Received: 05 Dec 2024 | Revised: 03 Mar 2026 | Accepted: 25 Mar 2026 | Available online: 12 Jun 2026
https://doi.org/10.13057/ijas.v9i1.95849
E-ISSN: 2621-086X
https://jurnal.uns.ac.id/ijas
Indonesian Journal of Applied Statistics Vol. 9, No.1, pp. 43-54, 2026

Value at Risk Estimation of Portfolio Affected by the BDS Movement: A Copula Approach

Binarvian Sofawi*, Dhoriva Urwatul Wutsqa
Study Program of Statistics, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia
*Corresponding Author, E-mail: binarvians@gmail.com

Abstract

This study aims to estimate value at risk (VaR) as a measure of the maximum potential loss in an investment portfolio through the application of a Copula approach to stocks affected by the Boycott, Divestment, and Sanctions (BDS) Movement. The data used are the daily return data of MAPI from PT Mitra Adiperkasa, Tbk, FAST from PT Fast Food Indonesia, Tbk, and UNVR from PT Unilever Indonesia, Tbk obtained from the closing stock prices. The returns used are daily simple returns from March 1, 2019, to February 29, 2024, consisting of 1,130 days. The model used in this study is the ARMA-GARCH Copula model. Autoregressive moving average (ARMA) is used due to the involvement of time influence in estimation, while generalized autoregressive conditional heteroskedasticity (GARCH) is used to address the high volatility in stocks. The selection of the best copula model using maximum likelihood estimation (MLE) involves five copulas: gaussian copula, t-Student copula, Clayton copula, Frank copula, and Gumbel copula. The results of the analysis show that Clayton copula is the best model, with VaR of the portfolio of stocks affected by the Boycott, Divestment, and Sanctions (BDS) movement at the 99%, 95%, and 90% confidence levels are 3.45%, 2.11%, and 1.55%, respectively. These findings suggest that lower tail dependence plays an important role in portfolio risk, indicating the potential for simultaneous extreme losses. Therefore, investors are encouraged to consider copula-based risk measurement methods and diversification strategies to minimize potential portfolio losses.

Keywords: ARMA, copula, GARCH, returns, value at risk.

How to Cite:
B. Sofawi and D. U. Wutsqa, “Value at risk estimation of portfolio affected by the BDS Movement: A copula approach,” *Indonesian Journal of Applied Statistics,* vol. 9, no. 1, pp. 43-54, 2026, doi: 10.13057/ijas.v9i1.95849.

1. INTRODUCTION

Stocks can be defined as proof of capital participation by an individual or an entity (business organization) in a company or limited liability corporation. Stocks are one of the most widely chosen investment instruments because they are capable of providing attractive returns to investors [1]. The basis of investment decisions consists of the expected rate of return, the level of risk to be borne, and the relationship between return and risk [2]. Return refers to the expected gain from an investment, whereas risk is defined as the probability of deviation from the expected rate of return, which can be measured using statistical techniques [3]. This shows that measuring investment risk is essential to achieve maximum profit with minimal risk.

Stock returns are influenced by both micro and macro factors. Micro factors refer to internal company conditions, such as return on assets, debt to equity ratio, price to book value, and other financial ratios. Meanwhile, macro factors refer to external conditions, including macroeconomic factors such as inflation rates, exchange rates, general domestic interest rates, and global economic conditions as well as non-economic macro factors such as political events, environmental issues, demonstrations, and wars [4].

Recently, geopolitical tensions have become a significant macro factor influencing financial markets. One notable event is the escalation of the Palestine-Israel conflict since October 7, 2023, which has triggered global political and social responses. Israel's counterattacks are considered excessive and are considered a form of genocide against the Palestinian people, giving rise to the Boycott, Divestment, and Sanctions (BDS) Movement. Boycott, Divestment, Sanctions (BDS) is a Palestinian-led initiative advocating freedom, justice, and equality. BDS upholds the simple principle that Palestinians are entitled to the same rights as the rest of humanity [5]. The BDS movement in Indonesia has become increasingly popular after the issuance of the MUI (Majelis Ulama Indonesia/Indonesian Council of Ulama) Fatwa Number 83 of 2023 on November 8, 2023 concerning the law on support for the Palestinian. The results of Nurasiah et al. [6] research on the stock prices of products affiliated with Israel showed that affiliated stocks weakened significantly after the announcement of the MUI fatwa.

