Al-Tijary
Jurnal Ekonomi dan Bisnis Islam

2020, Vol. 6, No. 1, Hal. 17 – 30

P-ISSN: 2460-9404; E-ISSN:2460-9412
doi:http://dx.doi.org/10.21093/at.v6i1.2468

Modeling of Jakarta Islamic Index Stock Volatility Return Pattern with Garch Model

Faizul Mubarok
UIN Syarif Hidayatullah
fayzmubarok@uinjkt.ac.id

Muhammad Faturrahman Aria Bisma
UIN Syarif Hidayatullah
faturariab@gmail.com

Abstract

Along with the large number of investors transacting on Islamic stocks, the movement of stock prices 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 contained in the Jakarta Islamic Index during the period January 1, 2009, to December 31, 2019. 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 error and return volatility of the previous day. This is indicated by the GARCH effect on each regression result. The results of the study are beneficial for an investor, and if you want to invest with a low level of risk, you can choose TLKM shares. But if you're going to get a high level of return, you can invest in UNTR shares. For securities analysis, you can use the GARCH model that has been tested to predict volatility in the Jakarta Islamic Index.

Keywords: GARCH, Volatility, Jakarta Islamic Index, Return, Stock

INTRODUCTION

Since the beginning of its emergence, investment using Islamic principles has been quite attractive to many circles. In Indonesia, the number of sharia capital market investors increased by 41% in 2019, and the number of sharia capital market investors in 2018 was 44,536, to 62,840 investors in 2019. Besides the number of investors, the market capitalization of sharia stock indexes in Indonesia continues to increase, from the beginning of its emergence in 2000, the market capitalization of the sharia stock index in 2019 has increased by 3,022%.

Investment growth using sharia principles is not only developing and emerging in Muslim-majority countries but also in countries with a majority of non-Muslims (Boukhatem & Moussa, 2018). Many factors cause investment with sharia principles to be increasingly in demand, in addition to increasing Muslim growth there are too many findings that say investment assets that are based on sharia principles, provide a better diversification effect than investments with general laws (Hkiri, Hammoudeh, Aloui, & Yarovaya, 2017; Saiti, Bacha, & Masih, 2014).

However, this advantage does not make sharia-based investment instruments risk free (Robiyanto, Santoso, & Ernayani, 2019). One of the risks of investing, especially in stocks, is changes in asset prices (Huber, Palan, & Zeisberger, 2019). This price change can occur with an increase in rate or a decrease in price caused by the sale and purchase of stock instruments in real-time every second on the capital market—the stock market experiences fluctuating price changes every day (Wahyudi & Sani, 2014). In the long run, the stock market is a promising place to invest, but in the short term, there are daily, weekly, and monthly stock prices that need to be anticipated (Yildiz, Karan, & Pirgaip, 2017). Daily, weekly and monthly volatility can be a source of reference to predict how the next stock price will move (Tan, Yan, & Zhu, 2019). This volatility creates a risk where market value is sensitive to changes in stock prices, interest rates, and the exchange rate (Byström, 2014; Mahapatra & Bhaduri, 2019).

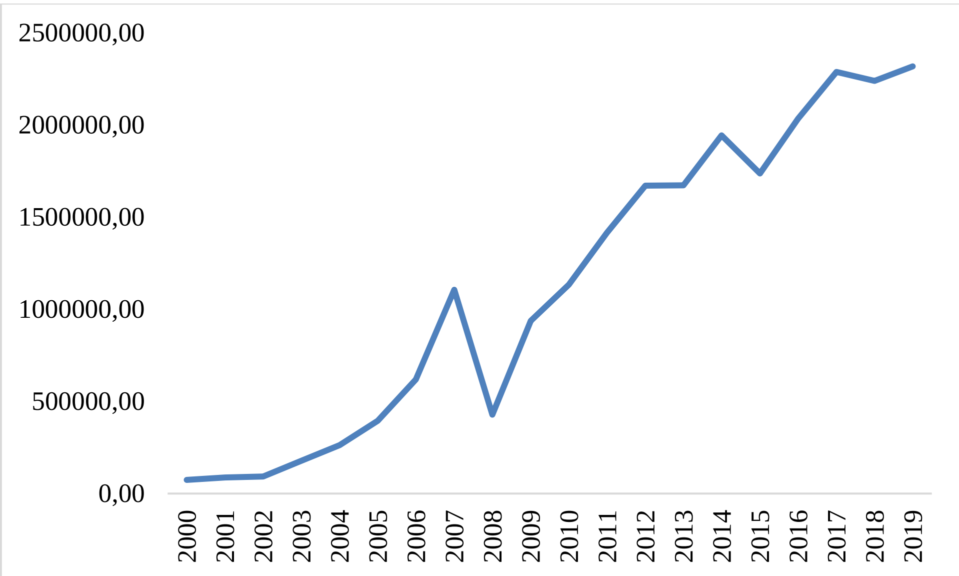


Figure 1 Growth of Sharia Stock Market Market Capitalization (in Billion Rupiahs) (Source: Financial Services Authority, 2019)

