Jurnal Ekonomi Modernisasi
http://ejournal.unikama.ac.id/index.php/JEKO

Modeling the returns volatility of Indonesian stock indices: The case of SRI-KEHATI and LQ45

Regi Muzio Ponziani*
Jurusan Akuntansi, Sekolah Tinggi Ilmu Ekonomi Trisakti, Indonesia

Abstract

The purpose of this research is to model the volatility of Stock Indices in Indonesian capital market. This research focuses on two stock indices namely SRI-KEHATI and LQ45. SRI_KEHATI is a stock index that consists of companies whose operations are sustainable and environmentally friendly. This stock index is also known as "green index" due to its environment and sustainability concern. This is the novelty of this research that fills in the gap in the literature in which not much known regarding this green index. As the comparison, LQ45 stock index was modeled. The data used in this model were daily returns data of both index. The research period extended from 2 January 2019 to 1 November 2021. The research employed four models i.e. ARCH (1), ARCH (2), GARCH (1,1) and GJR-GARCH (1,1) for both indices returns. The ARCH and GARCH model were employed to capture the conditional variance of the indices return, while GJR-GARCH was specifically chosen to investigate whether there exists asymmetric effect in which return reacts more to bad news than good news. Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) were chosen as the parameters for choosing the best models. Data analysis showed that GJR-GARCH was the best model for modeling the returns volatility of SRI-KEHATI and LQ45. This model was able to capture the essential property of asymmetric effect present in both models. The second best model was ARCH (2). Apparently, returns variance of Indonesian stock indices are affected more by lagged residuals. The limitation of this research lies in its research period that covered both pre-pandemic and post-pandemic period. Stock market behavior might be very different between these two periods. Future research may endeavor to investigate how the volatility of stock differs between pre-pandemic and post-pandemic period .

Keywords: Autoregressive Conditional Heteroscedasticity, Asymmetric Effect, Returns Volatility

Introduction

Stock prices are very dynamic. They always change as a result of trading activities in the stock market. This dynamic change in stock price is called volatility. However, volatility also applies to the returns received by investors. Over time, the returns always change following the change in stock price. The higher the speed of change in stock price, the higher the volatility of stock returns (Sasikirono *et al.*, 2020). Investors will consider the change in returns as an indicator of risks. High return volatility will render a stock riskier and low return volatility will indicate low risk investment (Andika *et al.*, 2019). Risky investment can cause decrease in wealth when the investment value decreases. Investors will try to access more information in order to

Permalink/DOI : https://doi.org/10.21067/jem.v18i1.6411

How to cite : Ponziani, R. M. (2022). Modeling the returns volatility of Indonesian stock indices: The case of SRI-KEHATI and LQ45. *Jurnal Ekonomi Modernisasi*, *18*(1), 13-21.

Article info : Received: Dec 2021; Revised: Feb 2022; Accepted: March 2022

*Corresponding Author:
Jurusan Akuntansi, Sekolah Tinggi Ilmu Ekonomi Trisakti (STIE Trisakti)
E-mail: regi@stietrisakti.ac.id, meponzie@gmail.com

ISSN 0216-373X (print)
ISSN 2502-4578 (online)

mitigate the risk in the investment. More readily information will render the volatility anticipated so that investors know in advance how certain event will influence their information (Emenike & Enock, 2020). However, for a certain type of investor, higher volatility presents the opportunity for taking profit when there is a price change (Nugroho & Robiyanto, 2021). This investor is known as risk-taker investor. Therefore, volatility of stocks is always observed by the investors in the stock market.