This study was conducted to estimate value at risk (VaR) as a tool to measure losses in stocks of companies affected by the BDS Movement. The companies used in this study were companies listed on the Indonesia Stock Exchange, namely PT Mitra Adiperkasa, Tbk (MAPI) which houses Starbucks, PT Fast Food Indonesia, Tbk (FAST) which houses KFC, and PT Unilever Indonesia, Tbk (UNVR) which houses various Unilever products in Indonesia. Given the characteristics of financial time series data, an appropriate modeling approach is required to obtain accurate risk estimates.

Financial data exhibit two important characteristics, fat-tailed distributions indicated by positive kurtosis and the presence of volatility clustering [7]. These characteristics may lead to violations of the normality assumption commonly used in classical financial modeling. In addition, the dependence structure among stocks is generally non-linear rather than linear. Such deviations can result in invalid value at risk (VaR) estimates, particularly when conventional models fail to capture extreme movements and complex dependencies. To address these limitations, the Copula function was introduced as a flexible approach to model non-linear dependence structures separately from marginal distributions.

Based on these considerations, this study used the ARMA–GARCH copula method to estimate portfolio VaR. Generalized autoregressive conditional heteroskedasticity (GARCH) was used to overcome high volatility in stocks. While autoregressive moving average (ARMA) was used because of the involvement of time influence in the estimation. The best ARMA-GARCH Copula model was then used to estimate value at risk for the portfolio.

2. METHODS

2.1. Autoregressive Moving Average (ARMA)

The autoregressive (AR) model can be effectively combined with the moving average (MA) model to form a common and useful time series model called the autoregressive moving average (ARMA). The ARMA model can only be used when the data are stationary. The ARMA model can be extended to non-stationary data by allowing differencing of the data, which is then called the autoregressive integrated moving average (ARIMA) model [8].

The ARIMA model notation can be written as ARIMA(p, d, q), where p denotes the AR order, d denotes the order for differencing, and q denotes the MA order. Several ARIMA models are formulated as follows [9].

a. ARIMA$(0,0,q)$ or MA(q) Model

$$Y_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} \tag{1}$$

b. ARIMA$(p,0,0)$ or AR(p) Model

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + a_t \tag{2}$$

c. ARIMA$(p,0,q)$ or ARMA(p,q) Model

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} \tag{3}$$

https://doi.org/10.13057/ijas.v9i1.95849
E-ISSN: 2621-086X

d. ARIMA(p, d, q) Model

$$\begin{aligned} W_t &= \nabla^d Y_t \\ W_t &= \phi_1 W_{t-1} + \phi_2 W_{t-2} + \cdots + \phi_p W_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} \end{aligned} \quad (4)$$

In the models above, ϕ represents the autoregressive parameters and θ represents the moving average parameter. The parameter p denotes the autoregressive order, d represents the number of differencing, and q denotes the moving average order. Meanwhile, α_t represents the residual at time-t, which is assumed to be white noise.

2.2. Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

Financial time series data such as stock indices, returns, exchange rates, and others tend to fluctuate over time. Time series data whose residual variance depends on the residual variance of the previous period, or contains volatility, cannot be analyzed using ordinary time series analysis, which assumes homoscedasticity. Therefore, autoregressive conditional heteroskedasticity (ARCH) was developed to estimate the existence of heteroscedasticity in time series data so that the resulting model is more accurate. ARCH is used to produce a systematic volatility model. Specifically, the ARCH(m) model can be formulated as

$$\begin{aligned} a_t &= \sigma_t \epsilon_t \\ \sigma_t^2 &= \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 \end{aligned} \quad (5)$$

with ϵ_t assumed to be independent and identically distributed random variables with zero mean and one variance, $\alpha_0 > 0$, and $\alpha_i \geq 0$ for $i > 0$ [10]. Although simple, the ARCH model often requires many parameters to describe the return of an asset. To overcome this problem, an alternative model was then developed by Bollerslev in 1986 known as the generalized ARCH (GARCH) model.