For investors, it is essential to analyze the volatility of stock price movements to get high stock returns (Tan & Tas, 2019). High data volatility can lead to the emergence of current period errors that are affected by previous period errors (Sugiharti, Esquivias, & Setyorani, 2020). If this is not handled, it will be difficult to estimate, because there is a high error value (Natarajan, Singh, & Priya, 2014). This happens because data with high volatility usually has heteroscedasticity (Hong & Lee, 2017).

Volatility cannot be observed with a simple method, because it has heteroscedasticity (Ismail, Audu, & Tumala, 2016). Various models have been created to estimate volatility, one of which is widely known is the conditional heteroscedastic model (Livingston, Yao, & Zhou, 2019). The main objective of building this model is to make good predictions for further volatility movements, which can help determine portfolio allocations more efficiently and more accurate risk management (Chandrinos & Lagaros, 2018; Nayak, Pai, & Pai, 2016).

One application of modeling volatility in the real world is the Capital Asset Pricing Model (CAPM). According to Bodie, Kane, and Marcus , CAPM is a model that describes the relationship between systematic risk and expected return on assets. This model can be used as a reference to whether an investment is feasible (Bodie, Kane, & Marcus, 2008). Expectations of higher returns must accompany additional risks contained in finance. The CAPM model suggests that assets with a high degree of sensitivity to market volatility should have higher return expectations (Southall, 2008).

Research related to the volatility of the Islamic stock index has been previously conducted by Nasr, Lux, Ajmi, & Gupta (2016) on the Islamic stock index in America. Then by Gold, Wang, Cao, & Huang (2017) in the capital markets in Canada. 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, Jebran, Chen, & Zubair (2017) on the Islamic and conventional indexes on the Pakistan capital market. Lin (2018) on the stock index on the Shanghai stock exchange. 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 Salisu & Gupta (2019) on local indexes of BRICS countries (Brazil, Russia, India, China, and South Africa). Then Erdogan, Gedikli, & Çevik (2020) on the Islamic stock index and foreign exchange markets in Turkey, India, Malaysia. And Rizvi & Arshad (2017) on the global Islamic and conventional index.

From the research that has been studied, no one studies the effects of volatility found on the Jakarta Islamic Index (JII) in Indonesia. 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 research can contribute, first, consideration for business entities in anticipating changes. Second, the results of this study predict stock movements with reasonable accuracy using a different approach. Third, this research is also a reference for stakeholders in determining policy. Fourth, this study is useful for investors in analyzing the volatility of stock price movements to obtain the expected stock returns.

LITERATURE REVIEW

Research related to volatility has been conducted several times by various researchers in the world, including research conducted by Erdogan, Gedikli, and Cevic a study 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 (Erdogan et al., 2020). This study uses the Generalized Autoregressive Conditional Heteroscedasticity or GARCH (1,1) model.

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, Lux, Ajmi, and Gupta found that because basically some of the stocks contained in the Dow Jones Islamic Stock Market Index are also in the conventional index, the risk and volatility characteristics of the Dow Jones Islamic Stock Market Index are not much different from conventional ones (Nasr et al., 2016). This is in line with the results of researchers' testing by using the Fractionally Integrated Generalized Autoregressive Conditional Heteroscedasticity (FIGARCH) model and the Fractionally Integrated Time-Varying Generalized Autoregressive Conditional Heteroscedasticity (FITVGARCH).

Abdulkarim, Akinlaso, Hamid, and Ali 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 (Abdulkarim et al., 2020). Meanwhile, Rizvi and Arshad 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 (Rizvi & Arshad, 2018).

Research related to volatility modeling has also been carried out on the stock market in Chin a.Lin found that the SSE Composite Index, has a time-varying and clustering pattern, this result is in line with the discovery of the Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) effects on the index (Lin, 2018). Saiti, Bacha and Masih used the Dynamic Multivariate Generalized Autoregressive Conditional Heteroscedasticity method (Saiti et al., 2014). 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, Chen and Tauni, 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 (Jebran et al., 2017).

Babu and Reddy using partition interpolation based on the model 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 (Babu & Reddy, 2015). Hkiri, Hammoudeh, Aloui and Yarovaya 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 (Hkiri et al., 2017).

Birau and Trivedi estimated the long-term volatility on the National Stock Exchange of India 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 (Birău & Trivedi, 2015). Vipul and Sharma 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 compared to the EGARCH and RGARCH models (Vipul & Sharma, 2016).

