Jakarta Islamic Index Stock Volatility and Forecasting Using Realized GARCH Model

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ABSTRACT

Along with the large number of investors transacting on Islamic stocks, stock prices' movement becomes more volatile. The purpose of this research is to examine the behavior of volatility patterns in shares incorporated in the Jakarta Islamic Index using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. This study uses daily data from six stocks in the Jakarta Islamic Index during the period of January, 2009, to December, 2020. Data volatility is seen using the GARCH model. Estimation results for daily data show that the volatility of ASII, SMGR, TLKM, UNTR, and UNVR shares is influenced by the previous day's risk and return volatility. This is indicated by the GARCH effect on each regression result. The study results are beneficial for an investor, and invest with a low level of risk can choose ASII shares. Nevertheless, if going to get a high level of return can invest in UNTR shares. For securities, analysis can use the GARCH model tested to predict volatility in the Jakarta Islamic Index.

1. INTRODUCTION

Since it first appeared, many people have been interested in investing with sharia principles. In Indonesia, the number of Islamic capital market investors in 2018 was 44,536 investors, increasing to 62,840 investors in 2019. In addition to the number of investors, the market capitalization of the Islamic stock index in Indonesia continues to increase until 2019, the market capitalization of the Islamic stock index has increased by 3.02%.

Investment growth with sharia principles is developing in various countries, both with a Muslim majority and some non-Muslims(Boukhatem & Moussa, 2018; Tatiana, Igor, & Liliya, 2015). Many factors cause investment with sharia principles to be increasingly in demand, such as risk, profit-sharing rates, motivation to apply maqasid sharia, knowledge, and perceptions(Abdullah, 2015; Yesuf & Aassouli, 2020).In addition to the increasing growth of Muslims, there are also many findings stating that investment assets based on sharia principles provide a better diversification effect when compared to non-sharia investment(Hkiri, Hammoudeh, Aloui, & Yarovaya, 2017; Saiti, Bacha, & Masih, 2014).

However, Islamic investment's advantages do not make Islamic investment instruments free from risk(Robiyanto, Santoso, & Ernayani, 2019). As for investing in stocks, there is a risk of changing asset prices(Huber, Palan, & Zeisberger, 2019). Price changes can occur due to an increase or decrease in prices due to the real-time sale and purchase of stock instruments every second in the capital market, where the capital market experiences fluctuating price changes(Abraham, Cortina, & Schmukler, 2021; Wahyudi & Sani, 2014). The stock market is an excellent place to invest in the long term, but it cannot be promising in the short term because it must anticipate daily, weekly, and monthly movements of stock prices(Yildiz, Karan, & Pirgaip, 2017). Volatility is a calculation that determines the rise and fall of a stock's price.Daily, weekly, and monthly volatility can be a reference source in predicting future stock price movements (Atkins, Niranjan, & Gerding, 2018; Audrino, Sigrist, & Ballinari, 2020). Volatility can create a risk where market value is susceptible to stock prices, interest rates, and exchange rates(Byström, 2014; Mahapatra & Bhaduri, 2019).

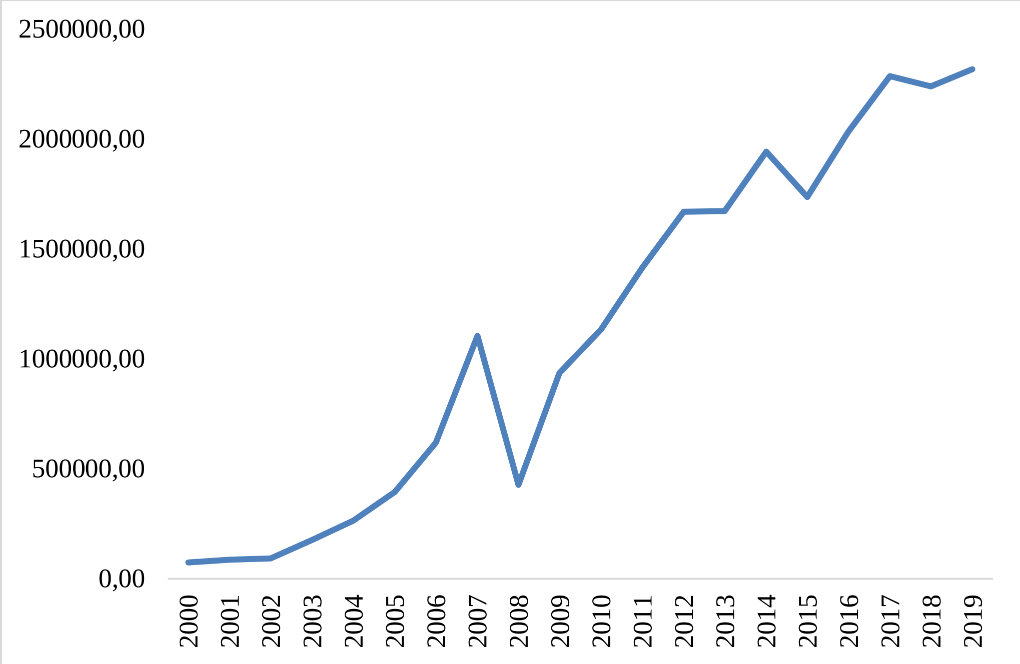


Figure 1. Growth of Sharia Stock Market Market Capitalization (in Billion Rupiahs)
(Source: Financial Services Authority, 2019)