The GARCH model assumes that the average model follows the ARIMA model. Suppose $a_t = r_t - \mu_t$, then a_t follows the GARCH(m,s) model if

$$\begin{aligned} a_t &= \sigma_t \epsilon_t \\ \sigma_t^2 &= \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \end{aligned} \quad (6)$$

with ϵ_t assumed to be independent and identically distributed random variables with zero mean and one variance, $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$ for $i > 0$ and $\sum_{i=1}^{\max(m,s)} (\alpha_i + \beta_i) < 1$ [10].

2.3. Copula

Copula is one of the methods used to construct multivariate distributions by identifying the dependence structure of asset returns while allowing for different marginal distributions [11]. It is also defined as a function that relates the univariate marginal distribution to its multivariate distribution [12]. The commonly known copula families are the Elliptical Copula and the Archimedean copula. The Elliptical copulas that are frequently used include the gaussian copula and the t-Student copula. Meanwhile, the commonly used Archimedean copulas include the Clayton Copula, the Frank Copula, and the Gumbel Copula. The Archimedean copula is one of the most important copula families and is widely applied in the field of finance because it offers a flexible and diverse dependence structure.

Theorem 2.3: *Sklar's Theorem. Let H be a joint distribution function with margins F and G. Then there exists a copula C such that for all x,y in* $\overline{\boldsymbol{R}}$,

$$H(x, y) = C\big(F(x), G(y)\big) \quad (7)$$

If F and G are continuous, Copula C is unique; otherwise, Copula C is uniquely determined on RanF × RanG. Conversely, if C is a copula and F and G are distribution functions, then the function H defined by (7) is a joint distribution function with margins F and G [13].

Gaussian Copula

In general, the Gaussian Copula function is expressed in equation (8).

$$C_{Ga}(u_1, \dots, u_d) = \phi_\rho\big(\phi^{-1}(u_1), \dots, \phi^{-1}(u_d)\big), \qquad -1 < \rho < 1 \quad (8)$$

https://doi.org/10.13057/ijas.v9i1.95849
E-ISSN: 2621-086X

with $\boldsymbol{\phi}_\rho$ is the bivariate normal cumulative distribution function with correlation ρ and ϕ^{-1} is the inverse standard normal cumulative distribution function. Thus, the three-dimensional Gaussian Copula function is

$$C_{Ga}(u_1, \ldots, u_d) = \phi_\rho\left(\phi^{-1}(u_1), \phi^{-1}(u_2), \phi^{-1}(u_3)\right) \tag{9}$$

t-Student Copula

In general, the t-Student copula function is expressed in equation (10).

$$C_t(u_1, \ldots, u_d) = t_{d,\rho}\left(t_d^{-1}(u_1), \ldots, t_d^{-1}(u_d)\right) \tag{10}$$

with t_d is the cumulative distribution function of the multivariate t-distribution with degrees of freedom d and correlation matrix ρ. Thus, the three-dimensional t-Student copula function is

$$C_t(u_1, u_2, u_3) = t_{d,\rho}\left(t_d^{-1}(u_1), t_d^{-1}(u_2), t_d^{-1}(u_3)\right) \tag{11}$$

Clayton Copula

In general, the Clayton copula function is expressed in equation (12).

$$C_{clay}(u_1, \ldots, u_d) = \left(\left[\sum_{i=1}^{d} u_i^{-\gamma} - d + 1\right]\right)^{-\frac{1}{\gamma}}, \qquad \gamma > 0, \tag{12}$$

so that the three-dimensional Clayton copula function is

$$C_{clay}(u_1, u_2, u_3) = \left(u_1^{-\gamma} + u_2^{-\gamma} + u_3^{-\gamma} - 2\right)^{-\frac{1}{\gamma}} \tag{13}$$

Frank Copula

In general, the Frank copula function is expressed in equation (14).

