“Risk measurement models for top 10 cryptocurrencies: A comparison of VaR and volatility models”

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RISK MEASUREMENT MODELS FOR TOP 10 CRYPTOCURRENCIES: A COMPARISON OF VAR AND VOLATILITY MODELS

Abstract

This study evaluates and compares risk measurement models for ten major cryptocurrencies: Bitcoin, Ethereum, Tether, Ripple, Dogecoin, Cardano, Binance Coin, Polkadot, Solana, and USD Coin. Using daily log-return data from January 2017 to October 2024, the analysis applies Modified Cornish-Fisher Value-at-Risk and standard, exponential, threshold, and Markov-switching generalized autoregressive conditional heteroskedasticity models. The main comparison is conducted at the 99% confidence level, while model reliability is assessed through out-of-sample backtesting using 500 observations and the Kupiec unconditional coverage and Christoffersen conditional coverage tests. The results reveal substantial heterogeneity in cryptocurrency risk. Modified Cornish-Fisher Value-at-Risk produces highly sensitive estimates for assets with extreme skewness and kurtosis, particularly Ripple, Cardano, and Dogecoin. However, no single model performs consistently better across all assets. Bitcoin is the only cryptocurrency for which all tested models pass both backtesting procedures. The Markov-switching specification provides acceptable coverage for Bitcoin, Ripple, and Dogecoin but does not consistently outperform conventional volatility models. Standard and asymmetric volatility models provide stronger support for Cardano, Binance Coin, and Polkadot, whereas Ethereum, Solana, and USD Coin remain difficult to model under the examined specifications. These findings demonstrate that cryptocurrency risk measurement requires asset-specific model selection based on both estimated loss magnitude and formal backtesting evidence.

Keywords backtesting, cryptocurrency risk, tail risk, value-at-risk, volatility modeling

JEL Classification G11, G12, G14, G17

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INTRODUCTION

The cryptocurrency market has expanded rapidly over the past decade, attracting both individual and institutional investors due to its potential for substantial returns. Unlike traditional financial assets, cryptocurrencies are characterized by extreme price volatility, frequent regime shifts, and non-normal return distributions, which pose significant challenges for conventional risk measurement frameworks. As cryptocurrencies become increasingly integrated into the global financial system through derivatives, exchange-traded products, and institutional portfolios, understanding and accurately quantifying their risk exposure has become a critical concern for investors, risk managers, and regulators alike.

From a broader investment-management perspective, prior studies in emerging equity markets also demonstrate that portfolio construction, diversification, and risk-adjusted asset allocation depend on the interaction between return, beta, variance, and changing market conditions (Kristanti et al., 2022; Salim et al., 2024a, 2024b).

Existing risk measurement approaches developed for traditional financial markets have demonstrated limited effectiveness when applied to cryptocurrency assets. Value-at-Risk (VaR), one of the most widely used risk metrics, tends to underestimate extreme tail risks that frequently occur in crypto markets (Likitratcharoen et al., 2023). Meanwhile, standard volatility models such as generalized autoregressive conditional heteroskedasticity (GARCH) models, while capable of capturing time-varying volatility, often fail to accommodate the structural breaks and regime changes that are inherent to cryptocurrency price dynamics (Queiroz & David, 2023; Ampountolas, 2022; Kim et al., 2021). These limitations are further compounded by the heterogeneous volatility characteristics of cryptocurrency assets, which vary across individual assets and market conditions (Faruq et al., 2025; Waspada et al., 2023).

Despite growing academic interest in cryptocurrency risk, the existing literature remains fragmented. Most studies apply a single risk estimation method to a limited set of assets without systematically comparing model performance across cryptocurrencies with heterogeneous return dynamics. In particular, the comparative effectiveness of regime-switching volatility models, such as Markov-Switching GARCH, relative to conventional and asymmetric GARCH-type models has not been sufficiently examined within a unified multi-asset framework.

This gap raises an important scientific problem: given the structural complexity and heterogeneous volatility characteristics of major cryptocurrencies, which risk measurement models provide the most accurate and reliable Value-at-Risk estimates across different crypto assets?

1. LITERATURE REVIEW

Risk measurement in financial markets has long relied on Value-at-Risk (VaR) as a standard tool for quantifying potential losses over a given time horizon at a specified confidence level. In the context of cryptocurrency markets, however, the application of conventional VaR has shown notable limitations. Likitratcharoen et al. (2023) demonstrated that standard VaR models tend to underperform during periods of extreme market stress in crypto markets, as they fail to adequately capture fat-tailed return distributions. To address this, the Modified Cornish-Fisher VaR has been proposed as a more robust alternative, as it incorporates skewness and kurtosis adjustments that better reflect the non-normal distributional properties of cryptocurrency returns (Lazar et al., 2024; Li et al., 2023). Expected Shortfall complements VaR by providing information about losses beyond the VaR threshold and is therefore useful for assessing extreme tail risk (Li et al., 2023). However, this study focuses on VaR because its objective is to compare exceedance-based forecasting performance across the selected volatility models. Furthermore, conventional VaR is relatively straightforward to compute but is less effective in capturing extreme tail risks that frequently characterize digital asset markets (Mozumder et al., 2024).

Beyond distribution-based approaches, volatility models have become central to cryptocurrency risk estimation (Bawa, 2026; Oben et al., 2025; Grobys et al., 2025; Rapos & Fountas, 2025). The GARCH model and its extensions are among the most frequently applied frameworks for capturing time-varying volatility in crypto asset returns (Afzal et al., 2021; Wahyuni et al., 2024). Standard GARCH models assume that positive and negative return shocks of equal magnitude have the same effect on conditional volatility, whereas cryptocurrency returns may exhibit asymmetric volatility responses (Ampountolas, 2022). To overcome this limitation, asymmetric variants such as exponential GARCH (EGARCH) and threshold GARCH (TGARCH) have been developed. EGARCH captures asymmetric volatility by modeling the logarithm of conditional variance, allowing the magnitude and direction of return shocks to affect volatility differently (Naimy et al., 2021; Rakshit et al., 2023). Similarly, TGARCH introduces a threshold mechanism that distinguishes between the effects of positive and negative return innovations on conditional variance, making it particularly suited to assets that exhibit stronger volatility responses to adverse market events (Fakhfekh & Jeribi, 2020). While these asymmetric models improve upon standard GARCH, their effectiveness depends on appropriate parameter calibration and

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may still fall short in markets characterized by sudden structural breaks (Wahyuni et al., 2024).

A more recent and increasingly relevant development in cryptocurrency volatility modeling is the Markov-Switching GARCH (MSGARCH) framework, which accommodates structural breaks and regime changes in volatility dynamics. Unlike conventional GARCH-type models that assume a single volatility regime, MSGARCH allows the conditional variance process to switch between multiple states governed by a Markov transition matrix, enabling more flexible and realistic modeling of the abrupt volatility shifts commonly observed in crypto markets. Chan et al. (2023) found that the MSGARCH model more effectively captures regime changes in Bitcoin volatility compared to single-regime specifications, particularly during halving cycles and periods of heightened market uncertainty. De la Torre-Torres et al. (2021) similarly demonstrated that regime-switching GARCH models enhance VaR estimation accuracy in volatile financial environments. Naik and Mohan (2021) further confirmed that regime-switching techniques provide superior volatility estimation in markets prone to sudden structural shifts, while Ampountolas (2024) showed that flexible volatility specifications consistently outperform standard GARCH models in forecasting accuracy across commodity and financial markets.

