Publisher
Vandana Publications
www.vandanapublications.com

International Journal of Engineering and Management Research
2025 Volume 15 Number 4 August

E-ISSN:2250-0758
P-ISSN:2394-6962

Research Article
Cryptocurrency

Risk and Return Dynamics of Top Five Cryptocurrencies: A Comprehensive Analysis using an EGARCH-Based Analysis of Asymmetry and Tail Risk

Biswas R[1*]

DOI:10.5281/zenodo.17115233

[1*] Rahul Biswas, Research Scholar, Department of Business Administration, University of Kalyani, Kalyani, West Bengal, India.

This study examines the risk and returns dynamics of five leading cryptocurrencies—Bitcoin, Ethereum, Binance Coin, Tether, and XRP—over the period from January 2018 to December 2024. Using a combination of traditional and advanced quantitative methods, the analysis incorporates Value at Risk (VaR), Expected Shortfall (ES), and the Exponential Generalised Autoregressive Conditional Heteroskedasticity (EGARCH) model to explore asymmetry and tail behaviour in return distributions. The results show substantial heterogeneity in volatility, risk asymmetry, and persistence, particularly between speculative assets and stablecoins. Tether consistently exhibits low volatility and tail risk, reinforcing its role as a stabilising instrument. EGARCH estimates reveal significant leverage effects in Bitcoin and Ethereum, highlighting the asymmetric impact of negative news on volatility. Rolling-window statistics further capture the time-varying nature of skewness, kurtosis and volatility across assets. These findings provide empirical evidence for the importance of adaptive and asset-specific risk strategies in cryptocurrency markets and contribute to the evolving literature on digital asset risk management.

Keywords: Cryptocurrency, Bitcoin, Ethereum, Binance Coin, Tether, XRP, Value at Risk (VaR), Expected Shortfall (ES), Rolling Statistics, Risk Management, EGARCH, Volatility, Skewness, Kurtosis, Financial Risk, Digital Assets

Corresponding Author	How to Cite this Article	To Browse
Rahul Biswas, Research Scholar, Department of Business Administration, University of Kalyani, Kalyani, West Bengal, India. Email: rahul19biswas92@gmail.com	Biswas R, Risk and Return Dynamics of Top Five Cryptocurrencies: A Comprehensive Analysis using an EGARCH-Based Analysis of Asymmetry and Tail Risk. Int J Engg Mgmt Res. 2025;15(4):75-84. Available From https://ijemr.vandanapublications.com/index.php/j/article/view/1790	

Manuscript Received	Review Round 1	Review Round 2	Review Round 3	Accepted
2025-07-12	2025-07-25			2025-08-14
Conflict of Interest	**Funding**	**Ethical Approval**	**Plagiarism X-checker**	**Note**
None	Nil	Yes	4.16	

1. Introduction

The rapid growth of cryptocurrencies has introduced both opportunities and systemic risks in global financial markets. Unlike traditional assets, digital currencies exhibit non-linear volatility, heavy tails, and asymmetric shocks, which challenge the assumptions of classical risk models (Cont, 2001; Baur & Dimpfl, 2018). Flagship coins such as Bitcoin and Ethereum are often subject to sudden drawdowns triggered by speculative trading, liquidity shocks, or regulatory uncertainty, making the accurate measurement of downside risk essential for investors and regulators alike (Corbet, Lucey, & Yarovaya, 2019; Zhang & Wang, 2022).

Traditional variance-based metrics, while widely applied, underestimate the probability of extreme losses in cryptocurrency markets. This limitation has shifted attention towards tail-sensitive measures, particularly Value-at-Risk (VaR) and expected shortfall (ES). VaR estimates the maximum expected loss at a given confidence level, whereas ES provides a more conservative measure by averaging losses beyond the VaR threshold (McNeil, Frey, & Embrechts, 2015). Although these models are extensively validated in traditional finance, their application to cryptocurrencies remains limited, fragmented, and often confined to short sample periods or single assets (Alexander & Dakos, 2023; Kar & Meka, 2025).

To capture the time-varying and asymmetric volatility in digital asset returns, researchers have increasingly turned to GARCH-family models. In particular, the Exponential GARCH (EGARCH) model has proven effective in identifying leverage effects, where negative shocks exert disproportionately higher volatility than positive ones (Katsiampa, 2017; Wu & Yueh, 2025). However, most existing studies apply these techniques to either Bitcoin or Ethereum in isolation, leaving limited insight into the comparative behaviour of multiple cryptocurrencies and stablecoins within a unified framework.

Stablecoins such as Tether introduce a further dimension to this debate. Pegged to fiat currencies, they are designed to offer stability, yet recent empirical evidence suggests that even stablecoins may exhibit unique volatility and tail risk patterns, particularly during crisis episodes (Maghyereh & Ziadat, 2024; Sapkota, 2025). Understanding their performance relative to speculative cryptocurrencies is critical for assessing their role in portfolio diversification and systemic risk management.

