

Dynamic Volatility Dependence Analysis Between Cryptocurrency and the Indonesian Stock Market Using the DCC-GARCH-Copula Approach

Anindya Zhafira Noer Hafizhah¹, Prilyandari Dina Saputri²

^{1,2} Department of Actuarial Science, Institut Teknologi Sepuluh Nopember, Indonesia

Article Info

Article history:

Received 22/12/2025

Revised 04/09/2026

Accepted 05/09/2026

Keywords:

Bitcoin

DCC-GARCH-Copula

Ethereum

IHSG

Tail dependence

ABSTRACT

The popularity of cryptocurrency as an investment instrument has surged in recent years despite its high volatility, particularly for Bitcoin (BTC) and Ethereum (ETH). This study analyzed the volatility dependence between BTC, ETH, and the Indonesia Composite Index (IHSG) using the DCC-GARCH-Copula approach. The data consisted of daily closing prices from January 1, 2022, to December 31, 2024. The analysis began with univariate ARIMA-GARCH modeling, followed by the estimation of the DCC-GARCH model, and concluded with non-linear dependence modeling using Gaussian and Student-t copulas. The results indicated that BTC and ETH exhibited significantly higher volatility compared to the IHSG. The average dynamic correlation between IHSG-BTC and IHSG-ETH was relatively low, whereas the correlation between BTC-ETH was strongly positive, averaging 0.8399. The Student-t copula model demonstrated superior performance in capturing dependencies, especially during extreme events (tail dependence), with the highest tail dependence observed in the BTC-ETH pair, averaging 0.3798. These findings suggest a weak volatility connection between the stock market and cryptocurrencies, but a strong interdependence among crypto assets themselves, indicating that cryptocurrencies may serve as potential diversification instruments, albeit with considerable extreme risk that must be managed.

Copyright © 2020 Universitas Indraprasta PGRI.
All rights reserved.

Corresponding Author:

Prilyandari Dina Saputri,
Departemen Aktuaria,
Institut Teknologi Sepuluh Nopember,
Jl. Teknik Mesin, Sukolilo, Surabaya.
Email: prilyandaridina@its.ac.id

1. INTRODUCTION

In recent years, the role of cryptocurrency as an investment instrument has experienced highly significant growth. Data from the Indonesian Financial Services Authority (OJK) indicate that, as of September 2024, the number of crypto asset investors in Indonesia had reached 21.27 million individuals, and this condition continues to exhibit an increasing trend from month to month [1]. Interest in digital assets has emerged not only among individual investors but also among financial institutions that have begun utilizing these instruments to expand their portfolio diversification strategies [2]. According to the CoinGecko report (2025), the global cryptocurrency market capitalization reached USD 3.66 trillion in January 2025, reflecting

an increase of 116.42% compared with the previous year. As digital assets developed through cryptographic technology, cryptocurrencies employ blockchain systems to record coin ownership within decentralized distributed databases [3][4]. Since the emergence of Bitcoin in 2009, various other digital currencies such as Ethereum and Litecoin have also emerged and dominated the global market [5][6]. The primary attractiveness of cryptocurrencies lies in their decentralized characteristics, diversification potential, and prospects for high returns. Nevertheless, cryptocurrency markets are also recognized for their extreme volatility, making them high-risk investment instruments [7], particularly when compared with traditional financial instruments such as stocks [8].

Meanwhile, the Indonesia Composite Index (IHSG) represents the primary benchmark of the Indonesian capital market and reflects national economic conditions [9][10]. Introduced on April 1, 1983 with an initial base value of 100, the IHSG reflects the performance of all shares listed on the Indonesia Stock Exchange (IDX). Its value is highly influenced by global economic dynamics and domestic government policies. Therefore, understanding the relationship between cryptocurrency volatility and IHSG movements is essential for assessing diversification opportunities and portfolio risk management strategies amid continuously evolving market conditions.

Volatility in financial markets refers to the uncertainty associated with asset price movements, commonly measured using the standard deviation of returns. Greater deviations indicate higher volatility levels [11]. Engle (1982) introduced the GARCH modeling approach to capture time-varying volatility behavior by considering the influence of past information on asset return variance [12]. Therefore, this study focuses on volatility analysis to understand the relationship between cryptocurrency markets and the Indonesian stock market.

To examine this relationship, this study employs the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroscedasticity-Copula (DCC-GARCH-Copula) model. The DCC-GARCH model is utilized to analyze dynamic correlations among assets over time [13] [14], whereas Copula models are employed to identify nonlinear dependence structures [15][16]. The primary advantage of combining these two methods lies in their capability to capture complex financial market characteristics, including heteroskedasticity and tail dependence [17]. Several previous studies have also demonstrated that interactions between stock markets and cryptocurrency markets are not static but are highly influenced by external factors such as monetary policy and geopolitical tensions [2] [18] [19].

This study aims to evaluate the relationship between cryptocurrency markets and the IHSG through the DCC-GARCH-Copula approach. Bitcoin and Ethereum were selected as representatives of the cryptocurrency market because they account for more than 65% of the global crypto asset market capitalization as of January 2025. Meanwhile, the IHSG was selected as the primary indicator of the domestic stock market. We employed multiple bivariate DCC models, estimated separately for each asset pair. Accordingly, the analysis was conducted on three pairs: Bitcoin–IHSG, Ethereum–IHSG, and Bitcoin–Ethereum. Through this approach, the study is expected to contribute academically to the understanding of interactions between digital assets and traditional stock markets while also providing practical insights for investors in designing portfolio strategies involving cryptocurrencies and the IHSG.