Investors need to analyze stock price movements' volatility to get high stock returns(Tan & Tas, 2019). High data volatility can lead to the emergence of current period errors affected by previous period errors(Sugiharti, Esquivias, & Setyorani, 2020). If stock prices have high volatility and are not handled properly, it will be difficult to do calculations because the high error value is heteroscedasticity(Hong & Lee, 2017; Natarajan, Singh, & Priya, 2014).

The simple method cannot detect volatility because it has heteroscedasticity, so it requires a model that can consider these conditions with the conditional heteroscedastic model(Ismail, Audu, & Tumala, 2016; Livingston, Yao, & Zhou, 2019).The primary purpose of building a model is to make good predictions for the next volatility movement to help determine the portfolio allocation efficiently and risk management accurately(Chandrinos & Lagaros, 2018; Nayak, Pai, & Pai, 2016).

Research related to the Islamic stock index's volatility has been previously conducted by Gold, Wang, Cao, & Huang (2017) in Canada's capital markets, Nasr, Lux, Ajmi, & Gupta (2016)on the Islamic stock index in America, Oberholzer & Venter (2015)also examined the volatility of the stock market in London. In addition to the Americas and Europe, research related to stock volatility has also been studied by Abdulkarim, Akinlaso, Hamid, & Ali (2020)on Islamic stocks and crude oil prices in Africa,Ng, Chin, and Chong (2020)investigate the realized volatility transmission between the Malaysian Islamic market and various global sectoral Islamic stock markets, Lin (2018) on the stock index on the Shanghai stock exchange,Jebran, Chen, & Zubair (2017)on the Islamic and conventional indexes on the Pakistan capital market, and Birău & Trivedi (2015)on the Indian stock exchange. Not only that, but research on stock volatility has also been carried out on regional indexes, as conducted by Erdogan, Gedikli, & Çevik (2020)investigates volatility spillover effects between foreign exchange markets and Islamic stock markets in three major emerging countries, namely India, Malaysia, and Turkey, Salisu & Gupta (2019)on local indexes of BRICS(Brazil, Russia, India, China, and South Africa)countries, and Rizvi & Arshad(2017)on the global Islamic and conventional index.

No one studies the effects of volatility found on the Jakarta Islamic Index (JII) in Indonesia from the research that has been studied. One model that can overcome data volatility is using Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH). ARCH-GARCH can detect the effect of variance and squared error from its data series. ARCH-GARCH is a continuation of the Integrated Moving Average (ARIMA) autoregressive forecasting model where the model still contains heteroscedasticity, which is usually found in time-series data. The selection of the best model in ARCH-GARCH refers to the significance, the smallest error, and deviation, high correlation and fulfills the assumptions of normality and homoscedasticity to forecast the data value for the next period. Previous research has proven to solve problems in time series data in volatility and predict stock price movements using ARCH-GARCH (Abdulkarim et al., 2020; Erdogan et al., 2020; Gold et al., 2017; Jebran, Chen, & Tauni, 2017; Nasr et al., 2016; Ng et al., 2020; Salisu & Gupta, 2019). Considering that the market capitalization in JII and the number of sharia investors continue to increase, it is essential to study the patterns of volatility in the index. This study analyzes volatility and predicts stocks on the Jakarta Islamic Index (JII) using the GARCH model. This research can contribute, first, considerations for companies to anticipate existing changes. Second, predict stock movements with the right level of accuracy. Third, it helps investors analyze stock price movements' volatility to get the expected stock returns. Fourth, references for stakeholders in policymaking.

2. LITERATURE REVIEW

Changes in the price of individual shares in the market occur due to changes in supply and demand. Changes in supply and demand can occur due to rational or irrational factors. Rational factors include company performance, interest rates, inflation rates, growth rates, exchange rates, or other countries' stock price indexes, while irrational factors include rumors in the market or price play(Bertasiute, Massaro, & Weber, 2020; Tuyon & Ahmad, 2016). An increase or decrease in stock prices always makes mistakes, and usually, if the price continues to rise, there will be a decrease in price in the next period.