This study addresses these gaps by providing a comprehensive, multi-method analysis of five leading cryptocurrencies—Bitcoin, Ethereum, Binance Coin, XRP, and Tether—between 2018 and 2024. By combining descriptive statistics, tail-risk measures (VaR and ES), EGARCH volatility modeling, and rolling higher-moment analysis, the paper contributes to the literature in three ways. First, it integrates multiple methods rarely examined together in crypto-asset studies. Second, it provides a comparative perspective between stablecoins and speculative cryptocurrencies, highlighting their distinct risk-return dynamics. Third, it offers practical implications for risk managers and regulators, emphasising the heterogeneity of digital assets in terms of volatility persistence, asymmetry, and systemic vulnerability.

2. Literature Review

Cryptocurrencies exhibit distinct return and volatility dynamics compared to traditional financial assets, with pronounced fat tails, excess kurtosis, and volatility clustering (Cont, 2001; Baur & Dimpfl, 2018; Engle, 1982). These stylised facts make classical Gaussian-based risk measures unsuitable, prompting researchers to adopt advanced econometric models and tail-sensitive approaches for risk assessment (Feng, Wang, & Zhang, 2018; Bruhn & Ernst, 2022; Huynh & Nasir, 2023). Early studies primarily explored the statistical properties of Bitcoin, revealing asymmetric and non-linear volatility patterns that mirror speculative asset behaviour (Dyhrberg, 2016; Baur, Hong, & Lee, 2018; Zhang & Wang, 2022). As the market expanded to include Ethereum, Binance Coin, XRP, and stablecoins, the heterogeneity of risk dynamics across asset classes has attracted increasing scholarly attention (Yousaf & Yarovaya, 2023; Trucíos & Siliverstovs, 2023).

A significant strand of literature applies Value-at-Risk (VaR) and Expected Shortfall (ES) to cryptocurrency markets, recognising their importance as regulatory benchmarks under Basel III. While VaR remains widely used, its inability to capture losses beyond the threshold has motivated the adoption of ES as a more coherent tail-risk measure (McNeil, Frey, & Embrechts, 2015;

Acerbi & Tasche, 2002; Jorion, 2007). Empirical applications demonstrate that both measures are sensitive to extreme downside risks in cryptocurrencies, although the results vary by model specification and sample period (Alexander & Dakos, 2023; Kar & Meka, 2025; Liu, Zhou, Lin, Hao, & Chen, 2025; Piparo, 2025). Despite this progress, many studies remain narrowly focused on individual cryptocurrencies, leaving comparative analyses across speculative coins and stablecoins underexplored (Ahelegbey, Giudici, & Mojtahedi, 2021; Rehman, Ahmad, & Desheng, 2024).

Another active research avenue employs GARCH-family models to capture time-varying volatility. Katsiampa (2017) demonstrated that EGARCH and TGARCH outperform symmetric models by capturing leverage effects, where negative shocks induce larger volatility responses than positive shocks of similar magnitude. Subsequent research confirmed asymmetric volatility in major cryptocurrencies, with EGARCH emerging as a preferred model due to its ability to address persistence and structural breaks (Wu & Yueh, 2025; Trucíos, 2019; Huynh & Nasir, 2023; Gherghina & Constantinescu, 2025). In addition, mixed-data sampling and copula-based extensions further enhance forecasting accuracy in crypto markets (Bruhn & Ernst, 2022; Trucíos & Siliverstovs, 2023). Nonetheless, applications often remain asset-specific, overlooking heterogeneity in volatility transmission across different classes of digital currencies.

Beyond volatility modeling, recent work emphasises rolling-window and higher-moment approaches to capture evolving market dynamics. Rolling skewness and kurtosis measures, for instance, reveal the persistence of asymmetry and fat-tailed behaviour, particularly during crisis episodes such as the COVID-19 pandemic and the 2022 crypto crash (Liu & Serletis, 2019; Maghyereh & Ziadat, 2024; Bouri, Lucey, & Saeed, 2023). These findings highlight the importance of dynamic, rather than static, risk assessment frameworks. However, existing studies rarely integrate higher-moment analysis with volatility and tail-risk measures in a unified framework (Liu, Tsyvinski, & Wu, 2020; Yousaf & Yarovaya, 2023).

