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Value at Risk Performance and Backtesting of Cryptocurrencies

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ABSTRACT

Cryptocurrency has gained a lot of attention in recent times due to its high-risk high-return potential among the investor community. Therefore, cryptocurrency is being scrutinized heavily for its potential as a diversifying asset class. This study examines the performance of Value at Risk (VaR) measures in the context of the top twelve cryptocurrencies by market capitalization over the period from 2018 to 2023, by employing both historical and normal distribution-based approaches. By analyzing descriptive statistics such as means, variances, skewness, kurtosis, and correlation coefficients, we aim to understand the statistical properties of these cryptocurrencies. We compute Historical VaR (HVaR) and Normal VaR (NVaR) at various confidence levels to evaluate the tail risk associated with each cryptocurrency. Our findings reveal that Dogecoin, Cardano, and Chainlink exhibit the highest levels of risk, while stablecoins such as USDT and USDC show minimal risk exposure. The research highlights substantial limitations in the VaR models, with backtesting results from Kupiec's Proportion of Failures (POF) test, Christoffersen's Independence Test, and the Dynamic Quantile (DQ) test indicating significant inadequacies in capturing risk and predicting exceptions. Notably, both HVaR and NVaR models fail to account effectively for clustering of violations and extreme market conditions. We emphasize the importance of continuous monitoring of statistical indicators and correlations to navigate the volatile cryptocurrency market effectively. This study enhances the understanding of VaR performance and risk management in cryptocurrencies, offering valuable insights for both investors and researchers.

Keywords: *Value at Risk, Cryptocurrencies, Risk Management, Kupiec's POF-test, Christoffersen's Independence Test, Dynamic Quantile (DQ) test*

1. INTRODUCTION

The evolving role of cryptocurrencies in global financial markets has renewed focus on their performance and risk assessment has become even more relevant due to their dynamic price fluctuations (Kapar & Olmo, 2021; Rajharia & Kaushik, 2023). Cryptocurrencies are known for their extreme volatility (Wang et al., 2016) and unique risk profiles, which necessitate a thorough understanding to develop effective risk management strategies. Additionally, the increasing adoption of cryptocurrencies

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(Kaul, 2021) and their potential for regulatory scrutiny, market manipulation, and technological risks underscore the need for robust research to navigate the uncertainties and safeguard investments. Since Value at Risk (VaR) is the most commonly used tool to assess market risk, our research provides valuable insights into potential losses and risk exposure profile for cryptocurrencies, enabling investors and portfolio managers to make informed decisions.

The literature identifies several variables that significantly affect the performance of cryptocurrencies. Key factors include price determinants such as futures prices (Rajharia & Kaushik, 2023; Kapar & Olmo, 2021), market inefficiencies, trading volumes (Wang et al., 2016; Kristoufek, 2013) and correlations with traditional assets (Corbet et al., 2018; Symitsi & Chalvatzis, 2019) and stock indices. Investor sentiment, as influenced by attention-driven trading and search volumes from platforms like Google Trends and Wikipedia (Aslanidis et al., 2022; Kristoufek, 2013), also plays a crucial role. Moreover, the interconnectedness and spillover effects among cryptocurrencies (Zhang et al., 2021; Yi et al., 2018), regulatory changes, and macroeconomic variables like oil prices further impact their performance. These determinants collectively contribute to the volatility and risk associated with cryptocurrencies, necessitating comprehensive analysis to understand their VaR performance accurately.

The research on Value at Risk (VaR) performance of cryptocurrencies contributes significantly to the field by addressing several gaps in current literature. One primary contribution lies in its comprehensive analysis of VaR across twelve major cryptocurrencies—Bitcoin, Ethereum, Tether (USDT), Binance Coin (BNB), XRP, Solana, USD Coin (USDC), Cardano, Dogecoin, Avalanche, TRON and Chainlink, over the period from 2018 to 2023. Existing studies often focus on single cryptocurrencies or broader financial markets, neglecting the nuanced risk profiles of individual digital assets. This research fills this gap by providing detailed insights into the VaR characteristics of each cryptocurrency, considering their unique market behaviors, volatility patterns and interrelationships. By utilizing both Historical VaR (HVaR) and Normal VaR (NVaR) methodologies, the study not only quantifies potential downside risks at different confidence levels but also evaluates the impact of non-normal return distributions on risk assessment accuracy. This research thus offers a novel approach to understanding and managing risk in cryptocurrency markets, addressing a critical gap in the literature by providing actionable insights for investors, regulators, and financial institutions navigating the complexities of digital asset investments amidst evolving market dynamics and regulatory landscapes.