$$C_{Fr}(u_1, \ldots, u_d) = -\frac{1}{\gamma}\ln\left\{1 + \frac{\prod_{i=1}^{d}[e^{-\gamma u_i} - 1]}{[e^{-\gamma} - 1]^{d-1}}\right\}, \qquad \gamma > 0, \tag{14}$$

so the Frank copula function in three dimensions is

$$C_{Fr}(u_1, u_2, u_3) = -\frac{1}{\gamma}\ln\left\{1 + \frac{(e^{-\gamma u_1} - 1)(e^{-\gamma u_2} - 1)(e^{-\gamma u_3} - 1)}{[e^{-\gamma} - 1]^2}\right\} \tag{15}$$

Gumbel Copula

In general, the Gumbel copula function is expressed in equation (16)

$$C_{Gu}(u_1, \ldots, u_d) = \exp\left\{-\left[\sum_{i=1}^{d}(-\ln u_i)^\gamma\right]^{\frac{1}{\gamma}}\right\}, \qquad \gamma > 1, \tag{16}$$

so the three-dimensional Gumbel copula function is

$$C_{Gu}(u_1, u_2, u_3) = \exp\left\{-[(-\ln u_1)^\gamma + (-\ln u_2)^\gamma + (-\ln u_3)^\gamma]^{\frac{1}{\gamma}}\right\} \tag{17}$$

2.4. Value at Risk

Value at risk (VaR) is defined as the estimated maximum loss that may occur over a specified time period under normal market conditions at a given confidence level [14]. VaR can be determined from the density function of the future returns, $f(R)$ where R denotes the return. The probability that the return exceeds the worst possible return value, R^* can be expressed as

$$\int_{R^*}^{\infty} f(R)\ dR = 1 - \alpha \tag{18}$$

Meanwhile, the probability of a return being less than or equal to R^* is equal to α is

$$P(R \leq R^*) = \int_{-\infty}^{R^*} f(R)\ dR = \alpha \tag{19}$$

https://doi.org/10.13057/ijas.v9i1.95849
E-ISSN: 2621-086X

If the initial stock investment is denoted by W_0, the stock value at the end of the period is denoted by $W = W_0(1 + R)$. If the lowest stock value at the $(1 - \alpha)$ confidence level is $W^* = W_0(1 + R^*)$, then the Value at Risk at the $(1 - \alpha)$ confidence level is

$$VaR_{1-\alpha} = W_0 R^* \quad (20)$$

Value at risk at the $(1 - \alpha)$ confidence with the initial investment value W_0 and portfolio variance σ_p^2 can be written as

$$VaR = W_0 Z_{(1-\alpha)} \sigma_p \quad (21)$$

3. RESULTS AND DISCUSSION

3.1. Characteristics of Returns

Value at risk estimation using the ARMA-GARCH Copula method was conducted on the daily simple returns of MAPI, FAST, and UNVR for the period from March 1, 2019, to February 29, 2024. A descriptive analysis was first performed to identify the characteristics of returns for each stock.

Table 1. Statistics descriptive of MAPI, FAST, and UNVR returns

Stock Code	MAPI	FAST	UNVR
Average	0.00089	0.00009	-0.00083
Variance	0.00083	0.00043	0.00042
Minimum	-0.10714	-0.41667	-0.10703
Maximum	0.23362	0.92307	0.19383

Table 1 shows that MAPI and FAST returns have positive average value, indicating that they tend to generate gains for investors. Meanwhile, UNVR returns have a negative average value, indicating a tendency to generate losses during the observed period. The highest variance value is observed in MAPI returns, which is 0.00083. This indicating that MAPI returns were more volatile compared to FAST and UNVR. The lowest minimum and highest maximum return values among the three stocks were observed in FAST, indicating both the highest profit potential and the highest loss potential.

3.2. ARIMA Modeling

ARIMA model identification was performed by examining data stationarity and estimating the ARIMA model. Stationarity testing was conducted using the Augmented Dickey-Fuller (ADF) test. The results, as presented in Table 2, indicate that all three data series were stationary. Therefore, the appropriate model to be applied to the three series was the ARMA model.