Volatility in the stock market has been the focus of many researchers. Ningsih *et al.* (2019) investigated stock volatility of LQ45. Specifically, two models were employed namely exponential Generalized autoregressive conditional heteroscedasticity (EGARCH) and threshold GARCH (TGARCH). These models treat asymmetrically bad news and good news that will cause fluctuations in the stock price or stock returns. These models will be compared to the ordinary GARCH model that treats bad news and good news similarly. The results indicated that EGARCH (2,1) is the best model for mapping the volatility of LQ 45. This model has the lowest AIC compared to TGARCH and GARCH. In similar veins, Putra *et al.* (2021) also chose LQ45 as the research object. Specifically, they aimed to determine whether the holy month of Ramadhan affected the LQ45 index and its volatility. They used GARCH model in the research. They found that there was no direct influence of holy month of Ramadhan toward LQ45, but there was a direct effect toward the volatility. In the research, the holy month of Ramadhan was included as a dummy variable in the regression equation in which the variance of the return was the dependent variable. Raneo and Muthia (2018) were interested in modeling return volatility of IHSG. Using monthly return data from January 200 until December 2017, they compared the performance of GARCH, TARCH, and EGARCH. They found that EGARCH (1,1) was the best model for modeling the return volatility and outperformed all other methods. Stocks in the banking industry has always been a research object. Nurhasanah (2018) picked 10 biggest banks in Indonesia. She used various GARCH models to model the return volatility using ARCH, EGARCH, TGARCH, and ordinary GARCH. She found that EGARCH performed best in 4 out of 10 stocks. Other models performed best in 2 stocks each. This research provided foundations that asymmetric GARCH models are best to model volatility. Sudarto *et al.* (2021) also employed EGARCH dan TGARCH to model return volatility. Their research object was the stock return of banking industry that consisted of 20 banks. They corroborated the research result of Ningsih *et al.* (2019) that found EGARCH to be the best model to map the volatility of most stock returns. Specifically, TGARCH performed better in modeling four stock returns, while EGARCH outperformed TGARCH in the other 16 stocks. EGARCH. Mubarok and Sutrieni (2020) investigated the stocks of infrastructure, transportation, and utilities industry. Using monthly return from January 2014 to December 2019, they tried to test whether there exists ARCH effects on the stocks of the industry. They indeed found ARCH effects and used various GARCH model to model the volatility and forecast the stock price. They found further that GARCH model has the capability to model the volatility of stock returns of infrastructure, transportation and utilities industry. Legina *et al.* (2020) sampled companies that issued sukuk as their research object. They investigated whether sukuk issuance affected stock returns volatility. They used EGARCH to anticipate any asymmetric effect. They found that sukuk issuance affected volatility in only one company, out of 13 companies. They also found further that each company has special EGARCH model unique to its own volatility. Endri et al. (2021) used GARCH model to investigate volatility of stock price and returns during COVID pandemic. They conducted event study whose research period was divided into period before COVID and after COVID. The period before COVID extended for 40 days and after COVID extended for 10 days. They found that GARCH (1,2) was the best model for modeling the volatility. They found that there was an increase in price volatility and returns after COVID pandemic. Sharp increase in share price and return will be followed by sharp decrease. This causes price and returns to fluctuate more than before. The ramification of this is that the abnormal return that can be obtained by equity investors is decreasing. Hence, uncertainty is more evident after COVID pandemic. Jayanegara *et al.* (2021) also investigated the volatility behavior for property and real estate stocks returns during COVID pandemic. They found that GARCH (1,1) was the best model for modeling the volatility with symmetric effect. Further, they found that the majority of stock returns should be modeled using the asymmetric effect. Hence TGARCH was employed and could better model the volatility.

Some researchers do modeling on an international basis. Ahmad *et al.* (2016) investigated stock markets in Hong Kong, Japan, Korea, Japan, India and Pakistan. They compared ARCH dan GARCH for modeling the volatility of returns. They found GARCH (1,1) to be the best for volatility modeling. They also found that the best returns were achieved by Korea and India stock exchanges. Saria *et al.* (2017) investigated the volatility model of stock markets in Hong Kong, Singapore, Japan, and Indonesia. Several GARCH models were employed. Overall, the GARCH models can be categorized as symmetric and asymmetric models. Asymmetric model will treat bad news or information differently from good news or information. In general, investors will react more spontaneous when dealing with bad news. Bad news will cause more volatility in price and returns. They found that asymmetric GARCH outperformed symmetric GARCH in modeling the return volatility in all stock markets in the research. Lubis (2018) compared the volatility of Indonesian stock market return to other stock markets in Southeast Asia. He found that Indonesian stock index has the lowest volatility and therefore the lowest risk compared to other nations. Islamic stock index also has caught the attention of researchers. Amelia (2017) was interested to find out whether Jakarta Islamic Index (JII) could be modeled using EGARCH. In addition, she also compared EGARCH to several ARCH models. She found that EGARCH (3,3) was the best model for modeling the volatility of JII. The model outperformed any ARCH models in the modeling of volatility.

