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Volatility dynamics of cryptocurrencies: a comparative analysis using GARCH-family models

Çağlar SÖZEN[1*]

Abstract

Cryptocurrency markets have evolved into a vital segment of the global financial ecosystem, drawing considerable interest from both investors and regulatory bodies. Yet, their extreme price instability demands innovative strategies for risk mitigation and investment that diverge from conventional financial practices. This research focuses on analyzing the volatility patterns of leading cryptocurrencies—Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB)—by employing GARCH-family models such as GARCH, EGARCH, TGARCH, and CGARCH. Through a comparative evaluation of these models, the study identifies the optimal framework for characterizing cryptocurrency market volatility. Utilizing daily closing prices from Yahoo Finance (January 1, 2019, to January 8, 2025), the analysis reveals that TGARCH outperforms others for BTC, EGARCH for ETH, and CGARCH for BNB, underscoring the critical role of asymmetric volatility in these markets. This work advances existing research by offering a detailed comparison of GARCH-based approaches and practical insights for risk evaluation and portfolio optimization.

Keywords Cryptocurrency, Volatility modeling, GARCH models, Bitcoin, Ethereum, Binance coin, Risk management

JEL Classification C58, G17, G10, E44

Introduction

Cryptocurrency markets have grown into a cornerstone of the global financial system in recent years, capturing the attention of investors and policymakers alike. Indeed, the emergence of Bitcoin (BTC) in 2009 marked the beginning of this transformative era, which subsequently expanded with the development of diverse digital assets such as Ethereum (ETH) and Binance Coin (BNB). These innovations have significantly enhanced market depth and trading volume. BTC, ETH, and BNB are selected in this study due to their dominant roles in the cryptocurrency ecosystem. As of early 2025, these three assets collectively account for more than 60% of the total cryptocurrency market capitalization and consistently rank among the top traded cryptocurrencies by volume across major global exchanges [11]. Their liquidity, institutional adoption, and historical significance make them representative benchmarks for analyzing volatility dynamics in digital asset markets. However, the inherent characteristics of cryptocurrency markets—extreme volatility, limited liquidity, and sudden price fluctuations—demand risk management and investment strategies distinct from those employed in traditional financial markets. High-frequency panel data from 2020 to 22 show that daily leverage effects, signed volatility, and jump components drive realized volatility in major coins, with spikes often exceeding those observed in equity indices [9]. Empirical benchmarking finds that the standard deviation of crypto returns can be more than twice that of large-cap equities, underscoring the unique risk profile of digital-asset trading [17]. In addition, many trading venues exhibit limited liquidity—reflected in bid–ask spreads that average 0.1–0.5% on major exchanges and exceed 1% for mid-cap

*Correspondence:
Çağlar SÖZEN
caglar.sozen@giresun.edu.tr
[1] Giresun University, Giresun, Turkey

tokens—thereby amplifying execution risk for sizeable orders [8]. Fragmented and thin order books mean that relatively modest trades can move prices by several percentage points [1, 20]. Moreover, price jumps occur on over 50% of trading days, with negative jumps both more frequent and more severe than positive ones, revealing the strong sensitivity of cryptocurrency markets to external shocks and information flow [4].

In light of these features, accurately modeling the volatility structure of these markets is crucial for enabling informed investor decisions, optimizing portfolio management, and deepening the understanding of market risks. The pronounced volatility of cryptocurrencies necessitates the adoption of advanced modeling techniques. Consequently, ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models stand out. Introduced by Engle [15] and later expanded by Bollerslev [6], these frameworks remain foundational for analyzing volatility dynamics in financial time series. While machine learning and alternative forecasting methods are increasingly applied to volatility prediction, GARCH-based models retain their prominence due to their theoretical robustness, structured econometric framework, and widespread academic acceptance. Therefore, this study evaluates the performance of traditional GARCH models alongside their extended variants—EGARCH, TGARCH, and CGARCH—to identify the most effective volatility model for cryptocurrency markets.

The main research problem this study addresses is the absence of a unified framework that evaluates how different GARCH variants perform across distinct cryptocurrencies under varying market conditions. Our novel contribution is threefold: (1) a side-by-side comparison of five GARCH-family models (GARCH, EGARCH, TGARCH, CGARCH, AGARCH) across three leading cryptocurrencies (BTC, ETH, BNB); (2) an assessment of model performance over multiple market regimes (2019–2025), including crisis and bull periods; and (3) concrete, model-specific recommendations for practitioners in risk management and portfolio optimization.

Literature review

Volatility modeling occupies a central role in financial markets, particularly in risk management, portfolio optimization, and derivative pricing. The ARCH model, introduced by Engle [15], marked a pivotal advancement by capturing time-varying variance in financial time series. Building on this foundation, Bollerslev [6] expanded the framework into the GARCH model, enhancing its capacity for long-term volatility forecasting. The GARCH model excels in identifying volatility clustering—a phenomenon where periods of high volatility tend to follow one another—and provides critical insights for risk management and investment strategies by modeling how volatility evolves over time. Despite its widespread adoption, the traditional GARCH framework struggles to account for the asymmetric nature of volatility observed in financial markets. To address this limitation, several GARCH variants have been developed. For instance, Nelson's [21] EGARCH model incorporates asymmetric effects, effectively explaining how positive and negative shocks differentially impact volatility, a concept known as the leverage effect. Similarly, Zakoian's [24] TGARCH model introduces threshold-based adjustments to better capture the amplified volatility triggered by market downturns. Engle and Lee's (1999) CGARCH model further refines this approach by decomposing volatility into short-term and long-term components, offering enhanced flexibility in modeling regime shifts.