2. METHOD

2.1 Data

The data utilized in this study consist of secondary daily closing price data for the IHSG and cryptocurrencies during the period from January 1, 2022 to December 31, 2024. The data were collected from <https://id.investing.com/>.

2.2 Log Return

Return represents an indicator used to measure the level of profit or investment return generated from an investment activity. One common approach for calculating returns is the log return, formulated as shown in Equation (1).

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

In this formula, r_t represents the log return at time t , while P_t and P_{t-1} denote the asset closing prices at period t and the previous period $t - 1$, respectively [20].

2.3 Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA model is derived from the combination of the Autoregressive (AR), Moving Average (MA), and Autoregressive Moving Average (ARMA) models [20]. First, the AR(p) model or ARIMA($p,0,0$) model is expressed in Equation (2):

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \dots + \phi_p Z_{t-p} + a_t \quad (2)$$

Second, the MA(q) model or ARIMA(0,0, q) model is expressed in Equation (3):

$$Z_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q} \quad (3)$$

Third, the ARMA(p, q) model or ARIMA($p, 0, q$) model is expressed in Equation (4):

$$Z_t = \phi_1 Z_{t-1} + \dots + \phi_p Z_{t-p} + a_t - \theta_1 a_{t-1} - \dots - \theta_q a_{t-q} \quad (4)$$

Fourth, the ARIMA(p, d, q) model is expressed in Equation (5):

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B)a_t \quad (5)$$

The initial stage of the model identification process was conducted by examining the patterns of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots [21]. To examine the significance of the model parameters, hypothesis testing was conducted using the following hypotheses

$$H_0 : \theta = 0$$

$$H_1 : \theta \neq 0$$

The test statistic value was calculated using Equation (6), namely

$$t = \frac{\hat{\theta}}{SE(\hat{\theta})} \quad (6)$$

The decision to reject H_0 was made when the absolute value of the t-statistic exceeded the critical value $t_{\frac{\alpha}{2}, df=n-np}$ or when the p-value was smaller than the significance level α , where np denotes the number of estimated parameters. In addition to significance testing, model quality assessment was also performed using the Akaike Information Criterion (AIC), which is formulated in Equation (7) [22]:

$$AIC = 2p - 2\ln(\hat{L}) \quad (7)$$

where p denotes the number of parameters and $\hat{L}$ represents the maximum value of the likelihood function.

Residual diagnostic testing was conducted to evaluate the validity of the ARIMA model, particularly in ensuring that the residual assumptions of white noise and normal distribution were satisfied [23]. White Noise Test. To examine whether the residuals exhibit white noise characteristics, the Ljung–Box test was employed with the following hypotheses:

$$H_0 : \rho_1 = \rho_2 = \dots = \rho_k = 0$$

$$H_1 : \text{at least one } \rho_i \neq 0 \text{ for } i = 1, 2, \dots, k$$

The test statistic was calculated using Equation (8):

$$Q = n(n+2) \sum_{i=1}^k \frac{\hat{\rho}_i^2}{n-i}, \quad n > k \quad (8)$$

The decision to reject H_0 was made when the value of Q exceeded the chi-square distribution quantile $\chi_{(\alpha, df=k-p-q)}^2$, or when the p-value was smaller than the significance level α , where k denotes the maximum lag, n represents the number of observations, and $\hat{\rho}_i^2$ denotes the residual autocorrelation value at lag i .

Normality testing was conducted to verify whether the residuals followed a normal distribution, using the Kolmogorov–Smirnov test with the following hypotheses:

$$H_0 : F(a_t) = F_0(a_t)$$

$$H_1 : F(a_t) \neq F_0(a_t)$$

The test statistic was calculated using Equation (9):

$$D_{\text{statistic}} = \sup_{a_t} |F(a_t) - F_0(a_t)| \quad (9)$$

The null hypothesis was rejected if the calculated value of $D_{\text{statistic}}$ exceeded the critical value $D_{\alpha, n}$ or if the p-value was smaller than α . Furthermore, heteroskedasticity testing was conducted to identify the presence of ARCH effects in the residuals of the ARIMA model, using the Lagrange Multiplier (LM) test with the following hypotheses:

$$H_0 : \alpha_1 = \alpha_2 = \dots = \alpha_q = 0 \text{ (There is no ARCH effect.)}$$

$$H_1 : \text{at least one } \alpha_i \neq 0, \text{ for } i = 1, 2, \dots, q \text{ (there is ARCH effect.)}$$

The LM test statistic value was calculated based on Equation (10):

$$LM = TR^2 \quad (10)$$

where T denotes the number of observations and R^2 represents the coefficient of determination obtained from the auxiliary regression. The null hypothesis was rejected if the LM value exceeded the critical value of the chi-square distribution $\chi_{(\alpha, q)}^2$, indicating that the residuals contained ARCH effects and exhibited heteroskedasticity [24].

2.4 Model Generalized Autoregressive Conditional Heteroscedastic (GARCH)

Autoregressive Conditional Heteroscedasticity (ARCH) is a method that was first introduced by Engle (1982) as a solution to heteroskedasticity problems. The ARCH model was subsequently extended into the Generalized ARCH (GARCH) model by Bollerslev, allowing the conditional variance (h_t) to be influenced

not only by previous residual values but also by past variances. In general, the GARCH((p,q)) model can be expressed as shown in Equation (11) below [25]:

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i a_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j} \quad (11)$$

This equation indicates that the variance at period (t) is a function of the lagged squared residuals (the ARCH component) as well as the lagged variance itself (the GARCH component), thereby allowing greater flexibility in modeling time-varying volatility.