Similar to the previously mentioned research, this study also investigates the volatility of stock returns in Indonesian stock market. The stock index investigated is SRI-KEHATI. This is the novelty in this research. No research has focused on SRI-KEHATI index. SRI-KEHATI consists of companies who operate with environmental concern. Therefore, their operations are deemed environmentally conscious and green operations. LQ45 is also included as a comparation. Volatility will be investigated using ARCH and GARCH models for the symmetric effect and GJR-GARCH for the asymmetric effect. The use of GJR-GARCH is also scant in literature. Most literature more likely employ EGARCH and TGARCH to account for the asymmetric effect. Therefore, this research will shed light on the performance of GJR-GARCH in modeling volatility. Since the aim of this research is to find the best model for modeling the stock indices volatility, there is no hypothesis in this research.

Method

This research investigates the volatility of two stock indices i.e. SRI-KEHATI and LQ45. SRI-KEHATI consists of companies with green and sustainable investments that focus on environmentally friendly operations. LQ45 is taken as a comparation. The returns used as the sample are daily returns from 2 January 2019 to 1 November 2021. The stock index return is calculated as follows (Burhanuddin, 2020).

$$r_t = \log \frac{I_t}{I_{t-1}} \quad (1)$$

Equation 1 is calculated by forming a logarithmic ratio of stock index at a time divided by previous period stock index. Therefore, I_t denotes stock index at time t. After calculating the returns of each stock index, we will proceed to investigating the stationarity of the data. Augmented Dickey Fuller method will be used for this purpose. Next we will test for the ARCH effect of the data to ensure the ARCH and GARCH models are appropriate for the volatility modeling. Testing the ARCH effect will require the following equation (Nurhasanah, 2018):

$$e_t^2 = \gamma_0 + \gamma_1 e_{t-1}^2 + v_t \quad (2)$$

Equation 2 shows how the ARCH effect can be investigated by regressing current period residuals with prior period residuals. The term e_t is the residuals derived from the mean equation, that is regressing the stock index return against a certain constant. ARCH effect exists when the coefficient γ_1 is significant. The ARCH and GARCH models will be applied after testing the ARCH effect. The ARCH and GARCH Models account for the variance of the stock index returns, based on the equations 3 and 4.

$$\sigma_{t^2} = \lambda + \sum_{i=1}^{s} \alpha_i e_{t-i}^2 \quad (3)$$

$$\sigma_{t^2} = \lambda + \sum_{i=1}^{s} \alpha_i e_{t-i}^2 + \sum_{j=1}^{v} \beta_j \sigma_{t-i}^2 \quad (4)$$

Equation 3 is ARCH model in which the volatility of the data depends on the prior period residual. The equation 4 is a GARCH model that states that the volatility of the data depends on the prior period residual and volatility. We also employ GJR-GACRH to account for asymmetric effect. Scant literature mentions the using of GJR-GARCH model. Most literature prefer ARCH or TGARCH model. The GJR GARCH model is as depicted by equation 5 (Mubarokah et al., 2020).

$$\sigma_{t^2} = \lambda + \sum_{i=1}^{s} (\alpha_i + \gamma_i) e_{t-1}^2 + \sum_{j=1}^{v} \beta_j \sigma_{t-i}^2 \quad (5)$$

Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) will be used to determine the amount of *i* (lags) appropriate for each model.

Result and Discussion

The first panel of figure 1 shows the movement of SRI-KEHATI overtime, while the right panel of figure 1 displays the movement of LQ45. Both figures are very similar. The trend and seasonality of SRI-KEHATI and LQ45 are identical. When LQ45 experiences an increase in index, SRI-KEHATI also experiences similar event. What differentiates them is the magnitude of increase or decrease. For instance, we can see at 2018, LQ45 experiences a drastic increase followed by a sharp decrease. The curve is sharper for LQ45. For SRI-KEHATI, the event in 2018 is flatter a little bit. It is not as sharp as what LQ45 has experienced.

Figure 2 shows the plot of SRI-KEHATI and LQ45 return during the research period. The seasonality and trend of both indices returns are identical. Both returns hover around a certain mean. This indicates that visually both plots are stationary. A more formal stationary testing will be conducted next. The seasonality is also very similar. When SRI-KEHATI