Despite the growing body of literature on cryptocurrency risk measurement, existing studies remain fragmented in their scope and methodology. Existing studies generally focus on particular model classes or limited asset sets rather than comparing symmetric, asymmetric, and regime-switching volatility specifications within a unified multi-asset framework (Naimy et al., 2021; Chan et al., 2023). The comparative effectiveness of these models across cryptocurrencies with heterogeneous return dynamics and distinct volatility characteristics has therefore not been sufficiently established (Naimy et al., 2021; Queiroz & David, 2023).

This study aims to evaluate and compare the performance of Value-at-Risk (VaR), GARCH, EGARCH, TGARCH, and MSGARCH models in estimating Value-at-Risk for the top 10 cryptocurrencies by market capitalization, using daily data from January 2017 to October 2024. This study examines whether volatility models incorporating asymmetric effects and regime-switching mechanisms provide more reliable VaR estimates than standard GARCH-based approaches across cryptocurrency markets characterized by high volatility and structural shifts.

2. METHODOLOGY

This analysis uses secondary data of the time series type. According to Das (2019), time series data consist of observations on one variable or several variables collected over time. This study uses daily price data from various crypto assets, namely Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Ripple (XRP), Dogecoin (DOGE), Cardano (ADA), Binance Coin (BNB), Polkadot (DOT), Solana (SOL), and USD Coin (USDC). The selection of assets is based on market capitalization and liquidity as of October 2024 to ensure representativeness of major cryptocurrency market behavior. Data sources were obtained from Investing.com, which is one of the most trusted platforms for providing price data for financial assets, including cryptocurrencies.

The research period used covers January 2017 to October 2024, with a daily frequency. However, not all assets are available throughout the entire period due to differences in listing dates. As a result, the dataset is inherently unbalanced, particularly for assets such as SOL, DOT, USDC, BNB, and ADA, which entered the market at later stages. This unbalanced structure is retained to reflect real-world market conditions rather than imposing artificial alignment. This time span was chosen to cover various market phases, including periods of rapid growth, sharp corrections, and high volatility that often occur in the crypto ecosystem. Daily closing prices are used in this study because they reflect the last price at which an asset was traded in a period of time and are often used in financial analysis as the primary reference for calculating returns and volatility.

The final dataset consists of daily log returns for ten cryptocurrencies, although the number of observations differs across assets due to different listing dates and data availability. BTC, ETH, USDT, XRP, and DOGE each contain 2,852 daily

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observations from January 2, 2017 to October 23, 2024. BNB contains 2,646 observations from July 27, 2017 to October 23, 2024, ADA contains 2,578 observations from October 3, 2017 to October 23, 2024, USDC contains 2,206 observations from October 10, 2018 to October 23, 2024, SOL contains 1,656 observations from April 12, 2020 to October 23, 2024, and DOT contains 1,524 observations from August 22, 2020 to October 23, 2024. The dataset is therefore unbalanced by design, and model estimation is conducted using the available return series for each cryptocurrency.

The price series are based on standard daily closing prices obtained from Investing.com and denominated against the US dollar where available. Adjusted prices are not used because cryptocurrency assets do not have stock-like corporate actions such as dividends or stock splits. The daily closing convention follows the reporting convention available on Investing.com. Since cryptocurrency markets operate continuously, this timing convention is acknowledged as a limitation because different exchange cut-off times may produce slightly different daily return values. Zero returns are retained when they represent valid daily price observations, while missing values before the first available trading date of each asset are not interpolated. Stablecoin depegging episodes and other extreme observations are also retained because they represent economically meaningful risk events that are relevant for VaR estimation.

To ensure the data can be analyzed accurately, this study converts daily price data into price returns. Returns are calculated using the logarithmic return formula (Miskolczi, 2017):

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

where R_t is the return at time t, P_t is the asset price at time t, and P_{t-1} is the asset price at the previous time. The use of log returns is preferred due to its desirable statistical properties, including time-additivity and variance stabilization, which are particularly important in financial volatility modeling.

Missing observations resulting from different asset inception dates are handled using listwise deletion during model estimation. No interpolation or smoothing techniques are applied in order to preserve the natural structure of the data and to maintain the integrity of extreme market movements.

Furthermore, no winsorization or outlier trimming is performed, as extreme observations are a fundamental characteristic of cryptocurrency markets and are essential for accurate Value-at-Risk estimation. The processed log-return series are then used as input for all subsequent volatility and risk models implemented in R statistical software.

This study utilizes several risk estimation methods to evaluate potential losses in crypto assets. Value at Risk (VaR) – Modified Cornish-Fisher VaR: this approach is used because crypto asset returns are often not normally distributed (Samunderu & Murahwa, 2021). By considering skewness and kurtosis, Cornish-Fisher VaR provides a more accurate estimate of risk than conventional VaR, which assumes a normal distribution. This method is better able to capture tail risk, which is particularly important in volatile markets like crypto (Siu, 2021).

To determine the adjusted (ZCF_α), the Cornish-Fisher expansion is used as follows:

$$\begin{aligned} ZCF_\alpha &= Z_\alpha + \frac{1}{6}\left(Z_\alpha^2 - 1\right)S \\ &+ \frac{1}{24}\left(Z_\alpha^3 - 3Z_a\right)\left(K-3\right) \\ &- \frac{1}{36}\left(2Z_\alpha^3 - 5Z_a\right)S^2, \end{aligned} \tag{2}$$

where Z_α is the quantile of the standard normal distribution (for example, for a 99% confidence level, $Z_\alpha = 2.33$). S is the skewness of crypto asset returns. K is the kurtosis of crypto asset returns.

GARCH (Generalized Autoregressive Conditional Heteroskedasticity) Model is used to capture the dynamic volatility in crypto asset returns. The specifications used in this study include:

1. GARCH(p,q): A standard model that accounts for volatility based on changes in past volatility.

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The GARCH(p,q) model extends the ARCH model by adding a past volatility component to the calculation. The formula is as follows (García-Medina & Aguayo-Moreno, 2024):

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{3}$$

where σ_t^2 is the conditional variance at time t, ω is a positive constant, and a_i is a coefficient capturing the impact of previous return shocks on current volatility. β_j is the GARCH coefficient, which captures the effect of past volatility on current volatility. ε_t is the error term or unexpected return. If $(a + \beta \approx 1)$, then volatility is persistent, which is often the case in crypto assets.

2. EGARCH (Exponential GARCH): EGARCH was introduced by Nelson in 1991. This model captures volatility asymmetry, where price declines are often followed by larger volatility spikes than price increases (Rakshit et al., 2023; Iqbal et al., 2021). The formula can be written:

$$\log\left(\sigma_t^2\right) = \omega + \sum_{i=1}^{q} \alpha_i \left(\frac{\left|\varepsilon_{t-i}\right|}{\sigma_{t-i}} - E\left[\frac{\left|\varepsilon_{t-i}\right|}{\sigma_{t-i}}\right] \right) + \sum_{j=1}^{p} \beta_i \log\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{q} \gamma_i \frac{\varepsilon_{t-1}}{\sigma_{t-1}}, \tag{4}$$

where the logarithm of the variance ($\log(\sigma_t^2)$) ensures that the variance is always positive without requiring parameter restrictions as in GARCH. γ_i captures the asymmetric effect, where if $\gamma_i < 0$, then negative returns increase volatility more than positive returns. EGARCH is more suitable for assets that suffer from the leverage effect, where falling prices tend to increase volatility more than rising prices.

