Jurnal Varian
Vol. 8, No. 1, October 2024, pp 89–96
e-ISSN: 2581-2017

Application of VAR-GARCH for Modeling the Causal Relationship of JII Stock Prices in the Mining Sub-sector

Muhammad Nasrudin[1], Endah Setyowati[2], Shindi Shella May Wara[1]
[1]Universitas Pembangunan Nasional Veteran Jawa Timur, Surabaya, Indonesia
[2]Institut Agama Islam Negeri Ponorogo, Ponorogo, Indonesia

Article Info

Article history:

Received : 07-12-2024
Revised : 08-30-2024
Accepted : 10-18-2024

Keywords:

Generalized Autoregressive Conditional Heteroskedasticity;
Jakarta Islamic Index;
Stock price;
Vector Autoregressive.

ABSTRACT

Accurate modeling is expected to minimize risk and maximize profit in investment portfolios, one of which is in stock price modeling. This research aims to model the causal relationship between stock prices using the Vector Autoregressive - Generalized Autoregressive Conditional Heteroskedasticity (VAR-GARCH) model. The VAR-GARCH model is used to overcome heteroscedasticity and model dynamic volatility. The data used for the modeling consists of daily stock prices from July 2023 to May 2024 for mining sub-sector companies listed on the Jakarta Islamic Index (JII), including ADMR, ADRO, and ANTM. The results showed that the VAR(1) model is stable, but this model indicates the presence of heteroskedasticity or ARCH effects. Therefore, the VAR(1) model was combined with the GARCH model, and the results showed that the best model is VAR(1)-GARCH(1,1). The VAR(1)-GARCH(1,1) model is appropriate and meets the homoskedasticity assumptions for modeling the stock prices of the mining sub-sector in the Jakarta Islamic Index (JII). This indicates that the VAR-GARCH model could successfully handle the volatility of stock price data. In general, this research is in line with previous research, i.e., the VAR-GARCH model showed a better model for capturing the volatility patterns in the data.

Accredited by Kemenristekdikti, Decree No: 200/M/KPT/2020
DOI: https://doi.org/10.30812/varian.v8i1.4239

Corresponding Author:

Muhammad Nasrudin,
Department of Data Science, Universitas Pembangunan Nasional Veteran Jawa Timur,
Email: nasrudin.fasilkom@upnjatim.ac.id

How to Cite:
Nasrudin, M., Setyowati, E., & Wara, S. S. M. (2024). Application of VAR-GARCH for Modeling the Causal Relationship of JII Stock Prices in the Mining Sub-sector. *Jurnal Varian*, *8*(1), 89-96.

A. INTRODUCTION

The capital market plays a crucial role in the modern economy to raise company funds and provide investment opportunities for the public. One of the most popular investment instruments is stocks, which are traded on the Indonesia Stock Exchange (IDX), reflecting partial ownership of a company. In Indonesia, the Jakarta Islamic Index (JII) is one of the stock indices that includes stocks compliant with Islamic sharia principles (BEI, 2024). The JII index refers to Daftar Efek Syariah (DES) issued by the Indonesia Financial Services Authority (OJK). DES is an investment guide for Sharia mutual funds in placing their managed funds. It can also be used by investors who wish to invest in a sharia portfolio. The JII constituents consist of only 30 of the most liquid Sharia stocks listed on the IDX, which consist of several sub-sectors. Several studies have been conducted on stock price modeling from JII stock price (Hersugondo et al., 2022; Ponziani, 2022) and various sub-sectors, such as the energy subsector (Azhar et al., 2020). The mining sub-sector within the JII is of particular interest due to its significant contribution to the national economy and its high price volatility, which is influenced by global factors such as commodity prices and economic policies (World Bank 2020).

