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REVIEW ARTICLE

Accurate Conditional Variance Models for Predicting Asymmetric Volatility in Cryptocurrency Markets[1]

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Abstract

This study includes tests on the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model and its derivatives to conduct complex and detailed volatility analysis for the 5 highest-volume cryptocurrencies traded in September 2023. The tests have been conducted with Python, R, and Eviews software and analyses have been compared in terms of consistency and accuracy of the results across multiple software and programming languagse. In the testing process, observation of the volatility has been assessed by some variables such as skewness, kurtosis, and log-likelihood values, and these variables have been taken into consideration for testing. Tests such as Jarque-Bera and Augmented Dickey-Fuller (ADF) have been applied during the process to verify model correctness. The EGARCH, GJR-GARCH, and TGARCH models have been more effective in detecting volatility and market shocks in the relevant cryptocurrencies as a result of the tests conducted in the volatility analysis.

Keywords: *Cryptocurrencies, Conditional Variance, Asymmetric GARCH Models, GARCH, E-GARCH, GJR-GARCH, T-GARCH.*

Jel Codes: *C58, G17, E47, G15, L17*

Kripto Para Piyasalarında Asimetrik Volatilitenin Tahmininde Doğru Koşullu Varyans Modelleri

Özet

Bu çalışma, 2023 yılı Eylül ayında işlem gören en yüksek hacimli 5 kripto para için karmaşık ve detaylı volatilite analizi yapmak üzerine Genelleştirilmiş Otoregresif Koşullu Heteroskedastiklik (GARCH) modeli ve türevleri üzerine testler içermektedir. Analizler, Python, R ve Eviews programlarıyla yapılarak sonuçların tutarlılığı test edilmiş ve doğrulanmıştır. Test süreçlerinde, kripto para piyasalarında volatilite tahmini açısından en doğru yöntemin hangisi olabileceği, çarpıklık, basıklık ve log-likelihood değerleri dikkate alınarak sınanmış ve model doğruluğu için Jarque-Bera, ADF gibi testler uygulanmıştır. Yapılan sınanmalar sonucunda volatilite analizinde kripto piyasalar için GARCH modellerinde EGARCH, GJR-GARCH ve TGARCH modellerinin ilgili kripto para birimlerinde volatilite ve piyasa şoklarını tespit etmede etkin olduğu bulunmuştur.

Anahtar Kelimeler: *Kripto paralar, Koşullu Varyans, Asimetrik GARCH Modelleri, GARCH, E-GARCH, GJR-GARCH, T-GARCH.*

Jel Kodu: *C58, G17, E47, G15, L17*

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1. INTRODUCTION

Although blockchain technology is commonly associated with cryptocurrencies, its usage is increasingly diversifying. Expanding its influence in various sectors such as finance, commerce, and law, the journey that began with Satoshi Nakamoto's critiques of the 2008 financial crisis has offered an alternative approach to traditional financial systems with Bitcoin. Despite initially being viewed as a speculative bubble, especially during the significant surge in interest in 2017, cryptocurrencies have gradually gained broader acceptance. As Charlie Munger said, "Using volatility as a measure of risk is nuts. Risk to us is 1) the risk of permanent loss of capital, or 2) the risk of inadequate return." Keeping in mind that the real risks are systemic and long-term, this study does not entirely view volatility as a risk factor. However, the high volatility in cryptocurrency markets distinguishes this field from traditional financial markets. Considering the trillion-dollar market capitalization of cryptocurrencies, specialized models are needed to analyze this volatility.

This study examines volatility and its subcategories, volatility clustering, and leverage effects using variations of the GARCH models. The high structures of conditional variance have been tested with asymmetric GARCH models, and the performances of various cryptocurrencies have been evaluated. The research aims to comprehensively explore the correct model alternatives in the cryptocurrency markets through these analyses.

2. LITERATURE REVIEW

In the relevant section of this article, findings from significant local and international research on cryptocurrency and blockchain technology are summarized and presented, starting with the earliest studies and moving towards more recent research.

The historical significance of public-key cryptographic systems was highlighted by Griffith (2014), contributing to the development of this technology. Sherman et al. (2019) and Ruoti (2019) examined how David Chaum's method of cryptographic "blind signatures" inspired blockchain technology, while Merkle (1987) researched advancements provided by Merkle trees in transaction information transfer. Haber and Stornetta (1991) designed a blockchain-like system using Merkle blocks. Nick Szabo (1997), widely thought to be Satoshi Nakamoto himself, created the concept of digital smart contracts within contract law as part of his legal and technology research. As Grinberg (2011) mentioned, Szabo's work led to the creation of the alternative cryptocurrency concept (altcoin), paving the way for many other alternative cryptocurrencies (altcoins) like Litecoin and Dogecoin. Consequently, blockchain technology-based money transfer options increased with the proliferation of Bitcoin alternatives.

Nakamoto's (2009) introduction of a decentralized ledger system with Bitcoin was considered a significant transformation in the financial world by Güven and Şahinoz (2018). Davidson et al. (2016) and Anceaume et al. (2016) proposed how blockchain technology could enhance various governmental functions through smart contracts. These reviews provided an in-depth look into the economic and financial dimensions of blockchain technology and cryptocurrency markets.

The ARCH model, introduced by Engle (1982), was used to model fluctuations in financial time series. Bollerslev (1986) further developed this approach, introducing the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which became popular for modeling and forecasting financial time series volatility. Derman et al. (1999) investigated the impact of volatility fluctuations in financial markets under financial quantitative analysis. They derived mathematical formulas explaining the risk posed by a hedged position in the presence of volatility skewness and the challenges of managing volatility risk with ordinary instruments by focusing on the characteristics of variance and volatility swaps.

The volatility of cryptocurrency markets was assessed by Ghait et al. (2021) in terms of regulatory needs and examined the volatility of major cryptocurrencies using GARCH models. Balcilar et al. (2018) conducted studies on the economic dynamics of Bitcoin and cryptocurrency markets.

Güring and Grigg (2011) discussed a macroeconomic perspective on the high fluctuations of Bitcoin, the first cryptocurrency. Gronwald (2014) compared the gold and bitcoin markets, analyzing bitcoin and gold prices using GARCH models, and calculated that Bitcoin experienced much larger fluctuations compared to gold, indicating an immature market.

Yermack (2015), in his article, addressed whether Bitcoin, then newly popular, was a currency or an asset. He examined Bitcoin's volatility compared to fiat currencies like the dollar, euro, pound, yen, Swiss franc, and gold. He suggested that for Bitcoin to be considered a reliable and stable fiat currency, its daily price fluctuations needed to stabilize, but he speculated that it might serve reliably as a store of value and unit of account in future markets.

Beneki et al. (2019) analyzed rising-value altcoins in cryptocurrency volumes, particularly examining Ethereum's volatility with innovative VAR methodologies and its correlation with Bitcoin. They discovered a one-way volatility transfer from Ethereum to Bitcoin and predicted profitable trading strategies could be developed for Ethereum within a newly developed derivative market.