3. TGARCH (Threshold GARCH): This model considers the leverage effect, where the impact of volatility depends on whether returns are positive or negative (Naimy et al., 2021). The TGARCH(p, q) model was developed to capture asymmetric effects by adding an additional component that differentiates the effect of positive and negative returns on volatility (Duttilo et al., 2021). The TGARCH(p, q) formula can be written:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i + \gamma_i I_{t-1}) \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{5}$$

where I_{t-1} is an indicator that takes the value of 1 if $\varepsilon_{t-1} < 0$ (negative return) and 0 if $\varepsilon_{t-1} \geq 0$ (positive return). If $\gamma_i > 0$, negative returns cause volatility to increase more than positive returns. TGARCH is often used in markets that exhibit greater volatility reactions to negative events, such as crypto or technology stocks.

4. MSGARCH (Markov-Switching GARCH): A model that captures regime changes in market volatility, which is particularly useful in crypto markets that often transition between periods of high and low volatility. The MSGARCH model assumes that the market has several alternating volatility regimes, such as periods of high and low volatility (Benaid et al., 2024). The inter-regime changes are determined by a Markov Switching Process. MSGARCH Formula:

$$\sigma_{t,s}^2 = \omega_s + \sum_{i=1}^{q} \alpha_{i,s} \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_{j,s} \alpha_{t-j}^2, \tag{6}$$

where the index s denotes a state or regime in the Markov system. The inter-regime switching probability follows the Markov transition matrix P:

$$P = \begin{bmatrix} p11 & p12 \\ p21 & p22 \end{bmatrix}, \tag{7}$$

where p_{ij} is the probability of moving from regime i to regime j. MSGARCH is particularly useful in markets with drastically changing volatility, such as crypto markets, which often transition from periods of high volatility to low volatility.

All volatility models were estimated using R version 4.4.1. The standard GARCH-family models were implemented using the rugarch package, whereas the Markov-Switching GARCH model was estimated using the MSGARCH package. The specifications consisted of a standard GARCH(1,1), an exponential GARCH(1,1), and an fGARCH threshold GARCH(1,1). Each GARCH-family model employed an autoregressive moving average (ARMA) conditional mean equation of order (0,0), with a constant and standardized Student's t innovations to accommodate the heavy-tailed characteristics of cryptocurrency returns. The Markov-Switching GARCH specification consisted of two switching standard GARCH(1,1) regimes with Student's t conditional distributions and was estimated by maximum likelihood.

To evaluate out-of-sample forecasting performance, this study used a rolling one-step-ahead forecasting procedure with a recursive or expanding estimation window. The final 500 return observations for each cryptocurrency were reserved as the out-of-sample evaluation period, while all preceding observations formed the initial estimation sample. Accordingly, the initial estimation-window lengths were 2,352 observations for Bitcoin, Ethereum, Tether, Ripple, and Dogecoin; 2,146 for Binance Coin; 2,078 for Cardano; 1,706 for USD Coin; 1,156 for Solana; and 1,024 for Polkadot. Model parameters were reestimated every 50 observations using all available historical data up to each refitting point.

VaR forecasts were generated at the 99% confidence level, corresponding to a 1% lower-tail probability. For presentation purposes, VaR values are reported as positive loss magnitudes. During backtesting, however, the original negative lower-tail return thresholds generated by the models were used. An exceedance was recorded when the realized return fell below the corresponding one-step-ahead VaR threshold. Model performance was evaluated using Kupiec's unconditional coverage test, which assesses whether the observed exceedance frequency is consistent with the expected 1% violation rate, and Christoffersen's conditional coverage test, which jointly evaluates exceedance frequency and independence. Statistical decisions were based on a 5% significance level.

Model diagnostics for the GARCH-family models were conducted using the initial estimation samples. The Ljung-Box test was applied to the standardized residuals and squared standardized residuals at lag 10, while the autoregressive conditional heteroskedasticity Lagrange multiplier (ARCH-LM) test was used to detect remaining conditional heteroskedasticity. All 30 GARCH-family estimations achieved a convergence code of zero. The hybrid optimization solver was used to estimate the GARCH, EGARCH, and TGARCH models to reduce numerical optimization problems. For the MSGARCH model, convergence was monitored through the maximum likelihood estimation output, and only successfully converged estimates were retained for forecasting and backtesting. The diagnostic results indicated that several specifications adequately removed residual volatility dependence, although residual serial correlation remained in a number of asset-model combinations. Remaining conditional heteroskedasticity was also detected in selected specifications for XRP, ADA, and BNB. Diagnostic evidence was interpreted jointly with the out-of-sample Kupiec and Christoffersen backtesting results rather than treated as evidence of universal model adequacy.

3. RESULTS

Bitcoin as the first crypto asset has paved the way for various altcoins such as Ethereum, Binance Coin, Polkadot, Solana, and many others. One of the main characteristics of cryptocurrencies is their high volatility, which is influenced by various factors including market sentiment, regulation, and the adoption of blockchain technology (Ridwan et al., 2025; Wahyuni et al., 2024). The normalized price charts of some of the major cryptocurrencies in Figure 1 show a similar pattern of volatility, where sharp price increases are often followed by drastic drops, indicating the high risk inherent in crypto investments.

Based on the normalized price chart in Figure 1, it can be observed that BTC and ETH have relatively more stable price trends than other altcoins, although they still show significant fluctuations. BNB and SOL experienced more extreme price spikes in the 2021–2022 period, which was then followed by a period of fairly sharp corrections. Meanwhile, DOT showed a more volatile trend than BTC and ETH, but was more stable than SOL. This volatility is not only happening to the assets in the picture; several other crypto assets such as Dogecoin, Ripple, and Cardano are also experiencing the same thing. Even stablecoins like Tether and USD Coin have their own characteristics (Özdemir, 2022; Hsu, 2022). This variation confirms that each crypto asset has unique risk characteristics, which is the basis for determining the most appropriate risk measurement method for each asset.

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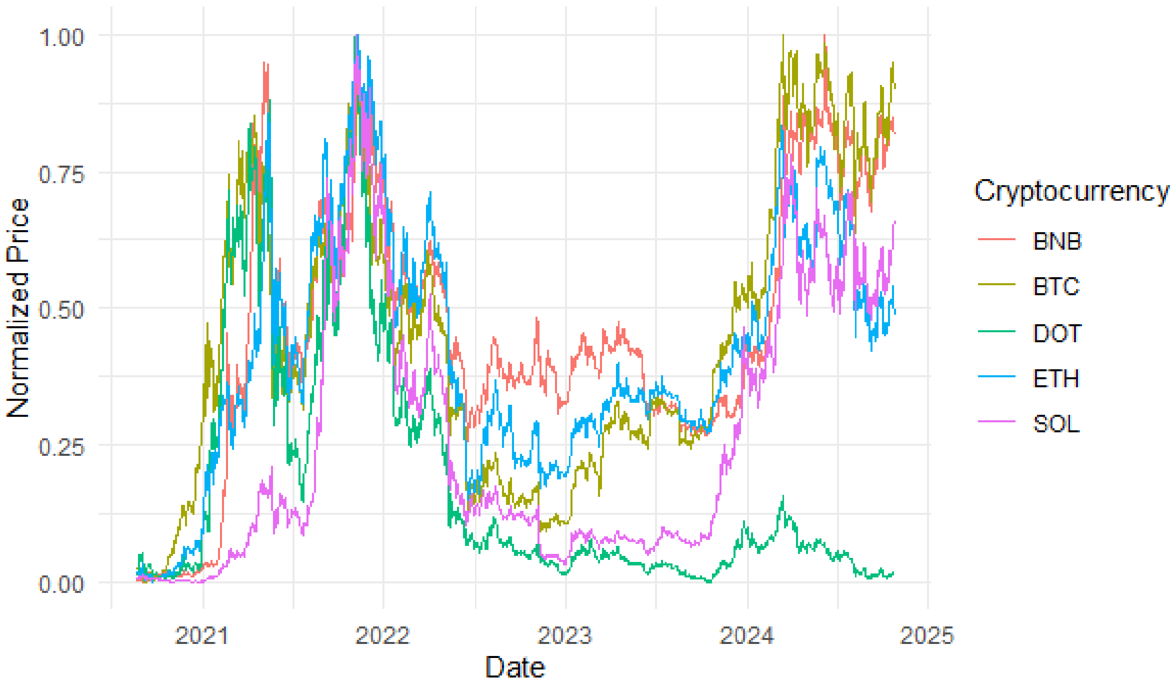

Note: BNB = Binance Coin, BTC = Bitcoin, DOT = Polkadot, ETH = Ethereum, SOL = Solana.

