MODELING AND FORECASTING STOCK RETURN VOLATILITY OF THE JAKARTA ISLAMIC INDEX: GARCH VS EGARCH MODEL

Luthfi Izzatun Nisa, Wiku Suryomurti
Institut Agama Islam Tazkia
E-mail: luthfiizzatun@gmail.com, wiku.suryomurti@tazkia.ac.id

ABSTRACT
The aim of this study is to determine the most effective method of predicting volatility in select stocks of the Jakarta Islamic Index. To achieve this objective, two models - Symmetric Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Asymmetric Exponential GARCH - were employed to identify any potential asymmetric effects. Daily data from May 1, 2018, to May 31, 2023, was used for this study, focusing on six stocks included in the Jakarta Islamic Index during the observation period - ADRO, ICBP, KLBF, TLKM, UNTR, and UNVR. The results of the study reveal that the Symmetric GARCH model is a suitable tool for analyzing volatility patterns in these six stocks. Moreover, the forecast results can be of great assistance to investors. Those who are willing to take risks may consider adding TLKM and KLBF to their portfolios, while those who prefer low-risk investments can opt for UNTR.

Key words: GARCH; Volatility; Jakarta Islamic Index; Return; Sharia Stock

Penelitian ini bertujuan untuk menemukan pemodelan terbaik guna meramalkan volatilitas beberapa saham yang terdaftar di Jakarta Islami Index. Penelitian ini menggunakan model simetris Generalized Autoregressive Conditional Heteroskedasticity (GARCH) dan model asimetris yaitu Exponential GARCH untuk menangkap efek asimetris jika ada. Penelitian ini menggunakan data harian dari tanggal 1 Mei 2018 sampai dengan 31 Mei 2023. Sampel penelitian ini adalah enam saham yang terdaftar di Jakarta Islamic Index selama periode pengamatan yaitu ADRO, ICBP, KLBF, TLKM, UNTR dan UNVR. Hasil dari penelitian ini bahwa model simetris GARCH adalah model yang tepat untuk menguji perilaku pola volatilitas pada kenam sample saham. Selain itu, hasil peramalah berguna bagi para investors. Bagi investor yang bersifat risk taker dapat menambahkan TLKM dan KLBF dalam portofolio. Sedangkan bagi investor yang hanya ingin berinvestasi pada tingkat risiko yang rendah dapat memilih UNTR.

Key words: GARCH; Volatilitas; Jakarta Islamic Index; Return; Saham Syariah

INTRODUCTION

The Sharia stock index exhibited growth relative to the close of 2021. As of June 2022, the ISSI had increased by 6.02% to reach 200.39, up from 189.02 in December 2021. ISSI's market capitalization rose by 6.92% to IDR 4,259.24 trillion. In addition, JII's share capitalization increased by 2.26 percent, for a total increase of 2.23 percent. In addition, the JII70 index increased by 0.74 percent, and market capitalization increased by 1.67 percent. However, IDX-MES BUMN 17 decreased by 0.31 percent, and its market capitalization decreased by 3.59 percent.

Amid the expansion of the Islamic capital market, prudent investor consideration of risk exposure remains crucial (Masrizal et al. 2021). Equities investing entails susceptibility to price fluctuations (Huber, Palan, and Zeisberger 2019), while Islamic investment entails downside and specific risk (Hayat and Kraeussl 2011) moreover also inherent systemic risk (Naveed, Khawaja, and Maroof 2020). Volatility stands as a paramount financial risk indicator, affecting decisions based on risk-return dynamics, significantly influencing global economic confidence. Financial economics' application seeks to model financial instrument volatility, essential for corporate estimation, investment, and funding decisions. Policymakers keenly monitor volatility as an early crisis warning (Liu and Hung 2010) (Karanasos, Yfanti, and Hunter 2022).Forecasting stock return volatility holds significance in financial domains, garnering attention for regulation, portfolio management, risk control, and financial decision-making (Hajizadeh et al. 2012) (Bollerslev, Patton, and Quaedvlieg 2016) (Nasr et al. 2016) (Wang et al. 2020) (Ellahie and Peng 2021), with real-time monitoring aiding investors in optimizing strategies and mitigating market risk.

