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Systemic Risk Dependence Analysis of Indonesian Banking Stocks Using Multivariate Copula Approach and Monte Carlo Simulation

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Abstract

This study aims to measure and analyze the dependence structure and systemic risk of the four largest banking stocks in Indonesia by market capitalization, namely BBCA, BBRI, BMRI, and BBNI, using the copula approach. Given the limitations of Pearson correlation in capturing nonlinear relationships and tail dependence phenomena under extreme market conditions, the copula approach serves as a superior alternative method due to its ability to separate the dependence structure from the marginal distributions of individual assets. The data employed are daily closing prices spanning from January 1, 2019, to December 31, 2025, covering the COVID-19 pandemic crisis period and the post-pandemic recovery phase. The analytical procedure begins with volatility modeling using an ARMA(1,0)-eGARCH(1,1) specification with Student-t distributed innovations to accommodate fat-tailed properties and asymmetric leverage effects. The model residuals are transformed into the uniform domain via pseudo-observations based on the empirical Probability Integral Transform (PIT). Five copula families are evaluated, namely Gaussian, Clayton, Gumbel, Frank, and Student-t, with model selection criteria based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Empirical results indicate that the Gaussian Copula emerges as the optimal model, yielding an AIC value of -2378.57 and a log-likelihood of 1190.29. This finding suggests that although a substantially positive correlation exists, the dependence structure among banking stocks tends to be linear and symmetric, with no evidence of significant lower tail dependence. Monte Carlo simulation with 50,000 iterations applied to an equal-weighted portfolio generates a daily Value-at-Risk (VaR) estimate of 0.2035% at the 95% confidence level and an Expected Shortfall (ES) of 0.1168% at the same confidence level. From a practical perspective, these findings confirm that diversification strategies within the Indonesian banking stock portfolio remain reasonably effective for mitigating daily market risk. Nevertheless, rigorous monitoring and the implementation of additional stress testing remain essential to anticipate large-scale systemic macroeconomic shocks.

Keywords: ARMA-GARCH, Banking stocks, Copula, Dependence, Expected Shortfall, Systemic risk, Value-at-Risk.

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1. Introduction

Modern capital markets, both globally and domestically integrated, exhibit high levels of complexity and are vulnerable to sudden macroeconomic shock transmissions. The phenomenon of financial asset interconnectedness has become a primary focus for market participants, investment managers, and financial regulatory authorities. The Indonesian banking sector, which is dominantly reflected in the Composite Stock Price Index (IHSG), holds a strategic role as the main driver of the national economy (Evkaya et al., 2024). Large-capitalization banking stocks, such as PT Bank Central Asia Tbk (BBCA), PT Bank Rakyat Indonesia (Persero) Tbk (BBRI), PT Bank Mandiri (Persero) Tbk (BMRI), and PT Bank Negara Indonesia (Persero) Tbk (BBNI), account for a very significant portion of total market capitalization. Consequently, the price movements of these banking stocks not only reflect the internal conditions of the respective companies but also serve as a primary barometer of the overall health of national financial stability. In the event of a shock or liquidity disturbance affecting one of these banking pillars, there exists a substantial potential for a contagion effect that may trigger systemic risk across the entire financial industry (Kusumahadi et al., 2025; Pratama & Henida, 2025).

Traditionally, risk management analysis, asset allocation, and optimal portfolio formation have been based on the Mean-Variance framework of Markowitz and the use of the Pearson correlation coefficient. Pearson correlation measures the strength and direction of the linear relationship between two random variables. However, modern financial

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modeling over the past few decades has identified various fundamental weaknesses of Pearson correlation when applied to empirical financial time series data. This traditional correlation is only capable of capturing linear dependence structures and assumes that data variance remains constant over time (homoscedasticity). In reality, financial asset returns almost invariably exhibit non-linear, asymmetric characteristics and possess heavy-tailed distributions (fat tails or leptokurtosis) (Handini et al., 2018; Phu Nguyen & Luu Duc Huynh, 2019; Prasetya et al., 2018). Furthermore, financial data often exhibit the phenomenon of volatility clustering, whereby periods of high volatility tend to be followed by subsequent high volatility, and calm periods tend to be followed by tranquility.

Another fundamental limitation of the Pearson correlation coefficient is its inherent inability to capture the phenomenon of tail dependence. Tail dependence refers to the propensity of financial assets to co-move downward during periods of extreme market declines (lower tail dependence) or to co-surge upward during episodes of extreme market rallies (upper tail dependence). Throughout financial crises including the stock market collapse induced by the global pandemic in early 2020 or the phase of global monetary policy tightening spanning 2023 to 2025 correlations among financial assets typically intensify dramatically in a non-linear fashion. (Budiarti et al., 2023; Karimalis & Nomikos, 2018) Employing Pearson correlation under such circumstances yields an underestimation of risk, a condition that may have severe and potentially fatal implications for bank capital adequacy as well as the overall resilience of investment portfolios (Das & Fasen-Hartmann, 2025; Maghyereh et al., 2022; Zhang et al., 2023).