2.5 Dynamic Conditional Correlation-GARCH

The DCC-GARCH model was introduced by Engle (2002) to model dynamic correlations among variables within a multivariate system. The covariance matrix H_t is decomposed into the conditional standard deviation matrix D_t and the correlation matrix R_t , both of which are time-varying [1]. The dynamic conditional correlation matrix is formulated as shown in Equation (12) below:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (12)$$

where Q_t^* denotes a diagonal matrix containing the square roots of the diagonal elements of (Q_t), in which Q_t is a positive definite matrix representing the variance–covariance matrix of the conditional standard deviation matrix, as formulated in Equation (13) below:

$$Q_t = (1 - \alpha - \beta) \bar{Q} + \alpha z_{t-1} z_{t-1}^T + \beta Q_{t-1} \quad (13)$$

2.6 Copula

In general, copulas are classified into two primary groups, namely Archimedean Copulas and Elliptical Copulas. This study specifically employs the Elliptical Copula approach, which originates from multivariate elliptical distributions and is recognized for its ability to represent more complex dependence structures. There are two primary types of Elliptical Copulas, namely the Gaussian Copula and the t-Copula. The Gaussian Copula is defined based on the transformation of the multivariate normal distribution and is expressed in Equation (14). [26]:

$$C_{\rho}^{Ga} = \Phi_{\rho}^d(\Phi^{-1}(u_1), \dots, \Phi^{-1}(u_d)) \quad (14)$$

The t-Copula is derived from the multivariate t-distribution with degrees of freedom (v), which provides greater flexibility in capturing extreme dependence (tail dependence), and is expressed in Equation (15) [27]:

$$C_{\rho}^{Ga} = \Phi_{\rho}^d(\Phi^{-1}(u_1), \dots, \Phi^{-1}(u_d)) \quad (15)$$

2.7 Tail Dependence

One of the important characteristics of the t-Copula is its symmetric property, which causes the dependence levels in the upper tail and lower tail to be equivalent. In other words, the probability of simultaneous extreme events occurring during both bullish and bearish market conditions possesses the same intensity. These dependence measures, known as upper tail dependence (λ_U) and lower tail dependence (λ_L), can be expressed mathematically as identical, as shown in Equation (16) [28]:

$$\lambda_U = \lambda_L = 2t_{v+1} \left(-\frac{\sqrt{v+1}\sqrt{1-\rho}}{\sqrt{1+\rho}} \right) \quad (16)$$

3. RESULT AND DISCUSSION

3.1 Data Characteristics

The data utilized in this study consist of secondary daily closing prices of the Indonesia Composite Index (IHSG) and cryptocurrencies, namely Bitcoin (BTC) and Ethereum (ETH). The observation period in this study spans from January 1, 2022 to December 31, 2024. The data were collected from the website <https://id.investing.com/>. Daily closing prices of Bitcoin (BTC) and Ethereum (ETH), denominated in U.S. dollars (USD). To synchronize the stock market and cryptocurrency data, only common trading dates were retained, with cryptocurrency prices matched to the corresponding IHSG observations. Cryptocurrency observations on weekends and Indonesian stock market holidays were excluded from the analysis. The data were retrieved in February 2025. Graphically, the movements of the IHSG, BTC, and ETH are presented in Figure 1.

The visualization of the daily price movements of Bitcoin (BTC), Ethereum (ETH), and the Indonesia Composite Index (IHSG) during the period from January 1, 2022 to December 31, 2024, as presented in Figure 1, reveals significant differences in the volatility characteristics of each asset. The IHSG exhibits a relatively stable price pattern with moderate fluctuations, whereas BTC and ETH demonstrate substantially more volatile and turbulent price movements, indicating the high volatility associated with cryptocurrency assets. Descriptive

statistical analysis was also conducted on the closing price and log return data to understand the fundamental characteristics of the data employed in this study.

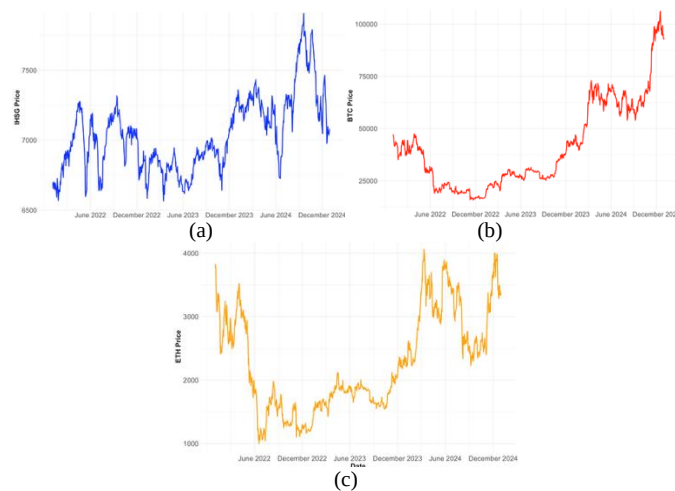


Figure 1. Time Series Plot of Closing Prices: (a) IHSG, (b) BTC, and (c) ETH

Table 1. Descriptive Statistics of Cryptocurrency and IHSG Closing Prices

	IHSG	BTC	ETH
Minimum	6.566.00	15.776.00	995.600
Q_1	6.839.78	24.648.48	1.641.81
Median	7.009.68	35.249.50	2.046.54
Mean	7.042.00	41.024.00	2.276.10
Q_3	7.219.48	59.093.77	2.958.76
Maximum	7.905.00	106.139.00	4.065.00
Standard Deviation	270.11	20.741.58	777.66

The information presented in Table 1 reinforces these observations. The IHSG exhibited a relatively narrow price range, fluctuating between 6,566 and 7,905, along with a low standard deviation of 270.11, indicating the relative stability of the domestic stock market. In contrast, BTC demonstrated an extremely wide price range, from 15,776 to 106,139, with a high standard deviation of 20,741.58. The interquartile range of BTC was also substantial, with the first quartile (Q_1) at 24,648.48 and the third quartile (Q_3) at 59,093.77, indicating extreme price variability. ETH exhibited similar characteristics, although at a lower magnitude than BTC, with prices ranging from 995.6 to 4,065 and a standard deviation of 777.66, indicating that ETH volatility remained significantly higher than that of the IHSG.