Engle's pioneering work in (1982) introduced the ARCH framework as a tool to comprehend the inherent residual volatility present within financial datasets. Evaluating the ARCH model necessitates accounting for variance dependent on past periods' volatility, thereby augmenting the estimation of conditional variance parameters. Precisely estimating these factors remains challenging. Bollerslev's subsequent contribution in (1986) presented a methodology facilitating straightforward forecasting of financial time series. Leveraging the GARCH non-constant volatility model enables the representation of volatility within conditional variances and temporal dynamics. This framework demonstrates conditional heteroscedasticity while maintaining homoscedasticity. The GARCH model, attuned to the asymmetric impact of negative versus positive information, encompasses innovations like the Threshold GARCH (TGARCH) (Zakoian 1994) and Exponential GARCH (EGARCH) models (Nelson 1991).

Numerous scholars have focused on identifying optimal forecasting methods, and the GARCH family models have demonstrated precision in predicting stock return volatility. Scholarly discourse highlights that combining the GARCH family model with other statistical techniques yields superior results. Notably, GARCH (1, 1) adeptly characterizes symmetric volatilities and returns in contexts with balanced information. Recent research indicates the GARCH model's applicability in forecasting stock indices across Asia, including India, Japan, China, Singapore, Malaysia, and Indonesia. Conversely, empirical evidence supports the superiority of the EGARCH model in predicting stock prices within the Indonesian composite stock price index, effectively capturing asymmetric effects stemming from disparate impact of negative and positive information. Empirical investigations favor the EGARCH model over TARCH for asymmetric volatility forecasting, as confirmed by their respective forecast outcomes.

As an emerging market, Indonesia Capital Market has high volatility (Rahmi et al. 2016). In particular, the Jakarta Islamic Index also has a high degree of fluctuations (Suryomurti 2017). Since its inception in 2000, the Jakarta Islamic Index's market capitalization has continued to rise. In December 2022, the market capitalization of the Jakarta Islamic Index reached IDR 2,155,449.41 billion. According to data from the Indonesia Stock Exchange, the number of Sharia investors reached 114,116 on September 30, 2022. In addition, the trading activity of Sharia investors on the stock exchange has reached IDR 8.3 trillion, with 24 billion shares changing hands. Considering the volatility and rapid growth of the Islamic capital market in Indonesia, it is crucial to examine the patterns and volatility forecasting of the Jakarta Islamic Index.

In this research, the author explores the modeling and forecasting of six stocks that have not left Jakarta Islamic Indices (JII) for the last five years. The six shares include Adaro Energy Indonesia Tbk (ADRO) from coal industry, Indofood CBP Sukses Makmur Tbk (ICBP) from processed food industry, Kalbe Farma Tbk (KLBF) pharmaceutical industry, PT Telkom Indonesia (Persero) Tbk (TLKM) from telecommunication services industry, United Tractors Tbk (UNTR) from machinery industry and Unilever Indonesia Tbk (UNVR) from personal care product industry.

LITERATURE REVIEW

Volatility in the stock market, measured by price fluctuations over time, is a crucial risk indicator influencing investment decisions. Researchers note strong correlations between stock market volatility and market uncertainty, emphasizing its significance in portfolio management (Green and Figlewski 1999). Heightened volatility's impact on economic development is debated; Schwert (1989) links it to future economic activity through unpredictability in cash flows and discount rates. Structural change's effects on GDP growth are explored, revealing the role of cost of capital and equity in mediating market volatility's influence (Campbell et al. 2001). International events and domestic indicators, including macroeconomic data releases, impact stock market volatility (Bomfim 2003) (Kim and In 2002) (Kim, McKenzie, and Faff 2004) (Jiang, Konstantinidi, and Skiadopoulos 2012). Efficient market assumptions drive restricted post-release impact assessment, while public perception focuses on point changes rather than percentage fluctuations (Schwert 1990).

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is widely employed for forecasting financial data, especially in capturing volatility clustering. This feature addresses the tendency of financial data to exhibit clustered volatility, where significant changes are followed by more significant ones and small changes lead to further small changes (Mandelbrot, 1963). This model's flexibility in representing conditional variance, considering prior variances and past squared errors, is particularly relevant for intricate financial time series patterns (Brooks, 2008).