To overcome the limitations of linear correlation, the copula function methodology was introduced into quantitative finance as a revolutionary tool. Grounded in Sklar's Theorem, this approach provides a flexible framework for modeling dependence structures independently from marginal distributions (Geenens, 2024), The copula function enables researchers to separate the specification of marginal distributions of individual random variables from the joint multivariate dependence function. Through this approach, specific properties of individual time series data, such as fat-tailed distributions and leverage effects, can be modeled independently using univariate time series models, such as the Autoregressive Moving Average (ARMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). After filtering out these marginal effects, the standardized residuals are transformed into uniform variables to analyze their dependence structure using various families of copula functions, including both Elliptical types (Gaussian, Student-t) and Archimedean types (Clayton, Gumbel, Frank) (Ab Razak & Ismail, 2019; Duong & Huynh, 2020).

This research focuses on an in-depth empirical analysis of the systemic risk dependence structure among the four major banking stocks in Indonesia (BBCA, BBRI, BMRI, BBNI), utilizing an extensive data period spanning from January 1, 2019, to May 31, 2026. This period encompasses various critical market cycles, including the global health crisis, national economic recovery, and prolonged domestic and global macroeconomic uncertainty. By evaluating the performance of five distinct multivariate copula functions and applying the optimal model results to Monte Carlo simulations to estimate portfolio Value-at-Risk (VaR) and Expected Shortfall (ES), this study is expected to make novel theoretical contributions to the financial econometrics literature in Indonesia while providing high-value practical guidance for risk managers and financial regulatory authorities (Budiarti et al., 2023; Evkaya et al., 2024).

2. Literature Review

The theoretical foundation of this research is rooted in modern portfolio theory and non-linear time series econometric modeling. This section elaborates the rigorous mathematical formulations of return data transformation, asymmetric eGARCH marginal modeling, Sklar's Theorem, specific formulations of various copula families, and extreme risk measurement metrics including VaR and Expected Shortfall.

2.1. Logarithmic Stock Return Calculation

In quantitative financial analysis, the use of raw stock prices is often avoided due to their non-stationary nature. Therefore, daily closing stock prices are transformed into continuously compounded logarithmic returns (Sari et al., 2024). The mathematical formulation for logarithmic returns is specified as follows:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) = \ln(P_t) - \ln(P_{t-1}) \tag{1}$$

Where r_t denotes the logarithmic return of the stock on day t, P_t denotes the adjusted closing price of the stock on day t, and P_{t-1} denotes the stock price on the previous trading day $(t-1)$.

2.2. Marginal Modeling: ARMA-eGARCH

To filter out autocorrelation in the conditional mean and conditional heteroskedasticity in volatility, an ARMA(p,q) model specification integrated with the Exponential GARCH or eGARCH(1,1) model proposed by Nelson (1991) is employed. The eGARCH model has a key comparative advantage over the standard GARCH model as it is capable of capturing the leverage effect, whereby volatility tends to increase more in response to negative shocks (bad news) than to positive shocks (good news) of equal magnitude (Ab Razak & Ismail, 2019; Phu Nguyen & Luu Duc Huynh, 2019). The conditional mean equation of the ARMA(1,0) model is expressed as:

$$r_t = \mu + \phi_1 r_{t-1} + \varepsilon_t \tag{2}$$

Where μ is the mean constant, ϕ_1 is the first-order autoregressive parameter, and ε_t represents the residual or shock at time t which can be expressed as $\varepsilon_t = \sigma_t z_t$. The variable σ_t denotes the conditional volatility, while z_t epresents the standardized residual innovation assumed to follow a univariate Student-t distribution to capture heavy-tailed characteristics. Subsequently, the conditional variance equation of the eGARCH(1,1) model is formulated as follows:

$$\ln(\sigma_t^2) = \omega + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{3}$$

Where ω is the variance intercept constant, β_1 measures volatility persistence (the GARCH effect), α_1 represents the magnitude effect of shocks on volatility (the ARCH effect), and γ_1 denotes the asymmetry parameter or leverage effect. If $\gamma_1 < 0$ and is statistically significant, then there is strong evidence of a leverage effect, whereby bad news increases volatility more than good news (Ab Razak & Ismail, 2019).