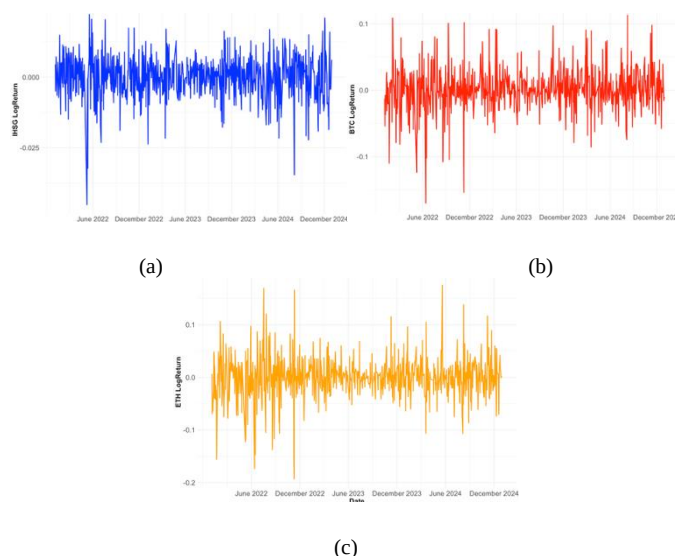


Figure 2. Time Series Plot of Log Returns: (a) IHSG, (b) BTC, and (c) ETH

The analysis of the daily log returns presented in Figure 2 reveals extreme fluctuation patterns in BTC and ETH, in contrast to the IHSG, which exhibits relatively stable return patterns. These findings indicate that cryptocurrency assets are substantially more sensitive to changes in market sentiment compared with the domestic stock market. The implications of these differences are important to consider in the formulation of portfolio diversification strategies, particularly within the context of risk management.

Table 2. Descriptive Statistics of Cryptocurrency and IHSG Log Returns

	IHSG	BTC	ETH
Minimum	-0.045155	-0.169947	-0.193045
Q_1	-0.004424	-0.013035	-0.019190
Median	0.000427	-0.000752	0.000431
Mean	0.000835	0.001061	0.000237
Q_3	0.005002	0.017061	0.020097
Maximum	0.022170	0.112750	0.175400
Standard Deviation	0.007575	0.031460	0.038974

Furthermore, the data presented in Table 2 confirm that the IHSG exhibits relatively stable return characteristics, with a minimum log return of -0.0452 , a maximum of 0.0222 , a mean of 0.0008 , a median of 0.0004 , and a standard deviation of 0.0076 . In contrast, BTC and ETH demonstrate substantially higher volatility levels, with standard deviations of 0.0315 and 0.0390 , respectively. BTC recorded a minimum log return of -0.1699 and a maximum of 0.1128 , while ETH exhibited a minimum log return of -0.1930 and a maximum of 0.1754 , further reinforcing the evidence of the highly dynamic price movements within cryptocurrency markets compared with the stock market.

3.2 ARIMA Modelling

Before conducting further analysis, the initial step involved testing the stationarity of the data using the Augmented Dickey-Fuller (ADF) method. Based on the test results presented in Table 3, all analyzed assets, namely the IHSG, Bitcoin (BTC), and Ethereum (ETH), with p-values below 0.01 , while all calculated t-statistics were lower than the critical ADF value at the 5% significance level (-2.86). These findings indicate that all log return series satisfied the stationarity requirement.

Table 3. Augmented Dickey-Fuller (ADF) Test Results

	t-statistic	p-value
IHSG	-9.0287	<0.01
BTC	-8.8118	<0.01
ETH	-8.9185	<0.01

The ARIMA model identification process was conducted by examining the patterns in the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. However, model selection was not based solely on visual inspection but also considered the principle of parsimony to avoid the risk of overfitting. The candidate ARIMA models were specified by considering orders from the lowest order up to order 3 for each parameter. The model selection was conducted manually by evaluating the candidate specifications with and without an intercept. The final model was selected based on two criteria: all ARIMA parameters had to be statistically significant, and among the models satisfying this criterion, the model with the lowest AIC was selected. The residuals were assumed to follow a normal distribution during estimation. Based on the estimation results obtained using Maximum Likelihood Estimation, as presented in Table 4, the ARIMA(2,0,2) model without mean was selected for the IHSG, whereas the ARIMA(1,0,1) model without mean was employed for BTC and ETH. These three models were selected because all estimated parameters were statistically significant, with p-values below 0.05 .