Overreaction occurs because of being too optimistic or pessimistic in responding to an event that affects the company's future performance(Parveen, Wajid, Abdul, & Jamil, 2020). Therefore, investors must be careful of stock price movements that rise too quickly or fall too quickly, or the term volatility of stock prices occurs. Investors' ability to predict the presence or absence of stock price volatility will affect the returns that investors will get.A highly volatile market will make it difficult for companies to raise their capital in the capital market. With the emergence of JII, it should be possible for investors to get alternative stock investments with a relatively small risk of uncertainty due to lower volatility compared to conventional stocks.

Research related to volatility has been conducted several times by various researchers globally, including research conducted byErdogan et al. (2020), examining the volatility spillover effect between the sharia stock market and the foreign exchange market found that the volatility spillover effect was only found in the Turkish sharia stock market, not with the Malaysian and Indian stock markets which were the object of research.

In addition to research conducted on the stock market in Europe and Asia, studies related to stock volatility on the Islamic index are also performed on the American continent.Nasr et al. (2016)found that because basically some of the Dow Jones Islamic Stock Market Index stocks are also in the conventional index, the Dow Jones Islamic Stock Market Index's risk and volatility characteristics are not much different from conventional ones. The Dow Jones Islamic Stock Market Index is in line with the results of researchers' testing using the Fractionally Integrated Generalized Autoregressive Conditional Heteroscedasticity (FIGARCH) model and the Fractionally Integrated Time-Varying Generalized Autoregressive Conditional Heteroscedasticity (FITVGARCH).

Abdulkarim et al. (2020), by using the Maximal Overlap Discrete Wavelet Transform (MODWT), Continuous Wavelet Transform (CWT), and multivariate Generalized Autoregressive Conditional Heteroscedasticity Dynamic Conditional Correlation (GARCH-DCC), found that almost all sharia indexes in the African continent have the advantage of diversification due to the low volatility of changes in crude oil prices.Meanwhile, Rizvi and Arshad (2017)conducted a study on global sharia, and conventional indices found that the sharia stock index tends not to be too affected by the global economic crisis, so the researchers concluded that the low systematic risk of sharia-based equity was able to offer better portfolio diversification opportunities.

Research related to volatility modeling has also been carried out on the stock market in China. Lin (2018)found that the SSE Composite Index has a time-varying and clustering pattern. This result is in line with discovering the Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) effects on the index. Saiti et al. (2014)used the Dynamic Multivariate Generalized Autoregressive Conditional Heteroscedasticity method. Researchers found that shares based on sharia principles have no leverage effect due to the upper limit of the amount of debt-based assets issued by the sharia supervisory board.

Jebran et al. (2017), using several methods to examine the transmission of volatility and the relationship between Islamic indices and conventional indices, using the Vector Error Correction Model (VECM), researchers found that there were significant short and long term relationships between the Islamic index and conventional indices, meanwhile using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) models found asymmetric bidirectional volatility spillover between sharia index and conventional index.

Babu and Reddy (2015)used partition interpolation based on the Auto-Regressive Integrated Moving Average - Generalized Autoregressive Conditional Heteroscedasticity (ARIMA-GARCH) model to predict stocks in India. The results of these models can forecast well, unlike the traditional ARIMA model. Hkiri et al. (2017)found that when the global economic crisis, assets with Islamic principles have better performance than conventional assets, this study found a time-varying pattern and testing using the GARCH model.

Birău and Trivedi (2015)estimated India's National Stock Exchange's long-term volatility using the GARCH model. The results showed that the CNX-100 index is part of the Indian NSE has a more energetic volatility pattern and a positive market trend after 2013. Vipul (2016)forecast volatility in various stock indices in the world using multiple conditional variance models. The results show that the Exponential Weighted Moving Average (EWMA) model has a superior performance in predicting volatility than the EGARCH and RGARCH models.

3. METHOD

This study uses the Jakarta Islamic Index 30 (JII 30) daily stock data from 2009 to 2020. The selection of JII 30 as the object of observation follows the sharia principles that underlie the index formation and the index's liquidity status. Six companies that never left the Sharia index 30 during the observation year, namely two companies engaged in services, namely PT. Telekomunikasi Indonesia, Tbk (TLKM) in the infrastructure, utilities, transportation sectors, and PT. United Tractors Indonesia, Tbk (UNTR) in trade, service, and investment sectors, one company in the primary and chemical industry sectors, namely PT. Semen Indonesia, Tbk(SMGR), Furthermore, three companies engaged in manufacturing consisting of one company in the different industry sectors, namely PT. Astra Internasional, Tbk (ASII), two companies in the consumer goods industry sector, namely PT. Kalbe Farma, Tbk (KLBF), and PT. Unilever Indonesia, Tbk (UNVR).

Financial data that are time series have the characteristics of extended memory, leptokurtic, volatility clustering(Boako, Agyemang-Badu, & Frimpong, 2015). The use of the Ordinary Least Square (OLS) model on data that has volatile characteristics will cause the model not to be able to explain conditions well because volatility in the data indicates changes in the mean and variance, while the OLS model requires that the mean and variation must be constant (Enders, 2004).