The GARCH model effectively accommodates dynamic volatility patterns seen in financial data by incorporating historical information. Unlike conventional models, like ARIMA, which assume constant variance, GARCH recognizes heteroscedastic conditional variances, thus enabling more accurate volatility-informed forecasts (Bollerslev, 1986). GARCH addresses the limitations of traditional models in capturing volatility and nonlinearity, making it suitable for time series forecasting, as evidenced by recent research (Pahlavani & Roshan, 2015; San K. Lee & Lan T. P. Nguyen, 2017; Bhardwaj et al., 2014; Azimi & Shahidzada, 2019).

Bhowmik & Wang (2020) conducted an empirical study to investigate effective GARCH models suggested for analyzing market returns and volatility. The studies find that several researchers assert that the GARCH family model yields superior results when paired with another statistical method. Aliyev et al. (2020) estimate the volatility of the returns of the Nasdaq-100, a nonfinancial, innovative, and high-tech stock index, using GARCH, EGARCH and GJR-GARCH. The results indicate the GARCH (1, 1) model and EGARCH and GJR-GARCH models demonstrate that the series has a leverage effect and that the impact of shocks is asymmetric.

Anggita et al. (2020) assessed the accuracy of stock price forecasts by observing the volatility of stock prices. This quantitative and descriptive-analytic study aims to acquire an overview of the level of stock price volatility and stock price forecasting in Indonesia using the ARCH/GARCH model. The results indicate that the EGARCH model is the most accurate volatility model for predicting stock prices, with an error rate of less than 5%, meaning the model is entirely accurate at predicting stock prices.

Sharma et al. (2021) compared the linear (symmetric) and nonlinear (asymmetric) Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models for forecasting the volatility of the top five major emerging countries among the E7. The results revealed that the GARCH (1, 1) model is preferable to nonlinear GARCH models for forecasting volatility due to the insignificance of leverage. Mubarok & Sutrieni (2021) examines the behavior of volatility patterns in the infrastructure, utility, and transportation sectors using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The results indicate that the error and volatility return of the preceding month affects the volatility of all equities within the scope of this study.

METHOD

This research uses secondary data. The study employs daily stock data from May 1, 2018, to May 31, 2023, considering the forecasting horizon's impact on historical data selection. Given volatile fluctuations over time, a large sample doesn't ensure an unbiased volatility model. A trade-off exists between data quantity and obsolescence elimination. For short horizons, recent observations capture volatility clustering and prevailing market conditions. Short forecasting requires intraday data for precise daily volatility estimates; otherwise, the pre-forecast data lengthens, excluding outdated observations for optimal accuracy (Bunjaku and Näsholm 2010). Therefore, the in-sample data period is set to five years, from May 1, 2018 to May 31, 2023, and the out-of-sample forecasted period is set to one year, from April 1, 2023 to May 31, 2024. The population of this research is 30 stocks listed in Jakarta Islamic Index. The sample of this research is six stocks that always stayed in Jakarta Islamic Index during the observation year: ADRO, ICBP, KLBF, TLKM, UNTR, and UNVR.

The author used the library research method to collect data to support this research. The data search includes secondary data searches through searches on the websites of Yahoo Finance, Indonesia Stock Exchange, and bibliographical references. Available secondary data can contain general to specific information. All data in the form of qualitative and quantitative collected beforehand to form the basis of research and support the research conducted. The GARCH Family model is the analytical tool, processed using the software "Eviews 12".

The research employs the symmetric Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and asymmetric Exponential Generalized Autoregressive Conditional Heteroscedasticity models to fulfill the study's objective. To initiate the analysis, the first stage calculates returns to ascertain volatility. Subsequently, descriptive statistics unveil essential information influencing subsequent data analysis. The third step tests data stationarity through the Augmented Dickey-Fuller (ADF) Test, ensuring stability for time series analysis (Greunen et al., 2014).