Table 2. ADF test results

Stock Code	ADF	p-value
MAPI	-10.369	0.01
FAST	-12.056	0.01
UNVR	-11.969	0.01

ARMA model estimation was performed using the *auto.arima* functions in RStudio. The optimal ARMA model was selected based on the smallest Akaike information criterion (AIC) value. The estimation results indicate that the best model for MAPI stock returns is ARMA(2,0), for FAST stock returns is ARMA(1,2), and for UNVR stock returns ARMA(3,0). In the ARMA estimation results, insignificant parameters were considered not to be used in the ARMA model. Then, the final ARMA models consist only of statistically significant parameters for each stock, as presented in Table 3.

https://doi.org/10.13057/ijas.v9i1.95849
E-ISSN: 2621-086X

Table 3. Results of significance test of ARMA model parameters

Stock Code	Model	Parameter	Estimate	p-value	Information
MAPI	ARMA ([2],0)	AR(2)	-0.10027	0.00041	Significant
FAST	ARMA (1,2)	AR(1)	-0.79462	0.00000	Significant
		MA(1)	0.67091	0.00000	Significant
		MA(2)	-0.18363	0.00000	Significant
UNVR	ARMA ([2,3],0)	AR(2)	-0.05600	0.04796	Significant
		AR(3)	0.10834	0.00013	Significant

The obtained ARMA model were then evaluated using the Ljung-Box test and the Kolmogorov-Smirnov test. The results of the Ljung-Box test, as presented in Table 4, indicate that the residuals of the three models exhibit white noise behavior. While the Kolmogorov-Smirnov test results, as presented in Table 5, shows that the residuals are not normally distributed. This finding suggests the presence of heteroscedasticity and indicates a potential ARCH effect in the models.

Table 4. Results of the Ljung-Box test

Saham	Model	Lag	p-value	Information
MAPI	ARMA([2],0)	6	0.2508	White Noise
		12	0.1817	White Noise
		18	0.1657	White Noise
		24	0.1040	White Noise
FAST	ARMA(1,2)	6	0.5240	White Noise
		12	0.3967	White Noise
		18	0.3691	White Noise
		24	0.1534	White Noise
UNVR	ARMA([2,3],0)	6	0.9082	White Noise
		12	0.1313	White Noise
		18	0.3743	White Noise
		24	0.3090	White Noise

Table 5. Results of the Kolmogorov-Smirnov test

Saham	Model	D	p-value
MAPI	ARMA([2],0)	0.06281	0.00012
FAST	ARMA(1,2)	0.14133	0.00000
UNVR	ARMA([2,3],0)	0.09184	0.00000

Testing for ARCH effects in the squared residuals was conducted using the Lagrange multiplier (LM) test to determine the presence of heteroscedasticity [15]. The results as presented in Table 6, indicate that ARCH effects were present in all three models, implying that the data exhibit heteroscedasticity.

Table 6. Results of the Lagrange multiplier test

Saham	Model	Order	LM	p-value
MAPI	ARMA([2],0)	4	1556	0.000
		12	311	0.000
		24	127	0.000
FAST	ARMA(1,2)	4	2733	0
		12	746	0
		24	262	0

https://doi.org/10.13057/ijas.v9i1.95849
E-ISSN: 2621-086X

Saham	Model	Order	LM	p-value
UNVR	ARMA([2,3],0)	4	1257	0
		12	391	0
		24	185	0

3.3. ARCH/GARCH Modeling

The ARCH/GARCH estimation models used to explain the presence of heteroscedasticity in the data are ARCH(1), ARCH(2), and GARCH(1,1). The results of the significance test of the ARCH/GARCH estimation model parameters for each stock are shown in Table 7, Table 8, and Table 9.

Table 7. Results of significance test of ARCH/GARCH model parameters for MAPI stocks

Model	Parameter	Estimate	p-value	Information
ARMA([2],0)-ARCH(1)	ϕ_2	-0.12420	0.00000	Significant
	ω	0.00072	0.00000	Significant
	α_1	0.10971	0.01912	Significant
	λ	1.10887	0.00000	Significant
	η	5.70688	0.00000	Significant
ARMA([2],0)-ARCH(2)	ϕ_2	-0.11896	0.00003	Significant
	ω	0.00069	0.00000	Significant
	α_1	009603	0.03517	Significant
	α_2	0.06013	0.10488	Not Significant
	λ	1.11233	0.00000	Significant
	η	5.93405	0.00000	Significant
ARMA([2],0)-GARCH(1,1)	ϕ_2	-0.12355	0.00001	Significant
	ω	0.00005	0.03237	Significant
	α_1	0.04814	0.00594	Significant
	β_1	0.88152	0.00000	Significant
	λ	1.09948	0.00000	Significant
	η	6.71067	0.00000	Significant

Based on Table 7, all parameters in the ARCH(1) and GARCH(1,1) models were significant, so both models can be considered as the best models. Meanwhile, the ARCH(2) model contained one insignificant parameter, therefore, it was not considered further.