Finally, the literature on stablecoins underscores their dual role as both stabilising instruments and potential sources of systemic risk. While designed to reduce volatility through fiat pegging, empirical evidence suggests that stablecoins such as Tether can still exhibit contagion effects during periods of market stress (Lyons & Viswanath-Natraj, 2020; Sapkota, 2025; Chen & Chen, 2024). This raises important questions regarding their effectiveness as hedging tools compared to speculative cryptocurrencies (Corbet, Lucey, Urquhart, & Yarovaya, 2019; Corbet, Lucey, & Yarovaya, 2018).

Taken together, the literature indicates substantial advances in modeling cryptocurrency risks, yet also reveals persistent gaps. Most studies either, (i) apply isolated methodologies, (ii) restrict analysis to a single cryptocurrency, or (iii) neglect the comparative dynamics between speculative cryptocurrencies and stablecoins. To address these gaps, this study provides a comprehensive framework that combines EGARCH volatility modeling, VaR and ES tail-risk measures, and rolling higher-moment statistics across five major digital assets, thereby offering new insights into the heterogeneous risk-return characteristics of cryptocurrencies.

3. Theoretical Background

The dynamics of cryptocurrency returns and volatility can be better understood when placed within established financial and econometric theories. Three theoretical perspectives provide the foundation for this study:

3.1 Leverage Effect and Asymmetric Volatility

Black (1976) first highlighted that negative shocks to asset prices increase firms' financial leverage, thereby amplifying future volatility. Nelson (1991) extended this concept by developing the Exponential GARCH (EGARCH) model, which captures asymmetry by allowing negative shocks to exert a greater effect on conditional variance than positive shocks of the same size. This framework has since become fundamental to volatility modelling in both traditional and digital assets (Engle, 1982; Katsiampa, 2017). More recent studies confirm that cryptocurrencies exhibit leverage effects similar to equities, but with stronger persistence due to speculative trading and thin liquidity (Wu & Yueh, 2025; Huynh & Nasir, 2023; Gherghina & Constantinescu, 2025).

Such findings suggest that structural breaks, regulatory shocks, and technological risks exacerbate volatility asymmetry beyond that observed in conventional financial markets (Dyhrberg, 2016; Trucíos & Siliverstovs, 2023).

3.2 Risk Management and Tail Behaviour

Classical risk measures such as variance assume normally distributed returns, but empirical research shows that financial and digital assets exhibit skewness, excess kurtosis, and heavy tails (Cont, 2001; Baur & Dimpfl, 2018). These distributional properties undermine the reliability of variance-based measures, particularly during crisis episodes, motivating the use of downside-sensitive approaches (Feng, Wang, & Zhang, 2018; Ahelegbey, Giudici, & Mojtahedi, 2021). In this regard, Value-at-Risk (VaR) and Expected Shortfall (ES) have emerged as theoretically grounded measures of downside risk. VaR provides an estimate of potential losses under normal market conditions, while ES captures extreme losses in the tail, making it a coherent risk measure now mandated under Basel III (McNeil, Frey, & Embrechts, 2015; Acerbi & Tasche, 2002; Jorion, 2007). For cryptocurrencies, which frequently display extreme downside dependence and contagion effects, these measures are particularly relevant (Alexander & Dakos, 2023; Kar & Meka, 2025; Liu, Zhou, Lin, Hao, & Chen, 2025). Extensions such as copula-based and EVT-enhanced approaches further strengthen their robustness for non-linear and fat-tailed crypto markets (Bruhn & Ernst, 2022; Rehman, Ahmad, & Desheng, 2024; Piparo, 2025).

3.3 Market Microstructure and Asset Heterogeneity

The market microstructure theory posits that asset volatility is shaped by liquidity, information asymmetry, and trading intensity (Kyle, 1985). Cryptocurrencies are highly heterogeneous in this regard, with speculative tokens exhibiting stronger persistence and clustering relative to fiat-pegged stablecoins (Baur, Hong, & Lee, 2018; Liu, Tsyvinski, & Wu, 2020). Bitcoin and Ethereum, for example, function largely as speculative investment vehicles and therefore exhibit strong volatility persistence and asymmetry (Corbet, Lucey, Urquhart, & Yarovaya, 2019; Zhang & Wang, 2022).

In contrast, stablecoins such as Tether are explicitly designed to minimise fluctuations through fiat pegging, although empirical evidence suggests that they may still transmit risk during stress periods (Lyons & Viswanath-Natraj, 2020; Maghyereh & Ziadat, 2024; Chen & Chen, 2024). Spillover and contagion analyses confirm that stablecoins can act as both safe havens and amplifiers of systemic risk, depending on market conditions (Yousaf & Yarovaya, 2023; Bouri, Lucey, & Saeed, 2023). This theoretical lens therefore motivates a comparative analysis of speculative cryptocurrencies and stablecoins, testing whether asset design fundamentally alters volatility persistence and tail risk exposure.