Following data preparation, the study determines the optimal Autoregressive Integrated Moving Average (ARIMA) model, a prevalent choice for mean forecasting. The next phase involves eliminating serial correlations through sample mean extraction and testing for Autoregressive Conditional Heteroscedasticity (ARCH) effects (Tsay, 2002; Ou et al., 2022). Heteroscedasticity is assessed using the Autoregressive Conditional Heteroscedasticity-Lagrange Multiplier (ARCH-LM). Lastly, the ARIMA model integrates the ARCH-GARCH approach to select the most suitable model—GARCH or EGARCH. The trial process to find the best model use the following equation:

$$\boldsymbol{\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2}$$

The ARCH equation above denote where α_t^2 known as conditional variance, α_0 as Constanta, and $\alpha_1 u_{t-1}^2$ as random variables in the previous period.

$$\boldsymbol{\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2}$$

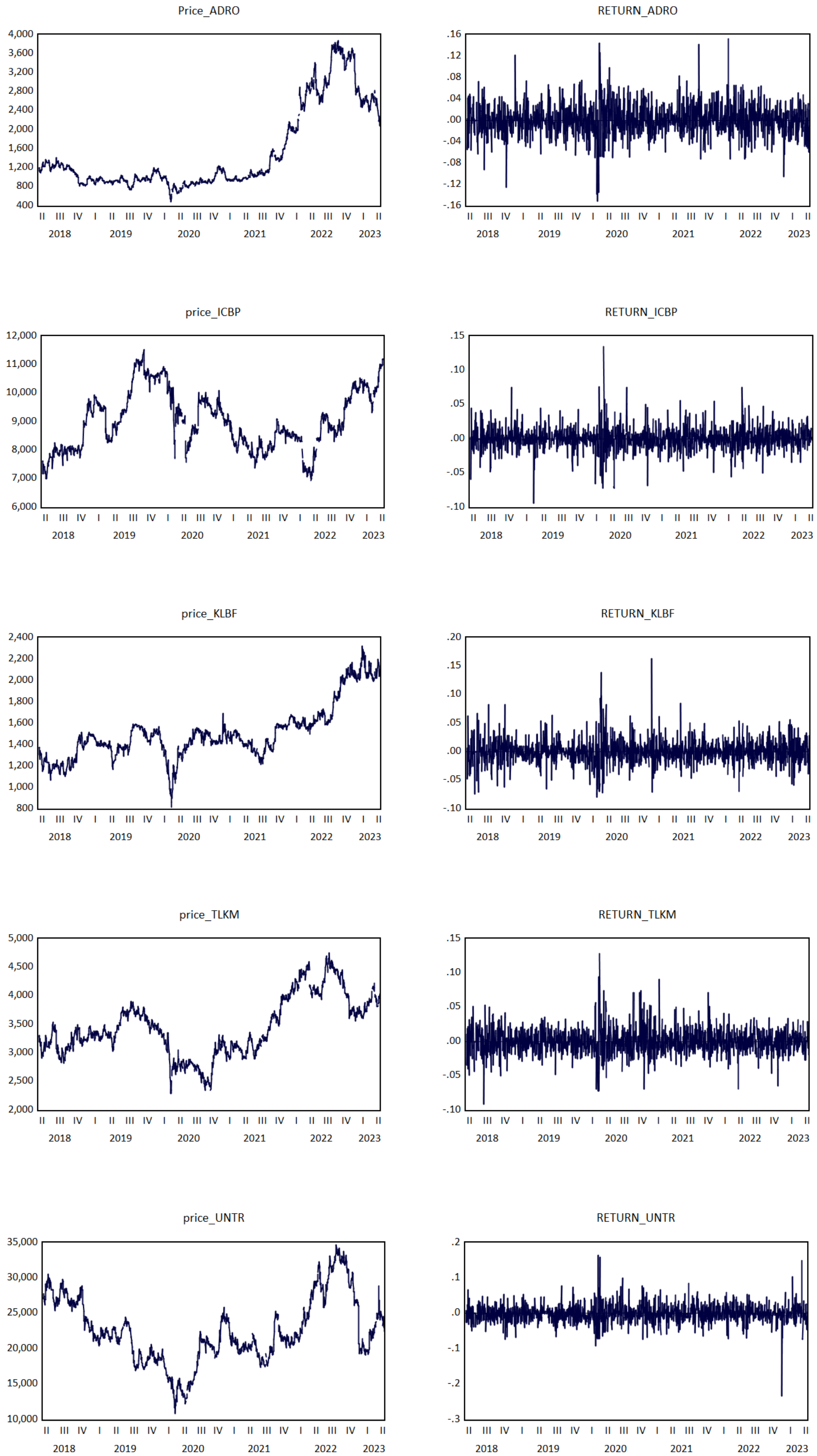
The GARCH equation above denote where σ_t^2 denote conditional variance, α_0 as Constanta, $\alpha_1 u_{t-1}^2$ denote past error, $\beta\sigma_{t-1}^2$ show the fitted variance of the model during the previous period.