To overcome this, the model that can capture dynamic data is the Autoregressive Conditional Heteroscedasticity (ARCH) (Engle, 1982). Then by Bollerslev, the model was re-developed into Generated Autoregressive Conditional Heteroscedasticity (GARCH). This study analyzes volatility and predicts stocks on the JII 30 using the GARCH model. The GARCH model is a model that can function for forecasting using variance data in the previous data (t-1). Before forecasting using the variance in period t-1, researchers conduct trials first by modeling the Box-Jenkins ARIMA modeling. The aim is to determine an excellent statistical relationship between the predicted variables with the variable's historical value to forecast using the model. The Box-Jenkins ARIMA model is a model that can predict using original t-1 period data(Box, Jenkins, Reinsel, & Ljung, 2015).

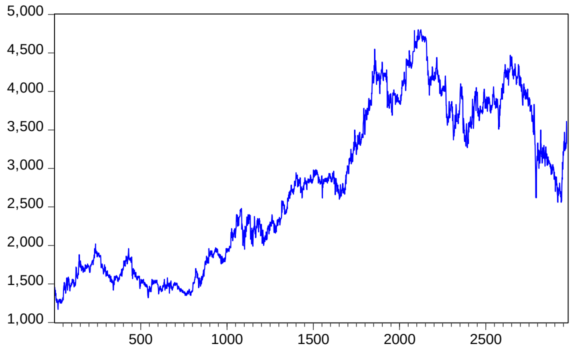
The GARCH model has several assumptions that must be met. Namely, the data must be stationary, and the data has a heteroscedasticity effect. To do a stationary test, the writer uses the Unit Root Test. The best model has been found, and the data contains heteroscedasticity through the ARCH-LM test, then the trial continues with the ARCH-GARCH model.Where h_t is variance at time t, ξ is constant variable, $\boldsymbol{e}^{\boldsymbol{2}}_{t-\mathrm{m}}$ is volatility in the previous period (ARCH term), $\propto_0$, $\propto_1$,…,$\propto_{\mathrm{m}}$ is estimated coefficient of order m, k is constant variance, $\mathrm{h}_{\mathrm{t-r}}$ is variance in the previous period (GARCH term), δ_1, δ_2,…,δ_{r} is is estimated coefficient of order r.

$$h_t = \zeta + \propto_0 \boldsymbol{e_t^2} + \propto_1 \boldsymbol{e_{t-1}^2} + \propto_2 \boldsymbol{e_{t-2}^2} + \cdots + \propto_m \boldsymbol{e_{t-m}^2} \;\; ; \;\; \text{ARCH(m)}$$

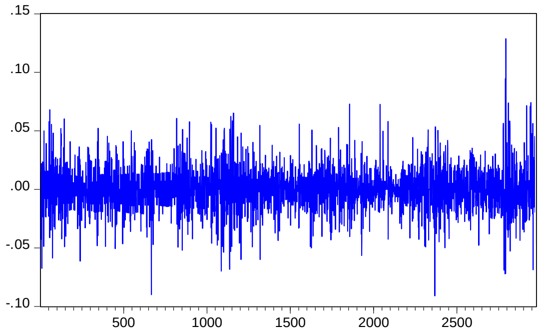
$$h_t = \mathrm{k} + \delta_1 \mathrm{h}_{t-1} + \delta_2 \mathrm{h}_{t-2} + \cdots + \delta_r \mathrm{h}_{t-r} + \propto_1 \boldsymbol{\varepsilon_{t-1}^2} + \propto_2 \boldsymbol{\varepsilon_{t-2}^2} + \cdots + \propto_m \boldsymbol{\varepsilon_{t-m}^2} \; ;\text{GARCH(r,m)}$$

4. RESULTS AND DISCUSSION

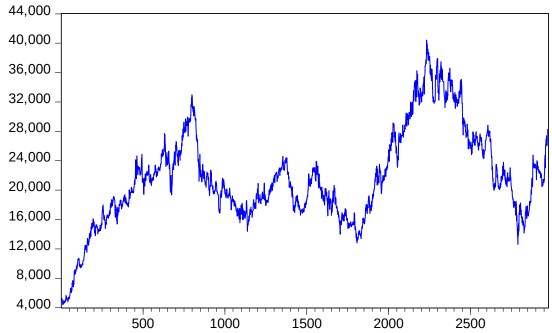
Figure 2 shows the daily price movement and the regular return movement of the observed object. Based on this picture, each of the stock returns and stocks that were the object of observation has a high volatility level In general, the six stock prices' movement shows varying volatility from time to time (time-varying volatility) and tends to cluster in specific periods. The phenomenon of volatility that is not constant over time may have a heteroscedasticity effect. Also, volatility has autocorrelation, which means the current volatility depends on past volatility.