It is essential to model the causal relationships among stock prices within this sub-sector to understand stock price dynamics, especially in a volatile sector like mining. One approach that can be utilized is the Vector Autoregression (VAR) model, which allows for analyzing dynamic relationships between multivariate time series. The VAR model is based on the idea that each model on a variable is influenced by the previous time factors on that variable and also the previous time factors of other variables (Kilian & Lütkepohl, 2017). Stock price modeling using the VAR model has been widely used (Suharsono et al., 2017; Suharsono et al., 2018). This research uses explanatory variables as other variables, even though the VAR model can also be used to determine the causal relationship of the same variable in different types or locations. However, there are several cases where the VAR model is typically inadequate for dealing with varying volatility. Due to the spikes typical of commodity volatility, the VAR model is fat-tailed (Barbaglia et al., 2020). Thus, this research will combine the VAR method with one that can overcome data volatility.

The method that can be used to model volatility is the Generalized Autoregressive Conditional Heteroskedasticity (GARCH). The GARCH model was developed by Bollerslev (1986), and the Autoregressive Conditional Heteroskedasticity (ARCH) model was proposed by Engle (1982). The GARCH model is used to model volatility and has been developed in various studies, especially on stock data, which tends to have high fluctuations (Lin, 2018; Njagi, 2018; Yaya et al., 2024). Thus, the GARCH model can also be used to overcome heteroscedasticity in the VAR model, known as VAR-GARCH. The VAR-GARCH model is a VAR model combined with GARCH to model the volatility or inhomogeneity of the VAR model. In previous research, the VAR-GARCH model showed a better model for capturing the volatility patterns in the data (Hashmi et al., 2022; Manasseh et al., 2019; Massadikov, 2021). The difference between this study and other studies is the relationship between the variables. Previous studies used variables that were not too closely related, while this study used variables from the same field.

This research aims to apply the VAR-GARCH model to analyze the causal relationships of stock prices in the mining sub-sector listed on the Jakarta Islamic Index (JII). Consequently, this research is expected to provide deeper insights into the interactions and volatility of stock prices, thereby assisting investors and policymakers in making better-informed decisions. The VAR-GARCH model will be used to examine how the stock price movements of one company can influence and be influenced by the stock price movements of other companies within the same sub-sector and identify potential volatility patterns. Accurate modeling is expected to minimize risk and maximize returns in investment portfolios, particularly in the mining sub-sector, known for its high volatility.

B. RESEARCH METHOD

1. Statistical Models

Multivariate time series is the study of statistical models and analytical methods that describe the relationships among multiple time series data Wei (2007). The goal of this analysis and modeling is to understand the dynamic relationships between series and to improve the accuracy of forecasting each series by using the information available from related series.

a. Vector Autoregressive (VAR) Model

In many cases, time series data consists of observations of several variables. When two or more variables have reciprocal or interrelated relationships, the modeling of such variables is often referred to as multivariate time series modeling (Sharma et al., 2018). The Vector Autoregressive (VAR) model is an extension of the Autoregressive (AR) model in univariate time series models. Sims introduced the VAR model as a tool for analyzing macroeconomic data. The VAR model treats all involved variables symmetrically (Sims, 1980). Generally, the VAR(p) model, with p being the order of the model, is as follows.

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \varepsilon_t \tag{1}$$

with

$y_t \quad = (y_{1,t}, \ldots, y_{k,t})^t$

$\alpha \quad = (\alpha_{10}, \alpha_{20}, \ldots, \alpha_{k0})^t$ estimated using the formula.

Vol. 8, No. 1, October 2024, pp 89–96
DOI: https://doi.org/10.30812/varian.v8i1.4239

$\alpha = \frac{(\sum y_t)(\sum y^2{}_{t-1})-(\sum y_{t-1})(\sum y_{t-1}y_t)}{n\sum y^2{}_{t-1}-(\sum y_{t-1})^2}$, $\beta = \frac{n\sum y_{t-1}y_t-(\sum y_{t-1})(\sum y_t)}{n\sum y^2{}_{t-1}-(\sum y_{t-1})^2}$ is the coefficient matrix of size ε = vector $(n \times 1)$ from error term.