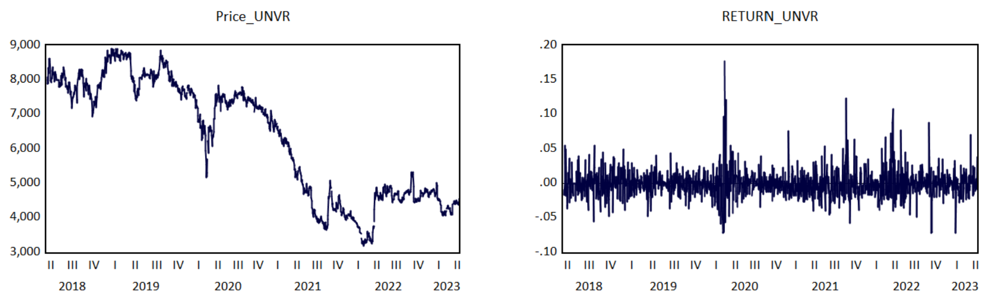
$$\boldsymbol{\ln(\sigma_t^2) = \omega + \beta\ln(\sigma_{t-1}^2) + \gamma\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha\left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right]}$$

The EGARCH equation above denote where ω intercept for the variance is, β is coefficient for the logged GARCH term, $\ln(\sigma_{t-1}^2)$ is logged GARCH term, γ denote scale of the asymmetric volatility, $\gamma\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}}$ is the last period's shock, which is standardized and $\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}$ is the parameter that takes into account the absolute value of the last period's volatility shock. After getting the optimal GARCH model, a diagnostic model is run to determine if the model still exhibits heteroscedasticity. Then, forecast the volatility of stock return using the selected GARCH or EGARCH model..

RESULTS AND DISCUSSION

Figure 1 depicts the first stage in this research procedure, which is to examine the stock price movements and stock returns of each company. According to this graph, each of the observed stock returns and securities exhibits a high level of volatility. The price fluctuations of the six equities exhibit time-varying volatility and a tendency to concentrate during specific periods. Heteroskedasticity may be the result of time-varying volatility. Moreover, volatility has autocorrelation, meaning that the current volatility is dependent on past volatility.





Source: www.finance.yahoo.com, processed in Eviews 12

Figure 1 Graph of Adjusted Close Price (Left) and Graph of Return (Right)

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The descriptive statistic where ICBP's standard deviation value has the lowest value (0.017067), indicating it has the lowest risk of volatility among the other five stocks, is shown in Table 3 below. Moreover, UNVR stock has the highest return with a value of 0.177170, while UNTR companies have the lowest return at -23.25%. In addition, all data has a kurtosis greater than 3, which indicates that heteroskedasticity was already present.

Table 1 Descriptive Statistic

	ADRO	KLBF	ICBP	TLKM	UNTR	UNVR
Mean	0.00044	0.00033	0.00030	0.00013	0.00017	0.00045
Maximum	0.15250	0.16318	0.13503	0.12874	0.16430	0.17717
Minimum	-0.15070	-0.08004	-0.09385	-0.09097	-0.23254	-0.07174
Std. Dev	0.02951	0.02202	0.01706	0.01913	0.02592	0.02016
Skewness	0.15357	0.63881	0.26119	0.40481	0.04386	1.28730
Kurtosis	6.02988	8.10249	9.37382	6.89030	11.5925	12.1245
Jarque-Bera	487.299	1456.01	2148.87	829.632	3879.64	4730.28

Source: Data Processed in Eviews 12

The results of the unit root test using the Augmented Dickey-Fuller test are presented in Table 2. All data is stationary because the statistical value of the Augmented Dickey-Fuller test is less than the 5% critical value. After assuring that the data is stationary, the next step is to choose the most effective ARIMA model. Table 3 presents the best ARIMA model (p, d, q) using the minimal Akaike Info Criterion (AIC) value criterion, and each variable's probability value is statistically significant.