2.3. Sklar's Theorem and the Definition of the Copula Function

Sklar's Theorem (Geenens, 2024) serves as the principal mathematical nexus that fundamentally underpins the entire theoretical edifice of copula-based dependence modeling. The theorem formally posits that any multivariate cumulative distribution function (CDF) of dimension d can be expressed as a composition of its univariate marginal distribution functions and a copula function that uniquely characterizes the dependence structure among the constituent random variables (Prasetya et al., 2018). Let H denote a $d-dimensional$ joint cumulative distribution function characterized by continuous marginal distribution functions $F_1, F_2, \dots, F_d$ $F_1, F_2, \dots, F_d$, Then there exists a unique copula function C defined on the $d-dimensional$ unit hypercube $[0,1]^d$ such that for every point $x = (x_1, \dots, x_d) \in \mathbb{R}^d$ the following equality holds:

$$H(x_1, x_2, \dots, x_d) = C\big(F_1(x_1), F_2(x_2), \dots, F_d(x_d)\big) \tag{4}$$

Conversely, if C is a copula function and F_1, $F_2, \dots, F_d$ are univariate distribution functions, then the function H defined in the preceding equation represents a valid joint distribution function with marginal distributions $F_1, F_2, \dots, F_d$. To extract the copula function from the joint distribution, we can apply the Probability Integral Transform (PIT) through the inverse of the marginal distribution functions F_i^- $F_i^{\{-1\}}$ (Duong & Huynh, 2020):

$$C(u_1, u_2, \dots, u_d) = H\big(F_1^{-1}(u_1), F_2^{-1}(u_2), \dots, F_d^{-1}(u_d)\big) \tag{5}$$

Where $u_i = F_i(x_i) \in [0,1]$ represents the uniform variables resulting from the marginal transformation.

2.4. Characteristics of the Copula Family

In this study, five types of multivariate copulas were tested, classified into two main groups: elliptical copulas (Gaussian and Student's t) and Archimedean copulas (Clayton, Gumbel, and Frank). Each possesses unique geometric properties for capturing patterns of data interdependence.

2.4.1 Gaussian Copula

The Gaussian copula is a symmetric elliptical copula with no tail dependence (tail dependence coefficient $\lambda_L = \lambda_U = 0$) (Prasetya et al., 2018). Its purely linear dependence is based on the correlation matrix Σ . The density of the Gaussian copula is defined as:

$$C_{\text{Gauss}}(u) = \Phi_R\left(\Phi^{-1}(u_1), \dots, \Phi^{-1}(u_d)\right) \tag{6}$$

Where Φ_R s the joint normal distribution with correlation matrix R, and $\Phi^{\{-1\}}$ is the inverse of the standard univariate normal CDF.

2.4.2 Student-t Copula

The Student-t copula is an elliptical copula capable of capturing symmetric tail dependencies at both ends of the distribution (the upper and lower tails have the same value, $\lambda_L = \lambda_U > 0$). This model estimates the probability of simultaneous extreme events based on the degrees of freedom ν and the correlation matrix Σ (Prasetya et al., 2018):

$$C_t(u) = t_{R,\nu}\left(t_\nu^{-1}(u_1), \dots, t_\nu^{-1}(u_d)\right) \tag{7}$$

2.4.3 Clayton Copula

The Clayton copula is an asymmetric member of the Archimedean family; it is highly sensitive to correlations in the left tail (lower tail dependence, $\lambda_L > 0$), but exhibits no dependence in the right tail ($\lambda_U = 0$) (Maghyereh et al., 2022) The bivariate Clayton copula equation is written as:

$$C_{\text{Clayton}}(u, v) = \left(u^{-\theta} + v^{-\theta} - 1\right)^{-1/\theta} \tag{8}$$

2.4.4 Gumbel Copula

The Gumbel copula is the inverse of the Clayton copula; the Gumbel copula exhibits a right-skewed bias (upper tail dependence, $\lambda_U > 0$) and is sterile in the lower tail ($\lambda_L = 0$) (Maruddani & Safitri, 2025). Its geometric equation is:

$$C_{\text{Gumbel}}(u, v) = \exp\left(-\left[(-\ln u)^\theta + (-\ln v)^\theta\right]^{1/\theta}\right) \tag{9}$$

2.4.5 Frank Copula

The Frank copula is a symmetric Archimedean copula with no tail dependence ($\lambda_L = \lambda_U = 0$), but it is very effective at modeling dependence in the central part of the distribution (Handini et al., 2018):

$$C_{\text{Frank}}(u, v) = -\frac{1}{\theta}\ln\left(1 + \frac{\left(e^{-\theta u} - 1\right)\left(e^{-\theta v} - 1\right)}{e^{-\theta} - 1}\right) \tag{10}$$

2.5. Formulas for Value-at-Risk (VaR) and Expected Shortfall (ES)

Value-at-Risk (VaR) is defined as an estimate of the maximum financial loss that an investment portfolio may incur over a given time period at a confidence level of α (Evkaya et al., 2024). Mathematically, VaR is a quantile of the return distribution of portfolio *X*:

$$\text{VaR}_\alpha(X) = \inf\{ x \in \mathbb{R}: P(X \le x) \ge 1 - \alpha\} \tag{11}$$

Although VaR is very popular, this metric has been criticized for not satisfying the property of coherence (subadditivity) and for failing to indicate the magnitude of the loss if the VaR threshold is exceeded. To address this, Expected Shortfall