Recent studies have applied these models to cryptocurrency markets, reflecting the unique characteristics of digital assets. Katsiampa's [18] comparative analysis of GARCH-family models for Bitcoin volatility identified the CGARCH model as superior in capturing long-term volatility components. In a subsequent study, Katsiampa [19] demonstrated that the EGARCH model outperforms others in reflecting the impact of negative news shocks on Bitcoin's volatility. Together, these findings highlight the context-dependent performance of GARCH derivatives, suggesting that no single model universally dominates across all market conditions. Further research has expanded the application of GARCH models to other cryptocurrencies and incorporated additional variables. Chi and Hao [10] evaluated the effectiveness of different volatility models for Bitcoin and Ethereum, finding that the single-variate GARCH model performed well both in-sample and out-of-sample, while the GJR-GARCH model did not show significant asymmetric volatility responses to past returns. Bergsli et al. [5] focused on forecasting Bitcoin volatility, concluding that EGARCH and APARCH models were the most effective among GARCH variants, while HAR models based on realized variance from high-frequency data outperformed GARCH models that relied on daily data, especially for short-term volatility forecasts. Moreover, studies have explored the impact of external events on cryptocurrency volatility. Apergis [3] examined the impact of the COVID-19 pandemic on the conditional volatility of returns for eight cryptocurrencies using an asymmetric GARCH modeling approach, finding that the pandemic positively influenced conditional volatility and improved the accuracy of volatility forecasts. In addition to traditional GARCH models, researchers have investigated alternative approaches. For instance, Pratas et al. [22] compared the forecasting abilities of classic GARCH models with deep learning methodologies, including MLP, RNN, and LSTM architectures, for predicting Bitcoin's volatility. The study found that deep learning models offered superior forecast quality, although with significant computational costs. Despite these advancements, there remains a gap in comprehensive comparative analyses of GARCH-family models across multiple cryptocurrencies. This study addresses this gap by systematically comparing the performance of GARCH, EGARCH, TGARCH, and CGARCH models for major cryptocurrencies—Bitcoin, Ethereum, and Binance Coin—thereby enriching the literature with actionable insights for both researchers and practitioners.

Materials and method

This study employs financial time series analysis to examine the price movements and volatility dynamics of cryptocurrency assets. The methodology spans a comprehensive range of techniques, including data transformation processes, statistical testing, and advanced volatility modeling.

Logarithmic returns and transformation

To analyze price movements in financial time series, logarithmic returns were employed as the primary metric. This transformation provides a relative measure of price changes, enabling the capture of nonlinear dynamics in financial data [12]. Logarithmic returns are calculated as:

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

where r_t represents the logarithmic return at time t, and P_t and P_{t-1} denote the closing prices at times t and $t-1$, respectively. The logarithmic transformation not only stabilizes variance but also facilitates normalization of the distribution, offering a robust foundation for volatility analysis.

Elliot, rothenberg and stock (ERS) test

Stationarity analysis is critical for assessing the suitability of time series in econometric modeling. In this study, the Elliott, Rothenberg, and Stock (ERS) test was employed to evaluate the stationarity properties of logarithmic return series. The ERS test offers higher statistical power compared to the traditional Dickey-Fuller test and delivers more reliable results for series with limited observations [14].

The ERS test is based on the regression model specified in Eq. 2:

$$\Delta y_t = \phi y_{t-1} + \beta t + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + \varepsilon_t \tag{2}$$

In this model, y_t represents the value of the series at time t. The time variable t accounts for trend components in the series, while the parameter ϕ serves as the key coefficient for testing the presence of a unit root. The lag length p is optimized to control for autocorrelation effects. The error term ε_t, assumed to follow white noise properties, captures unexplained random variations.

The null hypothesis (H_0) of the ERS test posits that the series contains a unit root (i.e., it is non-stationary), whereas the alternative hypothesis (H_1) asserts stationarity. The test statistic is computed as shown in Eq. 3:

$$\text{ERS} = \frac{\widehat{\phi}}{SE(\widehat{\phi})} \tag{3}$$

Here, $\widehat{\phi}$ denotes the estimated regression coefficient, and $SE(\widehat{\phi})$ represents its standard error.

ARIMA models

Autoregressive Integrated Moving Average (*ARIMA*) models are widely used to forecast future values in time series by modeling the relationship between past observations, error terms, and current values. The ARIMA framework combines three components: autoregressive (*AR*) terms, differencing (*I*) to achieve stationarity, and moving average (*MA*) terms. Notably, *ARIMA* models excel in handling non-stationary series through differencing, making them versatile tools in econometric analysis [7].

The general formulation of an *ARIMA* model is given in Eq. 4:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \phi_j \varepsilon_{t-j} \tag{4}$$

Here, y_t represents the observed value of the series at time t. The constant term c reflects the series' average level, often capturing its long-term trend. The autoregressive order p denotes the number of lagged observations included in the model, with coefficients ϕ_i quantifying the influence of past values on the current observation. The error term ε_t, assumed to follow a white noise process with zero mean and constant variance, captures random fluctuations unexplained by the model. The moving average order q specifies the number of lagged error terms, with coefficients ϕ_j measuring their impact on the current value. Together, these components enable ARIMA to leverage historical patterns and residual errors for forecasting.

A key strength of ARIMA lies in its adaptability to the stationarity properties of the series. For non-stationary data, differencing is applied to stabilize the mean and variance. The differencing operation, shown in Eq. 5, involves taking the first difference $(d = 1)$ or higher-order differences $(d > 1)$:

$$y_t^{(d)} = \Delta^d y_t = y_t - y_{t-1} \tag{5}$$

where d represents the differencing order. Stationarity transformation enhances model performance and ensures the validity of subsequent econometric analyses. To select the optimal ARIMA model, information criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were employed. These metrics, defined in Eq. 6, balance model fit and complexity:

$$\mathrm{AIC} = -2ln(L) + 2k \tag{6}$$

$$\mathrm{BIC} = -2ln(L) + kln(n)$$

Here, L is the maximum likelihood estimate reflecting the model's goodness-of-fit, k denotes the number of parameters, and nn is the total number of observations. Developed by Akaike [2], these criteria prioritize models with lower values, indicating a better trade-off between explanatory power and parsimony.