Table 4. Estimation Results of the Best ARIMA Model

Data	Model	ϕ_1	ϕ_2	θ_1	θ_2	AIC
IHSG	ARIMA (2,0,2)	0.8302	-0.8707	-0.8880	0.9209	-5011.69
BTC	ARIMA (1,0,1)	0.8369	-	-0.8556	-	-2945.00
ETH	ARIMA (1,0,1)	0.7828	-	-0.8161	-	-2637.29

where ϕ represent the AR model and θ represent the MA model. To evaluate the validity of the model, residual diagnostic testing was conducted to ensure that the white noise assumption was satisfied using the Ljung–Box test. In addition, residual normality testing was performed using the Kolmogorov–Smirnov approach. Based

on the results presented in Table 5, the calculated test statistic $\chi^2_{statistic}$ was found to be smaller than the critical value $\chi^2_{0,05,K-p-q}$, while the obtained p-values also exceeded the 5% significance level.

Table 5. Ljung–Box Test Results for Cryptocurrency and IHSG

Data	Model	Lag	$\chi^2_{statistic}$	p-value	$\chi^2_{(\alpha,K-p-q)}$
IHSG	ARIMA (2,0,2)	12	9.176	0.3277	15.507
		24	20.122	0.4503	31.410
		36	27.686	0.6848	46.194
		48	35.590	0.8129	60.481
BTC	ARIMA (1,0,1)	12	7.756	0.6527	18.307
		24	24.280	0.3328	33.924
		36	40.030	0.2201	48.602
		48	60.910	0.0694	62.830
ETH	ARIMA (1,0,1)	12	13.974	0.1742	18.307
		24	29.225	0.1386	33.924
		36	49.752	0.0397	48.602
		48	74.350	0.0051	62.830

The IHSG and BTC models satisfied the white noise assumption across all tested lags. However, ETH exhibited significant residual autocorrelation at lags 36 and 48, suggesting that the ARIMA(1,0,1) model did not completely capture the temporal dependence structure

Table 6. Normality Test Results for Cryptocurrency and IHSG

	D-statistic	p-value
IHSG	0.041123	0.1733
BTC	0.084372	<0.0001
ETH	0.072759	0.0001

Furthermore, the residual normality test results presented in Table 6 indicate that the IHSG log return residuals followed a normal distribution, as evidenced by p-values exceeding the 0.05 significance threshold and a calculated D statistic of 0.041123, which was smaller than $D_{0,05;723}$ (0.05057894), thereby satisfying the normality assumption. In contrast, the residuals of BTC and ETH did not satisfy the normality assumption, as their p-values were below 0.05 and the calculated D statistics exceeded $D_{0,05;723}$, indicating deviations from normal distribution behaviour in both cryptocurrency assets.

3.3 GARCH Modelling

After obtaining the optimal ARIMA models for each asset, the subsequent step involved detecting heteroskedasticity symptoms in the residuals using the ARCH-LM test. Based on the results presented in Table 7, the IHSG residuals exhibited ARCH effects, as indicated by the values of χ^2_{hitung} consistently exceeding $\chi^2_{(0.05,q)}$ across lags 3 to 5, with p-values below 0.05. For BTC, indications of heteroskedasticity were observed only at lags 1 and 3 ($\chi^2_{statistic} > \chi^2_{(\alpha,0.05)}$) and p-value < 0.05), suggesting the presence of low-order ARCH effects. Meanwhile, ETH demonstrated significant results across all lags from 1 to 5, with $\chi^2_{statistic}$ values exceeding $\chi^2_{(\alpha,0.05)}$ and p-values below 0.05, indicating the presence of relatively strong heteroskedasticity within the data.

Table 7. ARCH-LM Test Results

	Lag	$\chi^2_{statistic}$	p-value	$\chi^2_{(\alpha,q)}$
IHSG	1	0.0401	0.8396	3.8415
	2	0.0476	0.9765	5.9915
	3	24.884	<0.0001	7.8147
	4	24.932	<0.0001	9.4877
	5	24.904	0.0002	11.0705
BTC	1	4.5569	0.0328	3.8415
	2	4.5603	0.1023	5.9915
	3	8.6342	0.0346	7.8147
	4	9.0445	0.0600	9.4877
	5	9.1025	0.1050	11.0705
ETH	1	47.417	<0.0001	3.8415
	2	47.631	<0.0001	5.9915
	3	50.651	<0.0001	7.8147
	4	52.290	<0.0001	9.4877
	5	52.565	<0.0001	11.0705

In response to these findings, conditional volatility modeling was conducted using the GARCH(1,1) approach. The GARCH model was estimated assuming Gaussian innovations for the error terms. The GARCH(1,1) model was selected for all three assets because it is a widely applied approach in financial literature for capturing volatility dynamics. This model is recognized as effective in representing the phenomenon of volatility clustering, namely the tendency for periods of high or low volatility to occur consecutively [29]. Furthermore, GARCH(1,1) provides a balance between simplicity and predictive capability, offering a parsimonious parameter structure while still being capable of comprehensively describing variance dynamics, in accordance with the principle of parsimony in statistical modeling.

Table 8. Estimation Results of the GARCH(1,1) Model

Estimated Model	Parameter	Estimation	p-value
IHSG GARCH(1,1)	α_0	<0.0001	<0.0001
	α_1	0.0703	<0.0001
	β_1	0.8486	<0.0001
BTC GARCH(1,1)	α_0	<0.0001	0.0019
	α_1	0.0159	0.1336
	β_1	0.9739	<0.0001
ETH GARCH(1,1)	α_0	0.0002	0.1249
	α_1	0.0406	0.0010
	β_1	0.9493	<0.0001

Furthermore, the parameter estimation results presented in Table 8 indicate that, for the IHSG, all parameters in the GARCH(1,1) model were statistically significant (p-value < 0.05), suggesting that both ARCH and GARCH effects contributed to the formation of IHSG volatility dynamics. For BTC, only the parameter β_1 was statistically significant, indicating the dominance of the GARCH component or variance persistence within the model. Meanwhile, for ETH, both parameters α_1 and β_1 were statistically significant, indicating that the GARCH(1,1) model was able to adequately capture the volatility behavior of ETH. These findings are consistent with the results reported by Sharma (2021), which demonstrated the empirical superiority of the GARCH(1,1) model compared with nonlinear models such as E-GARCH and T-GARCH in terms of efficiency and accuracy in volatility modeling [30].