Kyriazis et al. (2019) selected various altcoins (DOGE, ZEC, OMG, BTG, BCN, LSK, XTZ, XEM, DCR, NANO, and BTS) to research the impact of the top three capitalization cryptocurrencies (Bitcoin, Ethereum, and Ripple) on other high-capitalization digital currencies. They examined with DCC-GARCH models that most cryptocurrencies complement Bitcoin, Ethereum, and Ripple and found no hedging ability among the major digital currencies during troubled times. Ghaiti et al. (2021) attempted to find the best model to predict the volatility of Bitcoin, Bitcoin Cash, Litecoin, Dogecoin, and Ethereum by applying five GARCH-type models with t-distribution to the closing prices of selected cryptocurrencies. They calculated the volatility of cryptocurrencies using the EGARCH (1,1) model for Bitcoin, Litecoin, Dogecoin, and Ethereum, and the GARCH (1,1) model for Bitcoin Cash, noting the impact of various days of the week on volatility in different cryptocurrencies. Vidal and Meléndez (2016) analyzed that Bitcoin and some cryptocurrencies exhibited behavioral characteristics consistent with the Fractal Market Hypothesis (FPH), providing a deeper understanding of how new markets function to comprehend the volatile nature of cryptocurrencies.

In a study conducted by Dyhrberg (2016), the focus was on classifying Bitcoin as a financial asset and determining its role in the market. This study used GARCH models to evaluate whether Bitcoin resembled the US dollar (as a currency and medium of exchange) or gold (as a store of value and a commodity used for hedging in financial risk situations). It was found that Bitcoin exhibited stock market characteristics and responded to Federal fund rates. Additionally, it was observed that Bitcoin responded to similar variables as gold, indicating its hedging properties. The study also noted that Bitcoin showed symmetric responses to various speculations and news. Similarly, Gronwald (2014) compared the gold and bitcoin markets and analyzed bitcoin prices using GARCH models, predicting that the crypto market had large fluctuations and an immature market.

Chu et al. (2017) investigated which GARCH models could be appropriately adapted to Bitcoin, Dash, Dogecoin, Litecoin, Maidsafecoin, Monero, and Ripple. Nadarajah et al. (2017) observed that the IGARCH and GJRGARCH models provided the most suitable modeling for the volatility of the most popular cryptocurrencies during their hunting periods. Guesmi et al. (2018) used different multivariate GARCH methodologies to examine the conditional cross-effects and volatility transmissions between Bitcoin and financial indicators for the period from January 2012 to January 2018. Their results revealed that the VARMA (1, 1), DCC-GJR-GARCH specification was most suitable for predictions. Guesmi et al. (2019) demonstrated that hedging strategies involving gold, oil, emerging stock markets, and Bitcoin resulted in lower risk when Bitcoin was not included, indicating that Bitcoin is a riskier asset compared to selected variables (Gold, oil, stocks, etc.). Ural and Demireli's (2020) analysis examined the volatility of the USD/KZT exchange rate returns with asymmetric GARCH models, highlighting their short half-lives and tendency to respond quickly to market dynamics.

In 2022, Jeong and others published a study titled "More to cryptos than bitcoin: A GARCH modelling of heterogeneous cryptocurrencies," focusing on GARCH modeling for various cryptocurrencies. Additionally, Khan et al. investigate market volatility during COVID-19, focusing on Bitcoin, EUR, S&P 500, Gold, Crude Oil, and Sugar, using GARCH models from 2018 to 2021. It reveals increased volatility and positive asymmetry in Crude Oil and the S&P 500, highlighting EGARCH's effectiveness pre-pandemic and GARCH models' utility during the pandemic.

3. DATA AND METHODOLOGY

The data set used in this study comprises the daily closing values of five different cryptocurrencies against the US dollar (USD) from January 1, 2019 to September 11, 2023. The cryptocurrencies are Bitcoin (BTC), Ethereum (ETH), Tether (USDT), USD Coin (USDC), and Binance Coin (BNB). These cryptocurrencies were selected due to their status as the five with the highest market capitalization as of September 2023. The data set was obtained from the Yahoo Finance website using the Python programming language and the Yahoo Finance API (Application Programming Interface). All data analysis work was carried out using the Python and R programming languages, with relevant libraries loaded. The results were verified using Eviews.

There are a total of 1715 observations for each cryptocurrency. In the data set, the natural logarithm (base e) of all values was taken to perform log transformations. Subsequently, any missing or infinite values resulting from the logarithmic transformation were removed from the data to minimize error effects in the calculations. After cleaning the data, 1709 observations remained.

The formula for calculating the percentage change in returns is as follows:

$$Percentage\ Return\ = ((Final\ Price\ -\ Initial\ Price)\ /\ Initial\ Price)\ \times\ 100$$

This formula allows us to express the price change in each period as a percentage. The Augmented Dickey-Fuller (ADF) unit root test, a common statistical method used to test whether a time series is stationary, has been applied (Çil, 2004).

The ADF test was applied under different configurations (with constant, with constant and trend, without constant and trend). The choice of these configurations is due to the presence of many different time series behaviors in the real world, which increases the accuracy of calculations for financial assets like cryptocurrencies that have volatility sensitivity. Therefore, in this study, calculations were also made for versions with constants, with constants and trends, and without constants and trends.

3.1 Stationarizing the Series

$$\Delta yt = \alpha + \beta t + \gamma yt - 1 + \delta 1 \Delta yt - 1 + \epsilon t$$

In this formula,

- Δyt: Represents the first difference of the series at time t.
- α: Is the constant term.
- βt: Trend term.
- γyt−1: The coefficient of the series value at time t−1. The ADF test checks whether this coefficient is zero.

- δi: The coefficients of the series' past values.
- εt: The error term.

If the series are not stationary, they are made stationary by taking the first differences: yt′=yt−yt−1

In this formula, y′ represents the first difference of the series at time t, while yt represents the value of the series at time t. The first difference refers to the difference between two consecutive values of the series.

3.2 Jarque-Bera Test

Most statistical methods assume a normal distribution, but data do not always conform to this distribution. The Jarque-Bera test, developed by Carlos Jarque and Anil Bera, is a test that evaluates the suitability of data to the normal distribution based on skewness and kurtosis values. This test is particularly used to examine the distribution of cryptocurrencies and to check the suitability of GARCH models for the data.

$$\text{JB} = \left(\frac{n}{6}\right)\left(S^2 + \frac{1}{4(K-3)^2}\right)$$

JB : Jarque-Bera Test Statistic.

n: Number of observations.

S: Skewness value. If S=0, the distribution is symmetric; if S>0, the distribution is right-skewed; and if S<0, the distribution is left-skewed.

K: Kurtosis value. For a normal distribution, the K value is 3. If K>3, the distribution's tails are thicker and the peak is higher than a normal distribution. If K<3, the distribution's tails are thinner and the peak is flatter than a normal distribution.

The Jarque-Bera statistic, as observed in this study, measures how much the distribution deviates from a normal distribution. Skewness and Kurtosis are significant statistical measures that help test whether a data distribution conforms to normal distribution characteristics, particularly through skewness, kurtosis, and normality tests.

3.3 In analyses of Skewness and Kurtosis

Skewness determines whether a distribution is symmetric. Mathematically, skewness is calculated using the following formula:

S = σ3μ3

In this formula:

μ3: Represents the third moment.

σ: Is the standard deviation.

If S = 0, the distribution is symmetric. If S > 0, the distribution is right-skewed, indicating positive skewness. If S < 0, the distribution is left-skewed, indicating negative skewness.

Kurtosis: Kurtosis defines the shape of the tails and the peak of a distribution. Mathematically, kurtosis is calculated using the following formula :

K = σ4μ4

In this formula:

μ4: Represents the fourth moment.