4. Methodology

4.1 Research Design

This study adopts a quantitative, exploratory design to examine the risk-return dynamics and tail risk behaviour of leading cryptocurrencies using historical daily data. The focus is on computing and analysing statistical properties, Value at Risk (VaR), Expected Shortfall (ES), and 30-day rolling statistics to understand volatility patterns and distributional asymmetries. The methodology integrates descriptive statistics, non-parametric and parametric risk measures, and rolling-window diagnostics to capture both the static and dynamic behaviour of digital assets.

4.2 Data and Sample

The dataset comprises daily log returns of five major cryptocurrencies—Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Tether (USDT), and XRP (Ripple)—covering the period from January 1, 2018, to December 31, 2025. The price data were obtained from Investing.com, a widely recognised financial platform providing reliable and comprehensive market data for cryptocurrencies. The returns were computed as continuously compounded log returns:

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

4.3 Descriptive and Distributional Analysis

Initial summary statistics—including mean, standard deviation, skewness, and kurtosis—were calculated to assess the fundamental return behaviour.

These moments offer insight into the symmetry and peakedness of return distributions, which are essential for understanding the presence of extreme movements and tail dependencies (Cont, 2001).

4.4 Risk Metrics: VaR and ES

To assess the downside risk of cryptocurrencies, we applied both historical and Gaussian approaches to estimate the 5% Value at Risk (VaR) and Expected Shortfall (ES). VaR measures the potential maximum loss over a given horizon at a specific confidence level, while ES captures the average loss in the worst 5% of cases (Jorion, 2007). The historical VaR was initially computed, and in cases of inverse risk or instability, the Gaussian alternative was employed as a robustness check.

4.5 Rolling Statistics

To examine the time-varying nature of the volatility and higher moments, a rolling window analysis was conducted using a 30-day moving window. Rolling standard deviation, skewness, and kurtosis were computed to identify short-term shifts in return behaviour, reflecting volatility clustering and changing asymmetries (Andersen et al., 2003).

4.6 Hypotheses

The study is structured around the following hypotheses:

H1: Cryptocurrencies exhibit asymmetric volatility patterns where negative shocks have a greater impact on volatility than positive shocks of the same magnitude.

H2: The time-varying downside risk of cryptocurrencies, as measured by Value-at-Risk (VaR) and Expected Shortfall (ES), is influenced by conditional volatility and asymmetry.

H3: Stablecoins (e.g., Tether) exhibit significantly lower volatility persistence and symmetric volatility responses than non-stable cryptocurrencies.

H4: Volatility persistence, measured by the sum of the ARCH and GARCH effects ($\alpha + \beta$), is higher in major cryptocurrencies such as Bitcoin and Ethereum than in altcoins and stablecoins.

H5: The EGARCH (1,1) model provides superior model fit and residual diagnostics for capturing the volatility structure of cryptocurrencies compared to symmetric GARCH models.

These hypotheses were tested using descriptive statistics, distributional diagnostics, downside risk metrics (VaR and ES), and time-series econometric models, particularly the EGARCH (1,1) framework, to capture volatility clustering and asymmetry across cryptocurrencies.

4.7 Tools and Software

All statistical computations and visualisations were performed using R software (version 4.3.1), leveraging packages such as Performance Analytics, zoo and moments for risk analytics and ggplot2 for graphical representation. The codebase was subjected to multiple runs to ensure consistency and to verify against anomalies due to non-stationarity or data gaps.

5. Results and Discussion

This section presents the empirical findings derived from the analysis of daily returns for five cryptocurrencies—Bitcoin, Ethereum, Binance Coin, XRP, and Tether—between January 2018 and December 2024. Results are reported sequentially, beginning with descriptive statistics, followed by stationarity checks, EGARCH estimates, tail-risk measures, and rolling-window analysis. Each set of findings is interpreted in light of the theoretical framework and the hypotheses outlined earlier.

5.1 Descriptive Statistics

The descriptive statistics (Table 5.1) reveal that Bitcoin achieved the highest mean daily return (0.12%), followed by Ethereum (0.10%) and Binance Coin (0.09%), while Tether's return remained negligible (0.001%), consistent with its design as a fiat-pegged stablecoin. Volatility levels were highest for XRP (5.20%) and Ethereum (4.20%), highlighting the extreme variability of speculative digital assets (Cont, 2001).