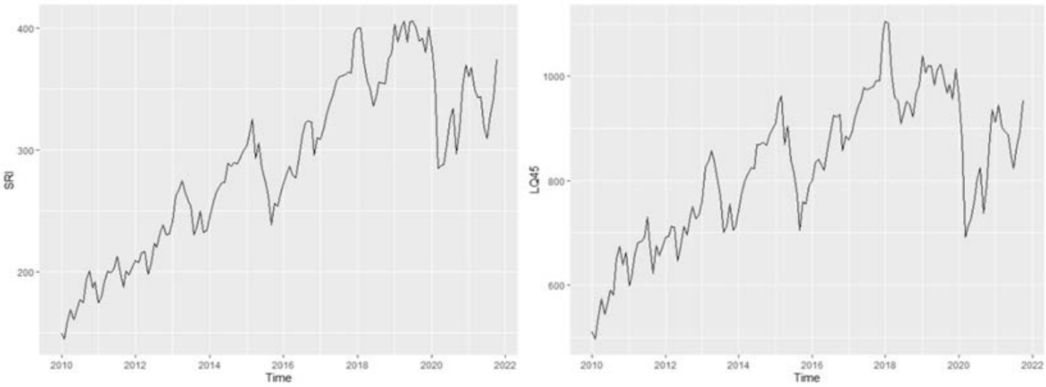

Figure 1 SRI-KEHATI and LQ45 historical movement

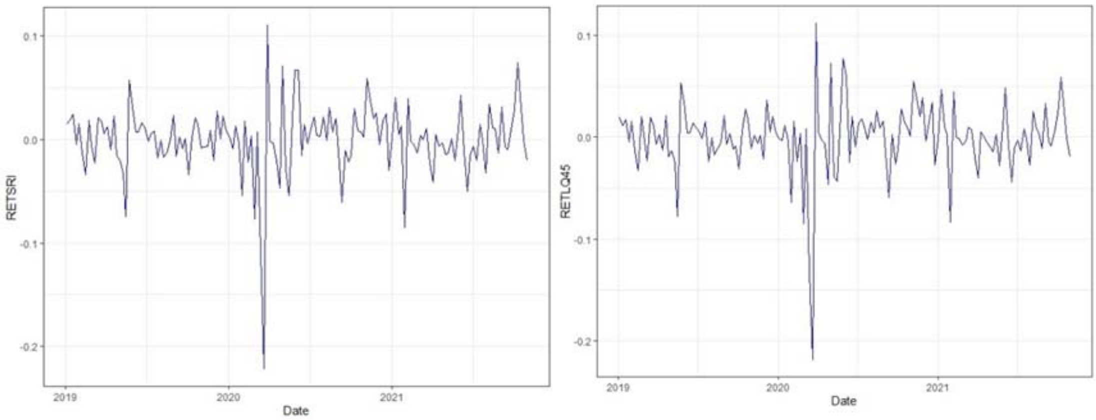

Figure 2 SRI-KEHATI and LQ45 Index Returns

experience an increase or decrease in returns, LQ45 also suffers from the same phenomena. The most significant changes of return happen at the early 2020 when pandemic first hit. A sharp decrease in returns happens to both indices. The returns plunge almost 20%. This stayed for a few moments. Subsequent to that, returns start increasing almost drastically. The increase goes on until it reached 10% returns and decrease began. During pandemic, the volatility of returns escalates than before. Figure 3 displays the conditional variance of both indices return. As can be seen, Figure 3 shows the conditional variance of both indices. At the start of the pandemic, the variance increases.

This means a sharp decrease is followed by a sharp increase. This raises the variance of the indices returns. The magnitude of the variance at the beginning of pandemic is starkly different from other variances during the research period. This shows the impact of the pandemic to the stock markets. Investors were trying to see how the pandemic impacted the economy. This triggered a short of stocks. The price declined and so did the return. After sometime, investors could see that the economy may recover from pandemic. They started to set their expectations and returns started to jump. The variance during pandemic is higher than before pandemic. Before pandemic, variance fluctuated markedly in one occasion. During pandemic, there are several occasions in which variance increases. Subsequently, the results of Augmented Dickey Fuller stationarity tests are as follow:

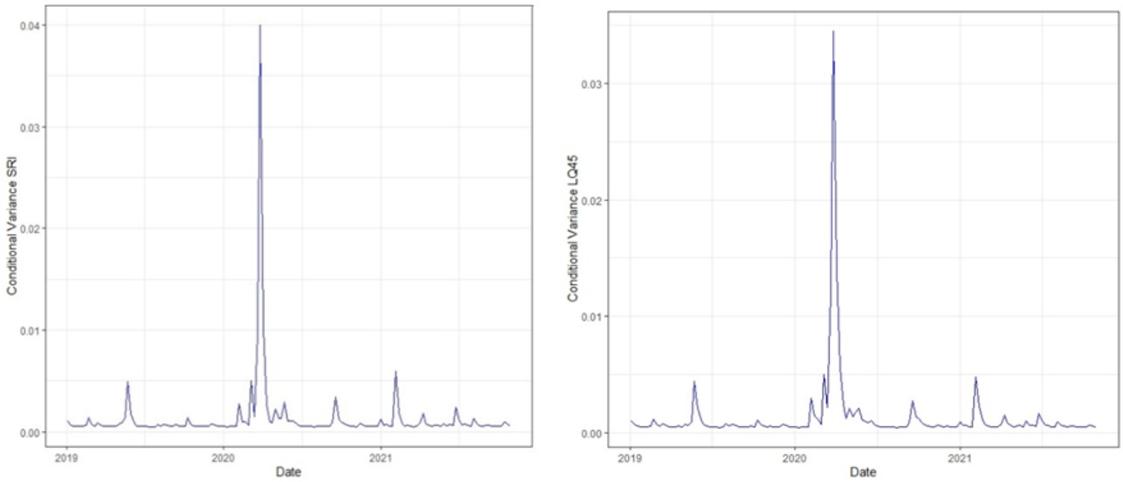

Figure 3 SRI-KEHATI and LQ45 Conditional Variance

<u>SRI-KEHATI</u>

Dickey-Fuller = -4.6462, Lag order = 5, p-value = 0.01

<u>LQ45</u>

Dickey-Fuller = -4.5738, Lag order = 5, p-value = 0.01

The hypotheses are that both series are not stationary. The ADF test shows that the hypotheses are rejected (p-value < 0.05). Therefore, we conclude that both indices returns are stationary. Next step is the testing of ARCH effect as shown below:

<u>SRI-KEHATI</u>

$e_t^2 =$ 0.0007316 + 0.3882116*** e_{t-1}^2
se (0.0003479) (0.0765264)

<u>LQ45</u>

$e_t^2 =$ 0.0006462 + 0.4669242 *** e_{t-1}^2
se (0.0003347) (0.0734375)

ARCH effect presents when the current period residual is affected by previous period residuals. The result of testing above shows that, for both indices, the prior period residuals have significant effect on the current period residuals. This confirm the existence of ARCH effect. Therefore, the use of ARCH-GARCH models can be justified. Table 1shows how the models are applied to capture the volatility on both indices.

Table 1 shows the modeling of volatility using designated models. ARCH models can extend up to 2 lags. Above 2 lags, the parameters are not significant. ARCH (1) model shows that all the coefficients are significant at 0.01. The AIC and SIC are -4.171094 and -4.171894. According to ARCH (1), the mean return of the SRI-KEHATI index is -0.00050378. These numbers are the highest of all models. Therefore, ARCH (1) is not the best model for volatility modeling. ARCH (2) model also has all significant parameters. The variance of the returns is affected by prior period residual and variance. The mean return is 0.0005143. The AIC and SIC of ARCH (2) is the second lowest of all models. Therefore, it is not the best model. GARCH (1,1) also shows that all the parameters significant. The mean return of the index is a positive number. However, the AIC and SIC is not the lowest. The last model is GJR-GARCH. Only three parameters are significant in the model. The insignificant parameter is for the prior period variance. The GJR-GARCH can pick up the asymmetric effect in the SRI-KEHATI return. Investors investing in the SRI-KEHATI companies' stocks will react more spontaneously when there is bad news than when there is good news. The

Table 1. Modeling The SRI-KEHATI returns

SRI-KEHATI	ARCH(1)	ARCH(2)	GARCH(1,1)	GJR-GARCH(1,1)
λ	0.00063641***	0.00048707***	0.00030682**	0.0003955 **
α_1	0.37371149***	0.40303150***	0.3964323***	0.00039555*
α_2	-	0.1662128800*	-	-
β_1	-	-	0.335770010*	0.218152950
γ_1	-	-	-	0.34234425*
Return	-0.00050378	0.00051430	0.00064696	-0.000327890
AIC	-4.171094	-4.200686	-4.194068	-4.229814
SIC	-4.171894	-4.202097	-4.195479	-4.231999

***significant at 0.01, **significant at 0.05, *significant at 0.1

AIC and SIC of GJR-GARCH is the lowest of all. Therefore, GJR-GARCH is the best model for modeling SRI-KEHATI volatility. Next, table 2 will show the modeling of LQ45 volatility returns.