METHOD

The data used are shares contained in the Jakarta Islamic Index 30 (JII 30) from 2009 to 2019 daily. The selection of JII 30 as an object of observation is based on sharia principles that underlie the formation of the index and the liquidity status of the index. Six companies that never left the Sharia index 30 during the observation year, namely four 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), and one company in the primary and chemical industry sectors, namely PT. Semen Indonesia, Tbk. (SMGR). Then there are two companies engaged in services, namely PT. Telekomunikasi Indonesia, Tbk (TLKM) in the infrastructure, utilities, and transportation sectors, and PT. United Tractors Indonesia, Tbk (UNTR) is located in the trade, service, and investment sectors.

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). So in the research that aims to see and model the volatility patterns on stocks contained in the JII 30 index, this study uses the GARCH model. GARCH model is a model that can be used for forecasting using variance data in period t-1. Before forecasting using the variance in period t-1, researchers conduct trials first by modeling the Box-Jenkins ARIMA modeling. The Box-Jenkins ARIMA model is a model that can predict using original t-1 period data (Box, Jenkins, Reinsel, & Ljung, 2015).

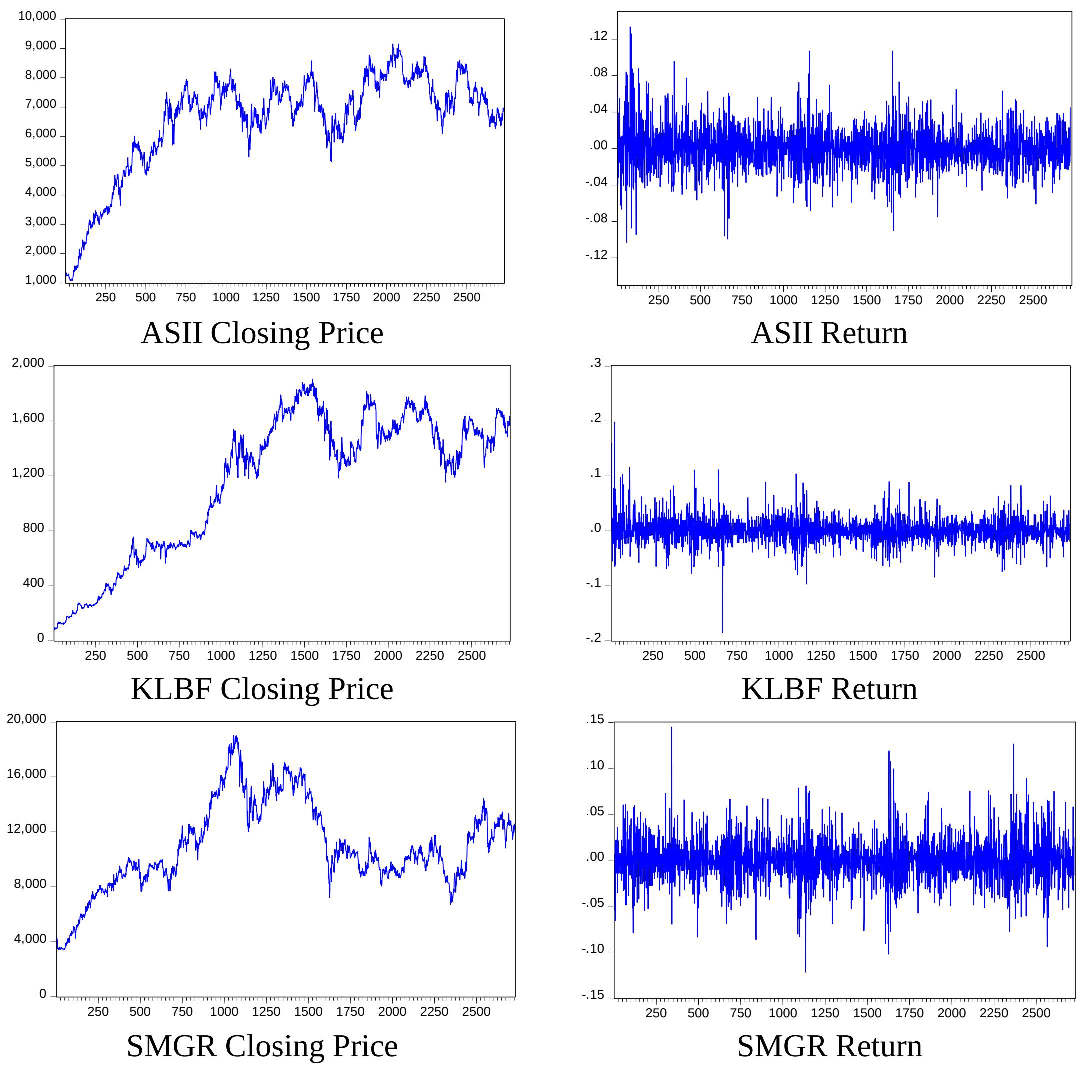
The GARCH model has several assumptions that must be met. Namely, the data must be stationary, and the data has a heteroscedasticity effect. To do a stationary test, the writer uses the Unit Root Test. Before doing the ARCH and GARCH models, the author first determines the Box-Jenkin ARIMA model. The best model has been found, and the data contains heteroscedasticity through the ARCH-LM test, then the trial continues with the ARCH-GARCH model.