ARC-LM test

Evaluating whether the variance of a time series changes over time is critical, particularly for financial data. In this context, the ARCH-LM test, developed by Engle [15], serves as a widely used method to detect conditional heteroskedasticity (time-varying variance) in a series. This test examines whether the variance of the error terms remains constant, establishing a foundational diagnostic step for volatility modeling.

The null hypothesis (H_0) of the ARCH-LM test states that no ARCH effects are present—i.e., the error terms exhibit constant variance. The alternative hypothesis (H_1) posits the presence of ARCH effects, indicating time-dependent variance. The test relies on the regression model in Eq. 7:

$$\varepsilon_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + u_t \tag{7}$$

Here,ε_t^2 represents the squared error term, enabling the analysis of heteroskedasticity. The coefficients α_i measure the influence of past squared errors on the current error term. The lag length q, determined to control for autocorrelation, specifies the number of lagged terms included. The white noise error term u_t follows a zero-mean, constant-variance structure, capturing random and unexplained variations. These components collectively assess the presence of conditional heteroskedasticity.

The ARCH-LM test statistic, derived from the regression's R^2 value, is calculated as shown in Eq. 8:

$$\mathrm{LM} = nR^2 \tag{8}$$

where n denotes the number of observations. The chi-square (χ^2) statistic is compared against critical values at a specified significance level (α). If the test statistic exceeds the critical value or the p-value falls below α, the null hypothesis is rejected, concluding that ARCH effects exist. This outcome necessitates further analysis with advanced volatility models to capture the series dynamic variance structure.

Durbin-watson test

The Durbin-Watson (DW) test is a fundamental statistical method used to assess the presence of autocorrelation in time series data. Autocorrelation refers to the dependency of an observation on its previous values, which can undermine the accuracy of predictive models. The DW test evaluates the independence of error terms to identify autocorrelation [13]. The DW statistic is calculated using Eq. 9:

$$\mathrm{DW} = \frac{\sum_{t=2}^{n} (e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \tag{9}$$

where e_t denotes the error term at time t.

The DW statistic ranges between 0 and 4. A value close to 2 indicates no autocorrelation. Values below 2 suggest positive autocorrelation, while values above 2 imply negative autocorrelation. The DW test is critical for validating the independence of error terms, as dependent errors can lead to biased model estimates.

GARCH and ıts derivative models

In financial time series, the fact that variance is not constant over time—known as conditional heteroskedasticity—is a key feature to consider, especially when modeling volatility. In this context, the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, developed by Bollerslev [6], is an effective method for modeling variance dynamics based on past error terms and previous variance values. GARCH models and their derivatives allow for detailed analysis of volatility clustering and asymmetric effects observed in financial series [6, 21, 24],Engle & Lee, 1999).

GARCH (1,1) model

The GARCH model expresses the conditional variance of the series using the formula shown in Eq. 10:

$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (10)$$

In this model, σ_t^2 represents the conditional variance at time t and reflects the series volatility. The parameter ω indicates the base level of variance in the series. The term $\alpha_1\varepsilon_{t-1}^2$ measures the impact of the previous period's squared error term on the current conditional variance, while $\beta_1\sigma_{t-1}^2$ explains how the previous period's conditional variance affects the current variance. Together, these components capture the dynamic structure of volatility in the series. The GARCH (1,1) model is widely used as a fundamental tool for understanding short-term volatility dynamics in financial time series [6].

Exponential GARCH (EGARCH) model

The EGARCH model, developed by Nelson [21], is an advanced framework designed to capture the asymmetric effects of positive and negative shocks on volatility. Its core equation is presented in Eq. 11:

$$\ln\left(\sigma_t^2\right) = \omega + \beta_1\ln(\sigma_{t-1}^2) + \gamma_1\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha_1\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| \quad (11)$$

Here, the parameter γ measures the asymmetry between positive and negative shocks. This structure effectively explains the leverage effect—a common phenomenon in financial markets where negative shocks (e.g., price declines) exert a stronger influence on volatility compared to positive shocks. The EGARCH model performs particularly well in scenarios where such asymmetric volatility dynamics dominate, such as during market downturns or periods of heightened uncertainty. By incorporating logarithmic transformations of conditional variance, the model ensures non-negativity constraints are naturally satisfied, enhancing its flexibility and robustness in volatility forecasting.

Threshold GARCH (TGARCH) model

The TGARCH model, introduced by Zakoian [24], aims to capture threshold effects between positive and negative shocks. The model is defined in Eq. 12:

$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \gamma_1\varepsilon_{t-1}^2 I(\varepsilon_{t-1} < 0) + \beta_1\sigma_{t-1}^2 \quad (12)$$

Here, $I(\varepsilon_{t-1} < 0)$ is an indicator function that equals 1 if the lagged error term ε_{t-1} is negative, and 0 otherwise. The parameter γ_1 quantifies the additional volatility impact of negative shocks. This structure makes the TGARCH model particularly effective for analyzing how adverse events, such as price declines or negative market news, amplify volatility. By distinguishing between positive and negative shocks, the model provides deeper insights into asymmetric market reactions during periods of financial stress.

Component GARCH (CGARCH) model

The CGARCH model, proposed by Engle [16], decomposes volatility into short-term and long-term components. The total conditional variance is expressed as:

$$\sigma_t^2 = q_t + s_t$$

where q_t represents the long-term component (persistent effects) and s_t captures the short-term component (transient effects). Equation 13 shows these components.

$$q_t = \omega + pq_{t-1} + \phi(\sigma_{t-1}^2 - q_{t-1}) \quad (13)$$

$$s_t = \alpha_1\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta_1 s_{t-1}$$

This framework allows for a nuanced analysis of volatility dynamics by separating temporary fluctuations from enduring trends. The long-term component q_t reflects gradual shifts in market conditions, while s_t accounts for immediate reactions to shocks. By isolating these effects, the CGARCH model enhances flexibility in modeling regime shifts and improves forecasts during periods of market instability.