σ: Standard deviation.

For a normal distribution, the K value is 3. If K > 3, the distribution's tails are thicker, and the peak is higher than a normal distribution, indicating leptokurtic (excessive kurtosis). If K < 3, the distribution's tails are thinner, and the peak is flatter than a normal distribution, indicating platykurtic (reduced kurtosis).

3.4 GARCH Model (Generalized Autoregressive Conditional Heteroskedasticity Model)

The high volatility of cryptocurrencies necessitates analysis with more sophisticated models. The GARCH model, developed by Robert Engle in 1982, is used to model volatility by considering an asset's past volatility and shocks. It is a common method for understanding the variability of financial series. GARCH assumes that volatility is dependent on both past errors and past values.

$$\sigma_t^2 = \alpha_0 + \Sigma\, \alpha_i \varepsilon_{t-i}^2 + \Sigma\, \beta_j \sigma_{t-j}^2$$

σ_t^2: Represents the conditional variance (volatility) at time t.

α_0: Constant term.

α_i: The coefficients of past error terms.

β_j: The coefficients of past volatility (variance) values.

ε_{t-i}: The error term at time t-i.

3.5 EGARCH (Exponential GARCH)

This model allows for modeling the leverage effect by taking the logarithm of the volatility equation, thus capturing the asymmetric effects between positive and negative shocks. The EGARCH model was developed by Nelson in 1991. By modeling the logarithm of volatility, it ensures that volatility is constrained in such a way that it cannot approach zero. The EGARCH model, considering asymmetric responses in returns and volatility clustering, offers a modeling approach more aligned with the characteristics of cryptocurrency returns.

$$\ln(\sigma_t^2) = \alpha_0 + \Sigma\alpha_i\left|\varepsilon_{(t-i)}\right| + \Sigma\gamma_i\varepsilon_{(t-i)} + \Sigma\beta_j\ln\left(\sigma_{(t-j)}^2\right)$$

In this formula;

- σ_t^2: Represents the conditional variance (volatility) at time t.
- α_0: Constant term.
- α_i ve γ_i: Are the coefficients of past error terms. Here, α represents the effect of absolute value errors, while γ focuses on the sign effect.
- β_j: Are the coefficients of past volatility (variance) values.
- $\varepsilon_{(t-i)}$: Is the error term at time t-i and is generally considered as white noise.

3.6 The GJR-GARCH (Glosten-Jagannathan-Runkle GARCH) Model

This model is an extension of the GARCH model and a more detailed version that incorporates asymmetric responses between positive and negative shocks into model predictions. The GJR-GARCH model was developed by Glosten, Jagannathan, and Runkle in 1993. It assumes that positive and negative shocks can have different effects on volatility. This model is particularly used in financial data where downtrends, i.e., negative return volatility, have a greater impact compared to positive return increases.

The GJR-GARCH (p, q) model is expressed as follows:

$$\sigma_t^2 = \alpha_0 + \Sigma\alpha_i\varepsilon_{(t-i)}^2 + \Sigma\gamma_i I_{(\varepsilon_{(t-i)}<0)}\varepsilon_{(t-i)}^2 + \Sigma\beta_j\sigma_{(t-j)}^2$$

In this formula:

- σ_t^2: Represents the conditional variance (volatility) at time t.
- α_0: Constant
- α_i ve γ_{i_i}: : Are the coefficients of past error terms, same as before, but this term is effective only when ε_(t-i) is negative.
- $I\_(\varepsilon\_(t-i) < 0$: Is an indicator function that takes the value 1 if ε_(t-i) is negative, and 0 otherwise.
- β_j ve $\varepsilon_{(t-i)}$: Are the same as in previous models.

3.7 TGARCH (Threshold GARCH)

This model allows for modeling volatility differently depending on whether the returns are below or above a certain threshold value. The TGARCH model was developed by Zakoian in 1994. It distinguishes between positive and negative shocks based on a specific threshold value. This is a suitable modeling approach, especially for assets with high volatility, such as cryptocurrencies.

$$\sigma_t^2 = \alpha_0 + \Sigma\alpha_i\varepsilon_{(t-i)}^2 + \Sigma\gamma_i I_{(\varepsilon_{(t-i)}<0)}\varepsilon_{(t-i)}^2 + \Sigma\beta_j\sigma_{(t-j)}^2$$

In this formula:

- σ_t^2: Represents the conditional variance (volatility) at time t.
- α_0: Constant term.
- α_i ve γ_i: Are the same, but this term is effective only when ε_(t-i) is negative.
- $\varepsilon_{(t-i)} < 0$: Is an indicator function that takes the value 1 if ε_(t-i) is negative, and 0 otherwise.
- β_j: Are the coefficients of past volatility (variance) values.
- $\varepsilon_{(t-i)}$: Is the same as in previous models.
- γ: Is the coefficient of the indicator function and represents the magnitude of the impact of negative shocks on volatility.

4. DATA ANALYSIS

Analyzing descriptive statistics of the five high-volume cryptocurrencies in the cryptocurrency markets is the first step in our data analysis. The initial phase of our comprehensive data analysis involves a thorough examination of descriptive statistics pertaining to the five cryptocurrencies with the highest volume in the cryptocurrency markets. This pivotal step not only sets the groundwork for our subsequent analytical endeavors but also provides a critical understanding of the underlying trends, variances, and overall market behaviors of these leading digital assets. By delving into the key statistical measures such as mean, median, mode, standard deviation, and range, we aim to paint a detailed picture of the current state and potential future movements of these prominent cryptocurrencies, thereby offering valuable insights into their market dynamics, volatility patterns, and investment potential. This foundational analysis is instrumental in guiding our further investigation into the intricacies of the cryptocurrency market, enabling us to develop a more nuanced and informed perspective on the factors driving the performance and valuation of these high-volume digital currencies.

Table 1: Descriptive Statistics

LCrypto Currency	Minimum	Median	Mean	Kurtosis	Skewness	Observations
LBTC-USD	-0.0518	0.0001	0.0001	24.6643	-1.4480	1708
LETH-USD	-0.1045	0.0001	0.0003	26.7002	-1.7093	1708
LUSDT-USD	-1649.1294	-0.1641	0.6782	1008.4259	21.1807	1708
LUSDC-USD	-224.2146	-0.4703	-0.3782	150.9223	1.4814	1708
LBNB-USD	-0.1936	0.0002	0.0007	33.6670	-1.3495	1708

LCryptocurrency: Due to our study on the percentage changes in returns of cryptocurrencies, the first differences of the logarithmically transformed values were taken, and the data were cleansed of missing and infinite values.

4.1 General Overview of the ADF Test

The ADF (Augmented Dickey-Fuller) unit root test was applied. Since the ADF test is applied in different configurations in order to handle different time series behaviors, the stationary, trend stationary, and non-stationary versions were calculated in this study.