Table 2 Unit Root Test

Company	ADF test statistic	Prob.
ADRO	-34.94015	0.0000
KLBF	-39.92268	0.0000
ICBP	-38.50153	0.0000
TLKM	-29.77518	0.0000
UNTR	-38.65246	0.0000
UNVR	-36.29162	0.0000

Source: Data Processed in Eviews 12

Table 3 Overfitting ARIMA models

Company	ARIMA (p,d,q)	Akaike Info Criterion	Prob
ADRO	(3,1,0)	-4.207946	(0)
KLBF	(1,0,2)	-4.807378	(0,0)
ICBP	(1,0,1)	-5.307538	(0,0)
TLKM	(1,0,2)	-5.093231	(0,0)
UNTR	(0,0,1)	-4.470839	(0)
UNVR	(2,0,3)	-4.974801	(0,0)

Source: Data Processed in Eviews 12

After deriving the ARIMA model, the heteroscedasticity test was performed using the Autoregressive Conditional Heteroscedasticity-Lagrange Multiplier (ARCH-LM) to determine the effect of heteroscedasticity. The ARCH-LM test was utilized to determine whether or not the residue had been standardized by exhibiting elevated ARCH. The data comprised heteroscedasticity, as each data's probability value was less than 5%, as shown in Table 4.

Table 4 Heteroskedasticity Test

Company	Prob.
ADRO	0.0232
KLBF	0.0000
ICBP	0.0000
TLKM	0.0000
UNTR	0.0375
UNVR	0.0000

Source: Data Processed in Eviews 12

The ARIMA model is then utilized with the ARCH-GARCH method to ascertain the GARCH model. Table 5 depicts the best GARCH model results for each variable, with the best model selected based on the smallest AIC value and statistically significant coefficient values.

Table 5 Overfitting GARCH models

Company	(p,q)	C	ARCH (t-1)	ARCH (t-2)	GARCH (t-1)	GARCH (t-2)	Prob.	AIC
ADRO	(1,2)	0.0000710	0.049102	-	1.438487	-0.572623	0	-4.282531
KLBF	(2,1)	0.0000207	0.228544	-0.156608	0.882464	-	0	-4.975803
ICBP	(1,1)	0.000110	0.229410	-	0.373726	-	0	-5.450766
TLKM	(2,1)	0.0000107	0.131905	-0.082523	0.918238	-	0	-5.212924
UNTR	(1,1)	0.000171	0.085283	-	0.656859	-	0	-4.513484
UNVR	(1,2)	0.0000387	0.167363	-	0.195580	0.534775	0	-5.167597

Source: Data Processed in Eviews 12

After obtaining the optimal GARCH model, a diagnostic model is executed to determine whether the model still displays heteroscedasticity. Table 6 displays the diagnostic model results using the GARCH model when all data are free of heteroscedasticity issues (greater than 5 percent).

Table 6 ARCH-LM Test

Company	Prob.
ADRO	0.1007
KLBF	0.8553
ICBP	0.9367
TLKM	0.8182
UNTR	0.8060
UNVR	0.6107

Source: Data Processed in Eviews 12

If the model can mitigate heteroskedasticity, the sign bias test is carried out to test if returns can be modeled by asymmetric distribution.