The general model of Equation (1) can be written in the following matrix form:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{k,t} \end{bmatrix} = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \\ \vdots \\ \alpha_{k0} \end{bmatrix} + \begin{bmatrix} \beta_{1,1} & \beta_{1,2} & \cdots & \beta_{1,k} \\ \beta_{2,1} & \beta_{2,2} & \cdots & \beta_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{k,1} & \beta_{k,2} & \cdots & \beta_{k,k} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ \vdots \\ y_{k,t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \beta_{1,1} & \beta_{1,2} & \cdots & \beta_{1,k} \\ \beta_{2,1} & \beta_{2,2} & \cdots & \beta_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{k,1} & \beta_{k,2} & \cdots & \beta_{k,k} \end{bmatrix} \begin{bmatrix} y_{1,t-p} \\ y_{2,t-p} \\ \vdots \\ y_{k,t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{k,t} \end{bmatrix} \tag{2}$$

The Equation (2) above can be expanded as follows:

$$\begin{aligned} y_{1,t} &= \alpha_{10} + \beta_{1,1}y_{1,t-1} + \beta_{1,2}y_{2,t-1} + \cdots + \beta_{1,k}y_{k,t-1} + \cdots + \beta_{1,1}y_{1,t-p} + \beta_{1,2}y_{2,t-p} + \cdots + \beta_{1,k}y_{k,t-p} + \varepsilon_{1,t} \\ y_{2,t} &= \alpha_{20} + \beta_{2,1}y_{1,t-1} + \beta_{2,2}y_{2,t-1} + \cdots + \beta_{2,k}y_{k,t-1} + \cdots + \beta_{2,1}y_{1,t-p} + \beta_{2,2}y_{2,t-p} + \cdots + \beta_{2,k}y_{k,t-p} + \varepsilon_{2,t} \\ &\vdots \\ y_{k,t} &= \alpha_{k0} + \beta_{k,1}y_{1,t-1} + \beta_{k,2}y_{2,t-1} + \cdots + \beta_{k,k}y_{k,t-1} + \cdots + \beta_{k,1}y_{1,t-p} + \beta_{k,2}y_{2,t-p} + \cdots + \beta_{k,k}y_{k,t-p} + \varepsilon_{k,t} \end{aligned} \tag{3}$$

b. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

Stock prices fluctuate daily and are unpredictable. The varying nature of their fluctuations demonstrates this. Due to high volatility, a specific model is required to handle it, namely the variance model approach using the ARCH and GARCH methods. The ARCH model requires a higher order for financial data with greater volatility to model its variance. This complicates the model's identification and estimation process. Therefore, the ARCH model was developed into Generalized ARCH (GARCH) to address the excessively high order in the ARCH model (Bollerslev, 1986). In the GARCH model, changes in conditional variance are influenced by previous random data and the variance of previous random data. The GARCH model is more suitable for modeling random data with high volatility. Generally, the GARCH (p, q) model is as follows:

$$\begin{aligned} \hat{\sigma}_t^2 &= a_0 + a_1\varepsilon_{t-1}^2 + \cdots + a_p\varepsilon_{t-p}^2 + \beta_1\hat{\sigma}_{t-1}^2 + \cdots + \beta_q\hat{\sigma}_{t-q}^2 \\ \hat{\sigma}_t^2 &= a_0 + \sum_{i=1}^{p} a_1\varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j\hat{\sigma}_{t-j}^2 \end{aligned} \tag{4}$$

2. Data Source

The data used in this research consists of the closing stock prices of mining sub-sector companies listed on the Jakarta Islamic Index (JII), i.e., ADMR (Adaro Minerals Indonesia), ADRO (Adaro Energy Indonesia), and ANTM (Aneka Tambang). The data is daily stock prices from July 2023 until May 2024 from the official Yahoo Finance website (https://finance.yahoo.com).

3. Analysis Procedure

The research analysis procedure starts with data collection and ends with interpretation and conclusion. If the ARCH test results show heterogeneity, further testing is conducted using the GARCH model; otherwise, the analysis is done using the VAR model. The flow chart analysis is shown in Figure 1.