Asymmetric GARCH (AGARCH) model

The AGARCH model is designed to capture the differential effects of positive and negative shocks on volatility, as well as the leverage effect. The model equation is presented in Eq. 14:

$$\sigma_t^2 = \omega + \alpha_1(\varepsilon_{t-1} - \gamma_1)^2 + \beta_1\sigma_{t-1}^2 \quad (14)$$

Here, γ measures the leverage effect. If $\gamma \neq 0$, it indicates that negative shocks have a different impact on volatility compared to positive shocks. The AGARCH model serves as a robust tool for assessing market risks from an asymmetric perspective [15].

Empirical results

In this study, the price movements and volatility dynamics of BTC, ETH, and BNB cryptocurrencies were analyzed. The dataset, which comprises daily closing prices from January 1, 2019 to January 8, 2025, was sourced from the Yahoo Finance platform (Yahoo [23]). Raw price data was transformed into log returns to prepare it for further analysis. Using log return series provides a solid foundation for investigating the nonlinear dynamics in price series and for effective volatility modeling. The selected period captures key structural shifts in cryptocurrency markets, including the COVID-19 crisis, the 2021 bull run, and subsequent market corrections.

Pre-2019 data were excluded to focus on the post-ICO maturity phase, during which crypto markets became more liquid, institutionalized, and analytically stable. Including earlier data would have introduced structural breaks due to the speculative and underregulated nature of early crypto trading.

Figure 1 displays the time series graph of log returns for BTC, ETH, and BNB-USD covering the period from January 1, 2019 to January 8, 2025. Although the returns generally cluster around zero, significant fluctuations are observed during specific periods. The phenomenon of volatility clustering—a characteristic feature of cryptocurrency markets—is clearly visible, as periods of low volatility tend to be followed by low volatility and periods of high volatility by high volatility. Notably, during the 2020–2021 period, dramatic market surges and declines resulted in extreme fluctuations in the log returns. Additionally, BNB's log returns show a wider dispersion compared to those of BTC and ETH, indicating a more volatile behavior.

Table 1 summarizes the basic descriptive statistics for the log returns of the three cryptocurrencies under investigation. In terms of minimum and maximum returns, BNB covers a wider range compared to BTC and ETH, indicating that BNB is more prone to extreme values. The average returns are positive across all series, calculated as 0.0015 for BTC, 0.0014 for ETH, and 0.0022 for BNB. These positive values suggest an overall upward trend during the analyzed period. Looking at volatility, measured by standard deviation, BNB exhibits higher volatility (0.046) compared to the other series. Both BTC and ETH display negative skewness, implying that the distribution of returns tends to lean to the left, making negative returns more likely. On the other hand, BNB's skewness is -0.1887, which points to a distribution that is relatively more symmetric. Moreover, all series have high kurtosis

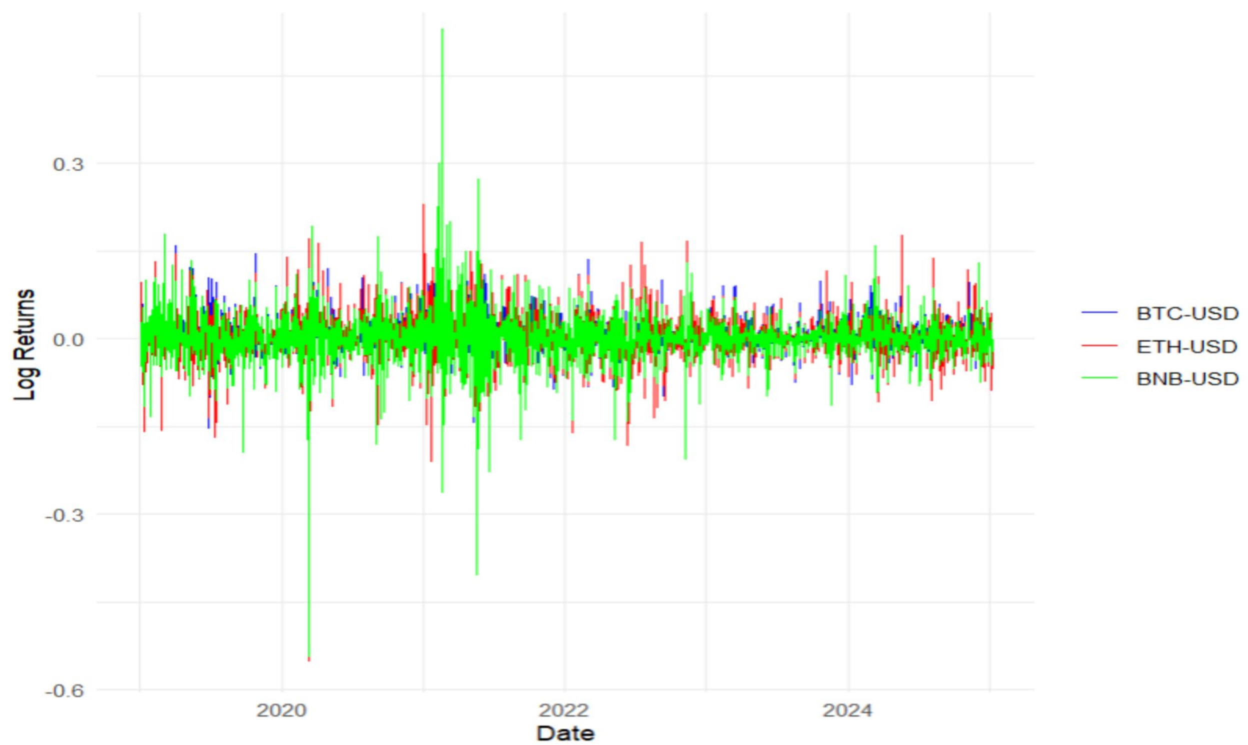

Fig. 1 Log returns for BTC-USD, ETH-USD and BNB-USD

Table 1 Log returns descriptive statistics

Series	Min	Max	Mean	S.D	Skewness	Kurtosis
BTC	-0.4647	0.1718	0.0015	0.0343	−1.1036	21.273
ETH	−0.5507	0.2307	0.0014	0.0436	−1.1312	18.3385
BNB	−0.5431	0.5292	0.0022	0.046	−0.1887	26.0042