The primary stakeholders of this research include investors, portfolio managers, financial institutions, and regulators. For investors and portfolio managers, the study provides actionable insights into the risk profiles and VaR performance of various cryptocurrencies, aiding in more informed investment decisions, enabling them to assess and manage their risk exposure effectively. Financial institutions can leverage these findings to enhance their risk assessment frameworks and compliance with regulatory requirements related to digital assets. Regulators can benefit from the research by gaining a deeper understanding of the risk dynamics in cryptocurrency markets, which can inform the development of more robust regulatory guidelines to ensure market stability and investor protection. Ultimately, this research aims to enhance market transparency, investor protection, and overall market resilience in the rapidly evolving landscape of cryptocurrencies.

Apart from the introduction section, the paper is structured into four key sections: Section 2 reviews literature on cryptocurrency performance determinants and identifies gaps in VaR analysis. Section 3 details the study's data sources, VaR models and backtesting methods. Section 4 presents descriptive statistics, correlation plots, VaR calculations at various confidence levels and backtesting results to elucidate cryptocurrency risk profiles. Section 5 concludes with a discussion of the results' implications, proposes risk management strategies, and outlines limitations and future research directions.

2. LITERATURE REVIEW

Cryptocurrencies have emerged as a pivotal area of study within financial markets, driven by their dynamic price fluctuations and evolving role in global economies. The volatility and risk associated with cryptocurrencies have gained significant scholarly attention, particularly in understanding their VaR performance. Studies have analyzed price fluctuations across multiple cryptocurrencies, identifying cointegration among them, suggesting long-term statistical relationships and significant correlations, particularly with Bitcoin (Rajharia & Kaushik, 2023). Post-industrial economic development has seen cryptocurrencies play a disruptive role, noted by (Aslanidis et al., 2022), who identified a bilateral relationship between cryptocurrency returns and Google Trends data. Various determinants influencing price movements, beginning with (Kapar & Olmo, 2021) investigation into Bitcoin pricing mechanisms, emphasizing the impact of futures prices on spot market valuation. (Subramaniam & Chakraborty, 2020) explored attention-driven trading impacts on major cryptocurrencies like Bitcoin and Ethereum, suggesting market dynamics are influenced by investor sentiment. (Nadarajah & Chu, 2017) highlighted inefficiencies in the Bitcoin market across different time periods. (Wang et al., 2016) studied Bitcoin price volatility in relation to stock indices and trading volumes, revealing transient associations with oil prices and significant impact from stock indices. (Kristoufek, 2013) explored the impact of Google Trends and Wikipedia on cryptocurrency returns, revealing an asymmetrical relationship between search volumes and Bitcoin prices.

The increasing adoption of cryptocurrencies in countries like India (Gkillas et al., 2022) showed less correlation between Bitcoin and crude oil compared to gold. (Zhang et al., 2021) found no convincing proof of Bitcoin causing spillover effects on other assets. (Kaul, 2021) underscores shifting investor preferences towards digital assets, contrasting traditional investments like gold. India's Supreme Court lifting the cryptocurrency ban led to a surge in investments, with over $1 billion invested by approximately 15 million Indians (Chauhan, 2022). In contrast, (Susilo et al., 2020) indicated that portfolios with multiple cryptocurrencies could effectively hedge equities and improve the Sharpe ratio. (Symitsi & Chalvatzis, 2019) examined Bitcoin's correlation with traditional assets, emphasizing its potential in portfolio diversification but noting bubble characteristics. Despite their growth, concerns persist regarding regulatory scrutiny, illicit use potential, and vulnerability to cybercrime (Feng et al., 2018). Cryptocurrency's emergence as an asset class has attracted attention, with studies like (Corbet et al., 2018) noting distinct advantages and risks compared to traditional assets. (Yi et al., 2018) explored volatility and spillover effects among cryptocurrencies, revealing interconnectedness and shock propagation across the network.