Table 2 shows that GJR-GARCH(1,1) scored lowest in terms of AIC and SIC (-4.240232 and -4.242416). All the parameters are significant. The variance of the returns is affected by prior period residual and variance. GJR-GARCH also proved the existence of asymmetric effect. The coefficient of γ_1 is significant at 0.05. Investors of LQ45 index will react more when there is bad news than when there is good news. ARCH (2) and GARCH (1,1) scored pretty similarly in terms of AIC and SIC (-4.201068 vs -4.200189 for AIC and -4.202479 vs -4.201599, for SIC). ARCH (2) scored lower than GARCH (1,1) in both numbers. All the coefficients are significant in both ARCH (2) and GARCH (1,1). According to both models, the average return will hover around a positive number (0.00123302 for ARCH (1) and 0.00090156 for GARCH (1,1)). This is in contrast to GJR-GARCH that considers the average return of a negative number, -0.000056641, if the variance model persists. ARCH (1) score higher among all the models. The coefficients are all significant. Therefore, ARCH (1) occupies the lowest position among all the models for LQ45.

Table 2 Modeling The LQ45 returns

SRI-KEHATI	ARCH(1)	ARCH(2)	GARCH(1,1)	GJR-GARCH(1,1)
λ	0.0007073***	0.00050904***	0.00022709***	0.00029589***
α_1	0.2818658***	0.30258883**	0.31542244***	0.25731000*
α_2	-	0.21648510*	-	-
β_1	-	-	0.47924919***	0.37890**
γ_1	-	-	-	0.55413**
Return	-0.0007208	0.00123302	0.00090156	-0.000056641
AIC	-4.138862	-4.201068	-4.200189	-4.240232
SIC	-4.139662	-4.202479	-4.201599	-4.242416

***significant at 0.01, **significant at 0.05, *significant at 0.1

Conclusion

This research purports to model the volatility of SRI-KEHATI and LQ45 indices. SRI-KEHATI is a stock index consisted of companies whose operations are environmentally friendly and sustainable. No research has been conducted to model this index volatility. LQ45 is an index of companies with highest market capitalization. The equations to model the returns volatility are ARCH (1), ARCH (2), GARCH (1,1), and GJR-GARCH (1,1). Other than the models mentioned, the parameters are not significant. The ARCH and GARCH models will capture the symmetric effect, while GJR-GARCH will capture the asymmetric effect. Selection of the best model are based on AIC and SIC score. Model with the lowest AIC and SIC score is the best model for volatility modeling. Based on the analysis, GJR-GARCH is the best model to account for volatility modeling of SRI-KEHATI and LQ45. GJR-GARCH proves that there is an asymmetric effect in which investors will react more when there is bad news than when there is good news. Other literature has also proved the existence of asymmetric effect in the Indonesian stock market by employing different models (TGARCH and EGARCH). This research corroborated the result of previous research and added GJR-GARCH as the other model for volatility modeling. This research has a limitation. The research period in this research covers both pre and post pandemic period. There could be a structural break that shows that the variance behavior might be different between pre- and post-pandemic period. Future research could endeavor to compare the volatility model between pre- and post-pandemic periods.

References

Ahmad, N., Raheem Ahmed, R., Vveinhardt, J., & Streimikiene, D. (2016). Empirical analysis of stock returns and volatility: evidence from Asian stock markets. *Technological and Economic Development of Economy*, *22*(6), 808–829. https://doi.org/10.3846/20294913.2016.1213204

Amelia, N. (2017). Pemodelan Volatilitas Menggunakan Metode EGARCH pada Jakarta Islamic Index. *Jurnal Humaniora Teknologi*, *3*(1). https://doi.org/10.34128/jht.v3i1.32

Andika, T., Fahmi, I., & Andati, T. (2019). The Macroeconomic Surprise Effects on LQ45 Stock Return Volatility. *Jurnal Aplikasi Manajemen*, *17*(2), 235–243. https://doi.org/10.21776/ub.jam.2019.017.02.06

Burhanuddin, B. (2020). Investigating volatility behaviour: empirical evidence from Islamic stock indices. *Journal of Islamic Monetary Economics and Finance*, *6*(4), 729–746. https://doi.org/10.21098/jimf.v6i4.1256

Emenike, K. O., & Enock, O. N. (2020). How Does News Affect Stock Return Volatility in a Frontier Market? *Management and Labour Studies*, *45*(4), 433–443. https://doi.org/10.1177%2F0258042X20939019

Endri, E., Aipama, W., & Septiano, R. (2021). Stock price volatility during the COVID-19 pandemic: The GARCH model. *Investment Management & Financial Innovations*, *18*(4), 12–20. https://doi.org/10.21511/imfi.18(4).2021.02

Jayanegara, I., Barry, H., & Hadikusuma, R. (2021). Analisis Volatilitas pada Return Saham Properti dan Real Estate dengan Menggunakan Model ARCH-GARCH di Masa Pandemi COVID-19. In *Thesis*. Politeknik Negeri Jakarta.