Table 2: ADF Test Results

Crypto Currency	Regression Models Tested	ADF Statistical Values Range	%5 Critical Value Range	H1 Conclusion
BTC-USD	Stationary, Trend stationary, Non-stationary	-19.64 to -19.48	-3.41 to -1.94	The series is stationary
ETH-USD	Stationary, Trend stationary, Non-stationary	-12.61 to -12.46	-3.41 to -1.94	The series is stationary
USDT-USD	Stationary, Trend stationary, Non-stationary	-41.38 to -41.3	-3.41 to -1.94	The series is stationary

USDC-USD	Stationary, Trend stationary, Non-stationary	-22.51 to -22.5	-3.41 to -1.94	The series is stationary
BNB-USD	Stationary, Trend stationary, Non-stationary	-10.14 to -9.77	-3.41 to -1.94	The series is stationary

4.2 Jarque- Bera Test

The Jarque-Bera test, which checks data normality, suggests non-normality when its value is over 30 with a p-value under 0.05. The data shows cryptocurrencies' closing values are not normally distributed, confirming the volatile nature of the crypto market.

The traditional GARCH model assumes that returns respond equally to volatility. However, this assumption is challenged by the phenomena of "volatility clustering" and the "leverage effect," which are frequently observed in financial time series.

In this context, resorting to alternative GARCH model versions, and especially the EGARCH and TGARCH models, may be a suitable choice to more effectively address the asymmetry of volatility by taking into account the leverage effect. These results also suggest that the use of alternative GARCH models such as EGARCH(1,1) and TGARCH(1,1) is supported by the literature, as these p and q valued models are often applied to financial time series. However, the correct p and q values should still be calculated by further analysis and added to the model setup.

Table 3: Jarque-Bera Normality Test Results

Crypto Currency	t-value	p-value	Normality assumption
BTC-USD	208.86	0.0	Declined
ETH-USD	226.40	0.0	Declined
USDT-USD	8489.71	0.0	Declined
USDC-USD	1269.68	0.0	Declined
BNB-USD	284.07	0.0	Declined

These results also suggest that the returns of cryptocurrencies may have a heavy-tailed and asymmetric distribution. This is a characteristic of financial time series, and it is particularly evident in assets with high volatility, such as cryptocurrencies.

4.3 The Effect of Crypto Skewness and Kurtosis Values on Cryptocurrency Returns

The distribution of cryptocurrency returns was assessed for normality using skewness and kurtosis measurements. Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean. In financial terms, skewness helps to understand the probabilities of extreme returns; positively skewed distributions signify more chances of extreme high returns. On the other hand, kurtosis measures the tails' heaviness of the distribution compared to a normal distribution. Higher kurtosis can be an indicator of potential risk in investments as it points to a higher likelihood of extreme values, both high and low.

Tablo 4: Skewness and Kurtosis Results

Crypto Currencies	Skewness	Kurtosis
BTC-USD	-1.24	18.67
ETH-USD	-1.24	14.98
USDT-USD	0.39	96.99
USDC-USD	0.81	44.28
BNB-USD	-0.21	20.99

The results suggest that cryptocurrency returns are not normally distributed. The skewness values are positive for all cryptocurrencies, indicating that the distribution is right-skewed. This means that there are more negative returns than positive returns. The kurtosis values are also high for all cryptocurrencies, indicating that the distribution is leptokurtic. This means that the distribution has fatter tails than a normal distribution. These results suggest that cryptocurrency returns are more volatile than traditional assets. The right-skewness indicates that there is a greater risk of negative returns, while the leptokurtosis indicates that there is a greater risk of extreme returns, both positive and negative.

4.4 The Comparative Analysis of Volatility Dynamics in Cryptocurrency Markets with EGARCH, GJR GARCH and T-GARCH Models

The results of the Jarque-Bera normality test showed that extended GARCH models such as EGARCH and TGARCH are more suitable for this type of data because of their ability to capture the fat-tailed and skew distributions of financial time series such as cryptocurrency returns. However, when we subjected the distribution characteristics of the price movements of each cryptocurrency to a goodness-of-fit test, it was found that the EGARCH and GJR-GARCH models were more suitable than others, especially for BTC-USD and BNB-USD. This suggests that both models are capable of capturing the dynamics of the volatility of these cryptocurrencies.

In this context, the most suitable (p,q) values were calculated by considering the similarities and differences between the EGARCH, GJR-GARCH, and T-GARCH models obtained in the test results, taking into account the asymmetric structure of the volatility of cryptocurrencies and the leverage effect. With the created code, the ARCH (Autoregressive Conditional Heteroskedasticity) model is applied to simulate the daily volatility of cryptocurrency prices. The model's basic parameters, p and q, determine how often past volatility values and error squares will be used. Comparative analysis was created with the best (p,q) parameters for the E-GARCH and GJR-GARCH models.

Tablo 5: Best Parameter Selection Table for E-GARCH, GJR – GARCH Models

Cryptocurrency	**Best *p* (EGARCH)**	**Best *q* (EGARCH)**	**Best *p* (GJR-GARCH)**	**Best *q* (GJR-GARCH)**
BTC-USD	4	3	4	3
ETH-USD	4	3	4	3
BNB-USD	4	3	4	3
USDC-USD	1	1	1	1
USDT-USD	1	1	1	1

Note: The best p and q parameters for each model, except for stable cryptocurrencies (stablecoins) USDC and USDT, were determined according to the AIC and BIC criteria.

The analysis indicates that GARCH-type models, including GJR-GARCH, present varying optimal parameters for distinct cryptocurrencies, reflecting their unique volatility dynamics. For instance, GJR-GARCH recommends a p-value of 1 for USDT, highlighting divergent market behaviors. T-GARCH model evaluations, informed by Jarque-Bera tests, delve into aspects like threshold and asymmetry to elucidate volatility reactions in crypto markets. It's noteworthy that the preferred p and q values for models, barring stablecoins USDC and USDT, were chosen based on AIC and BIC guidelines.

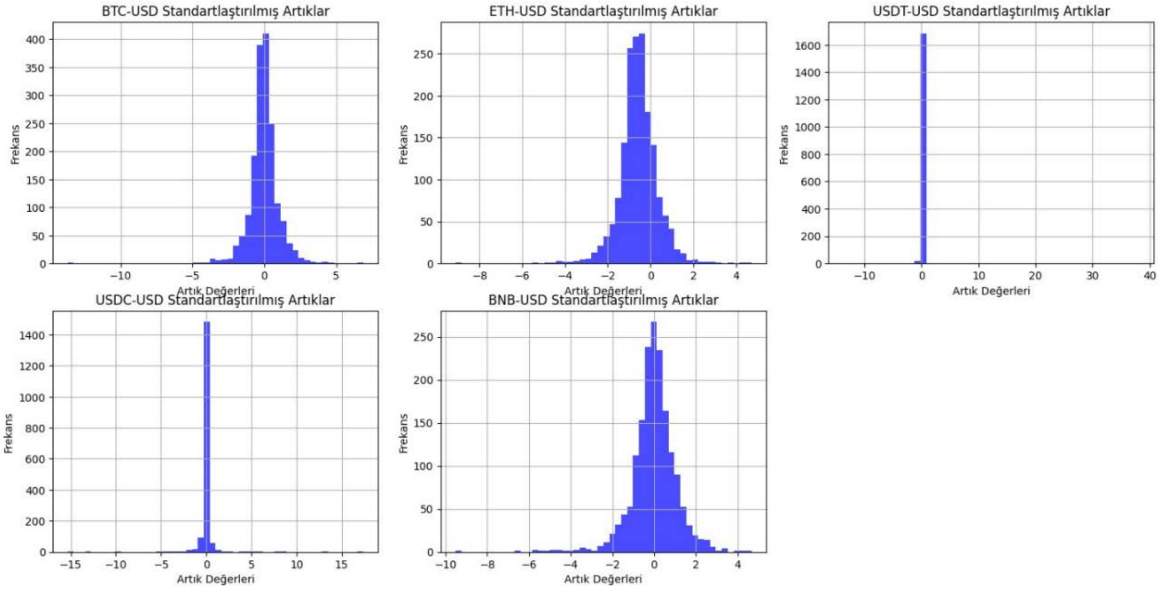
Table 6: Best Parameter Selection Table for T-GARCH Model

Cryptocurrency	**Best *p* (T-GARCH)**	**Best *q* (T-GARCH)**
BTC-USD	4	3
ETH-USD	4	3
USDT-USD	1	1
USDC-USD	1	1
BNB-USD	4	3

Note: The best p and q parameters for each model, except for stablecoins (USDC and USDT), were determined according to the AIC and BIC criteria.