(ES) or Conditional VaR (CVaR) is used. Expected Shortfall measures the expected average value of losses that occur when the VaR threshold has been exceeded (Evkaya et al., 2024; Habibi & Rusgianto, 2021; Sari et al., 2024):

$$\mathrm{ES}_{\alpha}(X) = \mathbb{E}[\, X \mid X \leq \mathrm{VaR}_{\alpha}(X)\,] = \frac{1}{1-\alpha}\int_{0}^{1-\alpha} \mathrm{VaR}_{u}(X)\ du \tag{12}$$

3. Research Methodology

This quantitative study was conducted using secondary data based on actual stock market data. The study's subject matter includes time-series data on the adjusted closing prices of the stocks BBCA, BBRI, BMRI, and BBNI. Data sources were obtained from the Yahoo Finance public financial database via the quantmod package in R Studio. The observation period was set from January 1, 2019, to December 31, 2025. This long time horizon was chosen to ensure the model could capture the dynamics of cross-regime dependencies in heterogeneous market conditions.

The computational implementation steps were carried out in a structured manner as follows: First, price data were transformed into log-returns and tested for stationarity using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests. Second, marginal modeling is performed to filter the univariate time series components via an ARMA(1,0)-eGARCH(1,1) specification with a Student-t distribution. The validity of the marginal model is verified to be free from autocorrelation issues and ARCH residual effects through the Ljung-Box test and the ARCH-LM test (Handriani, 2022). Third, the standardized residuals from each margin were converted into pseudo-observations with a uniform distribution [0,1] using the eCDF function.

Fourth, a multivariate fitting process was performed to estimate the parameters of the five candidate Copula models (Gaussian, Student-t, Clayton, Gumbel, Frank) using the Maximum Likelihood Estimation algorithm. The selection of the best Copula model was determined objectively by minimizing the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values (Darsono & Pratama, 2025). Fifth, the selected Copula model was used as the basis for a random number generator in a Monte Carlo simulation consisting of 50,000 iterations. These uniformly distributed multivariate random numbers are mapped back to the financial return scale via the inversion of the eGARCH marginal CDF to form an equal-weighted portfolio (each with a 25% weight). Finally, the VaR and Expected Shortfall values are calculated at the 95% and 99% confidence levels.

4. Results and Discussion

4.1. Descriptive Analysis and Data Stationarity Tests

The characteristics of the historical cumulative return movements of the four banking stocks during the 2019–2025 period indicate the occurrence of simultaneous extreme volatility shocks in the first quarter of 2020 as an initial impact of the external shock caused by the COVID-19 pandemic. This volatility clustering phenomenon aligns with the findings of (Ab Razak & Ismail, 2019) and (Budiarti et al., 2023) which state that the volatility of the financial sector index in Indonesia is highly sensitive to global macroeconomic sentiment. Following this phase, the four stocks experienced a recovery trend with varying cumulative growth patterns through 2026 (Darsono & Pratama, 2025).

Table 1. Results of the Augmented Dickey-Fuller (ADF) Unit Root Test

Variable Return	Statistics Dickey-Fuller	Lag Order	p-value
BBCA	-13.477	11	0.01 (Significance)
BBRI	-12.043	11	0.01 (Significance)
BMRI	-12.788	11	0.01 (Significance)
BBNI	-11.562	11	0.01 (Significance)

Table 1 show the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests applied to the log-return data yield the unequivocal conclusion that all data series are stationary at the first order (I(0)). The ADF statistic is well below the critical value at the 1% significance level, with a p-value consistently at the 0.01 level. This finding of stationarity allows for the continuation of time-series econometric modeling without the risk of spurious regression, in accordance with the standard methodology for multivariate financial data (Ab Razak & Ismail, 2019).

An analysis of Table 2 shows that the average daily return hovered very close to zero, with BBCA and BMRI stocks posting very slight positive returns, while BBRI and BBNI exhibited a marginal negative trend over the entire study period (2019–2025). The extreme minimum value was recorded for BMRI shares at -13.92%, followed by BBNI (-

12.46%) and BBRI (-10.67%). On the other hand, the highest potential for daily maximum surges was seen in BBRI shares, reaching 18.64%, and BBCA at 15.98%. This wide deviation range between minimum and maximum values indicates the presence of fat tails and a strong leptokurtic phenomenon, where large-scale market shocks have a significantly higher probability of occurrence than in a standard normal distribution.