Table 2 Elliot, Rothenberg and Stock Unit Root Test

Test	Seri	Statistic	Critical Value (1%)	Critical Value (5%)	Critical Value (10%)	Conclusion
Model	BTC	−9.1342	−3.48	−2.89	−2.57	stationary
	ETH	4.0185	−3.48	−2.89	−2.57	stationary
	BNB	−11.22	−3.48	−2.89	−2.57	stationary

Table 3 Automatic ARMA Selection for BTC, ETH, and BNB Log Returns

Series	Model	Parameters	Standard Errors	Log Likelihood	AIC	BIC	σ^2
BTC	ARIMA(1,0,1)	ar_1=-0.6473 $ma_1 = 0.5956$ $\mu = 0.0015$	ar_1= 0.1591 $ma_1 = 0.1673$ $\mu = 0.0007$	4304.85	−8601.70	−8578.92	0.001169
ETH	ARIMA(1,0,1)	ar_1=-0.7500 $ma_1 = 0.6949$ $\mu = 0.0014$	ar_1= 0.1225 $ma_1 = 0.1327$ $\mu = 0.0009$	3775.80	−7543.59	−7520.81	0.001891
BNB	ARIMA(2,0,2)	ar_1= 0.2324 $ar_2 = 0.6846$ ma_1=-0.2945 ma_2=-0.5935 $\mu = 0.0021$	ar_1= 0.1065 $ar_2 = 0.1114$ $ma_1 = 0.1179$ $ma_2 = 0.1234$ μ= 0.0013	3667.14	−7322.29	−7288.11	0.002089

values, indicating that the returns have heavier tails than a normal distribution, meaning that extreme events occur more frequently. Notably, BNB's kurtosis value (26.0042) is much higher than those of BTC and ETH, further suggesting that its returns are more susceptible to extreme fluctuations.

Table 2 presents the results of the Elliott-Rothenberg-Stock (ERS) unit root test. The test statistics obtained for BTC (–9.1342), ETH (–4.0185), and BNB (–11.2200) indicate that the log-return series of all three cryptocurrencies fall well below the critical values at the 1% (–3.48), 5% (–2.89), and 10% (–2.57) significance levels. This outcome provides strong evidence against the null hypothesis of a unit root, thereby confirming the stationarity of the return series. Accordingly, the log returns of Bitcoin, Ethereum, and Binance Coin exhibit stationary characteristics in terms of both mean and variance over time, which validates that the fundamental condition of stationarity required for subsequent ARIMA and GARCH modeling is satisfactorily met.

Table 3 shows the optimal ARIMA models selected for the crypto log returns. Model selection was based on the minimum AIC and BIC values. For BTC, an ARIMA(1,0,1) model was chosen, which includes first-order autoregressive (AR) and moving average (MA) components. The AR coefficient is -0.6473 and the MA coefficient is 0.5956. The model's log-likelihood is 4304.85, with an AIC of -8601.70 and a BIC of -8578.92, indicating a good fit for BTC returns. Similarly, ETH was modeled with an ARIMA(1,0,1) model, featuring an AR coefficient of -0.7500 and an MA coefficient of 0.6949. Its log-likelihood is 3775.80, AIC is -7543.59, and BIC is -7520.81. These results suggest that ETH exhibits similar dynamics, although with slightly higher volatility. The standard error values indicate that the model parameters are statistically significant. For BNB-USD, an ARIMA(2,0,2) model was selected, incorporating two autoregressive and two moving average terms. The estimated AR coefficients are 0.2324 and 0.6846, and the MA coefficients are -0.2945 and -0.5935. With a log-likelihood of 3667.14, an AIC of -7322.29, and a BIC of -7288.11, this more complex model reflects that BNB's dynamics require additional parameters. This complexity is attributable to BNB's higher volatility and more intricate behavior compared to BTC and ETH.

Table 4 ARCH-LM Test Results for BTC, ETH, and BNB Log Returns

Series	Chi-squared	df	*p*
BTC	44.424	7	1.769e-07
ETH	67.576	7	4.559e-12
BNB	186.48	10	< 2.2e-16

Table 4 presents the ARCH-LM test results for the log returns of BTC, ETH, and BNB. The ARCH-LM test is used to detect the presence of conditional heteroskedasticity (changing variance) in a series, a key aspect in financial time series volatility modeling. The null hypothesis of this test assumes that there are no ARCH effects, while the alternative hypothesis indicates the presence of ARCH effects. For BTC, the test yields a chi-square statistic of 44.424 and a p-value of 1.769×10^{-7}. Because this p-value is far below the 1% significance level, the null hypothesis is rejected, indicating that BTC exhibits time-varying variance and should be modeled with approaches such as GARCH. For ETH, a chi-square statistic of 67.576 and a p-value of 4.559×10^{-12} were obtained, strongly supporting the existence of ARCH effects. This result suggests that ETH's volatility changes over time and that its returns require a more sophisticated volatility model. In the case of BNB-USD, the chi-square statistic is 186.48 with a p-value of $< 2.2\times10^{-16}$, highlighting an even stronger ARCH effect compared to BTC and ETH. Consequently, more complex modeling approaches should be considered when analyzing BNB's volatility.

Table 5 shows the DW test outcomes, which assess the presence of autocorrelation in log returns. The DW test is a basic statistical tool for detecting serial correlation within a series. Its null hypothesis states that there is no autocorrelation. Values near 2 indicate no autocorrelation, while deviations from 2 suggest either positive or negative autocorrelation. For BTC, the DW statistic is calculated at 1.9945 with a p-value of 0.449. Since the statistic is very close to 2 and the p-value is above the significance level, there is no evidence of autocorrelation in BTC's series. ETH's DW statistic is 2.0042 with a p-value of 0.5394, and similarly, BNB's is 2.0002 with a p-value of 0.502, both confirming the absence of autocorrelation in their respective series.