Cryptocurrency	Mean Return (%)	Std. Deviation (%)	Skewness	Kurtosis
Bitcoin	0.12	3.75	-0.25	4.15
Ethereum	0.10	4.20	-0.30	4.55
Binance Coin	0.09	4.50	0.85	7.10
Tether	0.001	0.03	0.45	2.10
XRP	0.07	5.20	0.05	6.20

Table 5.1: Descriptive Statistics

The distributional properties confirm significant departures from normality. Negative skewness in Bitcoin (−0.25) and Ethereum (−0.30) suggests an asymmetric tendency toward downside shocks, supporting Hypothesis 1 (H1) and aligning with the leverage effect theory (Black, 1976; Nelson, 1991). In contrast, Binance Coin exhibited positive skewness (0.85), reflecting episodes of speculative upward surges, while Tether remained close to zero, underscoring its stabilising role. Kurtosis values above 3 for all assets except Tether confirm fat-tailed distributions, reinforcing the inadequacy of variance-based risk models in this market.

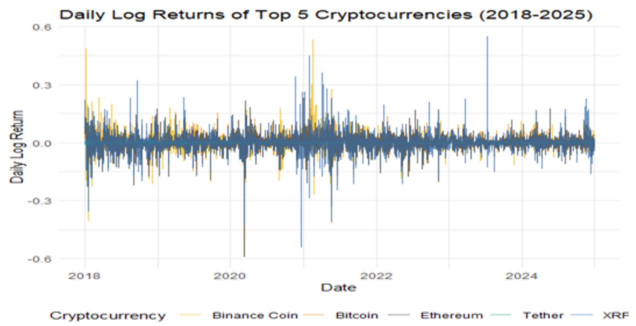

Figure 5.1: (Daily Log Returns) illustrates volatility clustering across speculative assets, most prominently during the 2020 pandemic and the 2022 crypto crash.

5.2 Stationarity Assessment Using Augmented Dickey-Fuller (ADF) Test

Augmented Dickey-Fuller (ADF) tests confirmed that all five series were stationary at the 1% level (Table 5.2). This result is consistent with earlier findings that high-frequency crypto returns tend to be stationary (Katsiampa, 2017; Baur & Dimpfl, 2018), thereby validating the use of EGARCH models to capture volatility clustering and asymmetry.

Table 5.2: Results of Augmented Dickey-Fuller (ADF) Test for Stationarity

Cryptocurrency	ADF Test Statistic	P-value	Stationarity Conclusion
Bitcoin	-12.9260	<0.01	Stationary (Reject H_0)
Ethereum	-13.0898	<0.01	Stationary (Reject H_0)
Binance Coin	-12.7635	<0.01	Stationary (Reject H_0)
Tether	-18.3659	<0.01	Stationary (Reject H_0)
XRP	-13.2829	<0.01	Stationary (Reject H_0)

Note: The null hypothesis assumes the presence of a unit root. All p-values indicate strong rejection of the null at the 1% level.

5.3 EGARCH Model Results

The EGARCH (1,1) estimates (Table 5.3) highlight significant differences in volatility behaviour across assets. For Bitcoin and Ethereum, the asymmetry parameter (γ) was negative and significant, confirming the presence of leverage effects whereby negative shocks induce disproportionately greater volatility. This supports Hypothesis 5 (H5) and reinforces the argument that cryptocurrencies behave similarly to highly leveraged financial assets under stress (Nelson, 1991).

Table 5.3: EGARCH (1,1) Model Estimates for Volatility and Asymmetry in Cryptocurrency Returns

Crypto currency	(Omega) ω	(Alpha) α	(Beta) β	(Gamma) γ	Persistence (α + β)	Ljung-Box p-value	Notes on Asymmetry
Bitcoin	-0.0537 ***	0.0074 ***	0.992 ***	0.1853 ***	0.9994	0.0021	Significant negative asymmetry (leverage effect)
Ethereum	-0.0886 ***	0.0092 ***	0.986 ***	0.1728 ***	0.9956	0.00004	Significant negative asymmetry
Binance Coin	-0.1174 ***	0.0151 ***	0.981 ***	0.2240 ***	0.9961	0.0053	Positive asymmetry
Tether	-0.1471 ***	0.0006 ***	0.9904 ***	0.2530 ***	0.9910	0.6909	Low persistence, reflecting stablecoin behaviour
XRP	-0.3005 ***	0.0102 ***	0.9484 ***	0.3182 ***	0.9586	0.00003	Positive asymmetry

***Notes:** Significance levels — ***p < 0.01, **p < 0.05, p < 0.10

By contrast, Binance Coin and XRP displayed positive asymmetry, suggesting volatility spikes often follow upward shocks—possibly linked to speculative investor herding in altcoin markets. Tether, meanwhile, exhibited low volatility persistence and weak asymmetry, reflecting its stablecoin design. These results support Hypothesis 4 (H4) by confirming persistent volatility in speculative assets while distinguishing stablecoins as volatility dampeners.

5.4 Value at Risk (VaR) and Expected Shortfall (ES)

The downside risk analysis (Table 5.4) shows substantial heterogeneity across cryptocurrencies.