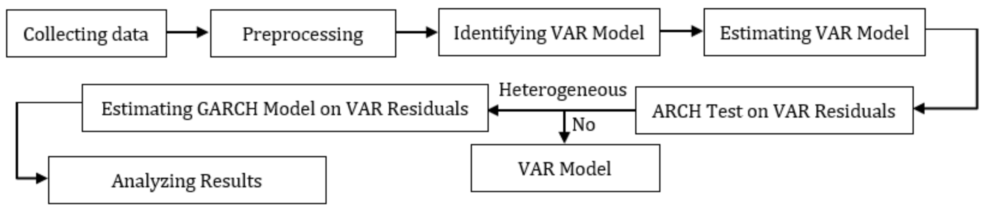

Figure 1. Flowchart of Analysis Procedure

C. RESULT AND DISCUSSION

1. Characteristics of JII Stock Price Data in the Mining Sub-sector

The stock price data used in this study are the closing stock prices of the mining sub-sector companies listed on the Jakarta Islamic Index (JII), namely ADMR, ADRO, and ANTM, for the period from July 2023 to May 2024. The stock price trends of these three companies are shown in Figure 2. Based on the time series plot, it can be seen that ADRO's stock price tends to be the highest, followed by ANTM's stock price, with ADMR's stock price being the lowest among the three. However, all three stock prices show a tendency to be stable around their averages, as indicated by a stationary pattern with respect to the mean but not stationary with respect to variance and the presence of structural breaks in the stock price data of all three companies.

Figure 2. Time Series Plot of JII Mining Sub-sector Stock Price Trends

Meanwhile, looking at the data characteristics through descriptive statistics provided in Figure 2, it can be observed that ADRO has the highest average stock price but with the highest variance. Regarding low variance, ADMR's stock is safer and more profitable.

Table 1. Characteristics of JII Mining Sub-sector Stock Prices from June 2023 to May 2024 (IDR)

Stock	Minimum	Maximum	Mean	Variance
ADMR	925	1555	1284	23235,63
ADRO	1984	2740	2299	32563,93
ANTM	1301	1882	1596	23977,35

2. Modeling Causal Relationships of Stock Prices in the JII Mining Sub-sector with VAR

VAR modeling begins with selecting the best order of the VAR model. The selection of the VAR order is based on model goodness-of-fit criteria such as AIC, HQ, SC, and FPE. A lower value of these criteria indicates a better model fit, suggesting less information loss from the constructed model. Based on the goodness-of-fit calculations in Table 2, it can be determined that the best VAR model order is VAR(1). This means that in modeling the stock prices of JII mining sub-sector companies, namely ADMR, ADRO, and ANTM, simultaneously, they are influenced by these variables' values in the previous period.

Table 2. Selection of the Best Order for the VAR Model

Model	AIC	HQ	SC	FPE
VAR(1)	21,50	21,55	21,64	$2,16 \times 109^9$
VAR(2)	21,55	21,67	21,84	$2,29 \times 109^9$
VAR(3)	21,58	21,76	22,01	$2,37 \times 109^9$
VAR(4)	21,63	21,86	22,20	$2,48 \times 109^9$
VAR(5)	21,67	21,96	22,38	$2,58 \times 109^9$

Based on the best VAR model order, the parameter estimates for modeling the JII mining sub-sector stock prices using the

Vol. 8, No. 1, October 2024, pp 89–96
DOI: https://doi.org/10.30812/varian.v8i1.4239

VAR(1) model are obtained with the following model equations.

$$\begin{pmatrix} Y_{ADMR,t} \\ Y_{ADRO,t} \\ Y_{ANTM,t} \end{pmatrix} = \begin{pmatrix} 0,968 & 0,011 & 0,012 \\ 0,036 & 0,975 & 0,009 \\ -0,024 & 0,023 & 0,985 \end{pmatrix} \begin{pmatrix} Y_{ADMR,t-1} \\ Y_{ADRO,t-1} \\ Y_{ANTM,t-1} \end{pmatrix} + \begin{pmatrix} e_{ADMR,t} \\ e_{ADRO,t} \\ e_{ANTM,t} \end{pmatrix}$$

The VAR(1) model results are followed by an analysis of residual goodness-of-fit through tests for heteroskedasticity, normality, and stability. Table 3 presents the results of the residual assumption tests for the VAR(1) model on the stock price data of the JII mining sub-sector. The heteroskedasticity test indicates that the residuals of the VAR(1) model do not satisfy the assumption of homoskedasticity, suggesting the presence of ARCH effects or heteroskedasticity. Additionally, based on the normality test, it is found that the residuals do not adhere to the assumption of normal distribution. However, the stability plot of the VAR(1) model shown in Figure 3 indicates that the VAR(1) model is stable, meaning it is reliable for modeling the JII mining sub-sector stock prices.