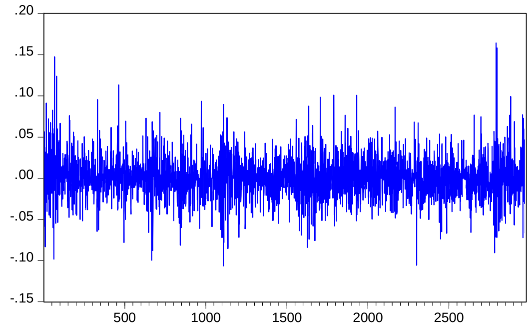
TLKMStock Price



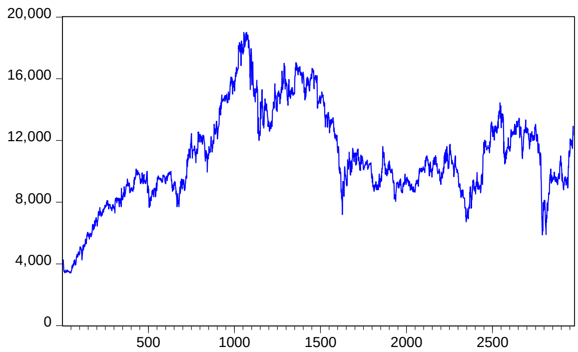
TLKM Return



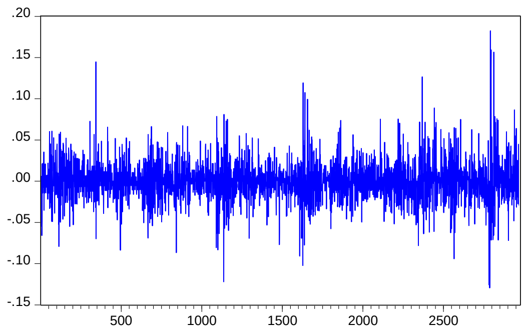
UNTRStock Price



UNTR Return



SMGR Stock Price



SMGR Return

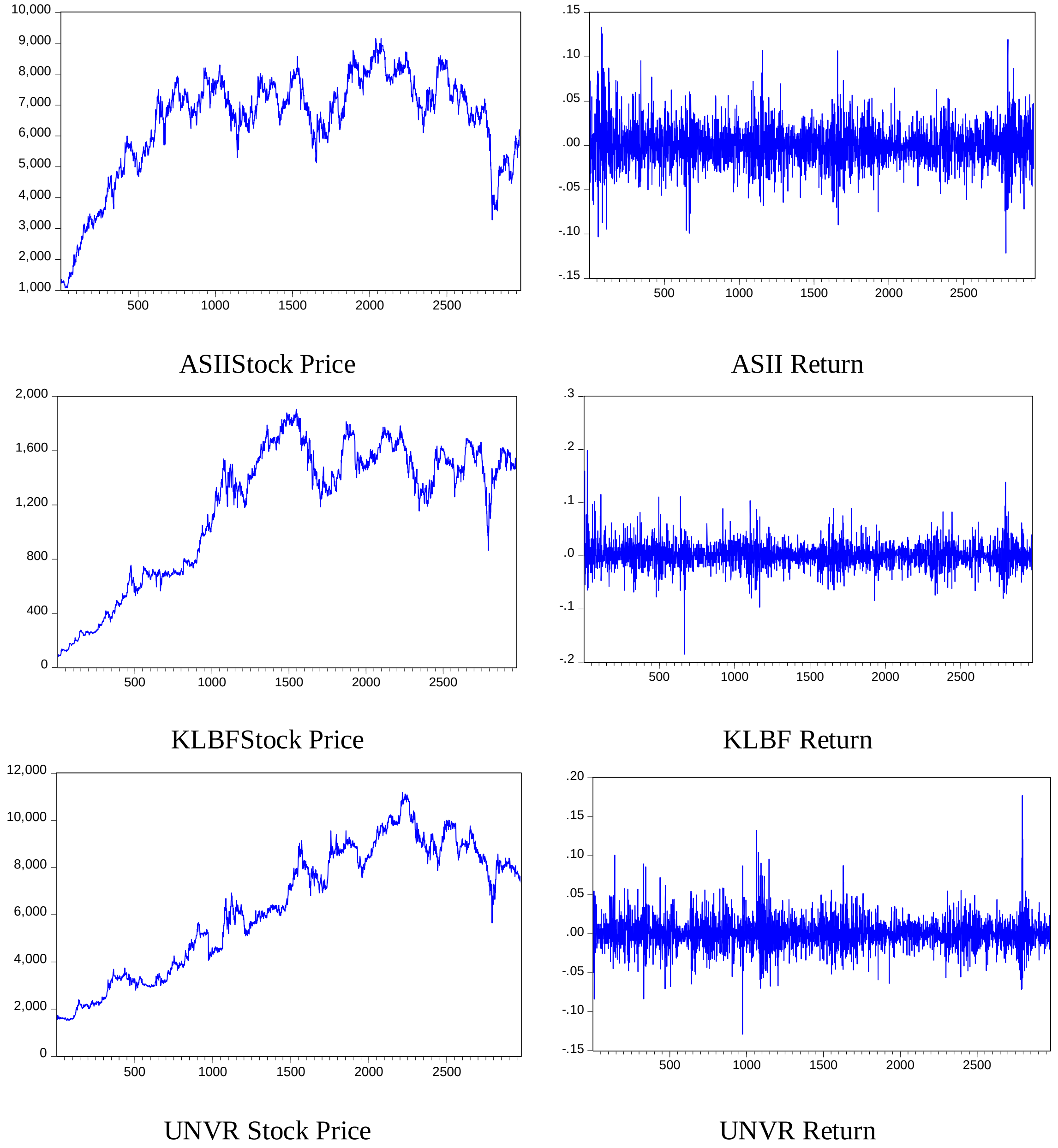


Figure 2. Stock Price and Return

Table 1 below describes the descriptive statistic where the standard deviation value of TLKM has the lowest value of 0.01851, which means it shows the smallest risk of volatility of the other five stocks. Meanwhile, KLBF stock return has the greatest return with a value of 0.19807 in line with a considerable risk of reaching 0.022362.

Table 1. Descriptive statistics

	TLKM	UNTR	SMGR	ASII	KLBF	UNVR
Mean	0.000275	0.000557	0.000364	0.000537	0.000976	0.000508
Maximum	0.128749	0.164303	0.182322	0.133531	0.19807	0.177169
Minimum	-0.09097	-0.10661	-0.12953	-0.12165	-0.18527	-0.12891
Std. Dev	0.01851	0.025087	0.023980	0.022245	0.022362	0.019371

Table 2 describes the unit root test results using the Augmented Dickey-Fuller test, where the statistical value of the Augmented Dickey-Fuller test is smaller than the critical value of 5%, which means that all data is stationary.After ensuring that the data is stationary, the next step is to determine the best ARIMA model. Table 3 shows the best ARIMA model (p, d, q) using the smallest Akaike Info Criterion (AIC) value criteria, and the probability value of each variable is significant.

Table 2. Unit root test

Company	Level	
	ADF test statistic	Prob.
TLKM	-31.60511	0.0000
UNTR	-41.05039	0.0000
SMGR	-55.57732	0.0001
ASII	-41.27728	0.0000
KLBF	-57.00215	0.0001