Table 8. Significance test results of ARCH/GARCH model parameters for FAST stocks

Model	Parameter	Estimate	p-value	Information
ARMA(1,2)-ARCH(1)	ϕ_1	0.98958	0.00000	Significant
	θ_1	-1.11696	0.00000	Significant
	θ_2	0.12390	0.00000	Significant
	ω	0.00064	0.00095	Significant
	α_1	0.99900	0.00068	Significant
	λ	1.00879	0.00000	Significant
	η	2.16652	0.00000	Significant
ARMA(1,2)-ARCH(2)	ϕ_1	-0.94291	0.00000	Significant
	θ_1	0.79808	0.00000	Significant
	θ_2	-0.14874	0.00000	Significant
	ω	0.00034	0.00006	Significant
	α_1	0.56282	0.00055	Significant
	α_2	0.43618	0.00146	Significant

https://doi.org/10.13057/ijas.v9i1.95849
E-ISSN: 2621-086X

Model	Parameter	Estimate	p-value	Information
	λ	1.01921	0.00000	Significant
	η	2.28008	0.00000	Significant
ARMA(1,2)-GARCH(1,1)	ϕ_1	-0.94338	0.00000	Significant
	θ_1	0.79336	0.00000	Significant
	θ_2	-0.15709	0.00000	Significant
	ω	0.00007	0.02392	Significant
	α_1	0.36798	0.00001	Significant
	β_1	0.63102	0.00000	Significant
	λ	1.02607	0.00000	Significant
	η	2.41534	0.00000	Significant

Based on Table 8, all parameters in the three models were significant. This means that the three models were considered as the best models to explain the presence of heteroscedasticity in FAST returns.

Table 9. Results of significance test of ARCH/GARCH model parameters for UNVR stocks

Model	Parameter	Estimate	p-value	Information
ARMA([2,3],0)-ARCH(1)	ϕ_2	-0.05111	0.03841	Significant
	ϕ_3	0.01700	0.50306	Not Significant
	ω	0.00029	0.00000	Significant
	α_1	0.45364	0.00001	Significant
	λ	1.13528	0.00000	Significant
	η	3.40347	0.00000	Significant
ARMA([2,3],0)-ARCH(2)	ϕ_2	-0.04551	0.08575	Not Significant
	ϕ_3	0.00205	0.93542	Not Significant
	ω	0.00025	0.00000	Significant
	α_1	0.40174	0.00003	Significant
	α_2	0.14008	0.01621	Significant
	λ	1.14341	0.00000	Significant
	η	3.49471	0.00000	Significant
ARMA([2,3],0)-GARCH(1,1)	ϕ_2	-0.04423	0.10104	Not Significant
	ϕ_3	0.00771	0.77625	Not Significant
	ω	0.00002	0.00499	Significant
	α_1	0.14838	0.00010	Significant
	β_1	0.82001	0.00000	Significant
	λ	1.14390	0.00000	Significant
	η	3.64032	0.00000	Significant

Based on Table 9, each model has insignificant ARMA parameters. However, all ARCH/GARCH parameters were significant. Therefore, the model was considered adequate to explain the presence of heteroscedasticity in UNVR returns.