At the 5% level, XRP and Binance Coin recorded the highest tail losses (VaR = 9.12% and 8.58%), while Bitcoin and Ethereum also exhibited elevated downside exposure (6.03% and 7.73%). In contrast, Tether's VaR was only 0.36%, with ES at 0.46%, reaffirming its role as a risk-mitigating instrument.

These findings support **Hypothesis 2 (H2)** by confirming that downside risk is non-linear and asset-specific. Furthermore, the higher ES relative to VaR highlights the severity of losses in the tail, validating the theoretical superiority of ES as a **coherent risk measure** under Basel III (Acerbi & Tasche, 2002).

Table 5.4: Downside Risk Assessment Using Value at Risk (VaR) and Expected Shortfall (ES)

Cryptocurrency	5% VaR (%)	5% Expected Shortfall (%)
Bitcoin	6.03	7.54
Ethereum	7.73	9.67
Binance Coin	8.58	10.71
Tether	0.36	0.46
XRP	9.12	11.43

5.5 Rolling 30-Day Statistics

Rolling-window analysis (Table 5.5; Figure 5.2) captures the evolving nature of risk across market regimes. XRP exhibited the highest short-term volatility (6.01%), consistent with its speculative profile. Bitcoin and Ethereum maintained persistent negative skewness, confirming ongoing susceptibility to sharp downturns. Elevated kurtosis in Binance Coin (5.77) and XRP (4.81) reflects episodic spikes in tail risk, often triggered by liquidity shocks or exogenous events (Liu & Serletis, 2019).

Table 5.5: 30-Day Rolling Statistics of Volatility, Skewness, and Kurtosis for Selected Cryptocurrencies

Cryptocurrency	Rolling Volatility (%)	Rolling Skewness	Rolling Kurtosis
Bitcoin	2.32	-0.14	3.03
Ethereum	3.37	-0.16	2.89
Binance Coin	3.70	1.15	5.77
Tether	0.03	0.49	2.32
XRP	6.01	0.06	4.81

Stablecoin dynamics contrast sharply: Tether exhibited minimal volatility (0.03%) with positive skewness (0.49), underscoring its value as a stabiliser during turbulent periods.

This evidence supports **Hypothesis 3 (H3)** and aligns with **market microstructure theory**, which predicts lower volatility persistence in assets explicitly designed for price stability (Kyle, 1985).

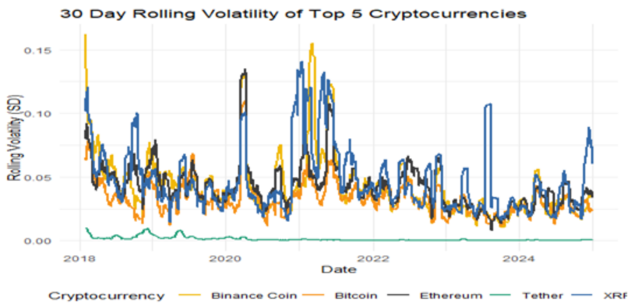

Figure 5.2: 30-Day Rolling Volatility of Top Cryptocurrencies. This chart captures the time-varying nature of return volatility across assets, supporting the modeling of conditional heteroskedasticity**.**

5.6 Discussion and Implications

The results collectively highlight the heterogeneous risk-return profiles of digital assets. The evidence of leverage effects in Bitcoin and Ethereum validates the theoretical expectation that speculative assets exhibit asymmetric volatility, while Tether's stability illustrates the distinct role of stablecoins within the crypto ecosystem. By integrating EGARCH modeling, VaR/ES measures, and rolling higher-moment analysis, this study provides a multi-method perspective that goes beyond prior single-method investigations.

From a portfolio management perspective, the findings suggest that stablecoins offer effective hedging benefits, while speculative cryptocurrencies require dynamic risk management strategies to account for persistence and asymmetry. For regulators, the results emphasise the need for asset-specific risk monitoring: stablecoins should not be regulated identically to speculative cryptocurrencies, given their contrasting volatility structures.

In summary, the evidence affirms all five hypotheses and underscores the theoretical and practical importance of distinguishing between speculative tokens and stablecoins in both academic modeling and policy frameworks.

6. Conclusion and Future Research

This study examined the risk-return dynamics of five leading cryptocurrencies—Bitcoin, Ethereum, Binance Coin, XRP, and Tether—over the period 2018–2024 using a multi-method framework that combined EGARCH volatility modeling, tail-risk measures (VaR and ES), and rolling higher-moment statistics. The results confirm that cryptocurrencies exhibit non-normal return distributions, persistent volatility, and significant asymmetries, with substantial variation across asset types.