UNVR	-42.89779	0.0000

Table 3. Best ARIMA models (p, d, q)

Company	ARIMA (*p*,*d*,*q*)	Akaike Info Criterion	Prob.
TLKM	ARIMA (2,0,2)	-5.155265	(0,0)
UNTR	ARIMA (1,0,1)	-4.535121	(0,0)
SMGR	ARIMA (1,0,1)	-4.622726	(0,0)
ASII	ARIMA (2,0,2)	-4.777887	(0,0)
KLBF	ARIMA (1,0,1)	-4.763456	(0,0)
UNVR	ARIMA (1,0,1)	-5.061921	(0,0)

Table 4 is a heteroscedasticity test using the ARCH-LM test where the test results show the data contains heteroscedasticity because the probability value is below a significant value of 5% so that it can continue with the ARCH-GARCH Model.

Table 4. ARCH-LM Heteroscedasticity Test

Company	Prob.
TLKM	0.0000
UNTR	0.0000
SMGR	0.0000
ASII	0.0000
KLBF	0.0000
UNVR	0.0000

After getting the best GARCH model, then make a mathematical equation from the model. All models provide information about market prices affecting the stock price index's volatility along with the previous day's standard deviation value. The stock price model of each stock index is as follows.

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$$TLKMh_t = 2.26\text{E-5} + 0.115741\varepsilon_{t-1^2} + 0.816961\text{h}_{t-1}$$

$$\text{UNTRh}_t = 3.42\text{E-5} + 0.076578\varepsilon_{t-1^2} + 0.867553\text{h}_{t-1}$$

$$\text{SMGR}_t = 3.10\text{E-5} + 0.203152\ \varepsilon_{t-1^2} + 0.841426\text{h}_{t-1}$$

$$\text{ASII}_t = 8.40\text{E-6} + 0.052885\ \varepsilon_{t-1^2} + 0.928813\text{h}_{t-1}$$

$$\text{KLBF}_t = 6.06\text{E-6} + 0.202381\ \varepsilon_{t-1^2} - 0.151409\varepsilon_{t-2^2} + 0.936691\text{h}_{t-1}$$

$$\text{UNVR}_t = 1.82\text{E-5} + 0.112475\ \varepsilon_{t-1^2} + 0.838337\text{h}_{t-1}$$