Legina, L., Muharam, H., & Naufa, A. M. (2020). The Sukuk Effect on Stock Return Volatility in Indonesia. *Perspektif Akuntansi*, *3*(2), 125–153.

https://doi.org/10.24246/persi.v3i2.p125-153

Lubis, I. (2018). Analisis Model Volatilitas Indeks dan Nilai Mata Uang di Asia Tenggara. *Jurnal Madani: Ilmu Pengetahuan, Teknologi, Dan Humaniora*, *1*(1), 123–142. https://doi.org/10.33753/madani.v1i1.7

Mubarok, F., & Sutrieni, E. (2020). GARCH Model For Forecasting Stock Return Volatility In The Infrastructure, Utilities And Transportation Sectors. *Eksis: Jurnal Riset Ekonomi Dan Bisnis*, *15*(2), 87–100. https://doi.org/10.26533/eksis.v15i2.646

Mubarokah, I. S., Fitrianto, A., & Affendi, F. M. (2020). Perbandingan Model GARCH Simetris dan Asimetris pada Data Kurs Harian. *Indonesian Journal of Statistics and Its Applications*, *4*(4), 627–637. https://doi.org/10.29244/ijsa.v4i4.709

Ningsih, S. R., Sumarjaya, I. W., & Sari, K. (2019). Peramalan Volatilitas Saham Menggunakan Model Exponential Garch Dan Threshold Garch. *E-Jurnal Matematika*, *8*(4), 309–315. https://doi.org/10.24843/MTK.2019.v08.i04.p270

Nugroho, A. D., & Robiyanto, R. (2021). Determinant of Indonesian Stock Market's Volatility During the Covid-19 Pandemic. *Jurnal Keuangan Dan Perbankan*, *25*(1), 1–20. https://doi.org/10.26905/jkdp.v25i1.4980

Nurhasanah, E. (2018). Comparison of Modeling Volatility of Indonesia Banks Using ARCH, GARCH, TARCH and EGARCH. *Jurnal Manajemen Dan Bisnis: Performa*, *XV*(2), 87–99. https://doi.org/10.29313/performa.v0i0.4422

Putra, D. W., Hasnawati, S., & Muslimin, M. (2021). Ramadan Effect and Volatility Risk by Garch Model: Evidence in Indonesia Stock Market. *Jurnal Bisnis Dan Manajemen*, *17*(2), 82–92. https://doi.org/10.23960/jbm.v17i2.220

Raneo, A. P., & Muthia, F. (2018). Penerapan Model GARCH Dalam Peramalan Volatilitas di Bursa Efek Indonesia. *Jurnal Manajemen Dan Bisnis Sriwijaya*, *16*(3), 194–202. https://doi.org/10.29259/jmbs.v16i3.7462

Saria, L. K., Achsanib, N. A., & Sartonoc, B. (2017). Pemodelan Volatilitas Return Saham: Studi Kasus Pasar Saham Asia Modelling Volatility of Return Stock Index: Evidence from Asian Countries. *Jurnal Ekonomi Dan Pembangunan Indonesia*, *18*(1), 35–52. https://doi.org/10.21002/jepi.v18i1.717

Sasikirono, N., Febriana, M. R., Made Sudana, I., & Meidiaswati, H. (2020). The effect of foreign ownership on stock return volatility, with government ownership as a moderator. *Journal of Innovation in Business and Economics*, *4*(01), 39–48. https://doi.org/10.22219/jibe.v4i01.10177

Sudarto, S., Wati, H. H., & Kurniasih, R. (2021). Memodel Volatilitas Return Saham dengan Model E-GARCH dan T-GARCH. *Jurnal Ekonomi, Bisnis, Dan Akuntansi*, *23*(2), 77–92. https://doi.org/10.32424/jeba.v23i2.1840