The T-GARCH model also offers different parameter choices for different cryptocurrencies. In particular, it is seen that the model suggests the p=1, q=1, and p=1, q=1 values for USDC and USDT. These results suggest that the volatility of cryptocurrencies may include such asymmetric responses. In particular, it has been observed that the volatility of stable cryptocurrencies, such as USDC and USDT, differs from that of other stables or different cryptocurrencies in GARCH modeling. Based on these results, GARCH models were established in our calculations with the relevant results.

Figure 1 : Standardized Residuals



4.5 Standardized Residuals

At the top of the graph, we see the frequency distribution of residual values.

The X-axis represents the residual values, while the Y-axis shows the number of occurrences of each residual value in this data set. The X-axis represents residual values, and the Y-axis represents the frequency of residual values.

BTC-USD Standardized Residuals

The graph displays the distribution of standardized residuals related to Bitcoin (BTC). The average value of the standardized residuals appears to vary approximately between -5 and 15.

ETH-USD Standardized Residuals

The frequency distribution of the residual values seems to reflect the volatility of Ethereum's price movements.

USDT-USD and USDC-USD Standardized Residuals

This graph shows the distribution of standardized residuals related to Tether (USDT) and USD Coin (USDC). As USDT and USDC are stablecoins representing the stability of other cryptocurrencies, it is important that their standardized residuals reflect the stability of such assets.

BNB-USD Standardized Residuals

This graph displays the distribution of standardized residuals related to Binance Coin (BNB), showing a residual distribution particularly similar to that of Ethereum. The standardized residual test is a statistical test used to assess whether the errors of a model have a constant variance over time. Applying this test before moving to conditional variance models can help reveal the structural features of the data and potential volatility clustering, thus providing a more solid foundation for model selection and risk assessment procedures. The presence of residuals that do not conform to a normal distribution in this model requires the use of more complex conditional variance models such as GARCH and its derivatives, since simple models are not able to adequately capture the changing market risks over time.

5. EMPIRICAL FINDINGS

Volatility and market behavior analysis necessitate time series analysis; thus, initially, stationarization applications were carried out. In the study, the Augmented Dickey-Fuller (ADF) test was used to examine the stationarity characteristics of the returns of Bitcoin (BTC), Ethereum (ETH), Tether (USDT), USD Coin (USDC), and Binance Coin (BNB). The findings indicated that the first differences in the return series were stationary. This indicates that the series are integrated, which is a suitable basis for GARCH, Vector Autoregression (VAR), and causality analyses. Furthermore, the series have been indexed to a constant mean and variance over time without showing a particular trend through this stationarization. This observation in cryptocurrencies suggests that the assumption of normal distribution accepted in conventional financial markets is not applicable to cryptocurrency markets, indicating the presence of extreme tail risks and potentially high profit opportunities.

In the GARCH (1,1) model results, especially BTC and ETH showed high volatility clustering, and market shock effects were observed to be long-lasting. Additionally, Bitcoin's beta coefficient indicated a tendency for the impact of market shocks to decrease over time, whereas Ethereum's alpha and beta coefficients pointed to more persistent effects of market shocks.

Table 7: GARCH (1,1) Results

Cryptocurrency	Variable (with symbols)	Coefficient	Std. Deviation	t-value	p-value	Log-Likelihood	AIC	BIC
BTC	mu μ	0.018	0.009	1.984	0.047	-661.548	1331.10	1352.87
	omega ω	0.0125	0.0043	2.885	0.0039			
	alpha α	0.1236	0.0684	1.807	0.0707			
	beta β	0.8016	0.0416	19.266	<0.001			
ETH	mu μ	0.0177	0.0142	1.244	0.214	-1724.25	3456.50	3478.28
	omega ω	0.0039	0.004	0.964	0.335			
	alpha α	0.0786	0.0386	2.037	0.0416			
	beta β	0.9214	0.0352	26.163	<0.001			
USDT	mu μ	110.183	140.452	0.784	0.433	-17779.6	35567.3	35589.0
	omega ω	1351700.0	990800.0	1.364	0.172			
	alpha α	0.0044	0.0077	0.57	0.569			
	beta β	0.9755	0.0047	206.943	<0.001			
USDC	mu μ	-34.978	29.696	-1.178	0.239	-14611.4	29230.9	29252.7
	omega ω	33307.0	10890.0	3.058	0.0022			
	alpha α	0.0032	0.0084	0.381	0.703			
	beta β	0.9779	0.0117	83.364	<0.001			
BNB	mu μ	0.0134	0.018	0.745	0.456	-2416.56	4841.11	4862.88
	omega ω	0.0127	0.0076	1.682	0.0925			
	alpha α	0.1334	0.0391	3.412	0.0006			
	beta β	0.8666	0.0334	25.947	<0.001			

For BNB, a high alpha value indicated a more sensitive structure to market shocks. According to the GARCH (1,1) model, the average return (μ) for Bitcoin was found to be 1.8%, omega (ω) 1.25%, and alpha (α) 12.36%. The persistence of volatility (β) was found to be 80.16%, with all coefficients being statistically significant at the 5% level.

For Ethereum, the coefficients are μ 1.77%, ω 0.39%, α 7.86%, and β 92.14%. For stablecoins USDT and USDC, the μ values are 110.183 and -34.978, respectively, indicating lower volatility and more stable returns for these cryptocurrencies. For BNB, the coefficients are μ 1.34%, ω 1.27%, α 13.34%, and β 86.66%, indicating less persistent volatility compared to other cryptocurrencies. This suggests Ethereum's alpha and beta coefficients point to more enduring effects of market shocks, while Binance Coin's high alpha value indicates greater sensitivity to market shocks. However, for stablecoins like Tether and USD Coin, lower volatility and the significance of the omega coefficient suggest the potential for unexpected events to increase volatility in these markets.

Incorporating sophisticated econometric models to unpack the intricacies of cryptocurrency volatility, our analysis embarked on utilizing the EGARCH (1,1) model to meticulously evaluate Bitcoin's market dynamics.

The EGARCH (1,1) model analysis for Bitcoin estimated the alpha (α) coefficient at 0.20 and the beta (β) coefficient at 0.92, both statistically significant (p-value < 0.05), indicating significant effects of past volatility shocks on current volatility. In other words, Bitcoin's average μ coefficient is 2% (p-value 0.17, not significant), and its omega ω coefficient is -14% (p=0.03, negative significant), showing the asymmetric impact of volatility. Alpha α at 20% (p<0.001) and beta β at 92% (p<0.001), both positive and highly significant, suggest high persistence of past shocks and volatility.