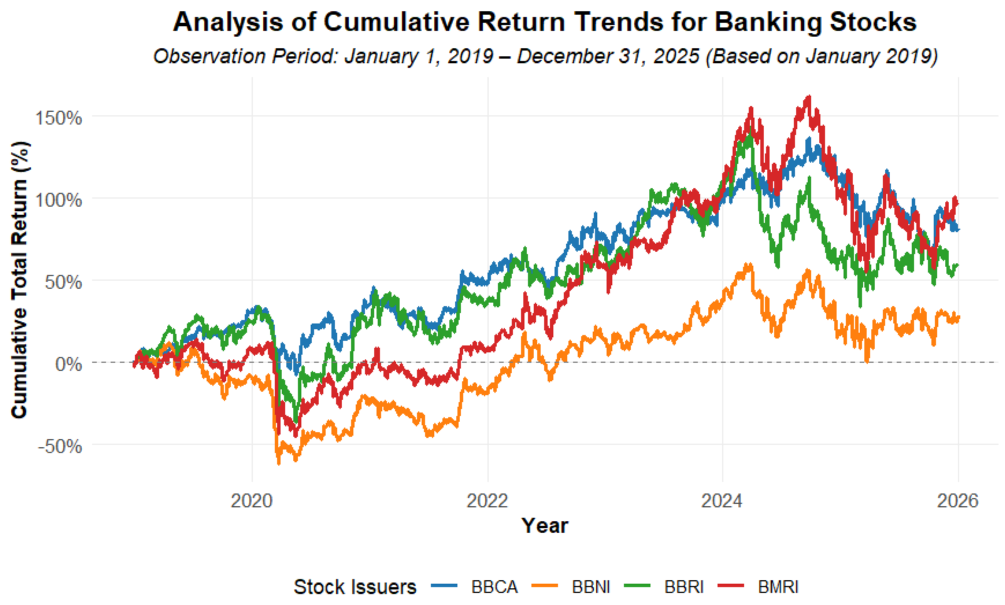

Figure 1. Historical Cumulative Return Trends for Major Banking Stocks (2019–2026)

Table 2. Descriptive Statistics of the Log-Returns of Banking Stocks

Stock	Minimum	Mean	Maximum
BBCA	-0.08915	0.0002583	0.15985
BBRI	-0.10673	0.0000559	0.18640
BMRI	-0.13917	0.0001903	0.14672
BBNI	-0.12464	-0.0000040	0.12793

4.2. Marginal Modeling ARMA(1,0)-eGARCH(1,1)

Volatility persistence and asymmetric leverage effects were filtered using an ARMA (1,0) mean filter specification and an eGARCH(1,1) conditional variance specification. The assumption of the innovation distribution used is the Student-t (std) distribution to account for the heavy tails of the residuals. The resulting standardized residuals are then transformed into the uniform domain [0,1] using a non-parametric Probability Integral Transform (PIT) (Empirical Cumulative Distribution Function / eCDF). This step separates the individual marginal behavior from their joint correlation structure. The PIT data check results show an initial minimum value of 0.0005868545 and an absolute maximum value of 1. To avoid numerical undefinedness issues (log-likelihood values of infinity at extreme limits), adjustments were made to the minimum and maximum values using a numerical tolerance limit (epsilon = $1e-10$) so that the PIT data distribution lies entirely within the open interior (0,1).

4.3. Determination of the Correlation Model and Selection of the Best Copula

After estimating the univariate ARMA(1,0)-eGARCH(1,1) model for each stock and extracting uniform pseudo-observations via the Probability Integral Transform (PIT), a goodness-of-fit evaluation was conducted for five multivariate Copula models. The results of the model performance comparison are systematically summarized in Table 3.

Based on the empirical data presented in Table 3, the Gaussian Copula model outperformed all other candidate models, achieving the highest log-likelihood value of 1190.29 and the lowest information criteria scores (AIC of -2378.57 and BIC of -2373.13). The superiority of the Gaussian Copula model provides a crucial theoretical indication regarding the structure of interdependence in Indonesia's banking financial markets. The selection of the Gaussian Copula model demonstrates that the joint dependency structure among the stocks of BBCA, BBRI, BMRI, and BBNI tends to be symmetric-linear and elliptical, without the influence of dominant tail dependence coefficients (Karimalis & Nomikos, 2018; Kusumahadi et al., 2025). This is supported by the visualization of the distribution of pseudo-observations forming regular elliptical clusters.

Table 3. A Comparison of Log-Likelihood Values and Information Criteria for Multivariate Copula Models

Copula Model	Log-Likelihood	AIC	BIC
Gaussian	1190.29	-2378.57	-2373.13
Student-t	1184.45	-2364.90	-2354.02
Frank	942.18	-1882.36	-1876.92
Gumbel	861.04	-1720.08	-1714.64
Clayton	724.50	-1447.00	-1441.56