3.4 DCC-GARCH-Copula Estimation

At the subsequent stage of this study, the DCC-GARCH-Copula model was estimated to evaluate the correlation dynamics and dependence structures among the analyzed asset pairs. The estimation procedure employed a two-stage Maximum Likelihood Estimation (MLE) approach, in which the first stage was conducted univariately to estimate the mean and conditional volatility parameters through the ARIMA-GARCH model. After obtaining the univariate estimations, the model residuals were normalized into standardized residuals to eliminate scale effects and ensure the stability of the correlation estimation. Subsequently, the standardized residuals were transformed into a uniform distribution on the interval [0,1], in accordance with the requirements of the copula structure, which operates based on marginal distributions transformed into the uniform domain. The next stage involved estimating the copula parameters using MLE by maximizing the copula log-likelihood function with respect to its dependence parameters. The estimation process utilized the results of the previous transformations to obtain the optimal parameter $\theta_2(\alpha, \beta)$.

Table 9. DCC-GARCH-Copula IHSG-BTC, IHSG-ETH, dan BTC-ETH

	Copula	Parameter	Estimate	Standard Error	t value	p-value	LL
IHSG-BTC	Gaussian Copula	α	<0.0001	0.0001	<0.0001	0.9999	4010.977
		β	0.9263	0.2627	3.5265	0.0004	
	t Copula	α	<0.0001	<0.0001	<0.0001	0.9999	4014.066
		β	0.9164	0.3335	2.7476	0.0060	
		ν	12.5761	6.2104	2.0250	0.0429	
IHSG-BTC	Gaussian Copula	α	<0.0001	0.0002	<0.0001	0.9999	3886.279
		β	0.9151	0.1542	5.9361	<0.0001	
	t Copula	α	<0.0001	0.0001	<0.0001	0.9999	3889.083
		β	0.8899	0.2253	3.9503	0.0001	
		ν	11.6468	7.0014	1.6635	0.0462	
IHSG-BTC	Gaussian Copula	α	0.0167	0.0162	1.0303	0.3029	3317.055
		β	0.9824	0.0207	47.4495	<0.0001	
	t Copula	α	0.0115	0.0088	1.3009	0.1933	3326.338
		β	0.9885	0.0124	79.4275	<0.0001	
		ν	9.2733	2.3345	3.9722	0.0001	

The results presented in Table 9 demonstrate that the DCC-GARCH model with t-Copula exhibited superior performance compared with the Gaussian Copula across all analyzed asset pairs. For the IHSG-BTC

pair, the t-Copula log-likelihood value reached 4014.066, which was higher than the Gaussian Copula value of 4010.977, with a degree of freedom parameter ν of 12.58 that was statistically significant at the 5% significance level. For the IHSG-ETH pair, the t-Copula again demonstrated superior performance with a log-likelihood value of 3889.083, exceeding the Gaussian Copula value of 3886.279, and a ν value of 11.65. Meanwhile, for the BTC-ETH pair, the performance difference was more pronounced, with the t-Copula log-likelihood value reaching 3326.338 compared with 3317.055 for the Gaussian Copula, along with a ν value of 9.27. These findings indicate that the t-Copula is more effective in capturing nonlinear dependence structures, particularly for the BTC-ETH pair, which exhibited the most significant extreme dependence among the three analyzed asset pairs..

3.5 Dynamic Conditional Correlation

Based on the estimation results of the DCC-GARCH-t Copula model, the dynamic conditional correlation matrix $\mathbf{R}_t$ was obtained. This matrix represents the linear relationship among assets throughout the observation period. The results indicate that the average value of $\mathbf{R}_t$ between the IHSG and BTC was 0.032, while the average correlation between the IHSG and ETH was 0.054. These values suggest that the level of volatility interconnectedness between the IHSG and cryptocurrency assets was very low and relatively stable. This weak correlation is consistent with the DCC parameter estimates, in which the value of α approached zero while β remained dominant, indicating that new market shocks did not exert a significant influence on the correlation dynamics among these assets.

In contrast, the BTC-ETH pair exhibited a conditional correlation pattern, visualized in Figure 3, with an average value of 0.839, indicating a very strong relationship in the volatility movements of the two cryptocurrency assets. This interconnectedness reflects similar responses to global market sentiment and comparable fundamental factors, causing both assets to frequently move in the same direction. Future research may consider incorporating domestic macroeconomic factors, such as interest rates and inflation, to better explain the dynamics of the Indonesian stock market and its relationship with cryptocurrency markets.