$$h_t = \propto_t + \propto_1 \boldsymbol{e}^2_{t-1} + \propto_2 \boldsymbol{e}^2_{t-2} + \cdots + \propto_n \boldsymbol{e}^2_{t-n}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \propto_t u^2_{t-1} + \sum_{j=1}^{q} \beta_j \sigma^2_{t-j}$$

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 level of volatility. In general, the movement of the seven variables above shows a significant change in return followed by a difference in a more substantial performance and a change in a small return followed by a change in a more modest return also in the next period, or commonly referred to as time-varying volatility.



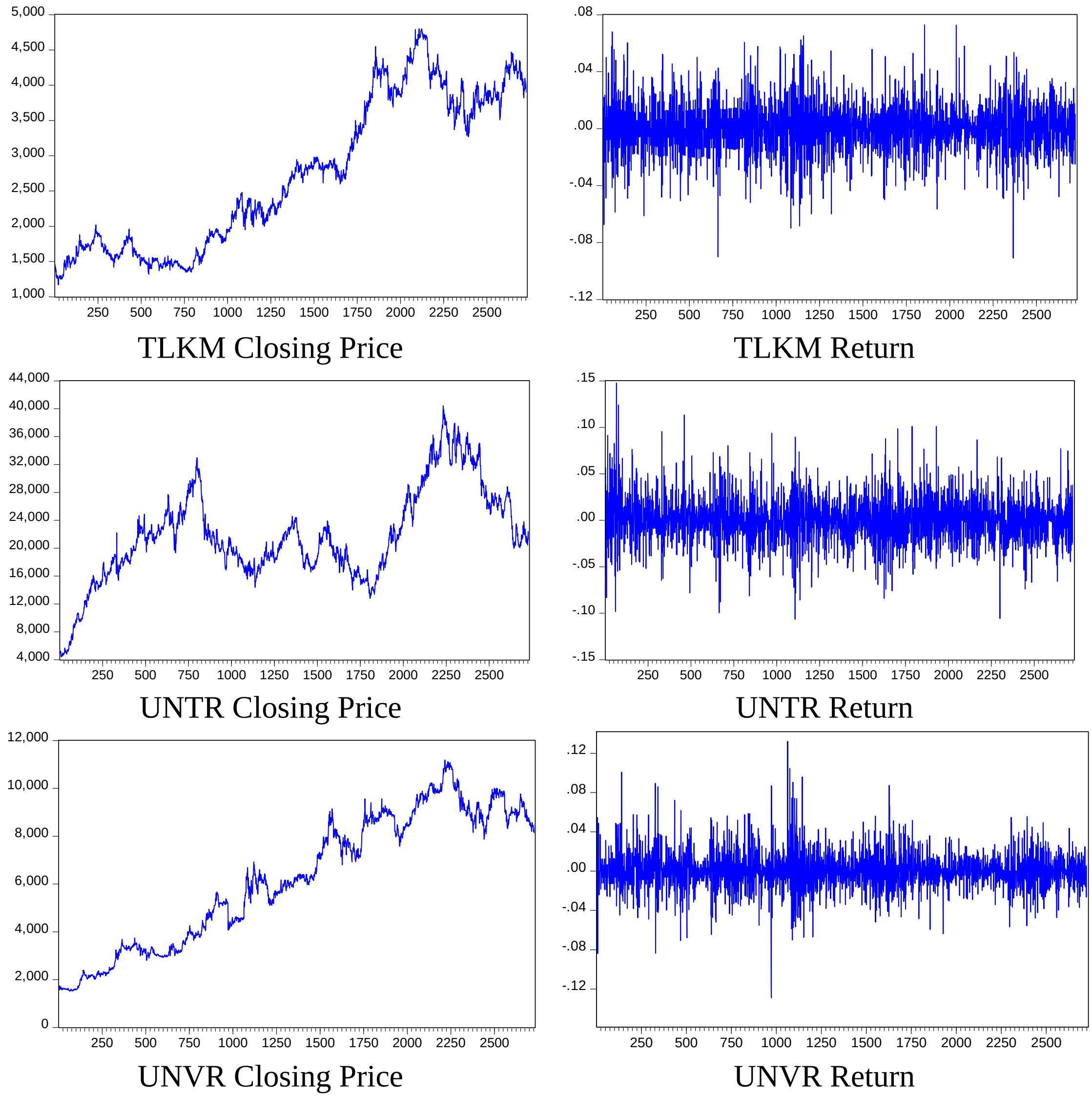


Figure 2. Stock Price and Return

Table 1, we can find that TLKM has the lowest data distribution; this shows that the data has the lowest volatility risk value compared to the other six stocks. Meanwhile, UNTR has the highest Maximum value of 0.14743. This indicates that within one day, the return from UNTR can reach 14,763%. Still, this high return is in line with high risk as well, UNTR has a value of data distribution or risk of 0.02427 or up to 2,427%, the biggest among other variables.