Table 7 Sign-bias Test

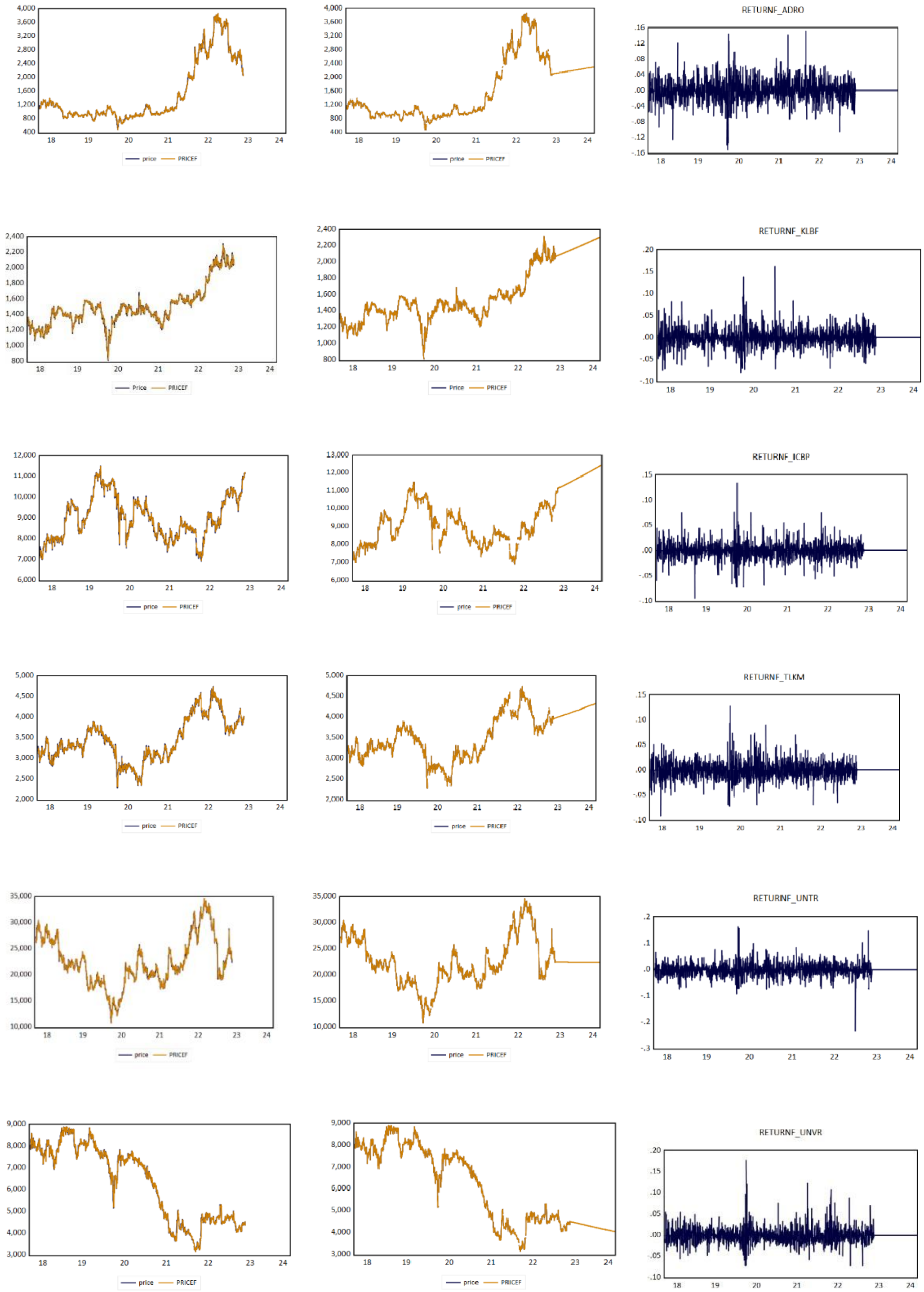
Company	Prob.			
	Sign-bias	Negative sign-bias	Positive sign-bias	Joint effect
ADRO	0.3965	0.6275	0.1417	0.4638
KLBF	0.1863	0.3462	0.3974	0.5766
ICBP	0.7175	0.2056	0.3531	0.3489
TLKM	0.8320	0.3682	0.3520	0.2202
UNTR	0.4751	0.9447	0.7832	0.8488
UNVR	0.4292	0.0855	0.5633	0.3101

Source: Data Processed in Eviews 12

Based on the sign bias test shown in Table 7 it can be seen that all the companies accept the null hypothesis because the p-value s greater than 0.05. It means the GARCH model is already specified, and the symmetric GARCH model models all the data.

$$\text{ADRO}h_t = 7.10\text{E-}5 + 0.049102\varepsilon_{t-1}{}^2 + 1.438487h_{t-1} - 0.572623h_{t-2}$$
$$\text{KLBF}h_t = 2.07\text{E-}5 + 0.228544\varepsilon_{t-1}{}^2 - 0.156608\varepsilon_{t-2}{}^2 + 0.882464h_{t-1}$$
$$\text{ICBP}h_t = 1.10\text{E-}4 + 0.229410\varepsilon_{t-1}{}^2 + 0.373726h_{t-1}$$
$$\text{TLKM}h_t = 1.07\text{E-}5 + 0.131905\varepsilon_{t-1}{}^2 - 0.082523\varepsilon_{t-2}{}^2 + 0.918238h_{t-1}$$
$$\text{UNTR}h_t = 1.71\text{E-}4 + 0.085283\varepsilon_{t-1}{}^2 + 0.656859h_{t-1}$$
$$\text{UNVR}h_t = 8.37\text{E-}5 + 0.167363\varepsilon_{t-1}{}^2 + 0.195580h_{t-1} + 0.534775h_{t-2}$$