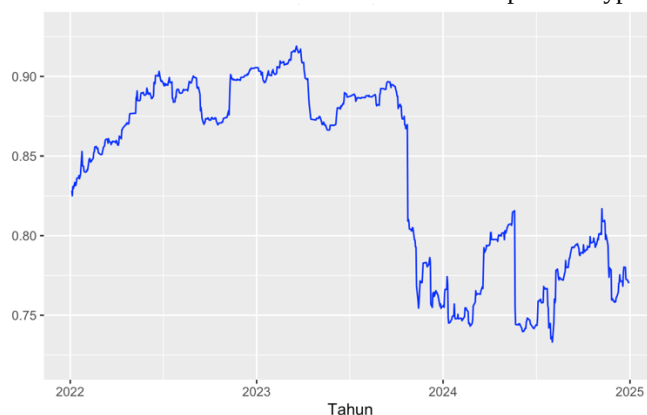


Figure 3. BTC-ETH Dynamic Correlation

3.6 Tail Dependence

The estimation results of the DCC-GARCH-t Copula model produced the degrees of freedom parameter (ν) from the multivariate t-distribution, which was subsequently used as the basis for calculating the measure of extreme dependence among assets, commonly referred to as tail dependence. This measure reflects the probability that two assets experience simultaneous extreme movements, both during bullish and bearish market conditions within the t-Copula framework.

Table 10 IHSG-BTC, IHSG-ETH, dan BTC-ETH Tail Dependence

	(mean) ρ	ν	(mean) Tail Dependence
IHSG-BTC	0.0324766	12.576183	0.0032346
IHSG-ETH	0.0549898	11.646777	0.0052457
BTC-ETH	0.8399439	9.273287	0.3798037

Based on Table 10, the BTC-ETH asset pair exhibited the highest tail dependence value, namely 0.3798. This value indicates a strong interconnectedness between the two cryptocurrency assets during extreme market conditions, implying that extreme price movements tend to occur simultaneously. In contrast, the tail dependence values for the IHSG-BTC and IHSG-ETH pairs were very low, specifically below 0.01, indicating an almost non-existent extreme relationship between the Indonesian stock market and cryptocurrency assets.

These findings reinforce the conclusion that extreme dependence is more prevalent among digital assets themselves, whereas the IHSG demonstrates relatively independent movement characteristics with respect to extreme fluctuations in cryptocurrency markets. Therefore, these results strengthen the argument that combining cross-asset classes, particularly domestic stock market assets and cryptocurrencies, may provide strategic potential for portfolio diversification in reducing systemic risk.

4. Conclusion

The analysis conducted in this study demonstrates that the volatility of Bitcoin (BTC) and Ethereum (ETH) is significantly higher than that of the Indonesia Composite Index (IHSG). This finding is reflected in the sharp price movements and large standard deviation values of cryptocurrencies, whereas the IHSG exhibits relatively stable characteristics as a representation of the domestic stock market. The estimation results obtained using the DCC-GARCH-Copula model confirm that the t-Copula outperforms the Gaussian Copula in capturing nonlinear dependence structures, particularly under extreme market conditions. This superiority is indicated by higher log-likelihood values and significant degrees of freedom parameters. The average dynamic correlations between IHSG-BTC and IHSG-ETH were recorded at 0.0325 and 0.0549, respectively, indicating weak relationships between the Indonesian stock market and cryptocurrency markets. In contrast, the correlation between BTC and ETH reached 0.8399, demonstrating a very strong relationship between the two digital assets. Furthermore, the tail dependence analysis indicates that extreme dependence was detected only in the BTC-ETH pair with a value of 0.3798, whereas the IHSG-BTC and IHSG-ETH pairs exhibited near-zero extreme dependence values. These findings suggest that systemic risk potential is considerably more dominant among cryptocurrency assets themselves than between cryptocurrencies and the domestic stock market. Overall, the findings imply that combining domestic stock market assets with cryptocurrencies may provide diversification benefits due to their relatively weak interdependence. Nevertheless, investors should carefully consider the substantial systemic risk associated with cryptocurrency markets, particularly during periods of extreme volatility. Future research may compare GARCH(1,1) with alternative volatility models, such as ARCH, EGARCH, GJR-GARCH, and APARCH, as well as alternative innovation distributions, to identify the most appropriate specification for modeling financial market volatility.

REFERENCES

- [1] K. P. R. Biro Hubungan Masyarakat, "SIARAN PERS Tingkatkan Perlindungan Masyarakat, Bappebti Gelar FGD Aset Kripto di Surabaya," Jakarta, Oct. 2024.
- [2] S. Corbet, C. Larkin, and B. Lucey, "The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies," *Financ Res Lett*, vol. 35, Jul. 2020, doi: 10.1016/j.frl.2020.101554.
- [3] C. Zhu, J. Li, Z. Zhong, C. Yue, and M. Zhang, "A Survey on the Integration of Blockchains and Databases," Jun. 01, 2023, *Springer*. doi: 10.1007/s41019-023-00212-z.
- [4] S. Chan, J. Chu, Y. Zhang, and S. Nadarajah, "Blockchain and Cryptocurrencies," Oct. 01, 2020, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/jrfm13100227.
- [5] P. Gatabazi, G. Kabera, J. C. Mba, E. Pindza, and S. F. Melesse, "Cryptocurrencies and Tokens Lifetime Analysis from 2009 to 2021," *Economies*, vol. 10, no. 3, Mar. 2022, doi: 10.3390/economies10030060.
- [6] V. Candila, "Multivariate analysis of cryptocurrencies," *Econometrics*, vol. 9, no. 3, Sep. 2021, doi: 10.3390/econometrics9030028.
- [7] N. Lee, "Joint Impact of Market Volatility and Cryptocurrency Holdings on Corporate Liquidity: A Comparative Analysis of Cryptocurrency Exchanges and Other Firms," *Journal of Risk and Financial Management*, vol. 17, no. 9, p. 406, Sep. 2024, doi: 10.3390/jrfm17090406.
- [8] E. Bouri, D. Gabauer, R. Gupta, and A. K. Tiwari, "Volatility connectedness of major cryptocurrencies: The role of investor happiness," *J Behav Exp Finance*, vol. 30, Jun. 2021, doi: 10.1016/j.jbef.2021.100463.
- [9] A. D. Putra and Nurmatias, "Analisis indeks harga saham global dan inflasi terhadap indeks harga saham gabungan (IHSG)," *Ikraith Ekonomika*, vol. 7, no. 1, 2024, doi: 10.37817/ikraith-ekonomika.v7i1.
- [10] H. Sasono and N. Said, "Analisis Pengaruh Variabel Makro Terhadap IHSG di Indonesia Periode 2010 Sampai 2021," *Jurnal Penelitian Manajemen dan Inovasi Riset*, vol. 1, no. 4, pp. 11–25, 2023, doi: 10.61132/lokawati.v1i5.124.
- [11] K. Daly, "Financial volatility: Issues and measuring techniques," Apr. 15, 2008. doi: 10.1016/j.physa.2008.01.009.
- [12] A. Razouk, R. Ait Daoud, and M. El Mehdi Falloul, "Numerical optimization methods for financial time series GARCH(p, q) model, a comparative approach," in *8th International Conference on Optimization and Applications, ICOA 2022 - Proceedings*, Institute of Electrical and Electronics Engineers Inc., 2022. doi: 10.1109/ICOA55659.2022.9934755.