Table 1. Descriptive statistics

	ASII	KLBF	SMGR	TLKM	UNTR	UNVR
Mean	0.000635	0.001096	0.000384	0.000366	0.000529	0.000602
Maximum	0.133531	0.19807	0.144831	0.072925	0.147636	0.132172
Minimum	-0.10325	-0.18527	-0.12202	-0.09097	-0.106610	-0.128914
Std. Dev	0.021344	0.021786	0.022489	0.017638	0.024274	0.018871

From the unit root test using Augmented Dickey-Fuller (Table 2), it can be seen that the value of the Augmented Dickey-Fuller Test Statistics is smaller than the value of the critical values test at the 5% level) meaning that from this test it is found that all variables are stationary.

Table 2. Unit root test

Variable	Level	
	ADF test statistic	Prob*
ASII	-33.30286	0.0000
KLBF	-55.03628	0.0000
SMGR	-53.56912	0.0000
TLKM	-31.07779	0.0000
UNTR	-39.17189	0.0000
UNVR	-34.19500	0.0000

After ensuring the stationary data, the next step is to determine the best ARIMA model. After overfitting, Table 3 shows the best ARIMA model (p, d, q) with the criteria of having the smallest Akaike Info Criterion (AIC) value and the probability value of each significant variable.

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

Variable	ARIMA (*p*,*d*,*q*)	Akaike Info Criterion	Prob.
ASII	ARIMA (2,0,2)	-4.861780	(0,0)
KLBF	ARIMA (1,0,1)	-4.816387	(0,0)
SMGR	ARIMA (1,0,1)	-4.753522	(0,0)
TLKM	ARIMA (4,0,3)	-5.243202	(0,0)
UNTR	ARIMA ((2,0,3)	-5.248834	(0,0)
UNVR	ARIMA (1,0,1)	-5.113370	(0,0)

The results of heteroscedasticity testing (Table 4) using the ARCH-LM test found that the data contained heteroscedasticity because the probability value of the F Statistic was 0.0000 - 0.0001 below the significant amount of 0.05. So the data can be continued with the ARCH-GARCH Model test.

Table 4. ARCH-LM Heteroscedasticity Test

Variable	Prob.
ASII	0.0000
KLBF	0.0000
SMGR	0,0000
TLKM	0,0000
UNTR	0,0001
UNVR	0.0000

The results of selecting the best GARCH model for each variable (Table 5). The selection of the best model is based on the smallest AIC value and the significant coefficient value.

$$\text{ASIIh}_t = 5.74\text{E-}6 + 0.040143\ \varepsilon_{t-1^2} + 0.94601\text{h}_{t-1}$$

The ASII model provides information that the level of ASII stock risk is influenced by the amount of return value the previous day and the standard deviation of the average for the last day.

$$\text{KLBFh}_t = 4.64\text{E-}6 + 0.201118\ \varepsilon_{t-1^2} - 0.161579\ \varepsilon_{t-2^2} + 0.950452\text{h}_{t-1}$$

The KLBF model provides information that the risk level of KLBF shares is influenced by the amount of return value of two days before and the amount of standard deviation of the average for the previous day.

$$\text{SMGRh}_t = 3\text{E-}5 + 0.09051\varepsilon_{t-1^2} + 0.850636\text{h}_{t-1}$$

The SMGR model provides information that the risk level of SMGR shares is influenced by the amount of return value the day before and the amount of standard deviation of returns from the average for the previous day.

$$\text{TLKMh}_t = 2.58\text{E-}6 + 0.110825\varepsilon_{t-1^2} + 0.805676\text{h}_{t-1}$$

The TLKM model provides information that the level of TLKM stock risk is influenced by the amount of return value the day before and the amount of standard deviation of return from the average for the previous day.

$$\text{UNTRh}_t = 3.02\text{E-}5 + 0.063057\varepsilon_{t-1^2} + 0.884177\text{h}_{t-1}$$

The UNTR model provides information that the level of risk of UNTR shares is influenced by the amount of return value the day before and the amount of standard deviation of the average for the previous day.

$$\text{UNVRh}_t = 1.92\text{E-}5 + 0.101807\ \varepsilon_{t-1^2} + 0.844605\text{h}_{t-1}$$

The UNVR model provides information that the risk level of UNVR shares is influenced by the amount of return value the day before and the amount of standard deviation of return from the average for the previous day.