The subsequent phase is forecasting using the above model equation. The graph below is a graph depicting the results of the forecasting procedure. The first step is forecasting-in-sample to determine whether the model is forecasting-capable. As a consequence, the sample's predicted value is close to the actual value, as depicted in the graph on the left. In addition, forecasting-out-of-sample is performed to obtain daily stock price forecasts for the next year, as shown in the image's middle row. The image on the right depicts daily returns, both actual and projected.



Source: Data Processed in Eviews 12

Figure 2 Graph of In-Sample Forecasting (Left), Out-of-sample Forecasting (Middle), and Actual & Forecasting Return (Right)

According to the predicted outcomes, the forecast result illustrates that TLKM will have the most volatile stock returns among the five other securities. It can be seen from the distribution of forecasting data, where TLKM has the highest value, 0.015812%. KLBF is the second most volatile stock, with a standard deviation of 0.012048%. UNTR, with a forecast data distribution of 0.000002%, is the stock with the most stable return volatility experience.

Research about modelling and forecasting stock return volatility in Indonesia Stock Exchange specified by symmetric GARCH model align with the research conducted by Lee & Nguyen (2017) and Awalludin et al.,(2018). If focusing in the Jakarta Islamic Index, Bisma & Mubarok (2021) also conducted the forecasting of stock return volatility of this index using GARCH model. Moreover, Bisma & Mubarok (2021) discovered that nearly all the value of stock volatility in the Jakarta Islamic Index was impacted by the error and volatility of the return from the previous day. According to this study, ICBP and UNTR volatility is affected by the error and volatility of the previous day's return. KLBF and TLKM discovered that the value of stock volatility was influenced by risk from two days prior and the return volatility of a city from one day prior. Then ADRO and UNVR, affected by errors one and two days prior, returned volatility. This study is consistent with the principle of parsimony, which suggests that simpler models are typically preferable to more complex ones in terms of out-of-sample forecasting performance. (Sharma and Vipul 2015)

CONCLUSION

This research aims to perform the best model and to know the volatility forecasting of six stock listed in Jakarta Islamic Index at the end of May 2024. The specific stock objective of this research are Adaro Energy Indonesia Tbk (ADRO), Indofood CBP Sukses Makmur Tbk (ICBP), Kalbe Farma Tbk (KLBF), PT Telkom Indonesia (Persero) Tbk (TLKM), United Tractors Tbk (UNTR) and Unilever Indonesia Tbk (UNVR). The data of this research using intraday data from 1 May 2018 until 31 May 2023. During process running data using Eviews 12, the author find that the best model for the six stock above is GARCH model since the sign-bias test result showed that all of data higher than 5%, then there is no asymmetric effect by mean EGARCH model is not required.
Based on this research, the author can conclude that:

1. The GARCH model shows that the stocks in this study have volatility clustering where stock movements tend to increase and decrease in certain periods. Modeling these stocks by GARCH model shows that ICBP and UNTR volatility is influenced by the error and volatility of the return one day before (GARCH 1, 1). In the other hand, KLBF and TLKM found that the value of stock volatility was affected by an error two days back and the return volatility one day earlier (GARCH 2, 1). Then ADRO and UNVR that affected by the error one day before and two days back return volatility (GARCH 1, 2).
2. The daily forecasting results indicate that ADRO, KLBF, ICBP and TLKM will experience an increasing price trend by the end of May 2024. While UNTR slightly decrease in the middle period but overall tends to exhibit a neutral trend, while UNVR has declined. In addition, based on the forecasting result find that TLKM shares have the highest value of stock return volatility, followed by KLBF shares, and UNTR shares have the lowest value of stock return volatility. This study's findings are significant for practitioners' decision-making when constructing a stock portfolio. These outcomes indicate that risk-takers can include TLKM or KLBF shares in their portfolios. Meanwhile, risk-averse investors can incorporate UNTR shares into their portfolios.

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