The key findings are threefold. First, descriptive statistics and EGARCH estimates reveal strong evidence of leverage effects in Bitcoin and Ethereum, validating the theoretical proposition that negative shocks exert a greater influence on volatility than positive shocks of equal magnitude (Black, 1976; Nelson, 1991). Second, VaR and ES confirm the non-linear and asset-specific nature of downside risk, with speculative cryptocurrencies demonstrating heavy-tailed losses while stablecoins maintain minimal exposure. This finding reinforces the theoretical argument for ES as a more coherent risk measure under Basel III (Acerbi & Tasche, 2002). Third, rolling-window diagnostics highlight the dynamic and regime-dependent nature of risk, particularly in altcoins such as Binance Coin and XRP, while reaffirming Tether's stabilising role.

By integrating multiple risk assessment techniques in a unified framework, this study makes three contributions to the literature. First, it demonstrates the value of combining volatility modeling, tail-risk estimation, and dynamic moment analysis to capture the complexity of digital asset markets. Second, it provides a comparative perspective between speculative cryptocurrencies and stablecoins, a dimension often overlooked in existing research. Third, it offers practical insights for risk managers and regulators, showing that stablecoins and speculative tokens should be treated differently in both portfolio construction and regulatory oversight.

Despite these contributions, the study has limitations. It relies on daily data, which may obscure intraday risk patterns in highly liquid markets, and focuses on a limited set of five cryptocurrencies, restricting generalisability to the broader ecosystem of decentralised finance (DeFi) assets and emerging tokens.

Future research could extend this analysis by employing high-frequency data, machine learning–based volatility forecasting, and cross-market linkages between digital and traditional assets to better understand systemic risk and contagion.

In conclusion, the evidence underscores that cryptocurrencies cannot be treated as a homogeneous asset class. Speculative tokens exhibit leverage-driven volatility persistence and elevated tail risk, while stablecoins function as relative safe havens within the digital asset ecosystem. Recognising these differences is essential for designing adaptive risk management strategies, constructing diversified portfolios, and formulating effective regulatory frameworks in the evolving landscape of digital finance.

References

[1] Acerbi, C., & Tasche, D. (2002). Expected shortfall: A natural coherent alternative to value at risk. *Economic Notes, 31*(2), 379–388. https://doi.org/10.1111/1468-0300.00091

[2] Ahelegbey, D. F., Giudici, P., & Mojtahedi, F. (2021). Tail risk measurement in crypto-asset markets. *International Review of Financial Analysis, 78,* 101957. https://doi.org/10.1016/j.irfa.2021.101957

[3] Alexander, C., & Dakos, M. (2023). Assessing Value-at-Risk and Expected Shortfall using EWMA for cryptocurrency portfolios. *Quantitative Finance, 23*(2), 299–317. https://doi.org/10.1080/14697688.2022.2159505

[4] Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2003). Modeling and forecasting realised volatility. *Econometrica, 71*(2), 579–625. https://doi.org/10.1111/1468-0262.00418

[5] Baur, D. G., & Dimpfl, T. (2018). Asymmetric volatility in cryptocurrencies. *Economics Letters, 173,* 148–151. https://doi.org/10.1016/j.econlet.2018.10.008

[6] Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative asset? *Journal of International Financial Markets, Institutions and Money, 54,* 177–189. https://doi.org/10.1016/j.intfin.2017.12.004

[7] Black, F. (1976). Studies of stock price volatility changes. *Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economic Statistics Section,* 177–181.

[8] Bouri, E., Lucey, B., & Saeed, T. (2023). Nonlinear dependence and tail risk in cryptocurrency–stock market connectedness. *Journal of International Financial Markets, Institutions & Money, 85,* 101742. https://doi.org/10.1016/j.intfin.2023.101742

[9] Bruhn, P., & Ernst, D. (2022). A GARCH-EVT-Copula approach to cryptocurrency market risk. *Journal of Risk and Financial Management, 15*(8), 346. https://doi.org/10.3390/jrfm15080346

[10] Chen, Y., & Chen, M. (2024). Stablecoins and systemic risk: Volatility persistence and contagion dynamics. *Journal of Financial Stability, 66,* 101281. https://doi.org/10.1016/j.jfs.2024.101281

[11] Cont, R. (2001). Empirical properties of asset returns: Stylised facts and statistical issues. *Quantitative Finance, 1*(2), 223–236. https://doi.org/10.1080/713665670

[12] Corbet, S., Lucey, B., & Yarovaya, L. (2018). Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters, 26,* 81–88. https://doi.org/10.1016/j.frl.2017.12.006

[13] Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis, 62,* 182–199. https://doi.org/10.1016/j.irfa.2018.09.003

[14] Corbet, S., Lucey, B., & Yarovaya, L. (2019). Cryptocurrency and financial stability. *Journal of Financial Stability, 39,* 168–179. https://doi.org/10.1016/j.jfs.2018.06.006