Table 5. Overfitting Model GARCH (p,q)

	(p,q)	C	ARCH *(t-1)*	ARCH (*t*-2)	GARCH (t-1)	Prob	AIC
ASII	(1,1)	0,00000574	0.040143	-	0.94601	0	-4.981019
KLBF	(2,1)	0.00000464	0.201118	-0.161579	0.950452	0	-5.00668
SMGR	(1,1)	0.00003	0.09051	-	0.850636	0	-4.84947
TLKM	(1,1)	0.0000258	0.110825	-	0.805676	0	-5.32657
UNTR	(1,1)	0.0000302	0.063057	-	0.884177	0	-4.66679
UNVR	(1,1)	0.0000192	0.101807	-	0.844605	0	-5.25337

Testing the accuracy of the model to capture errors was tested with three test equipment, namely the ARCH-LM Test to examine whether there is still a heteroscedasticity effect on the error, Correlogram Q Statistics test to check whether the data is autocorrelated or not and Kurtosis test to see the distribution of errors. ARCH-LM test results found that the data did not contain heteroscedasticity effects after GARCH modeling. Correlogram Q Statistics test results found that the error was random, or the residual value was random. The normality test results by looking at kurtosis values indicate that the error distribution did not normally spread.

Table 6. Diagnostic Model

Heteroscedasticity	Autocorrelation	Normality
0.4161	0.642	4.517665
0.8058	0.344	7.254428
0.1418	0.166	6.130655
0.0954	0	4.83811
0.6415	0.559	4.881869
0.8	0.065	9.602536

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 Birau and Trivedi (Birău & Trivedi, 2015). The results show that stocks on the Jakarta Islamic Index have characteristics such as volatility clustering and leptokurtosis. 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 by Boako, Aegyamang-Badu and Frimpong (Boako et al., 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. Only the KLBF shares found that the value of stock volatility was affected by an error two days back, and the volatility of the return one day earlier. This is because the robust model for modeling KLBF stock volatility is the GARCH model (2,1). The results of diagnostic tests 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, Gedikli, and Cevic (Erdogan et al., 2020).

Table 7. Prediction of Return in the Following Month

Month	Prediction of Return	Month	Prediction of Return
1	0.29%	13	-0.02%
2	-0.14%	14	0.00%
3	-0.15%	15	-0.01%
4	-0.10%	16	0.09%
5	-0.13%	17	0.08%
6	-0.01%	18	-0.03%
7	0.06%	19	0.04%
8	-0.03%	20	-0.01%
9	0.02%	21	-0.10%
10	-0.06%	22	0.06%
11	-0.04%	23	0.06%
12	0.02%	24	0.00%

The Jakarta Islamic Index (JII) index consists of 30 stocks based on sharia principles that have high liquidity and sound financial performance. The number of Islamic stocks is 415, but 30 JII can be the leading stocks with principles that do not deviate from Islam. Like stock movements in general, JII is also affected by the sentiment that occurs globally and locally. The global sentiment that can influence the JII movement is the relationship between the United States (US) and China. Meanwhile, from local sentiment, the Central Statistics Agency (BPS) announced Indonesia's trade balance data (Trade Balance) for September with a US $ 160 million deficit. The next sentiment came from foreign investors who still tend to sell shares. Foreign investors have sold 2.5 trillion rupiahs of shares on the stock market. The figure even becomes 3.33 trillion rupiahs when added with transactions on the negotiable and cash markets.

However, the Jakarta Islamic Index (JII) has increased by 5.81% from the beginning of 2021 or greater than the strengthening of the Composite Stock Price Index (IHSG), which increase rise 4.66%, and the LQ45 index, which grew 4.75%. JII has strengthened higher due to the increase in the mining sector, which has a smaller weight on the JCI, but significantly in JII. Mining share prices have strengthened due to the sentiment of nickel commodity prices and the potential for excellent nickel demand in the future as raw material for electric batteries for electric vehicles (EV) and renewable energy materials.

CONCLUSION

Estimation results for daily data show that the volatility of ASII, SMGR, TLKM, UNTR, and UNVR shares is influenced by the error and return volatility of the previous day. This is indicated by the GARCH effect on each regression result. Meanwhile, KLBF shares were affected by the error of 2 previous periods and the volatility of the last day's return. If you look at the descriptive statistics table, then UNTR shares have the highest volatility risk, but also have the highest rate of return among all stocks tested.

The results of the study are beneficial for an investor, and if you want to invest following Islamic principles with a low level of risk, you can choose TLKM shares.

