over multiple days, whereas ADMR maintains slightly negative values throughout the horizon.

Furthermore, the forecasting performance of each model is supported by relatively low Average Mean Squared Error (AMSE) values, which reflect the overall predictive accuracy. The ARMA(1,1)–GARCH(1,1) model for ADMR yields an AMSE of 0.00224, while the AR(1)–GARCH(1,1) model for ADRO produces an AMSE of 0.00109, both indicating a good fit. The MA(2)–GARCH(1,1) model for AKRA results in a slightly higher but still acceptable AMSE of 0.00442. For ITMG, the AR(5)–GARCH(1,1) model achieves a lower AMSE of 0.00140, and the MA(1)–GARCH(1,1) model for PTBA records the lowest AMSE at 0.00065. These findings suggest that the selected GARCH-type models are capable of producing accurate short-term forecasts of stock returns and volatility in the energy sector, thereby offering valuable insights for investors and risk managers.

CONCLUSION

In conclusion, this study successfully analyzed the stock return volatility of seven energy sector companies included in the LQ45 index using the GARCH model. The results reveal that ARMA-GARCH models are effective in capturing the volatility patterns of most stocks, with significant long-term persistence observed in companies like ADMR, ADRO, AKRA, ITMG, and PTBA. The volatility forecasts using these models showed high accuracy, especially for stocks such as ADMR and ADRO. However, for MEDC and PGAS, the GARCH model was not applicable due to the absence of heteroskedasticity, indicating the need for alternative modeling approaches. Based on these findings, it is recommended that future research explore the integration of macroeconomic variables, such as oil prices and exchange rates, into volatility models. Moreover, exploring machine learning-based approaches could enhance model adaptability and accuracy. From a practical standpoint, investors and portfolio managers should tailor their asset allocation strategies based on the specific volatility characteristics of each stock, incorporating volatility predictions for more informed decision-making.

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