(Qadan et al., 2022) found asset pricing efficiency in cryptocurrencies, advocating for portfolio diversification. A study (Naeem et al., 2021) on asymmetric efficiency using MF-DFA suggested that COVID-19 negatively impacted the Bitcoin market's operation. Efficiency within the cryptocurrency realm was scrutinized by (Khuntia & Pattanayak, 2018), who applied the Adaptive Market Hypothesis to Bitcoin market returns, suggesting dynamic efficiency. Research in (Brauneis & Mestel, 2018) linked cryptocurrency predictability with liquidity, showing decreased predictability with higher liquidity. (Zumbach, 2007) introduces a new methodology for market risk evaluation by integrating advanced knowledge of financial time series, offering a conceptual comparison of performance measures across major risk methodologies. (Longerstaey & Zangari, 1996) document provides a comprehensive overview of RiskMetricTM framework, a standardized set of techniques and data designed to enhance market risk transparency and establish a benchmark for risk measurement across diverse financial instruments and derivatives.

Despite extensive research into cryptocurrency price fluctuations and their determinants (Rajharia & Kaushik, 2023; Kapar & Olmo, 2021), there remains a gap in understanding how these factors specifically impact Value at Risk (VaR) performance across different cryptocurrencies. While existing literature examines factors influencing price volatility and market efficiency, few studies directly address how these factors contribute to the accurate measurement and prediction of VaR in cryptocurrency markets. This research aims to address, understanding VaR performance is crucial for risk management strategies in cryptocurrency investments, necessitating further research to develop robust models that account for the unique characteristics and interconnectedness of cryptocurrencies in measuring and managing risk effectively.

3. DATA AND METHODOLOGY

This study comprehensively examines daily data of major cryptocurrencies i.e. Bitcoin, Ethereum, Tether USDT, Binance Coin, XRP, Solana, USD Coin, Cardano, Dogecoin, Avalanche, TRON, Chainlink from 2018 to 2023. It analyzes their risk using historical and normal VaR models, explores their statistical properties i.e. mean, variance, skewness, and kurtosis and evaluates correlations between them. Solana and Avalanche were excluded from the data analysis due to either data integrity issues or the timing of their issuance, which were pivotal factors in determining the cryptocurrencies to be included. We proceed with 10 cryptocurrencies for further analysis. The data is sourced from CoinMarketCap.

3.1 Historical Value at Risk (HVaR):

It is a non-parametric method used to estimate the potential loss in value of an asset or portfolio over a specified time period, based on historical price movements. It relies on the empirical distribution of past returns to determine the VaR at a given confidence level. HVaR does not assume a specific distribution for returns; instead, it uses actual historical data to model risk.

$$HVaR_{\propto} = -Quantile_{1-\propto}(R) \tag{1}$$

Where: α is the confidence level (e.g., 95%, 99%); $-Quantile_{1-\propto}(R)$is the (1-α)th percentile of the historical return distribution R.

3.2 Normal Value at Risk (NVaR):

It is a parametric approach that estimates the potential loss in value of an asset or portfolio over a specified time period, assuming that returns follow a normal distribution. It calculates VaR using the mean and standard deviation of returns.

$$NVaR_{\propto} = -(\mu + z_{\alpha}.\sigma) \tag{2}$$

Where: μ is the mean of the returns; σ is the standard deviation of the returns; $z_{\propto}$ is the z-score corresponding to the α confidence level from the standard normal distribution.

3.3 Performance Measurement of VaR:

We utilize backtesting techniques to evaluate the effectiveness of each VaR model in assessing the risk associated with cryptocurrencies. A straightforward approach to gauge the performance of these VaR models involves applying the methodologies established by (Kupiec, 1995) and (Christoffersen, 1998), which have been extensively utilized in prior research.

3.3.1 Kupiec's Proportion of Failures (POF) test:

It is a widely recognized method for backtesting VaR models (Kupiec, 1995). This test assesses the unconditional coverage property of the VaR model by examining the failure rate, i.e., the proportion of times the actual loss exceeds the VaR estimate. The test statistic, known as the Likelihood Ratio (LR) for the POF test, is calculated as follows

$$LR_{POF} = -2\,ln\left(\frac{(1-p)^{n-x}\,p^{x}}{\left(1-\frac{x}{n}\right)^{n-x}\,\left(\frac{x}{n}\right)^{x}}\right) \tag{3}$$

where x is the number of exceptions, n is the total number of observations, and p is the expected probability of failure. The test statistic follows a Chi-squared distribution with one degree of freedom. If the LR_{POF} value is below the critical value, the model passes the backtest. Higher values indicate an inaccurate model, leading to its rejection.