Observations show that TLKM shares have a lower standard deviation distribution than the other five Islamic stocks. But if you want to get a high level of return, you can invest in UNTR shares. For security analysis, it can use the GARCH model that has been tested to predict the volatility of the Jakarta Islamic Index. So it can calculate the right level of risk if you want to form an optimal portfolio containing shares from the Jakarta Islamic Index.

REFERENCES

Abdulkarim, F., Akinlaso, M., Hamid, B. A., & Ali, H. (2020). The Nexus between Oil Price and Islamic Stock Markets in Africa: A Wavelet and Multivariate-GARCH Approach. *Borsa Istanbul Review*, *20*(2), 108–120. https://doi.org/10.1016/j.bir.2019.11.001

Babu, N., & Reddy, E. (2015). Prediction of Selected Indian Stock Using a Partitioning–Interpolation Based ARIMA–GARCH Model. *Applied Computing and Informatics*, *11*(2), 130–143. https://doi.org/10.1016/j.aci.2014.09.002

Birău, R., & Trivedi, J. (2015). Estimating Long-term Volatility on National Stock Exchange of India. *Procedia Economics and Finance*, *32*(15), 574–579. https://doi.org/10.1016/s2212-5671(15)01434-3

Boako, G., Agyemang-Badu, A., & Frimpong, J. M. (2015). Volatility Dynamics In Equity Returns : A Multi-GARCH Approach. *European Journal of Business and Innovation Research2*, *3*(4), 36–45. https://doi.org/10.1017/CBO9781107415324.004

Bodie, Z., Kane, A., & Marcus, A. (2008). *Essential Of Investments 7th Edition*. New York: The McGraw-Hill.

Boukhatem, J., & Moussa, F. Ben. (2018). The Effect of Islamic Banks on GDP Growth: Some Evidence from Selected MENA Countries. *Borsa Istanbul Review*, *18*(3), 231–247. https://doi.org/10.1016/j.bir.2017.11.004

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time Series Analysis Forecasting and Control*. New Jersey: John Wiley & Sons, Inc.

Byström, H. (2014). The Impact of Currency Movements on Asset Value Correlations. *Journal of International Financial Markets, Institutions and Money*, *31*(1), 178–186. https://doi.org/10.1016/j.intfin.2014.03.014

Chandrinos, S., & Lagaros, N. (2018). Construction of Currency Portfolios by Means of an Optimized Investment Strategy. *Operations Research Perspectives*, *5*, 32–44. https://doi.org/10.1016/j.orp.2018.01.001

Enders, W. (2004). *Applied Econometrics Time Series*. New York: John Wiley & Sons Inc.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedacity with Estimates of variance of United Kingdom Inflation. *Journal of Econometrica*. https://doi.org/10.2307/1912773

Erdogan, S., Gedikli, A., & Çevik, E. İ. (2020). Volatility Spillover Effects Between Islamic Stock Markets And Exchange Rates: Evidence From Three Emerging Countries. *Borsa Istanbul Review*, 1–21. https://doi.org/10.1016/j.bir.2020.04.003

Gold, N., Wang, Q., Cao, M., & Huang, H. (2017). Liquidity and Volatility Commonality in the Canadian Stock Market. *Mathematics-in-Industry Case Studies*, *8*(1), 1–20. https://doi.org/10.1186/s40929-017-0016-9

Hkiri, B., Hammoudeh, S., Aloui, C., & Yarovaya, L. (2017). Are Islamic Indexes a Safe Haven for Investors? An Analysis of Total, Directional and Net Volatility Spillovers between Conventional and Islamic Indexes and Importance of Crisis Periods. *Pacific Basin Finance Journal*, *43*, 124–150. https://doi.org/10.1016/j.pacfin.2017.03.001

Hong, Y., & Lee, Y.-J. (2017). A General Approach to Testing Volatility Models in Time Series. *Journal of Management Science and Engineering*, *2*(1), 1–33. https://doi.org/10.3724/sp.j.1383.201001

Huber, J., Palan, S., & Zeisberger, S. (2019). Does Investor Risk Perception Drive Asset Prices in Markets? Experimental Evidence. *Journal of Banking and Finance*, *108*, 1–17. https://doi.org/10.1016/j.jbankfin.2019.105635

Ismail, M. T., Audu, B., & Tumala, M. M. (2016). Volatility Forecasting with the Wavelet Transformation Algorithm GARCH Model : Evidence from African Stock Markets. *The Journal of Finance and Data Science*, 1–11. https://doi.org/10.1016/j.jfds.2016.09.002

Jebran, K., Chen, S., & Zubair, M. (2017). Islamic and Conventional Equity Index Co-movement and Volatility Transmission : Evidence from Pakistan. *Future Business Journal*, *3*(2), 98–106. https://doi.org/10.1016/j.fbj.2017.05.001