Figure 1. Price dynamics of the top 10 cryptocurrencies during the observation period (January 2017 – October 2024)

To provide an initial overview of the return characteristics of the crypto assets analyzed, a graph of the return movement is displayed before entering the risk estimation stage. From the visualization results, there are significant differences in the volatility of each asset, reflecting different risk characteristics.

In Figure 2, BTC experiences significant return fluctuations, with periods of high volatility often associated with major market events, such as regulation or institutional adoption. ETH has a similar movement pattern to BTC, but is often more volatile due to its role as the main platform for smart contracts and decentralized applications. USDT and USDC show stable return movements, in keeping with their characteristics as stablecoins pegged to the US dollar. The minor fluctuations that do occur generally stem from changes in liquidity in the crypto market. XRP experienced spikes in returns during some periods, often influenced by regulatory developments and legal decisions regarding its status as a security.

DOGE, on the other hand, exhibits higher volatility than most other assets, often driven by market speculation and social media sentiment. ADA and DOT have relatively more stable return patterns compared to BTC and ETH, although they still show spikes in volatility during certain periods related to technology development and network updates. BNB shows high volatility, mainly influenced by the dynamics of the Binance ecosystem as well as policy changes affecting its use on the platform. SOL experiences sharp return fluctuations, often related to technical developments on its network, such as increased transaction capacity or technical issues that may affect investor confidence.

Overall, the variation in volatility suggests that cryptocurrencies have different risk characteristics. Further analysis using quantitative approaches is needed to more accurately gauge the level of risk and potential losses.

The cryptocurrency return data in Table 1 show the typical characteristics of digital assets with high volatility and abnormal distribution. This can be seen from the extreme skewness and kurtosis values of some assets, reflecting the existence of asymmetric price movements and the possibility of more frequent price spikes than a normal distribution. BTC has a standard deviation of 0.04,

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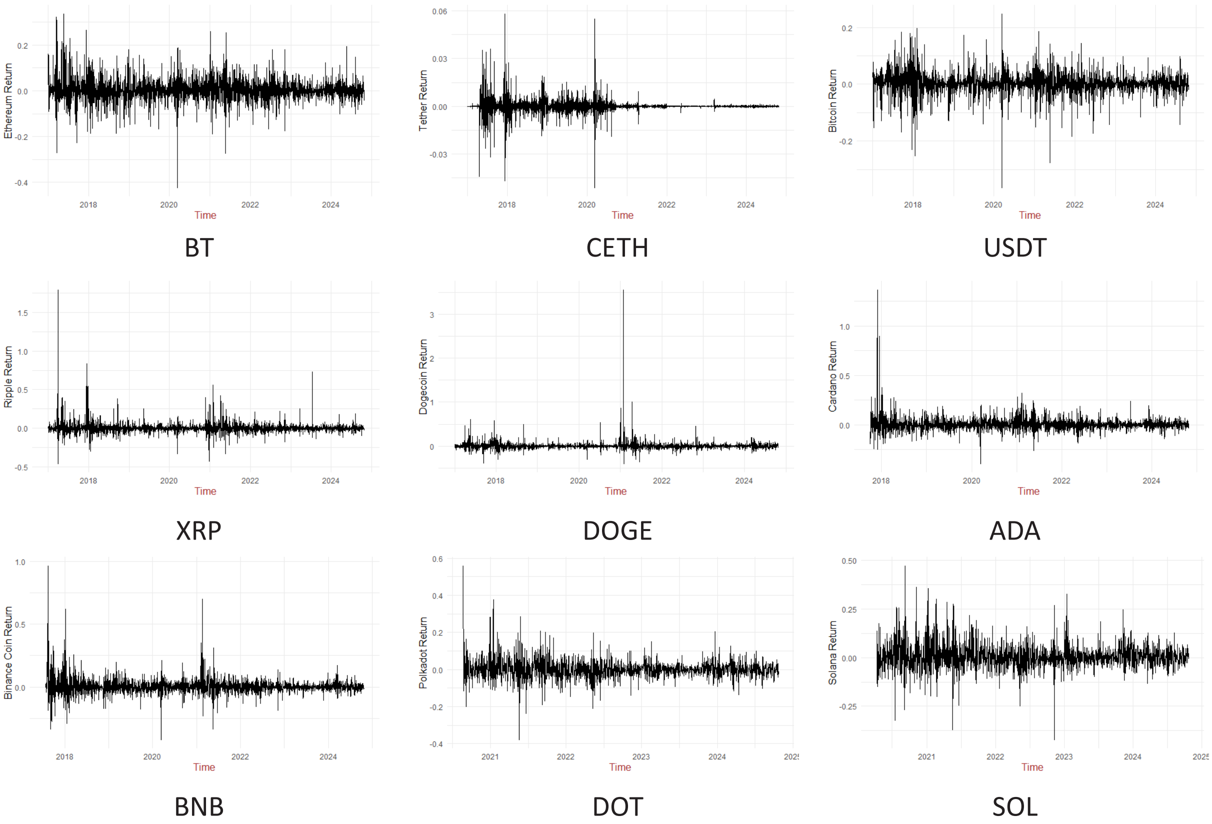

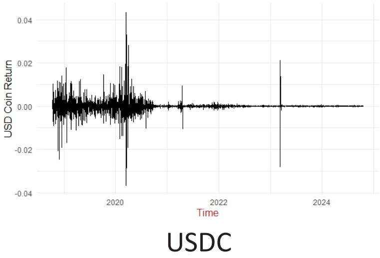

Note: BTC = Bitcoin, ETH = Ethereum, USDT = Tether, XRP = Ripple, DOGE = Dogecoin, ADA = Cardano, BNB = Binance Coin, DOT = Polkadot, SOL = Solana, USDC = USD Coin.

Figure 2. Return chart of 10 cryptocurrencies

indicating moderate volatility among major cryptocurrencies. BTC's skewness value is –0.62, indicating a slight tendency for negative returns to be more frequent than positive. However, BTC's kurtosis value of 9.21 indicates some significant price spikes. BTC's price return movement range stands at 0.61, which is relatively smaller than other more speculative cryptos such as DOGE or XRP, but still large enough to reflect significant price fluctuations.

ETH has similar characteristics to BTC, with a slightly higher standard deviation of 0.05, indicating slightly greater volatility. Unlike BTC, ETH has a positive skewness of 0.36, which indicates the tendency for positive returns to occur more

Table 1. Results of data descriptive statistics

Statistic	BTC	ETH	USDT	XRP	DOGE	ADA	BNB	DOT	SOL	USDC
Mean	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.00
SD	0.04	0.05	0.00	0.07	0.10	0.07	0.06	0.06	0.07	0.00
Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Min	–0.36	–0.42	–0.05	–0.46	–0.40	–0.40	–0.42	–0.38	–0.42	–0.04
Max	0.25	0.34	0.06	1.79	3.55	1.37	0.96	0.56	0.47	0.04
Range	0.61	0.76	0.11	2.25	3.96	1.76	1.38	0.94	0.90	0.08
Skew	–0.62	0.36	0.73	7.02	18.39	5.15	3.12	1.21	0.54	0.61
Kurtosis	9.21	7.02	41.34	138.82	637.84	85.51	37.90	12.29	5.34	43.92

Note: BTC = Bitcoin, ETH = Ethereum, USDT = Tether, XRP = Ripple, DOGE = Dogecoin, ADA = Cardano, BNB = Binance Coin, DOT = Polkadot, SOL = Solana, USDC = USD Coin.