Table 5. Best GARCH Model (p,q)

Company	(p,q)	C	ARCH (t-1)	ARCH (t-2)	GARCH (t-1)	Prob	AIC
TLKM	(1,1)	0.0000226	0.115741	-	0.816961	0	-5.280545
UNTR	(1,1)	0.0000342	0.076578	-	0.867553	0	-4.623550
SMGR	(1,1)	0.0000310	0.103152	-	0.841426	0	-4.792180
ASII	(1,1)	0.00000840	0.052885	-	0.928813	0	-4.21477
KLBF	(2,1)	0.00000606	0.202381	-0.151409	0.936691	0	-4.972909
UNVR	(1,1)	0.0000182	0.112475	-	0.838337	0	-5.257114

After obtaining the best GARCH model, a diagnostic model is carried out, aiming to check whether the model still has heteroscedasticity. Table 6 shows the diagnostic model results where all data are free from heteroscedasticity problems (greater than 5%) when using the GARCH model.

Table 6. Diagnostic Model

Company	Heteroscedasticity
TLKM	0.0853
UNTR	0.7313
SMGR	0.2869
ASII	0.2927
KLBF	0.7955
UNVR	0.0941

After obtaining the best ARCH-GARCH model, the next step is to forecast stock return volatility using the selected ARCH-GARCH model. Forecasting results are converted to monthly for 60 months for simpler results. The forecast results are shown in Figure 3, and Figure 4 shows that stock returns' volatility has two phases, namely the stable phase and the surge phase. The stable phase indicates the absence of volatility in the company's stock return, while the spike phase indicates volatility in its stock return.