Lin, Z. (2018). Modelling and Forecasting the Stock Market Volatility of SSE Composite Index using GARCH Models. *Future Generation Computer Systems*, *79*(3), 960–972. https://doi.org/10.1016/j.future.2017.08.033

Livingston, M., Yao, P., & Zhou, L. (2019). The Volatility of Mutual Fund Performance. *Journal of Economics and Business*, *104*, 1–19. https://doi.org/10.1016/j.jeconbus.2019.02.001

Mahapatra, S., & Bhaduri, S. (2019). Dynamics of the Impact of Currency Fluctuations on Stock Markets in India: Assessing the Pricing of Exchange Rate Risks. *Borsa Istanbul Review*, *19*(1), 15–23. https://doi.org/10.1016/j.bir.2018.04.004

Nasr, A. Ben, Lux, T., Ajmi, A. N., & Gupta, R. (2016). Forecasting the Volatility of the Dow Jones Islamic Stock Market Index: Long memory vs. Regime Switching. *International Review of Economics and Finance*, *45*, 559–571. https://doi.org/10.1016/j.iref.2016.07.014

Natarajan, V. K., Singh, A. R. R., & Priya, N. C. (2014). Examining Mean-volatility Spillovers Across National Stock Markets. *Journal of Economics, Finance and Administrative Science*, *19*(36), 55–62. https://doi.org/10.1016/j.jefas.2014.01.001

Nayak, A., Pai, M., & Pai, R. (2016). Prediction Models for Indian Stock Market. *Procedia Computer Science*, *89*, 441–449. https://doi.org/10.1016/j.procs.2016.06.096

Oberholzer, N., & Venter, P. (2015). Univariate GARCH Models Applied to the JSE/FTSE Stock Indices. *Procedia Economics and Finance*, *24*, 491–500. https://doi.org/10.1016/s2212-5671(15)00616-4

Rizvi, S. A., & Arshad, S. (2017). Understanding Time-varying Systematic Risks in Islamic and Conventional Sectoral Indices. *Economic Modelling*, *70*, 1–10.

https://doi.org/10.1016/j.econmod.2017.10.011

Robiyanto, R., Santoso, M. A., & Ernayani, R. (2019). Sharia Mutual Funds Performance in Indonesia. *Business: Theory and Practice*, *20*, 11–18. https://doi.org/10.3846/btp.2019.02

Saiti, B., Bacha, O., & Masih, M. (2014). The Diversification Benefits from Islamic Investment During the Financial Turmoil: The Case for the US-based Equity Investors. *Borsa Istanbul Review*, *14*(4), 196–211. https://doi.org/10.1016/j.bir.2014.08.002

Salisu, A., & Gupta, R. (2019). *Dynamic Effects of Monetary Policy Shocks on Macroeconomic Volatility*. *Journal of Monetary Economics*. https://doi.org/10.1016/j.jmoneco.2019.03.011

Southall, T. (2008). *European Financial Markets: The Effects of European Union Membership on Central and Eastern European Equity Markets*. New York: Springer Science & Business Media.

Sugiharti, L., Esquivias, M. A., & Setyorani, B. (2020). The Impact of Exchange rate Volatility on Indonesia's Top Exports to the Five Main Export Markets. *Heliyon*, *6*(1), e03141. https://doi.org/10.1016/j.heliyon.2019.e03141

Tan, S. D., & Tas, O. (2019). Investor Attention and Stock Returns: Evidence from Borsa Istanbul. *Borsa Istanbul Review*, *19*(2), 106–116. https://doi.org/10.1016/j.bir.2018.10.003

Tan, Z., Yan, Z., & Zhu, G. (2019). Stock Selection with Random Forest: An Exploitation of Excess Return in the Chinese Stock Market. *Heliyon*, *5*(8), e02310. https://doi.org/10.1016/j.heliyon.2019.e02310

Vipul, P. S. (2016). Forecasting Stock Market Volatility Using Realized GARCH Model: International evidence. *Quarterly Review of Economics and Finance*, *59*, 222–230. https://doi.org/10.1016/j.qref.2015.07.005

Wahyudi, I., & Sani, G. A. (2014). Interdependence Between Islamic Capital Market and Money Market: Evidence from Indonesia. *Borsa Istanbul Review*, *14*(1), 32–47. https://doi.org/10.1016/j.bir.2013.11.001

Yildiz, Y., Karan, M. B., & Pirgaip, B. (2017). Market Reaction to Grouping Equities in Stock Markets: An Empirical Analysis on Borsa Istanbul. *Borsa Istanbul Review*, *17*(4), 216–227. https://doi.org/10.1016/j.bir.2017.08.001