Table 3. Testing Heteroskedasticity and Normality in the VAR(1) Model

Type of test	Chi-Square	p-value
Heteroskedasticity	$449,02$	$0,034$
Normality	$63,521$	$8,644 \times 10^{-12}$

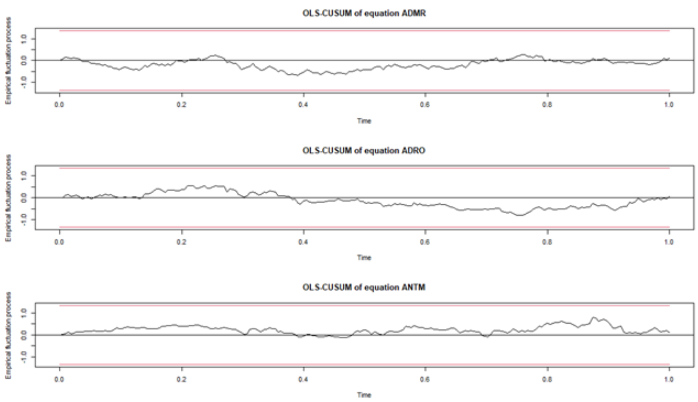

Figure 3. Plot of VAR(1) Model Stability

Furthermore, in this VAR(1) model, we can determine how the data series contribute through Forecast Error Variance Decomposition (FEVD). FEVD values can be used to understand the contribution from one variable to another, as shown in Figure 4.

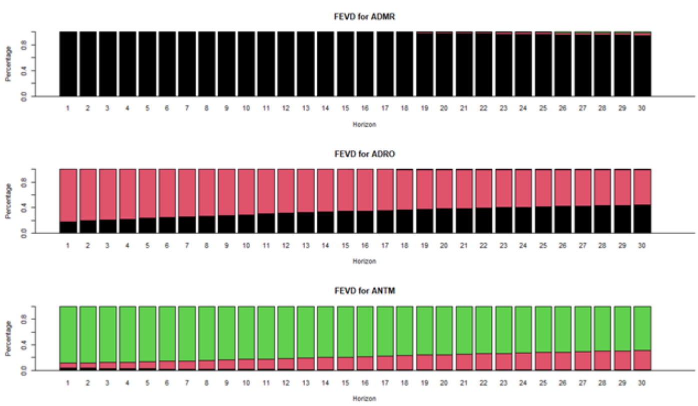

Figure 4. Plot of FEVD from VAR(1) Model

Vol. 8, No. 1, October 2024, pp 89–96
DOI: https://doi.org/10.30812/varian.v8i1.4239

Based on the FEVD plot in Figure 4, it is observed that the three stock price data series of the JII mining sub-sector are predominantly influenced by their values. For ADMR stock prices, it is noted that the prices of the previous period tend to influence the current ADMR stock price. Similarly, for ADRO stock prices, although mostly dominated by its contributions, there is also a gradual influence from ADMR stock prices. Likewise, ANTM stock prices initially show dominance from their contributions in the previous period. Still, there has also been a gradual contribution from ADRO stock prices to the current ANTM stock prices.

3. Modeling Causal Relationships of Stock Prices in the JII Mining Sub-sector with VAR-GARCH

Results from the VAR(1) model modeling JII mining sub-sector stock prices indicate non-compliance with the homoskedasticity assumption, suggesting ARCH effects. The VAR(1) model is extended to the VAR(1)-GARCH model to address this issue. The GARCH is a volatility model necessary when a data series exhibits heteroskedasticity. Table 4 shows the comparison of AIC values for various combinations of VAR(1)-GARCH models, revealing that the best model for modeling JII mining sub-sector stock prices is VAR(1)-GARCH(1,1).