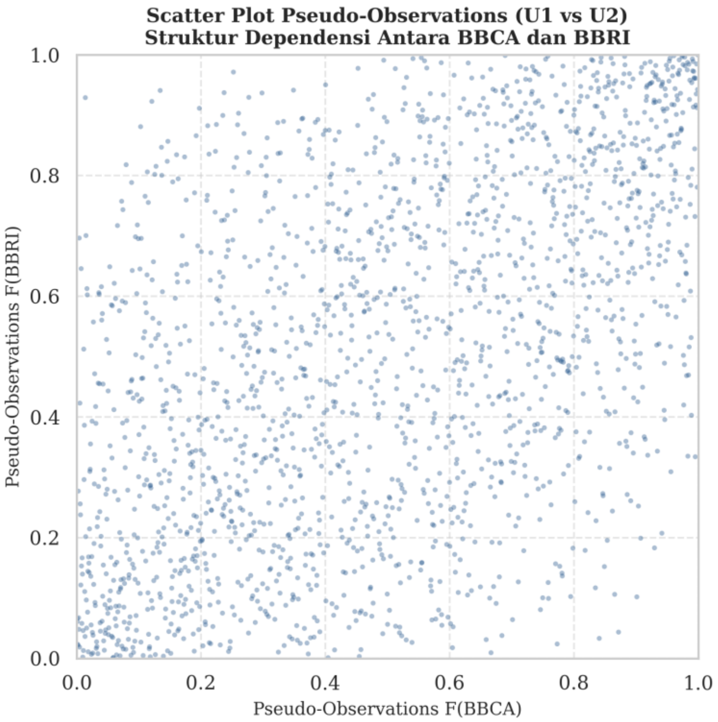

Figure 2. The Quantile Distribution of Pseudo-Observations Shows Elliptical Geometric Characteristics

The empirical evidence of the absence of acute lower-tail dependence (as indicated by the poor performance of the Clayton Copula with the highest AIC of -1447.00) suggests that Indonesia's major banking stocks do not have an inherent tendency to experience massive and simultaneous extreme price drops beyond the bounds of their normal correlation linearity. This finding differs from patterns in other emerging markets such as the BRICS or China, where correlations among commercial banks typically lock asymmetrically at the lower tail during crises (Rikhotso & Simo-Kengne, 2021) In other words, intra-sectoral diversification in Indonesia's banking sector still offers a reliable degree of risk absorption efficiency, as extreme negative movements do not reinforce one another exponentially over the observation period (Duong & Huynh, 2020).

4.4. Market Risk Projections Using Monte Carlo Simulation

Using the linear dependence parameters of the Gaussian Copula as the basis for the random sample generator algorithm, a Monte Carlo simulation was conducted with 50,000 iterations (Evkaya et al., 2024). This forward projection aims to.reconstruct the distribution of returns for an equal-weight portfolio (each stock weighted at 25%).

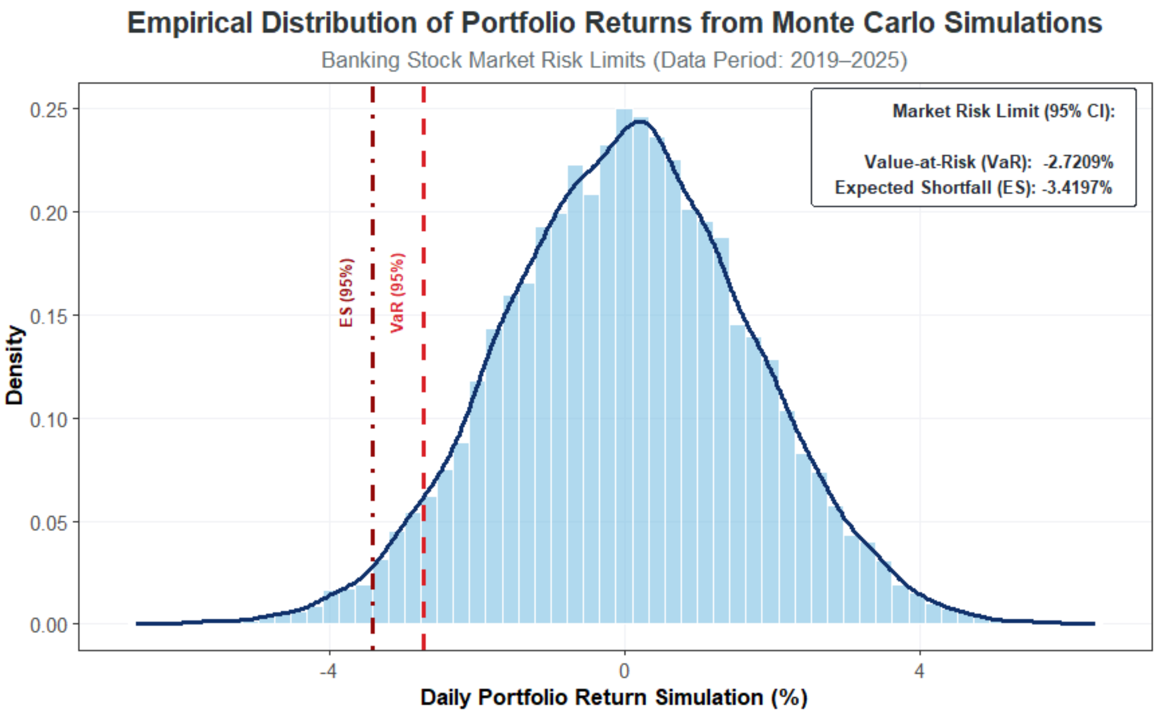

Figure 3. Frequency Distribution of Portfolio Returns from Monte Carlo Simulations, Along with VaR and ES Thresholds