Table 6 presents parameter estimates for various volatility models applied to the logarithmic returns of BTC, ETH, and BNB. The models evaluated—GARCH, EGARCH, TGARCH, CGARCH, and AGARCH—aim to capture volatility dynamics, persistence, and the asymmetric effects of market shocks. The mean logarithmic return for BTC is consistently low but positive across all models, averaging approximately 0.0009. The ARMA(1,1) structure, represented by statistically significant autoregressive (ar_1= −0.3337) and moving average (ma_1= 0.2796) parameters, confirms short-term dependencies in BTC returns. The baseline volatility ($\omega = 2.01\times10^{-5}$) is minimal, while the ARCH (α_1= 0.0689) and GARCH (β_1= 0.9301) terms highlight strong volatility persistence, with β_1 values ranging between 0.93 and 0.99, indicating long-term memory in market fluctuations. Asymmetric models (EGARCH and TGARCH) further reveal that negative shocks amplify volatility more than positive ones, as evidenced by the leverage effect (γ_1= 0.1526) and threshold effect (η_{11} = -0.1423). ETH exhibits a higher mean logarithmic return compared to BTC. While the ARMA(1,1) parameters (ar_1= -0.1439, ma_1= 0.0693) remain statistically significant, their magnitudes are weaker, suggesting less pronounced short-term dependencies. Volatility persistence is robust, with β_1 values (0.91–0.99) underscoring the enduring influence of past shocks. The EGARCH and TGARCH models emphasize asymmetric responses to shocks, where negative market events disproportionately increase volatility (γ_1= 0.1318, η_{11}=-0.1852). Additionally, the elevated $\boldsymbol{\nu}$ parameter (3.25) signals heavy-tailed return distributions, implying a higher likelihood of extreme price movements in ETH. BNB's mean logarithmic return fluctuates between 0.0011 and 0.0013, reflecting a positive trend. However, its volatility structure is more complex, requiring an ARMA(2,2) framework with significant autoregressive (ar_1= 0.47, ar_2= 0.2275) and moving average (ma_1 = -0.5517, ma_2= -0.1787) terms. The baseline volatility ($\omega = 5.46\times10^{-5}$) is higher than BTC and ETH, aligning with BNB's broader return dispersion. Persistent volatility is evident through β_1 (0.85–0.91), while asymmetric models highlight heightened sensitivity to adverse shocks (γ_1= 0.2062 in EGARCH, η_{11}= -0.071 in TGARCH). These results align with BNB's higher kurtosis (26.0042), suggesting frequent extreme price fluctuations.

Figure 2 visualizes the temporal evolution of volatility for each cryptocurrency, demonstrating that while all models broadly capture volatility fluctuations, EGARCH and TGARCH excel in representing abrupt volatility spikes during periods of market stress. This superiority stems from their ability to model asymmetric volatility and leverage effects—key features of financial markets where negative shocks exert a stronger impact on volatility than positive ones.

Table 7 details the performance metrics of the models, offering further insights into their suitability. For BTC, the TGARCH model performs best, with the lowest AIC (−4.2746) and BIC (−4.2539) values, alongside the highest Log-Likelihood (4707.92). This superior performance is attributed to the model's ability to effectively capture asymmetric effects in market conditions. Although the EGARCH model also delivers results close to those of the TGARCH, it is slightly less favorable for BTC. For ETH, the EGARCH model stands out as the most appropriate, achieving the lowest AIC (−3.7699) and BIC (−3.7492) values, and the highest Log-Likelihood (4153.00). EGARCH's strength lies in its capacity to model both the leverage effect and the asymmetric behavior of volatility

Table 5 Durbin-Watson (DW) Test Results

Series	DW	*p*
BTC	1.9945	0.449
ETH	2.0042	0.5394
BNB	2.0002	0.502

Table 6 Parameter Estimates for GARCH-Family Models

Series	Parameter	GARCH	EGARCH	TGARCH	CGARCH	AGARCH
BTC	μ	0.000958	0.000905	0.000899	0.000983	0.000958
	ar1	−0.3337	−0.3726	−0.3845	−0.3346	−0.3338
	ma1	0.2796	0.312	0.3226	0.2819	0.2796
	ω	2.01E-05	−0.0456	0.000262	1.96E-05	2.01E-05
	α_1	0.0689	0.0217	0.0794	0.00389	0.0689
	β_1	0.9301	0.9928	0.9475	0.9143	0.9301
	γ_1		0.1526			
	η_{11}			−0.1423	0.9905	
	η_{21}				0.0615	
	Student's t (ν)	2.9235	2.6733	2.725	3.1114	2.9235
ETH	μ	0.001275	0.001185	0.001159	0.001382	0.001275
	ar1	−0.1439	−0.1236	−0.1329	−0.1119	−0.1439
	ma1	0.0693	0.0437	0.0524	0.04	0.0693
	ω	3.26E-05	−0.0595	0.000346	4.68E-06	3.26E-05
	α_1	0.0834	0.0231	0.0701	0.0765	0.0834
	β_1	0.9156	0.9905	0.9466	0.8208	0.9156
	γ_1		0.1318			
	η_{11}			−0.1852	0.9979	
	η_{21}				0.0192	
	Student's t (ν)	3.2509	3.2433	3.2435	3.5864	3.2509
BNB	μ	0.001153	0.001294	0.001298	0.001125	0.001153
	ar1	0.47	0.4731	0.461	−0.9897	0.4709
	ar2	0.2275	0.2457	0.2577	−0.0626	0.2274
	ma1	−0.5517	−0.5564	−0.5457	0.9057	−0.5526
	ma2	−0.1787	−0.1949	−0.2049	−0.0051	−0.1785
	ω	5.46E-05	−0.1325	0.000777	2.25E-06	5.47E-05
	α_1	0.1451	0.0189	0.1135	0.1705	0.1452
	β_1	0.8529	0.9793	0.9056	0.6952	0.8528
	γ_1		0.2062			
	η_{11}			−0.071	0.9997	
	η_{21}				0.0185	
	Student's t (ν)	3.3835	3.4322	3.4351	3.4076	3.3839