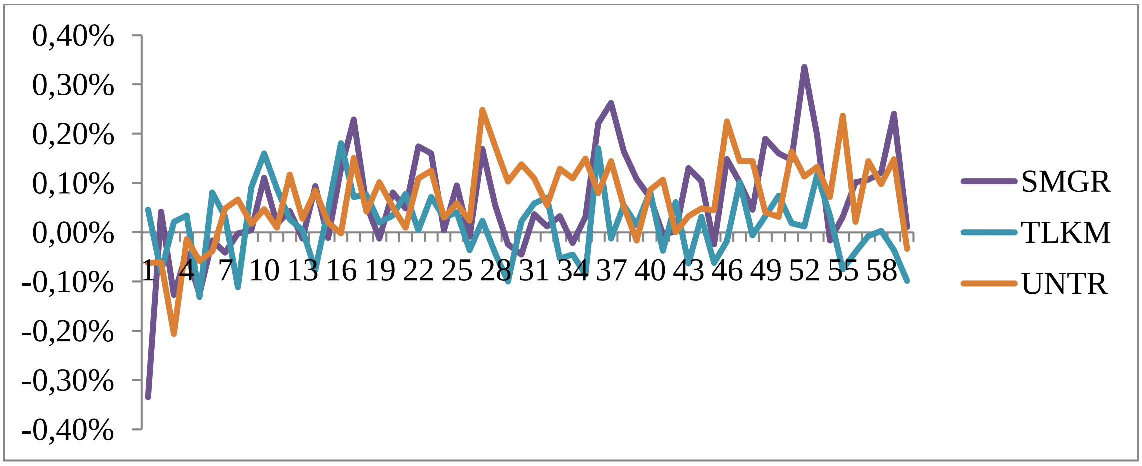

Figure 3. Prediction of the Volatility of Stock Returns of Each Company

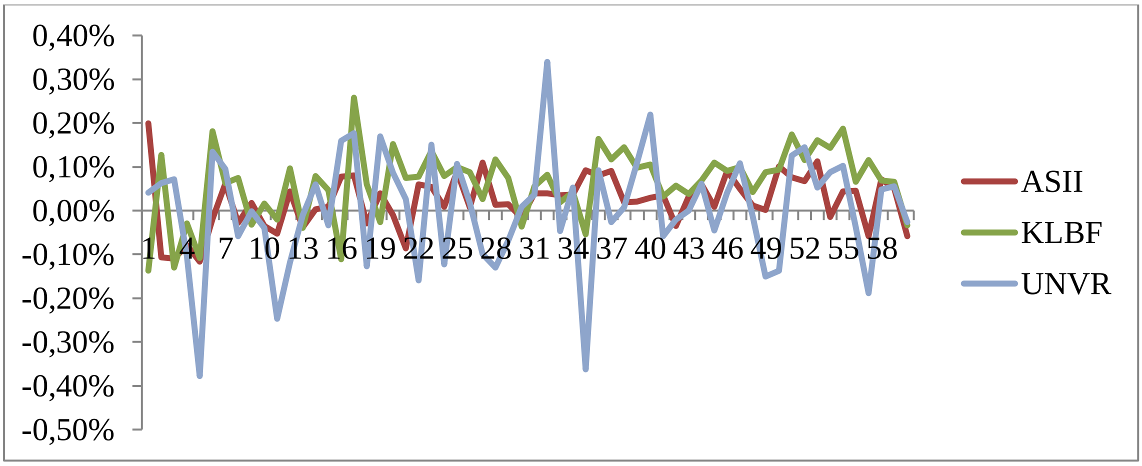

Figure 4. Prediction of the Volatility of Stock Returns of Each Company

The forecast results show that stock returns from UNTR will have the most volatile stock returns among the five other stocks. These results can be seen from forecasting data distribution, where UNVR has the greatest value, namely, 0.1289%. Not only that, the difference in the forecasting value of the UNTR return volatility between the maximum value and the minimum or the most considerable range is UNTR with 0.7176%.Meanwhile, the stock with the most stable return volatility experience is ASII, with a forecast data distribution of 0.0605%. The difference in value between the maximum and minimum return volatility forecasting value or the range is 0.3159%.

Research using the GARCH model to model volatility patterns on stocks is in line with previous studies on the same problem as the research conducted by Birău and Trivedi (2015). The results show that stocks on the Jakarta Islamic Index have characteristics such as volatility clustering and leptokurtosis. Volatility clustering occurs when large changes follow significant changes in stock returns in stock returns, and small changes follow small changes in stock returns in stock returns. Leptokurtosis means that the distribution of the stock returns is not normal. In other words, leptokurtosis indicates the possibility that there is a high value for the extreme value rather than the prediction in a series.This characteristic is very reasonable to be found in its financial time series data. This characteristic was also found in some previous studies, such as the research conducted byBoako, Agyemang-Badu, and Frimpong (2015). From testing the GARCH model, it was found that almost all the value of stock volatility in the Jakarta Islamic Index was influenced by the error and volatility of the return one day before. The Islamic stock index is beautiful because the market capital index is still tiny, so there is plenty of room for listed stocks to enter the JII index. Public awareness of Islamic stocks is increasing, so that many investors are starting to be interested in halal or haram to collect halal shares. The prospect of the Islamic stock index is attractive for investors to observe because the stocks listed in the Jakarta Islamic Index have performed well. Also, issuers listed on the sharia index are issuers that have healthy debt. Shares included in the Islamic index have a ratio between total debt based on interest compared to total assets of not more than 45% and a ratio between total interest income and non-halal income compared to the total income of not more than 10%. Investors can carry out accumulated purchases for stocks in the JII index if they want to invest for the long term, but if investors want to invest for the short and medium-term, investors should wait and see first because there is still market sentiment.

Only the KLBF shares found that the value of stock volatility was affected by an risk two days back and the return volatility one day earlier. The KLBF shares are because the robust model for modeling KLBF stock volatility is the GARCH model (2,1). The diagnostic test results show that the GARCH model tested passed the ARCH-LM test and serial correlation test, indicating that the GARCH model was correctly determined. This result is in line with the same research model by Erdogan et al. (2020).

5. CONCLUSION

This study aims to analyze the volatility of stock returns on the Jakarta Islamic Index 30. A total of six companies were analyzed. The six companies are PT. Telekomunikasi Indonesia, Tbk (TLKM), PT. United Tractors Indonesia, Tbk (UNTR), PT. Semen Indonesia, Tbk (SMGR), PT. Astra Internasional, Tbk (ASII), PT. Kalbe Farma, Tbk (KLBF), and PT. Unilever Indonesia, Tbk (UNVR). The results show that the volatility of ASII, SMGR, TLKM, UNTR, and UNVR stocks is influenced by risk and return volatility on the previous day. Meanwhile, KLBF shares are influenced by the risk on the previous two days and the return volatility on the previous day. If we look at the descriptive statistic table, KLBF shares have the highest risk of volatility.

The results show that in the next 60 months, UNVR shares have the most considerable stock return volatility value, while ASII shares have the lowest stock return volatility value. These results indicate that investors who are risk-takers can enter UNTR shares into their portfolio. Meanwhile, investors who are risk averters can enter ASII shares into their portfolios. The high volatility in UNVR is unique because the nature of UNVR shares is engaged in the consumer sector, a relatively stable sector. However, UNVR's share ownership based on the public expose shows that 85% of the majority of shares are owned by foreign investors where the portfolio is the Indonesian capital market and global so that there can be a change in position if the Indonesian stock exchange is volatile. Researchers recommend that investors and securities analysis assess and predict the volatility of the Jakarta Islamic Index 30. So it can calculate the right level of risk if investors want to form an optimal portfolio containing shares from the Jakarta Islamic Index.

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