The selected ARMA-ARCH/GARCH model were further evaluated using the weighted Ljung-Box test and the weighted Lagrange-multiplier test. The results of the diagnostic test and model evaluation indicate that the model with GARCH(1,1) for all three stocks successfully captured the autocorrelation patterns and adequately modeled heteroscedasticity. The final ARMA-GARCH models are written as follows.

a. MAPI return: ARMA([2],0)-GARCH(1,1)

$$\begin{gathered} Y_t = -0.12355Y_{t-2} + a_t \\ \hat{\sigma}_t^2 = 0.00005 + 0.04814a_{t-1}^2 + 0.88152\hat{\sigma}_{t-1}^2 \\ a_t \sim skt(1.09948; 6.71067) \end{gathered} \tag{22}$$

b. FAST return: ARMA(1,2)-GARCH(1,1)

$$Y_t = (-0.94338)Y_{t-1} + a_t - (0.79336)a_{t-1} - (-0.15709)a_{t-2}$$
$$\hat{\sigma}_t^2 = 0.00007 + 0.36798a_{t-1}^2 + 0.63102\hat{\sigma}_{t-1}^2 \quad (23)$$
$$a_t \sim skt(1.02607; 2.41539)$$

c. UNVR return: ARMA([2,3],0)-GARCH(1,1)

$$Y_t = (-0.04423)Y_{t-2} + 0.00771Y_{t-3} + a_t$$
$$\hat{\sigma}_t^2 = 0.00002 + 0.14838a_{t-1}^2 + 0.82001\hat{\sigma}_{t-1}^2 \quad (24)$$
$$a_t \sim skt(1.14390; 3.64032)$$

3.4. Copula Analysis

Copula analysis was performed using standardized residuals of each ARMA-GARCH model. Standardized residuals were used because they represent residuals that have been adjusted for volatility and to build dependencies between variables.

Copula analysis was chosen because it can capture non-linear dependencies and identify dependency structures that may not be detected through simple correlation analysis. Copula analysis was performed using Gaussian copula, Copula t-Student, Clayton copula, Gumbel copula, and Frank copula. The estimation results are presented in Table 10.

Table 10. Copula parameter estimation results

Copula	Parameter Estimation	Standard Error	Maximized Loglikelihood
Gaussian	0.1005	0.018	17
t-Student	0.0983 (df = 29.90097)	0.019	18.67
Clayton	0.1180	0.021	20.71
Gumbel	1.0517	0.013	10.79
Frank	0.5164	0.107	12.83

Based on Table 10, it is obtained that the Clayton copula model was the best copula with the largest maximized loglikelihood value, which is 20.71. The Clayton copula model for the three stocks is written as

$$C_{clay}(u_1, u_2, u_3) = \left(u_1^{-\gamma} + u_2^{-\gamma} + u_3^{-\gamma} - 2\right)^{-\frac{1}{\gamma}}$$
$$= (u_1^{-0.1180} + u_2^{-0.1180} + u_3^{-0.1180} - 2)^{-\frac{1}{0.1180}} \quad (25)$$

3.5. Value at Risk Estimation

Based on Figure 1, the standardized residuals exhibit fat tails. Therefore, the generalized pareto distribution was used for model the tails and the normal distribution was used for model the middle (inner) of each standardized residual. Overall, the residuals were modeled using the GNG (generalized pareto-normal-generalized pareto) distribution. Value at risk estimation was calculated by performing monte carlo simulation. In this study, monte carlo simulation was performed with 1000 repetitions. Uniformly distributed random samples [0,1] generated using the Clayton copula model were transformed into the residual distribution of each stock using the inverse cumulative distribution function of GNG of each stock. Then, the transformation results in the form of simulated standardized residuals were transformed into simulated returns.

https://doi.org/10.13057/ijas.v9i1.95849
E-ISSN: 2621-086X

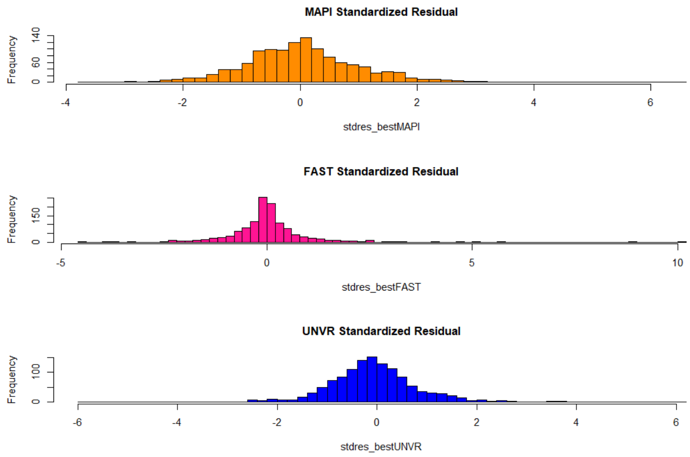

Figure 1. Standardized residual of ARMA-GARCH(1,1) model

Return simulation of each stock was then multiplied by the weight of each stock obtained from the weighting results using the minimum variance portfolio (MVP) method. Based on the weighting results, the weight of each return is shown in Table 11.