patterns. While the TGARCH model produces similar outcomes, it lags somewhat behind EGARCH for ETH. In modeling BNB's volatility dynamics, the CGARCH model emerges as the best option. It captures both short-term and long-term volatility trends effectively, as evidenced by the lowest AIC (–3.8703) and BIC (–3.8703) values, along with the highest Log-Likelihood (4266.40). The EGARCH model can also be considered a viable alternative for BNB. Overall, these results highlight that different GARCH-type models perform variably in capturing the volatility dynamics of cryptocurrencies. TGARCH is most suitable for BTC, EGARCH for ETH, and CGARCH for BNB.

Figure 3 shows the models that best explain the volatility of BTC, ETH and BNB. TGARCH for BTC, EGARCH for ETH and CGARCH for BNB stand out as the models that best explain the volatility patterns of the respective assets.

Results and discussion

This study presents a comprehensive analysis of the volatility dynamics of BTC, ETH, and BNB using various GARCH models. The findings reveal significant insights into the volatility structure of cryptocurrency markets and are evaluated in comparison with the existing literature.

Our finding that TGARCH best fits BTC diverges from Katsiampa [18], who showed that a CGARCH delivers the best in-sample fit for Bitcoin's long-run and short-run volatility components. Similarly, Chi & Hao [10] report

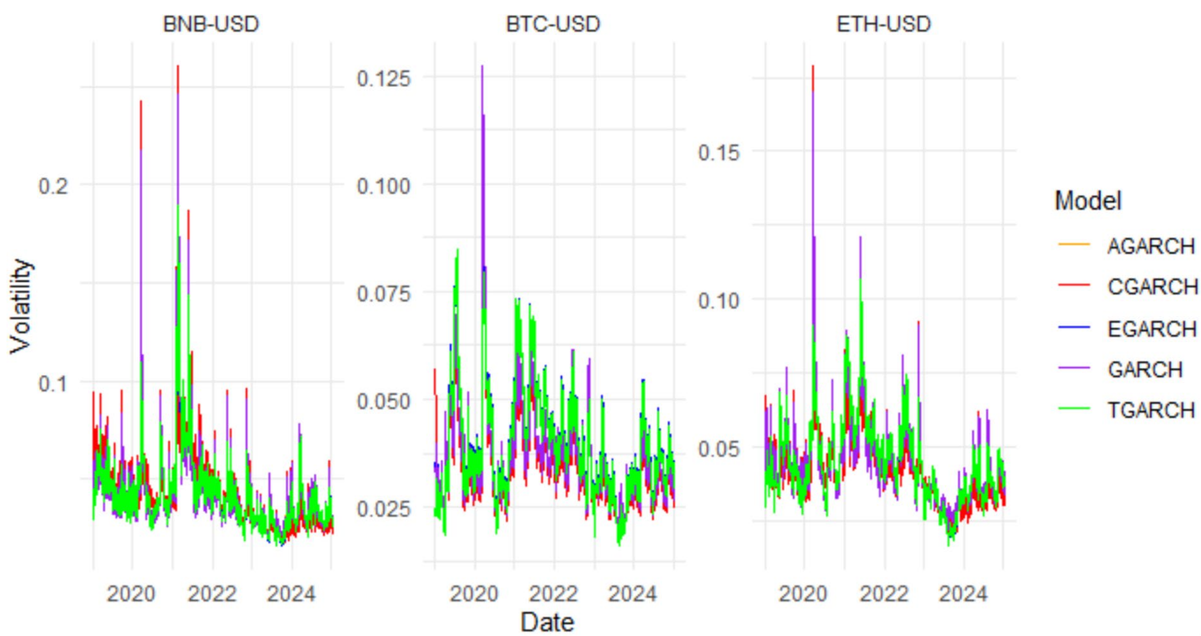

Fig. 2 Volatility Estimates for Different Models

that a vanilla GARCH(1,1) provides the most robust in- and out-of-sample forecasts for Ethereum, rather than EGARCH or TGARCH. Apergis [3], using an asymmetric GARCH framework across eight cryptocurrencies, demonstrates that incorporating an asymmetry term significantly improves volatility forecasts during the COVID-19 crisis, but does not single out EGARCH as uniquely sufficient for ETH beyond the pandemic period.

The analyses indicate that volatility in cryptocurrency markets is asymmetric and that traditional GARCH models may fail to adequately capture certain market characteristics. The fact that the TGARCH model is the best fit for BTC suggests that negative shocks have a stronger impact on volatility than positive shocks. This finding demonstrates that volatility increases more prominently during financial crises and sharp market declines. For ETH, the superior performance of the EGARCH model highlights the pronounced leverage effect in this asset, confirming that negative news has a greater impact on volatility. In the case of BNB, the CGARCH model provides the best results, indicating that volatility consists of both long-term and short-term components. This suggests that models capable of explaining the impact of market regime changes on volatility are more suitable for this asset.