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frequently than negative ones. However, the kurtosis of 7.02 shows that while ETH experiences price spikes, they are more moderate than BTC or other assets such as DOGE and XRP. ETH's range of 0.76, which is larger than that of BTC, indicates the potential for wider price movements within the analysis period. USDT and USDC, being stablecoins, showed very low volatility, as expected. USDT has a standard deviation of only 0.00, indicating almost no significant price fluctuations. USDT's skewness is 0.73, indicating a slight positive return trend. USDT's kurtosis of 41.34 indicates some extreme movements, but this is likely more due to exceptional events in the stablecoin market. USDC also shows similar characteristics, with a standard deviation of 0.00, skewness of 0.61, and kurtosis of 43.92, reflecting high stability with the possibility of some anomalies in price.

XRP has much higher volatility than BTC and ETH, with a standard deviation of 0.07. XRP's skewness of 7.02, indicating a tendency for large price spikes, is supported by its kurtosis of 138.82, which is one of the highest in this dataset. XRP's range is 2.25, which indicates that XRP has a very wide price fluctuation within the analysis period. This suggests that XRP has a higher level of risk than BTC or ETH. DOGE is the most volatile asset in this dataset, with a standard deviation of 0.10, which is larger than that of all other cryptocurrencies. DOGE's skewness of 18.39 indicates an extreme tendency of price spikes in the positive direction, which is confirmed by its kurtosis of 637.84, which is much higher than all other assets. DOGE's range of 3.96, which is the largest in the dataset, indicates that DOGE has high risk but also greater profit potential.

ADA is characterized by high volatility with a standard deviation of 0.07, similar to XRP. ADA's skewness of 5.15 indicates a sizable positive return tendency, but not as strong as DOGE or XRP. ADA's kurtosis of 85.51 shows that while price spikes occur, they are not as intense as DOGE or XRP. The range of ADA is 1.76, indicating significant price fluctuations. BNB has a standard deviation of 0.06, which is lower than ADA or XRP, but still shows significant volatility. The skewness of BNB is 3.12, indicating a moderate positive return trend. The kurtosis of BNB is 37.90, indicating some price spikes, but not as extreme as DOGE or XRP. BNB's range is 1.38, which is smaller than XRP or ADA, but still larger than stablecoins.

DOT has a standard deviation of 0.06, similar to BNB, which shows less volatility but is still significant. The skewness of DOT is 1.21, indicating that returns tend to be positive, but not as extreme as DOGE or XRP. The kurtosis of DOT is 12.29, indicating that there are some price spikes, but they are lower than DOGE, ADA, or XRP. DOT's range is 0.94, which is smaller than more speculative assets but still larger than stablecoins. SOL has a standard deviation of 0.07, showing volatility similar to ADA and XRP. SOL's skewness is 0.54, indicating that returns tend to be positive more often, but not as strongly as DOGE or XRP. SOL's kurtosis is 5.34, which is lower than most other assets, suggesting that SOL's price movements are more stable despite its high volatility. SOL's range is 0.90, indicating that SOL's price fluctuations are quite wide, but not as extreme as DOGE or XRP.

Overall, these results confirm that cryptocurrencies have completely different properties than traditional financial instruments. The high volatility and non-normal distribution of returns suggest that risk management is a very important aspect of crypto investment. Therefore, approaches such as Value at Risk (VaR), as well as GARCH, EGARCH, TGARCH, and MSGARCH volatility models used in this study, are highly relevant to understanding the potential risks and effects of price fluctuations in digital asset markets.

Modified Value at Risk (Cornish-Fisher) is used in this study; this is done to correct for the abnormal distribution of returns by considering skewness and kurtosis. Since asset returns are often not normally distributed, this approach is more accurate in capturing tail risk than conventional VaR.

Table 2 reports the Modified Cornish-Fisher VaR estimates at the 90%, 95%, and 99% confidence levels. The results show substantial variation across assets, indicating that cryptocurrency risk is strongly influenced by non-normal return characteristics. XRP, ADA, BNB, DOT, and SOL generate relatively large Cornish-Fisher VaR estimates, reflecting the influence of skewness and kurtosis in their return distributions. In contrast, BTC and ETH show more moderate estimates, while USDT

Table 2. Estimation results of the Value at Risk (VaR) method

Confidence Level	BTC	ETH	USDT	XRP	DOGE	ADA	BNB	DOT	SOL	USDC
90%	0.024	0.033	0.007	0.485	0.033	0.262	0.081	0.017	0.052	0.006
95%	0.059	0.066	0.002	0.304	0.066	0.141	0.017	0.556	0.089	0.001
99%	0.018	0.179	0.050	0.812	0.179	0.573	0.325	0.208	0.205	0.038

Note: BTC = Bitcoin, ETH = Ethereum, USDT = Tether, XRP = Ripple, DOGE = Dogecoin, ADA = Cardano, BNB = Binance Coin, DOT = Polkadot, SOL = Solana, USDC = USD Coin.

and USDC generally record lower values because of their stablecoin characteristics.

The Cornish-Fisher results should be interpreted with caution because several assets display non-monotonic VaR patterns across confidence levels. In theory, VaR is generally expected to increase as the confidence level rises. However, the Cornish-Fisher expansion adjusts the normal quantile using skewness and kurtosis. When return distributions are extremely skewed or leptokurtic, as observed for XRP, DOGE, ADA, USDT, and USDC, the higher-moment adjustment can distort the quantile approximation and produce unstable or non-monotonic estimates. Therefore, the Modified Cornish-Fisher VaR results are useful for identifying sensitivity to tail risk, but they should not be interpreted as definitive evidence of model reliability without comparison with dynamic volatility models and formal backtesting.

Based on the results of calculating Value-at-Risk (VaR) using the GARCH method in Table 3 at 90%, 95%, and 99% confidence levels, it can be concluded that the risk volatility in various crypto assets has a different pattern compared to the standard VaR method. DOGE has the highest VaR value at all confidence levels, with maximum potential losses of 0.052 at 90%, 0.066 at 95%, and 0.094 at 99%. This suggests that DOGE remains one of the riskiest assets, with significant volatility in price movements. SOL also shows high risk, with a value of 0.048 at 90%, increasing to 0.088 at 99%, signaling that this asset experiences considerable fluctuations under extreme market conditions.

ETH shows a fairly high level of risk, with the VaR value increasing from 0.043 at 90% to 0.079 at 99%. This suggests that ETH's risk of loss increases significantly under more volatile market conditions. DOT also shows a similar trend, with a VaR value of 0.041 at 90% and rising to 0.075 at 99%, reflecting high volatility but still below DOGE and SOL. BTC as the main crypto asset, has a lower VaR value compared to DOGE, SOL, and ETH, which is 0.033 at 90% and 0.061 at 99%. While still a significant risk, BTC appears more stable than some of the other altcoins, which is consistent with its position as the crypto asset with the largest liquidity and market capitalization.