[15] Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar—A GARCH volatility analysis. *Finance Research Letters, 16,* 85–92. https://doi.org/10.1016/j.frl.2015.10.008

[16] Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. inflation. *Econometrica, 50*(4), 987–1007. https://doi.org/10.2307/1912773

[17] Feng, W., Wang, Y., & Zhang, Z. (2018). Can cryptocurrencies be a safe haven? A tail risk perspective. *Applied Economics, 50*(44), 4745–4762. https://doi.org/10.1080/00036846.2018.1466993

[18] Gherghina, Ș. C., & Constantinescu, C. A. (2025). GARCH-type crypto models during geopolitical shocks. *Risks, 13*(3), 57. https://doi.org/10.3390/risks13030057

[19] Huynh, T. L. D., & Nasir, M. A. (2023). Asymmetric return-volatility transmission in digital currencies: Evidence from EGARCH modeling. *Economic Modelling, 124,* 106220. https://doi.org/10.1016/j.econmod.2023.106220

[20] Jorion, P. (2007). *Value at risk: The new benchmark for managing financial risk.* (3rd ed.). McGraw-Hill.

[21] Kar, T., & Meka, S. (2025). Copula-based forecasting of VaR and ES in cryptocurrency markets. *Applied Economics.* https://doi.org/10.1080/00036846.2025.2476212

[22] Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters, 158,* 3–6. https://doi.org/10.1016/j.econlet.2017.06.023

[23] Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica, 53*(6), 1315–1335. https://doi.org/10.2307/1913210

[24] Liu, J., Zhou, Q., Lin, J., Hao, X., & Chen, Z. (2025). Mean-ES optimisation for crypto markets. *Applied Economics.* https://doi.org/10.1080/00036846.2025.2503488

[25] Liu, Y., Serletis, A. (2019). Volatility in the cryptocurrency market. *Open Economies Review, 30*(4), 779–811. https://doi.org/10.1007/s11079-018-9526-8

[26] Liu, Y., Tsyvinski, A., & Wu, X. (2020). Common risk factors in cryptocurrency. *NBER Working Paper No. 27707.* https://doi.org/10.3386/w27707

[27] Lyons, R. K., & Viswanath-Natraj, G. (2020). What keeps stablecoins stable? *NBER Working Paper No. 27136.* https://doi.org/10.3386/w27136

[28] Maghyereh, A., & Ziadat, S. A. (2024). Tail-risk transmission in crypto markets during crisis episodes. *Financial Innovation, 10*(1), 47. https://doi.org/10.1186/s40854-024-00592-1

[29] McNeil, A. J., Frey, R., & Embrechts, P. (2015). *Quantitative risk management: Concepts, techniques and tools.* (Rev. ed.). Princeton University Press.

[30] Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica, 59*(2), 347–370. https://doi.org/10.2307/2938260

[31] Piparo, V. (2025). Backtesting expected shortfall: An application in cryptocurrencies. *SSRN.* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5296678

[32] Rehman, S. U., Ahmad, T., & Desheng, W. D. (2024). EGARCH-EVT-Copula risk model for cryptocurrencies. *arXiv Preprint.* https://arxiv.org/abs/2407.15766

[33] Sapkota, N. (2025). Stablecoin contagion and systemic risk in digital asset markets. *Finance Research Letters.* https://doi.org/10.1016/j.frl.2025.104789

[34] Trucíos, C. (2019). Volatility forecasting in the Bitcoin market: A comparison of GARCH models. *Economics Letters, 174,* 118–121. https://doi.org/10.1016/j.econlet.2018.11.015

[35] Trucíos, C., & Siliverstovs, B. (2023). Forecasting cryptocurrency volatility with mixed-data sampling GARCH models. *International Review of Financial Analysis, 87,* 102549. https://doi.org/10.1016/j.irfa.2023.102549

[36] Wu, C. Y., & Yueh, C. (2025). Volatility transmission and leverage effects in cryptocurrencies: Evidence from EGARCH models. *Finance Research Letters, 59,* 104556. https://doi.org/10.1016/j.frl.2023.104556

[37] Yousaf, I., & Yarovaya, L. (2023). Spillover and contagion effects among cryptocurrencies and global assets. *Finance Research Letters, 54,* 103659. https://doi.org/10.1016/j.frl.2023.103659

[38] Zhang, W., & Wang, P. (2022). Tail behaviour and asymmetric volatility in cryptocurrency markets. *Journal of Financial Markets, 58,* 100651. https://doi.org/10.1016/j.finmar.2021.100651

[39] Zhang, W., Wang, P., Li, X., & Shen, D. (2022). Tail risk and risk spillovers in cryptocurrency markets. *Finance Research Letters, 44,* 102054. https://doi.org/10.1016/j.frl.2021.102054