The results underscore that volatility in Bitcoin markets has a long memory, meaning that past fluctuations tend to influence future volatility over extended periods. This persistence could be indicative of a market that is highly reactive to new information and events, thus reflecting a sensitivity to external shocks and trends. Moreover, the negative omega suggests that the market may respond more to negative news, highlighting the importance of investor sentiment in cryptocurrency dynamics.

The long memory of Bitcoin volatility suggests that the market assimilates news and events over prolonged durations, possibly leading to momentum effects that can influence investment strategies. Such a reactive market might also amplify the impact of global economic shifts, requiring careful risk assessment and mitigation.

Furthermore, the alpha (α) and beta (β) coefficients derived from the EGARCH (1,1) model signify the responsiveness of Bitcoin’s volatility to market movements and information flow. A higher alpha indicates that past price movements significantly affect current volatility levels, serving as a barometer for market sentiment. Similarly, a substantial beta coefficient implies enduring volatility, suggesting that Bitcoin's market reacts and adapts to new information over time. Such insights are crucial for constructing robust risk management strategies and for investors to anticipate and navigate the volatile landscape of cryptocurrency markets effectively.

Table 8: EGARCH (1,1) Results

Cryptocurrency	Variable	Coefficient	Std. Error	t value	p-value	Log-Likelihood	AIC	BIC
BTC-USD	mu μ	0.02	0.01	1.39	0.17	-664.49	1336.97	1358.74
	omega ω	-0.14	0.06	-2.15	0.03			
	alpha α	0.2	0.06	3.14	0.0			
	beta β	0.92	0.03	30.23	0.0			
ETH-USD	mu μ	0.02	0.02	1.57	0.12	-1721.64	3451.27	3473.05
	omega ω	0.01	0.01	0.63	0.53			
	alpha α	0.15	0.06	2.67	0.01			
	beta β	0.99	0.01	121.4	0.0			
USDT-USD	mu μ	-0.75	0.51	-1.48	0.14	-16630.3	33268.7	33290.5
	omega ω	11.74	5.68	2.07	0.04			
	alpha α	16.86	6.58	2.56	0.01			
	beta β	1.0	0.02	48.78	0.0			
USDC-USD	mu μ	28.83	2.91	9.93	0.0	-14640.7	29289.3	29311.1
	omega ω	5.12	4.97	1.03	0.3			
	alpha α	0.21	0.24	0.86	0.39			
	beta β	0.65	0.34	1.92	0.06			
BNB-USD	mu μ	0.05	0.02	2.23	0.03	-2413.57	4835.15	4856.92
	omega ω	0.03	0.02	1.72	0.09			
	alpha α	0.28	0.09	3.25	0.0			
	beta β	0.99	0.01	110.47	0.0			

Below is a detailed summary of our findings from a specialized GARCH (1,1) analysis with a 't' distribution, which probes into the nuanced volatility structures of five prominent cryptocurrencies.

The T-GARCH model employed in our analysis, similar to EGARCH models, revealed that the volatility of cryptocurrencies does not respond uniformly to market conditions but is instead influenced by asymmetric effects, which manifest distinct reactions contingent upon whether the market experiences positive or negative shocks. Furthermore, the T-GARCH (1,1) model outcomes for Bitcoin reveiled that the alpha (α1) coefficient stands at approximately 9.79%, while the beta (β1) coefficient is around 93.61%, underscoring the notion that past volatility shocks exert a profound and persistent influence on the trajectory of future volatility levels. These coefficients highlight the importance of both short-term effects and long-term trends in the fluctuating market movements.

Table 9: T-GARCH (1,1) Results

Cryptocurrency	Variable	Coefficient	Std. Error	t-value	p-value	Log-Likelihood	AIC	BIC
BTC-USD	mu	0.004881	0.005366	0.90961	0.363027	-383.82	0.46	0.48
	omega	0.00366	0.002633	1.3903	0.164439			
	alpha1	0.09793	0.02105	4.65227	0.000003			
	beta1	0.936181	0.01437	65.1468	0.000000			
	eta11	-0.092421	0.108049	-0.85537	0.392349			
	shape	2.656018	0.202586	13.11056	0.000000			
ETH-USD	mu	0.010874	0.010775	1.00919	0.312883	-1546.51	1.82	1.84
	omega	0.005736	0.004318	1.32852	0.184005			
	alpha1	0.094131	0.023366	4.02855	0.000056			
	beta1	0.930185	0.018733	49.65503	0.000000			
	eta11	-0.089973	0.101777	-0.88403	0.376682			
	shape	3.27818	0.288239	11.37314	0.000000			
USDT-USD	mu	-4968.5	165.55	-30.01	0.00000	-17736.88	20.78	20.80
	omega	42443.0	36.1	1175.65	0.00000			
	alpha1	0.0	4e-06	33.64	0.00000			
	beta1	0.0	0.043634	0.0	1.00			
	eta11	-0.98	0.063341	-15.54	0.00000			
	shape	2.1	0.003086	680.48	0.00000			
USDC-USD	mu	-47.04	3.52	-13.35	0.00000	-12003.17	14.06	14.08
	omega	547.03	560.93	0.98	0.33			
	alpha1	0.0	4e-06	0.0	1.00			
	beta1	0.01	1.02	0.01	1.00			
	eta11	0.96	1.57	0.61	0.54			
	shape	2.1	0.003086	379.35	0.00000			
BNB-USD	mu	0.014475	0.014798	0.98	0.33	-2251.38	2.64	2.66
	omega	0.008969	0.005161	1.74	0.082251			
	alpha1	0.141573	0.02797	5.06154	0.000000			
	beta1	0.897975	0.020294	44.24846	0.000000			
	eta11	0.085603	0.079397	1.07816	0.280961			
	shape	3.478479	0.32063	10.84889	0.000000			

Additionally, Ethereum's volatility analysis revealed a pattern closely mirroring Bitcoin's, highlighted by an α1 coefficient of 9.41% and a β1 coefficient of 93.01%. These statistics emphasize the volatility connection between Ethereum and Bitcoin, showcasing their similar market behavior. The critical importance of the alpha and beta coefficients for these digital currencies indicates a heightened reactivity to past volatility and their own historical market performance. This points to a significant leverage effect within the cryptocurrency market. The leverage effect suggests that the volatility of these cryptocurrencies is not only influenced by recent market activities but also carries a 'memory' aspect that profoundly affects their future volatility levels. On the other hand, the unexpected findings related to USDT and USDC stablecoins raise questions about the T-GARCH model's suitability for these assets. It implies that the stablecoins' built-in stability features might not align with the typical volatility trends that the model, which is more suited for assets with greater price variability, aims to capture.