Table 4. Individual Quantitative Risk Projections Based on Empirical Quantile Functions

Stock Asset	VaR 95% (Daily)	VaR 99% (Daily)	ES 95% (Daily)	ES 99% (Daily)
BBCA	-2.2990%	-3.8221%	-3.4244%	-5.6454%
BBRI	-3.0516%	-5.7820%	-4.6579%	-7.1983%
BMRI	-3.2870%	-7.0295%	-5.0558%	-7.9009%
BBNI	-3.3006%	-6.7773%	-5.0425%	-7.6415%

B Based on the model estimates in Table 4, BBCA stock has the most conservative risk profile, with the lowest maximum daily loss (95% VaR) of -2.2990% and an Expected Shortfall (95% ES) of -3.4244%. Conversely, BMRI shares recorded the highest risk level with a 99% VaR reaching -7.0295% and a 99% ES of -7.9009%, closely followed by BBNI (99% VaR = -6.7773%). This indicates that BBCA's capital structure and market liquidity provide a stronger buffer against volatility compared to other state-owned banks.

Furthermore, the risk dynamics for the Equal-Weight Equity Investment Portfolio were evaluated based on a Monte Carlo simulation of 50,000 time-series iterations, yielding the following parameters:

Integrated Portfolio Risk Metrics:

a. Value-at-Risk (VaR) 95% Portfolio (1 Day): 0.2035%
b. Value-at-Risk (VaR) 99% Portfolio (1 Day): 0.0605%
c. Expected Shortfall (ES) 95% Portfolio: 0.1168%
d. Expected Shortfall (ES) 99% Portfolio: 0.0224%

Quantitative calculations from the simulation yield a daily Value-at-Risk (VaR) of 0.2035% at a 95% confidence level. This implies that if an investment manager invests Rp 10 billion in this banking portfolio, the maximum loss in a single trading day is projected not to exceed Rp 20.35 million with a 95% confidence level (Sari et al., 2024). At a stricter confidence level of 99%, the daily VaR quantile shifts to 0.0605%.

To address the limitations of the VaR metric in measuring risk levels outside the quantile, the 95% Expected Shortfall (ES) stands at 0.1168%, and the 99% ES at 0.0224%. These risk threshold figures provide a parametric reference for the banking risk management committee to determine the minimum capital allocation portion in order to maintain the company's daily liquidity stability against market shocks (Evkaya et al., 2024).

5. Conclusion

This comprehensive study provides an in-depth analysis of the structure of systemic risk interconnections among top-tier Indonesian banking issuers (BBCA, BBRI, BMRI, BBNI) from 2019 to 2026. Through the integration of the univariate ARMA-eGARCH time series model and multivariate Copula econometric theory, an absolute empirical conclusion was reached that the Gaussian Copula is the best function for mapping interdependencies among banks. This finding confirms that the interconnections across national banking assets operate in a symmetric-linear manner, without the threat of extreme tail dependence asymmetry that could lead to mass market panic in the form of simultaneous collapses beyond the predictions of normal correlation (Yang et al., 2022; Zhang et al., 2023).

The policy and practical implications for investment managers indicate that constructing a portfolio based on domestic banking blue-chip stocks remains highly effective in mitigating daily market idiosyncratic risk, given the absence of acute lower-tail dependence. For financial regulators such as the Financial Services Authority (OJK) and Bank Indonesia, the daily Monte Carlo Copula-VaR-based risk estimation metrics proposed in this study can be adopted as an early warning system to monitor the capital resilience of the national banking sector. However, due to the inherent nature of the Gaussian Copula, which tends to overlook extraordinary crisis scenarios (black-swan events), it is recommended that risk management practitioners consistently compare these regular VaR estimates with a macro-prudential stress testing framework on a periodic basis to anticipate potential anomalies in future global financial crises (Yang et al., 2022).

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References

Ab Razak, R., & Ismail, N. (2019). Dependence Modeling and Portfolio Risk Estimation using GARCH-Copula Approach. *Sains Malaysiana*, *48*(7), 1547–1555. https://doi.org/10.17576/jsm-2019-4807-24

Budiarti, R., Intansari, K., Purnaba, I. G. P., & Septyanto, F. (2023). Modelling Dependencies of Stock Indices During Covid-19 Pandemic by Extreme-Value Copula. *JTAM (Jurnal Teori Dan Aplikasi Matematika)*, *7*(3), 805. https://doi.org/10.31764/jtam.v7i3.15109

Das, B., & Fasen-Hartmann, V. (2025). Measuring risk contagion in financial networks with CoVaR. *Finance and Stochastics*, *29*(3), 707–755. https://doi.org/10.1007/s00780-025-00564-6

Duong, D., & Huynh, T. L. D. (2020). Tail dependence in emerging ASEAN-6 equity markets: empirical evidence from quantitative approaches. *Financial Innovation*, *6*(1), 4. https://doi.org/10.1186/s40854-019-0168-7