Table 4. Selection of the Best Order for VAR-GARCH Models

Model	AIC	BIC	SC
VAR(1)-GARCH(1,1)	30,136	30,448	30,120
VAR(1)-GARCH(1,2)	30,145	30,473	30,128
VAR(1)-GARCH(2,1)	30,142	30,470	30,125
VAR(1)-GARCH(2,2)	20,151	30,494	30,132

The VAR(1)-GARCH(1,1) model equation is provided as follows.

$$\begin{pmatrix} Y_{ADMR,t} \\ Y_{ADRO,t} \\ Y_{ANTM,t} \end{pmatrix} = \begin{pmatrix} 0,968 & 0,011 & 0,012 \\ 0,036 & 0,975 & 0,009 \\ -0,024 & 0,023 & 0,985 \end{pmatrix} \begin{pmatrix} Y_{ADMR,t-1} \\ Y_{ADRO,t-1} \\ Y_{ANTM,t-1} \end{pmatrix} + \begin{pmatrix} e_{ADMR,t} \\ e_{ADRO,t} \\ e_{ANTM,t} \end{pmatrix}$$

where

$$\begin{pmatrix} \sigma^2_{ADMR,t} \\ \sigma^2_{ADRO,t} \\ \sigma^2_{ANTM,t} \end{pmatrix} = \begin{pmatrix} 1568,7 \\ 1467,3 \\ 749,43 \end{pmatrix} + \begin{pmatrix} 0,114 & 0,001 & 0,001 \end{pmatrix} \begin{pmatrix} e_{ADMR,t-1} \\ e_{ADRO,t-1} \\ e_{ANTM,t-1} \end{pmatrix} + \begin{pmatrix} 0,001 & 0,210 & 0,143 \end{pmatrix} \begin{pmatrix} \sigma^2_{ADMR,t-1} \\ \sigma^2_{ADRO,t-1} \\ \sigma^2_{ANTM,t-1} \end{pmatrix}$$

The VAR(1)-GARCH(1,1) model then underwent checks to verify compliance with the homoskedasticity assumption. Based on the homoskedasticity test results, it was found that the VAR(1)-GARCH(1,1) model meets the homoskedasticity assumption in modeling the causal relationships of JII mining sub-sector stock prices. These results are in line with Manasseh et al. (2019), Hashmi et al. (2022), and Massadikov (2021). Results, i.e., the VAR-GARCH model, showed a better model for capturing the volatility patterns in the data.

D. CONCLUSION AND SUGGESTION

The results of the stock price characteristics of ADMR, ADRO, and ANTM in the JII mining sub-sector from July 2023 to May 2024 indicate that ADRO tends to have the highest prices, followed by ANTM, with ADMR having the lowest price among the three. However, ADMR's stock prices tend to be the safest due to having the lowest variance. The other result is the causal modeling of the three stock prices in the JII mining sub-sector, ADMR, ADRO, and ANTM, which showed that the best model uses the VAR(1) model. This indicates that in modeling the stock prices of ADMR, ADRO, and ANTM in the JII mining sub-sector, their values in the previous period are multivariate influenced by their values. The formed VAR(1) model has shown stability, but it was found that the VAR(1) model results indicate the presence of heteroskedasticity or ARCH effects. Therefore, the VAR(1) model was developed by combining it with the GARCH method, and the best model obtained is VAR(1)-GARCH(1,1). The VAR(1)-GARCH(1,1) model is suitable and meets the assumption of homoskedasticity in modeling the stock prices of ADMR, ADRO, and ANTM in the JII mining sub-sector.