Table 10: E-GARCH (4,3) Results

Cryptocurrency	Variable	Coefficient	Std. Error	t-value	p-value	Log-Likelihood	AIC	BIC
BTC-USD	mu μ	0.01	0.0	4.56	0.00	-610.90	1239.80	1288.79
	omega ω	-0.55	0.31	-1.76	0.08			
	alpha α	0.25	0.09	2.92	0.00			
	beta β	0.26	0.18	1.43	0.15			
ETH-USD	mu μ	0.02	0.01	1.37	0.17	-1695.20	3408.40	3457.38
	omega ω	0.01	0.01	0.9	0.37			
	alpha α	0.26	0.06	3.98	0.00			
	beta β	0.0	0.17	0.0	1.00			
USDT-USD	mu μ	123.43	106.98	1.15	0.25	-15128.1	30274.1	30323.1
	omega ω	19.84	5.55	3.57	0.00			
	alpha α	-0.24	0.32	-0.76	0.45			
	beta β	0.0	0.81	0.0	1.00			
USDC-USD	mu μ	12.84	0.42	30.91	0.00	-14542.9	29103.8	29152.8
	omega ω	5.12	21.22	0.24	0.81			
	alpha α	-0.11	0.3	-0.36	0.72			
	beta β	0.0	0.66	0.0	1.00			
BNB-USD	mu μ	0.05	0.02	2.17	0.03	-2389.21	4796.42	4845.41
	omega ω	0.06	0.04	1.59	0.11			
	alpha α	0.29	0.06	4.47	0.00			
	beta β	0.0	0.53	0.0	1.00			

The EGARCH (4,3) analysis conducted on Bitcoin and Ethereum showcased that volatility reacts differently to positive and negative market shocks, underscoring the diverse reactions of market participants to events and the intricacies involved in processing market information. Notably, the pronounced impact of negative shocks on volatility, as revealed through the EGARCH (4,3) model, vividly illustrates the leverage effect prevalent in the cryptocurrency market.

The GJR-GARCH (4,3) model results revealed a marked concentration of volatility clusters in specific periods, shedding light on the nuanced changes in investors' risk perceptions over time. This observation, known as the "volatility clustering effect," is a distinctive feature frequently observed in financial markets. It not only provides critical insights into the evolving nature of market dynamics but also signals significant shifts in investor sentiment and market behavior. This effect underscores the model's effectiveness in capturing the intricate patterns of risk perception changes.

Table 11: GJR-GARCH (4,3) Results

Cryptocurrency	Variable	Coeff	t value	p-value	Log-Likelihood	AIC	BIC
BTC-USD	mu µ	0.0117	1.477	0.14	-605.444	1230.89	1285.32
	omega ω	0.0459	3.274	0.001			
	alpha α	0.0032	0.112	0.00106			
	beta β	0.0737	0.207	0.836			
ETH-USD	mu µ	0.0146	1.094	0.274	-1706.24	3432.48	3486.91
	omega ω	0.009	0.946	0.344			
	alpha α	0.088	1.183	0.237			
	beta β	0.0122	0.261	0.794			
USDT-USD	mu µ	67.8563	0.905	0.366	-17725.6	35471.2	35525.6
	omega ω	6.75	1.013	0.311			
	alpha α	0.0669	1.57	0.116			
	beta β	0.0	0.0	1.0			
USDC-USD	mu µ	-37.77	-1.686	0.091	-14495.9	29011.8	29066.2
	omega ω	3.33	2.091	0.037			
	alpha α	3.0097e-08	1.749e-08	1.0			
	beta β	1.749e-08	0.007992	1.0			
BNB-USD	mu µ	0.0062	0.368	0.713	-2388.95	4797.90	4852.34
	omega ω	0.0342	1.688	0.091			
	alpha α	0.0691	1.629	0.103			
	beta β	0.0	0.0	1.0			

Note: In many contexts, the GJR-GARCH model is equivalent to the TGARCH model. Both models aim to capture the asymmetric response of volatility to positive and negative shocks, frequently observed in financial time series data. Therefore, a TGARCH (4,3) model has not been additionally established.

In the GJR-GARCH (4,3) results, Bitcoin's ω at 4.59% (p=0.001) represents a constant component of volatility, while α and β being low and not significant indicate a limited impact of new information and past volatility. For Ethereum, USDT, and USDC, μ, ω, α, and β values are low and generally statistically insignificant, and for BNB, α at 6.91% (p=0.103) and β at zero suggest a low impact of market shocks. The results from Bitcoin's GJR-GARCH modeling highlight the market's sensitivity to sudden changes and how investors' risk-averse behaviors during uncertain periods can trigger increases in volatility, potentially creating adverse effects on the stability of the overall cryptocurrency markets.

6. CONCLUSION

This review article comprehensively addresses the conditional variance volatility dynamics of five high-market-cap cryptocurrencies as of September 2023, namely Bitcoin (BTC-USD), Ethereum (ETH-USD), Tether (USDT-USD), USD Coin (USDC-USD), and Binance Coin (BNB-USD), based on statements from various popular cryptocurrency platforms. For each cryptocurrency, the series were rendered stationary through logarithmic differencing. Before stabilizing the series, checks were conducted to ascertain whether they were stationary. Subsequent tests reaffirmed their stationarity as per the Augmented Dickey-Fuller (ADF) test results. Upon stabilization, the Jarque-Bera test was utilized to assess the assumption of normal distribution, revealing a significant tendency for the cryptocurrency returns to deviate from a normal distribution. This structural difference in the series indicates that the assumption of normal distribution, commonly applicable in traditional stock markets or various derivative exchanges, does not hold true for cryptocurrency markets. This suggests the presence of extreme tail risks and potentially high-profit opportunities in the crypto markets, differentiating them from conventional financial markets. These findings underscore the unique characteristics and challenges of modeling and analyzing cryptocurrencies. The inherent volatility and the non-conformity to standard distribution models in the crypto markets necessitate specialized and sophisticated analytical approaches. This study highlights the importance of considering the distinctive behaviors and patterns of cryptocurrencies for accurate modeling and prediction. For financial professionals and investors, these insights are crucial for informed decision-making and effective risk management in the dynamic and evolving landscape of cryptocurrency investments. In the cryptocurrency markets, the use of advanced volatility modeling techniques such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models and their variations has been foundational to predicting the high volatility structures more effectively. This study employed these models to analyze the market behaviors of Bitcoin, Ethereum, Tether, USD Coin, and Binance Coin. The dataset utilized underwent tests for Skewness and Kurtosis coefficients to verify suitability for GARCH modeling. The GARCH (1,1) model results, tested in the Python environment, revealed particularly high volatility clustering in Bitcoin and Ethereum, indicating that market shocks could have prolonged effects. In the EGARCH model, it was observed that negative shocks in the cryptocurrency markets are more impactful than positive shocks, indicating the presence of asymmetric leverage effects. The study demonstrates that stablecoins like USDT and USDC exhibit similar levels of volatility, persistence, and sensitivity to external factors. These findings are critical for risk management and investment decisions in the cryptocurrency markets. They emphasize the need for a comprehensive analysis of the unique characteristics of different cryptocurrency units, highlighting the complexity and nuances in the behavior of these digital assets. This nuanced understanding is essential for developing effective strategies in the rapidly evolving and highly volatile world of cryptocurrencies. In the GJR-GARCH model for Bitcoin, it has been observed that this model is best suited for testing the presence of volatility clustering in cryptocurrency markets, and the values in the volatility metrics used should be considered in investors' risk assessments. The market's sensitivity to sudden changes and investors' tendency to avoid risk in uncertain situations, which trigger the volatile structure, have been noted. Additionally, it has been observed that this model falls short in capturing the persistence of volatility in stable cryptocurrencies like USDC and USDT, as well as in Binance Coin.The T-GARCH model, another GARCH variant applied in this study, like the EGARCH model, presents asymmetrical effects and different responses to market shocks in respective cryptocurrencies. The T-GARCH (1,1) model, implemented in the R program, has shown that investor responses to price fluctuations in these cryptocurrencies can be flexible. The findings from the T-GARCH (1,1) approach indicate that for Bitcoin, the alpha and beta values are approximately 9.79% and 93.61%, respectively. Similarly, for Ethereum, values of approximately 9.41% and 93% have been observed.In conclusion, this study has conducted time series stationarity integrations in the five cryptocurrencies with the highest market capitalization as of September 2023, using conditional variance modeling. Various aspects of volatility (volatility clustering, volatility spread, asymmetrical situations, and leverage effects) have been examined. The most suitable volatility clustering effect in the tests has been observed in the GJR-GARCH (4,3) model, while the most suitable leverage effect is noted in the EGARCH (4,3) model. The EGARCH and GJR-GARCH models in the analyses of stablecoins and cryptocurrencies have been observed to measure volatility factors more effectively in terms of leverage, volatility clustering, and asymmetric shocks. Therefore, it is recommended that these models be considered in volatility evaluations in cryptocurrency markets.