Evkaya, O., Gür, İ., Yıldırım Külekci, B., & Poyraz, G. (2024). Vine Copula Approach to Understand the Financial Dependence of the Istanbul Stock Exchange Index. *Computational Economics*, *64*(5), 2935–2980. https://doi.org/10.1007/s10614-023-10544-7

Geenens, G. (2024). (Re-)Reading Sklar (1959)—A Personal View on Sklar's Theorem. *Mathematics*, *12*(3), 380. https://doi.org/10.3390/math12030380

Habibi, Z., & Rusgianto, S. (2021). RISK OF RETURN CHARACTERISTICS OF ISLAMIC BANK FINANCING PORTFOLIO IN INDONESIA. *Jurnal Ekonomi Dan Bisnis Islam (Journal of Islamic Economics and Business)*, *7*(1), 72. https://doi.org/10.20473/jebis.v7i1.24571

Handini, J. A., Maruddani, D. A. I., & Safitri, D. (2018). COPULA FRANK PADA VALUE at RISK (VaR) PEMBENTUKAN PORTOFOLIO BIVARIAT (Studi Kasus : Saham-Saham Perusahaan yang Meraih Predikat The IDX Top Ten Blue Tahun 2017 dengan Periode Saham 20 Oktober 2014 – 28 Februari 2018). *Jurnal Gaussian*, *7*(3), 293–302. https://doi.org/10.14710/j.gauss.v7i3.26662

Karimalis, E. N., & Nomikos, N. K. (2018). Measuring systemic risk in the European banking sector: a copula *CoVaR* approach. *The European Journal of Finance*, *24*(11), 944–975. https://doi.org/10.1080/1351847X.2017.1366350

Kusumahadi, T. A., Saadah, S., & Permana, F. C. (2025). Interconnectedness and Systemic Risk: Insights from Indonesian Financial Conglomerates. *ETIKONOMI*, *24*(1), 53–68. https://doi.org/10.15408/etk.v24i1.38452

Maghyereh, A., Virk, N., Awartani, B., & Al Shboul, M. (2022). THE SYSTEMIC RISK IN THE GULF COOPERATION COUNCIL COUNTRIES' EQUITY MARKETS AND BANKING SECTORS: A DYNAMIC COVAR APPROACH. *Buletin Ekonomi Moneter Dan Perbankan*, *25*(3), 439–470. https://doi.org/10.21098/bmeb.v25i3.1870

Maruddani, D. A. I., & Safitri, D. (2025). Modeling the Volatility-Return Relationship in the Indonesian Stock Market using the GARCH-M Framework. *International Journal of Mathematics And Computer Research*, *13*(04). https://doi.org/10.47191/ijmcr/v13i4.03

Phu Nguyen, S., & Luu Duc Huynh, T. (2019). Portfolio optimization from a Copulas-GJR-GARCH-EVT-CVAR model: Empirical evidence from ASEAN stock indexes. *Quantitative Finance and Economics*, *3*(3), 562–585. https://doi.org/10.3934/QFE.2019.3.562

Prasetya, L. B., Ispriyanti, D., & Prahutama, A. (2018). ESTIMASI VALUE AT RISK PORTOFOLIO SAHAM MENGGUNAKAN METODE GARCH-COPULA (Studi Kasus : Harga Penutupan Saham Harian Unilever Indonesia dan Kimia Farma Periode 1 Januari 2013- 31 Desember 2016). *Jurnal Gaussian*, *7*(4), 397–407. https://doi.org/10.14710/j.gauss.v7i4.28867

Pratama, A., & Henida, D. E. (2025). Comparative analysis of stock valuation models: The case of the Indonesian banking sector. *International Journal of Applied Economics, Finance and Accounting*, *21*(2), 163–170. https://doi.org/10.33094/ijaefa.v21i2.2186

Rikhotso, P., & Simo-Kengne, B. D. (2021). *Dependence Structures Between Sovereign Credit Default Swaps and Global Risk Factors in Brics Countries*. https://doi.org/10.20944/preprints202111.0011.v1

Sari, N., Ibrahim, A., Muzammil, M., & Muksal, M. (2024). MANAGING FINANCING RISK OF ISLAMIC BANKING PRODUCTS IN INDONESIA: A VALUE AT RISK APPROACH. *Jurnal Ilmiah Islam Futura*, *24*(1). https://doi.org/10.22373/jiif.v24i1.17693

Yang, X., Chen, S., Liu, Z., Yang, X., & Huang, C. (2022). Systemically important financial institutions in China: from view of tail risk spillover network. *Applied Economics Letters*, *29*(19), 1833–1839. https://doi.org/10.1080/13504851.2021.1963405

Zhang, P., Lv, Z.-X., Pei, Z., & Zhao, Y. (2023). Systemic risk spillover of financial institutions in China: A copula-DCC-GARCH approach. *Journal of Engineering Research*, *11*(2), 100078. https://doi.org/10.1016/j.jer.2023.100078