ADA and BNB recorded more moderate VaR values of 0.046 and 0.029 at 90%, respectively, increasing to 0.083 and 0.052 at 99%. Meanwhile, Ripple (XRP) showed a smaller value of 0.026 at 90% and increased to 0.048 at 99%, indicating lower volatility than other altcoins such as DOT or SOL. As expected, stablecoins like USDT and USDC have very small VaR values, even close to zero. USDT registered 0.001 at 95% and 99%, while USDC remained at 0.000 at all confidence levels, indicating very low volatility. This reaffirms that stablecoins show lower daily return volatility in the face of extreme price fluctuations than other crypto assets.

Table 3. Estimation results of the Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) method

Confidence Level	BTC	ETH	USDT	XRP	DOGE	ADA	BNB	DOT	SOL	USDC
90%	0.033	0.043	0.000	0.026	0.052	0.046	0.029	0.041	0.048	0.000
95%	0.043	0.056	0.001	0.034	0.066	0.059	0.037	0.053	0.062	0.000
99%	0.061	0.079	0.001	0.048	0.094	0.083	0.052	0.075	0.088	0.000

Note: BTC = Bitcoin, ETH = Ethereum, USDT = Tether, XRP = Ripple, DOGE = Dogecoin, ADA = Cardano, BNB = Binance Coin, DOT = Polkadot, SOL = Solana, USDC = USD Coin.

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Table 4. Estimation results of the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) method

Confidence Level	BTC	ETH	USDT	XRP	DOGE	ADA	BNB	DOT	SOL	USDC
90%	0.036	0.044	0.001	0.047	0.057	0.044	0.029	0.045	0.047	0.000
95%	0.046	0.056	0.001	0.060	0.073	0.057	0.038	0.057	0.061	0.000
99%	0.065	0.080	0.001	0.085	0.104	0.080	0.053	0.081	0.086	0.000

Note: BTC = Bitcoin, ETH = Ethereum, USDT = Tether, XRP = Ripple, DOGE = Dogecoin, ADA = Cardano, BNB = Binance Coin, DOT = Polkadot, SOL = Solana, USDC = USD Coin.

Based on the results of the calculation of Value at Risk (VaR) using the EGARCH method in Table 4, at the 90%, 95%, and 99% confidence levels, it can be interpreted that the volatility of risk on various crypto assets has a more dynamic pattern than the standard VaR and GARCH methods. EGARCH considers the effect of asymmetric volatility, which means that spikes in volatility due to extreme events are better captured by this model, thus providing a more accurate picture of the risk in the crypto asset market.

DOGE continues to show the highest risk among other cryptocurrencies, with VaR values of 0.057 at 90%, 0.073 at 95%, and 0.104 at 99%. This confirms that DOGE experiences greater price fluctuations and is more susceptible to extreme market movements than other assets. SOL and XRP also show high levels of volatility, with 0.047 and 0.047 at 90%, respectively, increasing to 0.086 and 0.085 at 99%, indicating a similar risk pattern to DOGE, albeit slightly lower.

ETH and DOT also have significant levels of risk, with ETH's VaR value of 0.044 at 90% and rising to 0.080 at 99%, while DOT registers 0.045 at 90% and rising to 0.081 at 99%. Both show relatively high volatility, especially in more extreme market scenarios. BTC, while still carrying considerable risk, shows more manageable volatility compared to DOGE, SOL, ETH, and DOT, with VaR values of around 0.036 at 90% and 0.065 at 99%. This reflects greater stability than some altcoins, making it a more defensive asset in the face of market turmoil.

ADA and BNB have more moderate risks compared to DOGE or ETH, with 0.044 and 0.029 at 90%, respectively, increasing to 0.080 and 0.053 at 99%. This pattern shows that although ADA and BNB are still experiencing volatility, their values are relatively lower than higher-risk assets such as DOGE and SOL. As expected, stablecoins such as USDT and USDC show very small VaR values, even close to zero. USDT recorded 0.001 at all confidence levels, while USDC remained at 0.000, confirming that stablecoins have much lower volatility than other crypto assets. This makes them a lower-volatility instrument based on daily price movements in the face of market uncertainty.

Table 5 shows the results of the Value-at-Risk (VaR) calculation using the TGARCH method at a confidence level of 90%, 95%, and 99%. It can be interpreted that the risk volatility in various crypto assets remains high, with some assets showing greater sensitivity to negative price movements. The Threshold GARCH (TGARCH) model captures the asymmetric effect in volatility, where a price decrease has a greater impact than an increase in price.

Table 5. Estimation results of the Threshold Generalized AutoRegressive Conditional Heteroskedasticity (TGARCH) method

Confidence Level	BTC	ETH	USDT	XRP	DOGE	ADA	BNB	DOT	SOL	USDC
90%	0.036	0.044	0.001	0.048	0.059	0.045	0.031	0.045	0.049	0.000
95%	0.046	0.056	0.001	0.062	0.075	0.058	0.039	0.058	0.062	0.000
99%	0.065	0.080	0.001	0.087	0.107	0.082	0.056	0.082	0.088	0.000

Note: BTC = Bitcoin, ETH = Ethereum, USDT = Tether, XRP = Ripple, DOGE = Dogecoin, ADA = Cardano, BNB = Binance Coin, DOT = Polkadot, SOL = Solana, USDC = USD Coin.

DOGE again shows the highest risk among other crypto assets, with VaR values of 0.059 at 90%, 0.075 at 95%, and 0.107 at 99%. This confirms that DOGE experiences more extreme price fluctuations and is very vulnerable to negative market movements. SOL and XRP also show a high level of risk, with SOL recording a VaR of 0.049 at 90% and increasing to 0.088 at 99%, while XRP has a value of 0.048 at 90% and increases to 0.087 at 99%. ETH remains in the high-volatility asset category, with a VaR of 0.044 at 90% and increasing to 0.080 at 99%. DOT and ADA have a similar pattern, with a VaR value of 0.045 at 90% and increasing to 0.082 at 99%, indicating that although both have lower volatility than DOGE or SOL, their risk remains significant in extreme market conditions.

BTC shows a lower VaR value than DOGE, SOL, and ETH, with 0.036 at 90% and increasing to 0.065 at 99%. This indicates that BTC has more controlled volatility, although it remains vulnerable to significant market movements. BNB has lower volatility than BTC, with VaR values of 0.031 at 90% and 0.056 at 99%, reflecting greater stability than most other altcoins. Stablecoins USDT and USDC continue to show very small VaR values, even close to zero. USDT recorded 0.001 at all confidence levels, while USDC remained at 0.000, confirming its role as an asset with very low volatility, reflecting a lower daily-volatility profile during turbulent market conditions.

Based on the results of the Value at Risk (VaR) calculation using the Markov-Switching GARCH (MSGARCH) method, it can be seen that this model captures changes in volatility in the crypto market better, enabling more dynamic risk analysis in changing market conditions. DOGE continues to show the highest level of risk among other crypto assets, with a VaR of 0.062 at 90%, 0.080 at 95%, and increasing to 0.112 at 99%. This shows that DOGE experiences extreme price fluctuations in high-volatility regimes, which has the potential to cause large losses in unstable market conditions.

XRP also shows a significant increase in risk, with a VaR of 0.039 at 90%, 0.050 at 95%, and 0.071 at 99%, indicating that XRP has a fairly high sensitivity to changes in market volatility. ETH experiences increased risk compared to some previous models, with a VaR of 0.042 at 90%, 0.054 at 95%, and 0.077 at 99%, which shows that ETH is more susceptible to shifts between low and high volatility. SOL shows a similar pattern, with a VaR of 0.047 at 90% and increasing to 0.085 at 99%, which indicates high sensitivity to market uncertainty.