REFERENCES

Azhar, R., Kesumah, F. S. D., Ambya, A., Wisnu, F. K., & Russel, E. (2020). Application of Short-Term Forecasting Models for Energy Entity Stock Price (Study on Indika Energi Tbk, JII). *International Journal of Energy Economics and Policy*, *10*(1), 294–301. https://doi.org/10.32479/ijeep.8715

Barbaglia, L., Croux, C., & Wilms, I. (2020). Volatility spillovers in commodity markets: A large t-vector autoregressive approach. *Energy Economics*, *85*, 104555. https://doi.org/10.1016/j.eneco.2019.104555

BEI. (2024). *Indeks Saham Syariah*. https://www.idx.co.id/Id/Idx-Syariah/Indeks-Saham-Syariah

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, *50*(4), 987–1007. https://doi.org/10.2307/1912773

Hashmi, S. M., Ahmed, F., Alhayki, Z., & Syed, A. A. (2022). The impact of crude oil prices on Chinese stock markets and selected sectors: Evidence from the VAR-DCC-GARCH model. *Environmental Science and Pollution Research*, *29*(35), 52560–52573. https://doi.org/10.1007/s11356-022-19573-5

Hersugondo, H., Ghozali, I., Handriani, E., Trimono, T., & Pamungkas, I. D. (2022). Price Index Modeling and Risk Prediction of Sharia Stocks in Indonesia. *Economies*, *10*(1), 17. https://doi.org/10.3390/economies10010017

Kilian, L., & Lütkepohl, H. (2017). *Structural Vector Autoregressive Analysis*. Cambridge University Press. https://doi.org/10.1017/9781108164818

Lin, Z. (2018). Modelling and forecasting the stock market volatility of SSE Composite Index using GARCH models. *Future Generation Computer Systems*, *79*, 960–972. https://doi.org/10.1016/j.future.2017.08.033

Manasseh, C. O., Chukwu, N. O., Abada, F. C., Ogbuabor, J. E., Lawal, A. I., & Alio, F. C. (2019). Interactions between stock prices and exchange rates: An application of multivariate VAR-GARCH model (D. Tokic, Ed.). *Cogent Economics & Finance*, *7*(1), 1681573. https://doi.org/10.1080/23322039.2019.1681573

Massadikov, K. (2021). Volatility Spillovers Between Oil Prices and Stock Returns in Developing Countries. *International Journal of Energy Economics and Policy*, *11*(4), 121–126. https://doi.org/10.32479/ijeep.11117

Njagi, H. (2018). Modelling the Stock Price Volatility Using Asymmetry Garch and Ann-Asymmetry Garch Models. *International Journal of Data Science and Analysis*, *4*(4), 46. https://doi.org/10.11648/j.ijdsa.20180404.11

Ponziani, R. M. (2022). Forecasting of Jakarta Islamic Index (JII) returns using Holt-Winters family models. *Asian Journal of Islamic Management (AJIM)*, 111–122. https://doi.org/10.20885/AJIM.vol3.iss2.art4

Sharma, A., Giri, S., Vardhan, H., Surange, S., Shetty, R., & Shetty, V. (2018). Relationship between Crude Oil Prices and Stock Market: Evidence from India. *International Journal of Energy Economics and Policy*, *8*(4), 331–337. https://www.econjournals.com/index.php/ijeep/article/view/4439

Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica*, *48*(1), 1. https://doi.org/10.2307/1912017

Suharsono, A., Ahmad, I. S., Wibisono, A., & Pramesti, W. (2018). Modeling of autoregressive moving average and vector autoregressive for forecasting stock price index in ASEAN countries. *International Journal of Mechanical Engineering and Technology*, *9*(11), 309–319. http://www.scopus.com/inward/record.url?scp=85057528940&partnerID=8YFLogxK

Suharsono, A., Aziza, A., & Pramesti, W. (2017). Comparison of vector autoregressive (VAR) and vector error correction models (VECM) for index of ASEAN stock price, 020032. https://doi.org/10.1063/1.5016666

Wei, W. W. S. (2007). *Time series analysis: Univariate and multivariate methods* (2. ed.). Pearson Addison Wesley.

World Bank. (2020). *Commodity Markets Outlook April 2022*. Commodity Market.

Yaya, O. S., Adekoya, O. B., Vo, X. V., & Al-Faryan, M. A. S. (2024). Stock Market Efficiency in Asia: Evidence from the Narayan–Liu–Westerlund's GARCH-based unit root test. *International Journal of Finance & Economics*, *29*(1), 91–101. https://doi.org/10.1002/ijfe.2676

[This page intentionally left blank.]