Table 11. Weight of each stock in a portfolio

Share	Weight
MAPI	0.177
FAST	0.415
UNVR	0.408

The sum of the simulated returns from each weighted stock is called the simulated portfolio return. This simulated portfolio return was then used to calculate VaR at 99%, 95%, and 90% confidence levels. The results of the VaR estimation at each confidence level are presented in Table 12.

Table 12. Value at risk estimation results

Confidence Level	VaR	Standard Error
99%	0.03451742	0.0003542014
95%	0.02112812	0.0002025003
90%	0.01553215	0.0001478291

Based on Table 12, the VaR value at the 99% confidence level is higher than the VaR value at the 95% and 95% confidence levels, which is 3.45%. This means that with 99% confidence, the investment loss in the portfolio will not exceed 3.45% of the invested assets over the specified period.

The small standard error values at all confidence levels indicates that the VaR calculation was quite accurate. To prove the accuracy of the VaR estimate, backtesting of the VaR model was carried out using the binomial distribution test at each level of confidence. The results of the binomial distribution test are presented in Table 13.

Table 13. Binomial distribution test results

VaR Confidence Level	Actual Exceed	Max Expected Exceed	LR	p-value
99%	14	12.29	0.23000	0.25401
95%	59	61.45	0.10414	0.59356
90%	111	122.9	1.31891	0.86137

https://doi.org/10.13057/ijas.v9i1.95849
E-ISSN: 2621-086X

Based on Table 13, the actual exceed column represents the number of VaR violations or the number of losses exceeding the maximum loss threshold estimated by VaR. The max expected exceed column represents the maximum expected number of VaR violations. The comparison between the actual and expected exceedances indicates that the VaR model performs adequately, as the observed number of violations is close to the expected number. Therefore, the VaR estimates at all three confidence levels can be considered accurate.

4. CONCLUSION

The ARMA-GARCH modeling results indicate that the best models were ARMA([2],0)-GARCH(1,1) for MAPI returns, ARMA(1,2)-GARCH(1,1) for FAST returns, and ARMA([2,3],0)-GARCH(1,1) for UNVR returns. These specifications suggest that past return dynamics significantly influence current returns, as reflected in the AR and MA components, while the consistent selection of GARCH(1,1) across all stocks confirms the presence of volatility clustering and persistent conditional heteroskedasticity. In particular, the GARCH(1,1) structure implies that shocks to volatility are not short-lived but gradually decay over time, indicating that market reactions to events such as the issuance of MUI Fatwa Number 83 of 2023 have prolonged effects on return variability.

The Copula estimation results show that the Clayton copula best describes the dependence structure among the three stocks. The Clayton copula implies the existence of lower tail dependence, meaning that extreme negative returns tend to occur simultaneously across the stocks with higher probability than would be predicted by linear correlation alone. Economically, this indicates that during market downturns, the three stocks are more likely to experience joint declines.

Value at risk estimation conducted on the weighted returns using the Clayton copula indicates that the value at risk at 99%, 95%, and 90% confidence levels are 3.45%, 2.11%, and 1.55%, respectively. These results imply that, under normal market conditions, the portfolio is expected to experience a maximum one-day loss of 3.45% with 99% confidence. Similarly, at the 95% and 90% confidence levels, the maximum expected losses are 2.11% and 1.55%, respectively. As expected, higher confidence levels yield higher value at risk estimates because they account for more extreme adverse scenarios. Importantly, when interpreted alongside the Clayton copula findings, these value at risk reflect not only individual stock volatility but also the amplified joint downside risk arising from lower tail dependence. Therefore, the estimated value at risk captures systemic co-movement risk during periods of market stress, providing a more realistic assessment of potential portfolio losses.

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E-ISSN: 2621-086X