Meanwhile, BTC shows a lower level of risk compared to DOGE, XRP, ETH, and SOL, with a VaR of 0.038 at 90% and increasing to 0.069 at 99%. This indicates that although BTC is still experiencing volatility, its transition between high and low risk regimes is more stable than other altcoins. BNB also has a relatively more controlled risk profile compared to the majority of other altcoins, with a VaR of 0.031 at 90% and 0.054 at 99%.

Overall, the MSGARCH results show that regime-switching volatility dynamics produce relatively moderate VaR estimates across most cryptocurrencies, with DOGE recording the highest risk estimate under this model. However, these VaR magnitudes should not be interpreted as direct evidence of superior model performance. The reliability of MSGARCH must be evaluated together with formal backtesting results. For stablecoins such as USDT and USDC, the low VaR estimates mainly reflect low daily return volatility, but they do not capture stablecoin-specific risks such as depegging, liquidity risk, issuer risk, reserve transparency risk, and redemption risk.

Table 6. Estimation results of the Markov Switching Generalized Autoregressive Conditional Heteroskedasticity (MSGARCH) method

Confidence Level	BTC	ETH	USDT	XRP	DOGE	ADA	BNB	DOT	SOL	USDC
90%	0.038	0.042	0.001	0.039	0.062	0.046	0.031	0.043	0.047	0.001
95%	0.048	0.054	0.002	0.050	0.080	0.059	0.038	0.055	0.061	0.001
99%	0.069	0.077	0.002	0.071	0.112	0.084	0.054	0.078	0.085	0.001

Note: BTC = Bitcoin, ETH = Ethereum, USDT = Tether, XRP = Ripple, DOGE = Dogecoin, ADA = Cardano, BNB = Binance Coin, DOT = Polkadot, SOL = Solana, USDC = USD Coin.

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Table 7. Comparison of crypto risk estimation (99%) with various methods

Method	BTC	ETH	USDT	XRP	DOGE	ADA	BNB	DOT	SOL	USDC
VaR	0.018	0.179	0.050	0.812	0.179	0.573	0.325	0.208	0.205	0.038
GARCH	0.061	0.079	0.001	0.048	0.094	0.083	0.052	0.075	0.088	0.000
EGARCH	0.065	0.080	0.001	0.085	0.104	0.080	0.053	0.081	0.086	0.000
TGARCH	0.065	0.080	0.001	0.087	0.107	0.082	0.056	0.082	0.088	0.000
MSGARCH	0.069	0.077	0.002	0.071	0.112	0.084	0.054	0.078	0.085	0.001

Note: BTC = Bitcoin, ETH = Ethereum, USDT = Tether, XRP = Ripple, DOGE = Dogecoin, ADA = Cardano, BNB = Binance Coin, DOT = Polkadot, SOL = Solana, USDC = USD Coin.

Table 7 compares the 99% VaR estimates generated by the Modified Cornish-Fisher VaR, GARCH, EGARCH, TGARCH, and MSGARCH models. The table shows that risk estimates vary substantially across both assets and modeling approaches. The Modified Cornish-Fisher VaR produces the largest estimates for XRP, ADA, BNB, DOT, and SOL, reflecting its sensitivity to skewness and kurtosis in highly non-normal return distributions. However, the non-monotonic pattern observed in several Cornish-Fisher estimates indicates that higher-moment adjustments may generate unstable results when return distributions are extremely skewed or leptokurtic.

The GARCH, EGARCH, TGARCH, and MSGARCH models produce more stable VaR estimates because they incorporate conditional volatility dynamics. DOGE records the highest risk among the dynamic volatility models, followed by

Table 8. VaR backtesting results using Kupiec and Christoffersen tests at the 99% confidence level

Asset	Model	Actual Exceedance	Kupiec p-value	Kupiec Decision	Christoffersen p-value	Christoffersen Decision
BTC	GARCH	6	0.663	Fail to Reject	0.845	Fail to Reject
BTC	EGARCH	5	1.000	Fail to Reject	0.951	Fail to Reject
BTC	TGARCH	5	1.000	Fail to Reject	0.951	Fail to Reject
BTC	MSGARCH	6	0.663	Fail to Reject	0.845	Fail to Reject
ETH	GARCH	0	0.002	Reject	0.007	Reject
ETH	EGARCH	1	0.028	Reject	0.090	Fail to Reject
ETH	TGARCH	1	0.028	Reject	0.090	Fail to Reject
ETH	MSGARCH	1	0.028	Reject	0.090	Fail to Reject
USDT	GARCH	8	0.215	Fail to Reject	0.407	Fail to Reject
USDT	EGARCH	0	0.002	Reject	0.007	Reject
USDT	TGARCH	1	0.028	Reject	0.090	Fail to Reject
USDT	MSGARCH	1	0.028	Reject	0.090	Fail to Reject
XRP	GARCH	2	0.125	Fail to Reject	0.306	Fail to Reject
XRP	EGARCH	1	0.028	Reject	0.090	Fail to Reject
XRP	TGARCH	2	0.125	Fail to Reject	0.306	Fail to Reject
XRP	MSGARCH	2	0.125	Fail to Reject	0.306	Fail to Reject
DOGE	GARCH	2	0.125	Fail to Reject	0.306	Fail to Reject
DOGE	EGARCH	0	0.002	Reject	0.007	Reject
DOGE	TGARCH	1	0.028	Reject	0.090	Fail to Reject
DOGE	MSGARCH	4	0.641	Fail to Reject	0.869	Fail to Reject
ADA	GARCH	2	0.125	Fail to Reject	0.306	Fail to Reject
ADA	EGARCH	2	0.125	Fail to Reject	0.306	Fail to Reject
ADA	TGARCH	2	0.125	Fail to Reject	0.306	Fail to Reject
ADA	MSGARCH	3	0.331	Fail to Reject	0.021	Reject
BNB	GARCH	2	0.125	Fail to Reject	0.306	Fail to Reject
BNB	EGARCH	2	0.125	Fail to Reject	0.306	Fail to Reject
BNB	TGARCH	2	0.125	Fail to Reject	0.306	Fail to Reject
BNB	MSGARCH	1	0.028	Reject	0.090	Fail to Reject
DOT	GARCH	9	0.106	Fail to Reject	0.094	Fail to Reject
DOT	EGARCH	9	0.106	Fail to Reject	0.094	Fail to Reject

Table 8 (cont.). VaR backtesting results using Kupiec and Christoffersen tests at the 99% confidence level

Asset	Model	Actual Exceedance	Kupiec p-value	Kupiec Decision	Christoffersen p-value	Christoffersen Decision
DOT	TGARCH	9	0.106	Fail to Reject	0.094	Fail to Reject
DOT	MSGARCH	0	0.002	Reject	0.007	Reject
SOL	GARCH	19	< 0.001	Reject	< 0.001	Reject
SOL	EGARCH	19	< 0.001	Reject	< 0.001	Reject
SOL	TGARCH	19	< 0.001	Reject	< 0.001	Reject
SOL	MSGARCH	0	0.002	Reject	0.007	Reject
USDC	GARCH	1	0.028	Reject	0.090	Fail to Reject
USDC	EGARCH	0	0.002	Reject	0.007	Reject
USDC	TGARCH	0	0.002	Reject	0.007	Reject
USDC	MSGARCH	0	0.002	Reject	0.007	Reject

Note: The backtesting procedure uses 500 out-of-sample observations for each asset and model. At the 99% confidence level, the expected number of exceedances is five. The decision is based on a 5% significance level.

SOL, ADA, DOT, ETH, and XRP depending on the specification. BTC shows moderate risk relative to most altcoins, while USDT and USDC exhibit near-zero VaR estimates under several volatility models due to their low daily return volatility as stablecoins.