REFERENCES

Anceaume, E., Lajoie-Mazenc, T., Ludinard, R., and Sericola, B. (2016, October). *Safety analysis of Bitcoin improvement proposals.* In 2016 IEEE 15th International Symposium on Network Computing and Applications (NCA) (pp. 318-325). IEEE.

Balcilar, M., Gupta, R., and Pierdzioch, C. (2016). Does uncertainty move the gold price? New evidence from a nonparametric causality-in-quantiles test. *Resources Policy*, 49, 74-80.

https://doi.org/10.1016/j.resourpol.2016.04.004

Bayer, D., Haber, S., and Stornetta, W. S. (1993). *Improving the efficiency and reliability of digital time-stamping. In Sequences II: Methods in Communication, Security, and Computer Science* (pp. 329-334). Springer New York.

Beneki, C., Koulis, A., Kyriazis, N. A., and Papadamou, S. (2019). Investigating volatility transmission and hedging properties between Bitcoin and Ethereum. *Research in International Business and Finance*, 48, 219-227.

Bera, A. K., and Jarque, C. M. (1982). Model specification tests: A simultaneous approach. *Journal of Econometrics*, 20(1), 59-82. https://doi.org/10.1016/0304-4076(82)90103-8

Deavours, C. A., and Kruh, L. (1985). *Machine cryptography and modern cryptanalysis*. Artech House.

Chaum, D. (1983, August). *Blind signatures for untraceable payments*. Advances in Cryptology: Proceedings of Crypto 82 (pp. 199-203). Boston, MA: Springer US.

Munger, C. T. (2023). *Poor Charlie's Almanack: The essential wit and wisdom of Charles T. Munger.* Stripe Press.

Davidson, S., Filippi, P. D., and Potts, J. (2016). *Economics of blockchain*. Social Science Electronic Publishing. https://doi. org/10.2139/ssrn. 2744751.

Delfin-Vidal, R., and Romero-Meléndez, G. (2016). The fractal nature of bitcoin: Evidence from wavelet power spectra.*Trend in Mathematical Economics*. (pp. 73-98). Springer International Publishing.

Derman, E. (1999). Regimes of volatility. *Risk*,4, 55-59.

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar–A GARCH volatility analysis. *Finance Research Letters*, 16, 85-92.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal Of The Econometric Society*, 987-1007.

Fung, K., Jeong, J., and Pereira, J. (2022). More to cryptos than bitcoin: A GARCH modelling of heterogeneous cryptocurrencies. *Finance Research Letters*, 47, 102544.

Ghaiti, K. (2021). *The volatility of bitcoin, bitcoin cash, litecoin, dogecoin and ethereum* (Doctoral dissertation), University of Ottawa.

Glosten, L. R., Jagannathan, R., and Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, 48(5), 1779-1801.

Gronwald, Marc. (2014). The economics of bitcoins: market characteristics and price jumps. *Cesifo Working Paper,5121*. doi: 10.2139/ssrn.2548999.

Griffith, Ken. 2021. *A quick history of cryptocurrencies bbtc-before bitcoin*. Bitcoin Magazine. https://bitcoinmagazine.com/business/quick-history-cryptocurrencies-bbtc-bitcoin-1397682630

Grinberg, R. (2012). Bitcoin: An innovative alternative digital currency. *Hastings Sci. and Tech. LJ*, 4, 159.

Güring, P., and Grigg, I. (2011). Bitcoin and Gresham's Law-the economic inevitability of collapse. https://iang.org/papers/BitcoinBreachesGreshamsLaw.pdf

Haber, S., and Stornetta, W. S. (1991). How to time-stamp a digital document.*Advanced in cryptology:Crypto 90*. (pp. 437-455). Springer Berlin Heidelberg.

Khan, M., Kayani, U. N., Khan, M., Mughal, K. S., and Haseeb, M. (2023). COVID-19 pandemic and financial market volatility; evidence from GARCH models. *Journal of Risk and Financial Management*, 16(1), 50.

Merkle, R. C. (1987, August). *A digital signature based on a conventional encryption function*. Conference on the theory and application of cryptographic techniques (pp. 369-378). Berlin, Heidelberg: Springer Berlin Heidelberg.

Nadarajah, S., and Chu, J. (2017). On the inefficiency of Bitcoin. *Economics Letters*, 150, 6-9.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the econometric society*, 347-370.

Ruoti, S., Kaiser, B., Yerukhimovich, A., Clark, J., and Cunningham, R. (2019). SoK: Blockchain technology and its potential use cases. arXiv preprint arXiv:1909.12454.

Sherman, A. T., Javani, F., Zhang, H., and Golaszewski, E. (2019). On the origins and variations of blockchain technologies. *IEEE Security and Privacy*, 17(1), 72-77.

Szabo, N. (1997). Formalizing and securing relationships on public networks. *First Monday*,2(1). https://doi.org/10.5210/fm.v2i9.548

Ural, M., and Demireli, E. (2020). Asymmetrıc Garch-Type And Half-Life Volatility Modelling Of Usd/Kzt Exchange Rate Returns. *Eurasian Research Journal*, 2(2), 7-18.

Yavuz, N. Ç. (2004). Durağanlığın Belirlenmesinde Kpss ve Adf Testleri: İmkb Ulusal-100 Endeksi İle Bir Uygulama. *İstanbul Üniversitesi İktisat Fakültesi Mecmuası*, 54(1),239-248.

Yermack, D. (2015). *Is Bitcoin a real currency? An economic appraisal.* Handbook of digital currency (pp. 31-43). Academic Press.

Zakoian, J. M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control*, 18(5), 931-955.

Kyriazis, Nicholas, Kalliopi Daskalou, Marios Arampatzis, Paraskevi Prassa, and Papaioannou Evangelia. 2019. Estimating the volatility of cryptocurrencies during bearish markets by employing garch models. *Heliyon*, 5(8):e02239. doi: 10.1016/j.heliyon.2019.e02239.

Ghaiti, Khaoula. 2021. *The Volatility of Bitcoin, Bitcoin Cash, Litecoin, Dogecoin and Ethereum*. uOttawa. https://ruor.uottawa.ca/items/7a748f6d-8f64-48de-95a7-0e482d266eb0

Güven, V., and Şahinöz, E. (2018). *Blokzincir kripto paralar Bitcoin: Satoshi dünyayı değiştiriyor*. İstanbul: Kronik Kitap.