- [13] A. S. Kumar and S. Anandarao, "Volatility spillover in crypto-currency markets: Some evidences from GARCH and wavelet analysis," *Physica A: Statistical Mechanics and its Applications*, vol. 524, pp. 448–458, Jun. 2019, doi: 10.1016/j.physa.2019.04.154.
- [14] P. Zhang, Z. X. Lv, Z. Pei, and Y. Zhao, "Systemic risk spillover of financial institutions in China: A copula-DCC-GARCH approach," *Journal of Engineering Research (Kuwait)*, vol. 11, no. 2, Jun. 2023, doi: 10.1016/j.jer.2023.100078.
- [15] W. Yamaka, J. Liu, M. Li, P. Maneejuk, and H. Q. Dinh, "Analyzing the causality and aependence between exchange rate and real estate prices in boom-and-bust markets: Quantile causality and DCC Copula GARCH approaches," *Axioms*, vol. 11, no. 3, Mar. 2022, doi: 10.3390/axioms11030113.
- [16] F. Nsabimana, H. Waititu, and C. Nyakundi, "Modeling dependence using Copula Garch," *Asian Journal of Probability and Statistics*, vol. 24, no. 1, pp. 45–61, Aug. 2023, doi: 10.9734/ajpas/2023/v24i1517.
- [17] M. B. Righi and P. S. Ceretta, "Global risk evolution and diversification: A Copula-DCC-GARCH model approach," *Rev. Bras. Finanças (Online), Rio de Janeiro*, vol. 10, no. 4, pp. 529–550, 2012.
- [18] M. Wątopek, J. Kwapien, and S. Drożdż, "Cryptocurrencies are becoming part of the world global financial market," *Entropy*, Feb. 2023, doi: 10.3390/e25020377.
- [19] M. Youssef and S. S. Waked, "Herding behavior in the cryptocurrency market during COVID-19 pandemic: The role of media coverage," *North American Journal of Economics and Finance*, vol. 62, Nov. 2022, doi: 10.1016/j.najef.2022.101752.
- [20] R. S. Tsay, *Analysis of financial time series*, 2nd ed. John Wiley & Sons, Inc, 2005.
- [21] J. D. Cryer and K.-S. Chan, *Time series analysis with applications in R*, 2nd ed. Springer, 2008.
- [22] P. K. Burnham and R. D. Anderson, *Model selection and multimodel Inference*, 2nd ed. Springer, 2002.
- [23] W. S. W. Wei, "Nonstationary Time Series Models," in *Time series analysis univariate and multivariate method*, 2nd ed., Pearson Education, Inc., 2006, ch. 4, pp. 83–85.
- [24] V. Mahajan, S. Thakan, and A. Malik, "Modeling and Forecasting the Volatility of NIFTY 50 Using GARCH and RNN Models," 2022, doi: 10.3390/economies.
- [25] G. P. E. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time series analysis forecasting and control*, 5th ed. John Wiley & Sons, Inc., 2016.
- [26] T. Roncalli, "Copulas and dependence modeling," in *Handbook of Financial Risk Management*, CRC Press, 2020, ch. 11, pp. 735–727.
- [27] U. Cherubini, E. Luciano, and W. Vecchiato, "Market comovements and Copula families," in *Copula methods in finance*, John Wiley & Sons, Ltd, 2004, ch. 3, pp. 112–118.
- [28] Y. Man, S. Zhang, and J. Liu, "Dynamic connectedness, asymmetric risk spillovers, and hedging performance of China's green bonds," *Financ Res Lett*, vol. 56, Sep. 2023, doi: 10.1016/j.frl.2023.104083.
- [29] B. Setiawan, M. Ben Abdallah, M. Fekete-Farkas, R. J. Nathan, and Z. Zeman, "GARCH (1,1) models and analysis of stock market turmoil during COVID-19 outbreak in an emerging and developed economy," *Journal of Risk and Financial Management*, vol. 14, no. 12, Dec. 2021, doi: 10.3390/jrfm14120576.
- [30] S. Sharma, V. Aggarwal, and M. P. Yadav, "Comparison of linear and non-linear GARCH models for forecasting volatility of select emerging countries," *Journal of Advances in Management Research*, vol. 18, no. 4, pp. 526–547, Oct. 2021, doi: 10.1108/JAMR-07-2020-0152.