These results should be interpreted as comparative VaR magnitudes rather than definitive evidence of model superiority. A model that produces a moderate or conservative VaR estimate may still fail to provide statistically reliable risk coverage. Therefore, formal backtesting using Kupiec's unconditional coverage test and Christoffersen's conditional coverage test is required to determine whether the estimated VaR values are consistent with realized return behavior.

To validate the robustness of the VaR estimates, this study conducts formal backtesting using Kupiec's unconditional coverage test and Christoffersen's conditional coverage test at the 99% confidence level. The backtesting procedure uses 500 out-of-sample observations for each asset and model, with five expected exceedances under the 1% tail probability.

The backtesting results show that VaR model performance differs across assets and model specifications. BTC is the only asset for which all tested models pass both the Kupiec and Christoffersen tests. GARCH-type models provide adequate coverage for ADA, BNB, and DOT, while MSGARCH is rejected for these assets. For XRP and DOGE, MSGARCH passes both tests together with selected GARCH-type specifications, indicating that regime-switching dynamics are relevant for some high-volatility cryptocurrencies but not universally superior across the full sample. ETH, SOL, and USDC show rejection across all tested models, suggesting that their tail-risk behavior is more difficult to capture using the examined VaR specifications.

These findings indicate that model suitability cannot be inferred solely from the magnitude of VaR estimates. A model may generate moderate or conservative VaR values but still fail formal backtesting if the observed exceedance frequency or exceedance independence does not meet statistical criteria. Therefore, the results support an asset-specific approach to cryptocurrency risk modeling rather than a single universally superior model.

4. DISCUSSION

The empirical results of this study demonstrate that the Modified Cornish-Fisher VaR consistently produces higher risk estimates compared to GARCH-type models, particularly for assets with extreme skewness and kurtosis such as XRP, ADA, and DOGE. This pattern reflects the sensitivity of the Cornish-Fisher expansion to distributional irregularities, which is consistent with the argument by Samunderu and Murahwa (2021) that return-based risk measures adjusted for higher moments are more responsive to tail risk in non-normal distributions. However, this sensitivity also introduces instability in estimation, as evidenced by the unusually high VaR values for XRP (0.812) and ADA (0.573) at the 99% confidence level, which appear disproportionate relative to the estimates produced by dynamic volatility models. This finding aligns with Likitratcharoen et al. (2023), who noted that

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static risk models tend to overestimate risk during periods of distributional extremity without accounting for evolving market conditions.

In contrast, the GARCH-type and MSGARCH models produce more stable VaR estimates than the Modified Cornish-Fisher approach, but the formal backtesting results show that their reliability differs across assets. BTC is the only asset for which all tested models pass both the Kupiec and Christoffersen tests, indicating that symmetric, asymmetric, and regime-switching specifications all provide adequate VaR coverage for this asset. For XRP and DOGE, MSGARCH passes both tests together with selected GARCH-type models, suggesting that regime-switching dynamics may be relevant for some high-volatility cryptocurrencies. This result is consistent with Benaid et al. (2024), Chan et al. (2023), De la Torre-Torres et al. (2021), and Naik and Mohan (2021), who emphasize the usefulness of regime-switching volatility models in markets exposed to abrupt volatility shifts.

However, the evidence does not support the conclusion that MSGARCH is universally superior across the full cryptocurrency sample. For ADA, BNB, and DOT, the GARCH-type models pass both backtesting tests, while MSGARCH is rejected by at least one test. This indicates that regime-switching flexibility does not always translate into better VaR reliability. For ETH, SOL, and USDC, none of the tested specifications fully satisfies both backtesting criteria, showing that their tail-risk behavior remains difficult to capture using the examined models. Therefore, model performance must be interpreted as asset-specific rather than as evidence of one dominant volatility model.

The asymmetric models also show mixed results. EGARCH and TGARCH provide adequate coverage for BTC, ADA, BNB, and DOT, but they fail to satisfy the full backtesting criteria for ETH, SOL, USDT, USDC, and several high-volatility assets. These findings indicate that asymmetric volatility specifications are useful for some cryptocurrencies, but their suitability cannot be inferred only from leverage-effect arguments or VaR magnitude. Formal exceedance behavior remains necessary to determine whether a model provides statistically reliable VaR estimates.

For stablecoins, the results require cautious interpretation. USDT and USDC show near-zero VaR values under several GARCH-type specifications, reflecting their low daily return volatility as US dollar-pegged instruments. However, low daily volatility should not be interpreted as low overall risk. Stablecoins remain exposed to depegging risk, liquidity risk, issuer risk, reserve transparency risk, and redemption risk. The backtesting results further show that GARCH passes both tests for USDT, while all tested models are rejected for USDC. This implies that standard volatility models can capture part of stablecoin price stability, but they do not provide a complete framework for assessing stablecoin-specific risks.

The results have direct implications for model selection in cryptocurrency risk management. For BTC, the fact that all specifications pass both backtesting tests suggests that a parsimonious GARCH model may be sufficient when the primary objective is reliable VaR coverage, while more complex asymmetric or regime-switching models should only be selected when additional information about leverage effects or volatility regimes is required. For ADA, BNB, and DOT, the acceptance of GARCH-type models and rejection of MSGARCH indicate that greater model complexity does not necessarily improve predictive reliability. In contrast, the acceptable performance of MSGARCH for XRP and DOGE suggests that regime-switching behavior may be relevant for assets with abrupt and speculative volatility dynamics.

The rejection of all tested models for ETH, SOL, and USDC indicates that the examined specifications are insufficient for capturing their tail-risk behavior. For these assets, risk managers should consider alternative distributions, extreme-value-based methods, expected shortfall models, or more frequent parameter updating. The stablecoin results also demonstrate that low estimated volatility should not be equated with low total risk because conventional VaR models do not capture depegging, liquidity, issuer, reserve, and redemption risks. Therefore, practical model selection should be based on formal backtesting performance, asset-specific market characteristics, and the economic sources of risk rather than on VaR magnitude or model complexity alone.

CONCLUSION

This study compares the Modified Cornish-Fisher Value-at-Risk approach and four volatility models, namely GARCH, EGARCH, TGARCH, and MSGARCH, in measuring risk across ten major cryptocurrencies using daily data from January 2017 to October 2024. The results show that cryptocurrency returns have heterogeneous volatility characteristics, with substantial differences in skewness, kurtosis, and tail-risk behavior across assets. The Modified Cornish-Fisher VaR produces highly sensitive risk estimates for assets with extreme return distributions, especially XRP, ADA, and DOGE, but its estimates should be interpreted carefully because the higher-moment adjustment can generate unstable and non-monotonic results across confidence levels.

The backtesting results show that no single model is universally superior across all cryptocurrencies. BTC is the only asset for which all tested models pass both the Kupiec and Christoffersen tests. For XRP and DOGE, MSGARCH provides acceptable VaR coverage together with selected GARCH-type models, suggesting that regime-switching dynamics are relevant for some high-volatility assets. For ADA, BNB, and DOT, GARCH-type models provide stronger support than MSGARCH. For ETH, SOL, and USDC, none of the tested models fully satisfies both backtesting criteria, indicating that their tail-risk behavior remains difficult to capture using the examined specifications.

These findings imply that cryptocurrency risk measurement requires an asset-specific modeling strategy. Investors and risk managers should not select a model solely because it produces moderate or conservative VaR estimates. Model choice should consider both the magnitude of VaR and formal backtesting evidence. The results also suggest that stablecoin risk cannot be evaluated only through daily volatility, since depegging, liquidity, issuer, and redemption risks remain outside the scope of standard VaR-based volatility models. Future research should extend the analysis by incorporating alternative backtesting procedures, expected shortfall validation, higher-frequency data, and stablecoin-specific risk indicators.

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