The study's results demonstrate that volatility is highly persistent and that market shocks have long-lasting effects. The forecasts obtained using GARCH-family models indicate that volatility exhibits long memory and that uncertainties in financial markets create prolonged effects on cryptocurrencies. The beta coefficients ranging between 0.91 and 0.99 confirm that volatility has a long-term component and that fluctuations in market conditions generate sustained impacts. These findings support the volatility clustering hypothesis proposed by Engle [15] and Bollerslev [6]. Cryptocurrency market volatility appears to be more dynamic than that of traditional financial assets and varies depending on different market conditions. The results indicate that volatility dynamics differ significantly between market crashes and

Table 7 Performance Metrics of the Volatility Models

Seri	Model	AIC	BIC	Log Likelihood
BTC	GARCH	−4.2624	−4.2443	4693.55
	EGARCH	−4.2743	−4.2536	4707.63
	TGARCH	−4.2746	−4.2539	4707.92
	CGARCH	−4.2585	−4.2351	4691.18
	AGARCH	−4.2624	−4.2443	4693.55
ETH	GARCH	−3.7580	−3.7398	4138.84
	EGARCH	−3.7699	−3.7492	4153.00
	TGARCH	−3.7688	−3.7480	4151.79
	CGARCH	−3.7618	−3.7385	4145.13
	AGARCH	−3.7579	−3.7398	4138.84
BNB	GARCH	−3.8519	−3.8286	4244.22
	EGARCH	−3.8571	−3.8312	4250.84
	TGARCH	−3.8543	−3.8284	4247.85
	CGARCH	−3.8703	−3.8703	4266.40
	AGARCH	−3.8519	−3.8286	4244.22

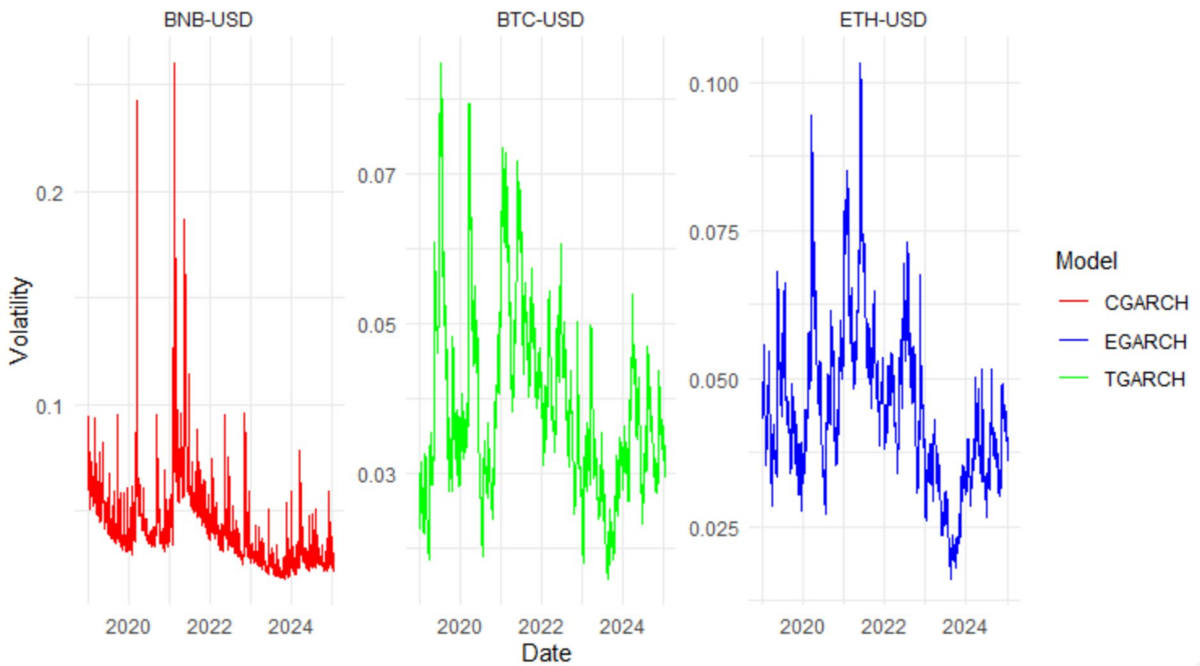

Fig. 3 Volatility Estimates of Selected Models

bull market periods, emphasizing the need for modeling methods that account for specific market conditions. Additionally, as the performance of volatility forecasting models may vary over time, more flexible modeling approaches that incorporate market regime shifts should be developed. However, this analysis is constrained by its use of daily data from 2019 to 2025 only, the assumption of Student's t error distributions across all models, and the absence of exogenous factors such as macroeconomic indicators or sentiment variables, which could further refine volatility forecasts.

This study contributes to the existing literature by providing new insights into cryptocurrency market volatility dynamics. By comparing the performance of different GARCH models, it reveals that each model exhibits varying levels of success depending on market conditions. Given that cryptocurrency markets exhibit higher volatility and asymmetric market reactions compared to traditional financial markets, the study concludes that volatility forecasting models should be tailored to account for the unique characteristics of these markets. These insights are crucial for institutional investors and hedge funds optimizing VaR and margin requirements, retail traders sizing positions and setting stop-losses, and regulators calibrating stress-test scenarios specific to crypto-asset volatility profiles.

Several key research areas emerge for future studies. First, evaluating the performance of GARCH models in comparison with machine learning and deep learning techniques for cryptocurrency volatility forecasting could be valuable. Nowadays, deep learning–based approaches such as LSTM and GRU are increasingly used in financial time series analysis. Comparing the volatility forecasting performance of these methods with traditional econometric models could provide new perspectives in model selection. Additionally, this study focuses only on major cryptocurrencies such as BTC, ETH, and BNB; future research could examine different types of crypto assets. Decentralized finance (DeFi) tokens, stablecoins, and lower-market-cap assets may exhibit distinct volatility patterns. Analyzing the volatility dynamics of these assets could contribute significantly to the development of risk management strategies in cryptocurrency markets. Lastly, future research could explore regime-switching models and methods such as Markov regime-switching models that can capture the evolving nature of cryptocurrency market volatility. Integrating sudden market fluctuations and regime changes into volatility modeling could help market participants generate more reliable risk assessments and policy recommendations.

Overall, this study provides a comprehensive comparison of volatility modeling in cryptocurrency markets, demonstrating how different modeling techniques may vary based on market conditions. The findings emphasize the importance of increasing the sensitivity of financial time series modeling methods to market characteristics and pave the way for new research areas aimed at improving the accuracy and effectiveness of volatility forecasting.

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Ç.S contributed to resources, conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing – original draft, writing – review and editing, visualization, and project administration.

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The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Declarations

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Consent for publication
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