3.3.2 Christoffersen's Independence Test:

While Kupiec's POF test evaluates the overall failure rate, it does not consider the independence of exceptions. (Christoffersen, 1998) Christoffersen's Independence Test addresses this by examining whether VaR exceptions are clustered or independently distributed over time. This test, also known as the Markov test, assesses the independence property by analyzing sequences of exceptions. The test statistic for the independence test is calculated as follows:

$$\mathrm{LR}_{\mathrm{Ind}} = -2\ln\left(\frac{(1-\pi)^{\mathrm{n}_{00}+\mathrm{n}_{10}}\ \pi^{\mathrm{n}_{01}+\mathrm{n}_{11}}}{(1-\pi)^{\mathrm{n}_{00}}\ \pi_0^{\mathrm{n}_{01}}\ (1-\pi)^{\mathrm{n}_{10}}\ \pi_1^{\mathrm{n}_{11}}}\right) \tag{4}$$

where n_{00} is the number of days with no exception followed by no exception, n_{01} is the number of days with no exception followed by an exception, n_{10} is the number of days with an exception followed by no exception, and n_{11} is the number of days with an exception followed by an exception. The probabilities π_0, π_1, and π are defined as:

$$\pi_0 = \frac{n_{01}}{n_{00}+n_{01}}, \qquad \pi_0 = \frac{n_{11}}{n_{10}+n_{11}}, \qquad \pi = \frac{n_{01}+n_{11}}{n_{00}+n_{01}+n_{10}+n_{11}}$$

Under the null hypothesis, the test statistic follows a Chi-squared distribution with one degree of freedom. A model passes the independence test if exceptions are independently distributed across days, indicated by equal probabilities ($\pi = \pi_0 = \pi_1$).

3.3.3 Dynamic Quantile:

Typical VaR tests often fail to account for the clustering of violations, meaning that while the overall average of violations may appear acceptable, these violations may still exhibit patterns or clustering over time. This can happen even if the average proportion of violations does not significantly deviate from the expected level of (where $\alpha = 1 - \mathrm{VaR}$).

To address this issue, the Dynamic Conditional Quantile (DQ) test is used. This test evaluates whether the conditional expectation of violations is zero, which implies that the violations are uncorrelated with their past values and other lagged variables, such as past returns r_t, squared returns r_t^2, or one-step-ahead forecast VaR. The DQ test involves computing the statistic:

$$DQ = \frac{Hit^T X (X^T X)^{-1} X^T Hit}{\alpha(1-\alpha)} \tag{5}$$

Where, X is the matrix of explanatory variables (e.g., past returns and their squares). $H_{it}$is the vector containing $H_{it}(\alpha)$, which represents the exceedances or violations. Under the null hypothesis, (Engle & Manganelli, 2004) demonstrate that this statistic DQ follows a chi-squared distribution with q degrees of freedom, where q is the rank of the matrix X.

4. DATA ANALYSIS

4.1 Cryptocurrency prices and returns charts (Annexure I):

The figure 1 shows the comparison between cryptocurrency prices. We observe that ETH, BNB, DOGE, and ADA show very low volumes / capitalization during the Covid period except that DOGE showcases a small spike whereas USDC volumes died in the later part of the analysis period. Figure 2 compares the cryptocurrency returns. We note that the all the cryptocurrency returns show spike during the Covid period. Also, the volatility levels are high for almost all the cryptocurrencies throughout the analysis period (and exceptionally high during the Covid period) except for USDC, DOGE, and later part of USDT.

4.2 Descriptive statistics (Annexure II):

The descriptive statistics in Annexure II reveals significant insights into the statistical properties and interrelationships among major cryptocurrencies. Across the analyzed assets in Table 1, the mean represents the average daily return for each cryptocurrency. Positive means for BTC, ETH, BNB, ADA, DOGE, and TRX indicate average gains, while near-zero means for USDT, XRP, and USDC suggest almost no average daily gains or losses. Variance, which measures the spread of returns around the mean, indicates greater volatility for XRP, ADA, and DOGE (0.024) compared to the minimal fluctuations in USDT and USDC (0.000). Skewness measures the asymmetry of returns, with negative skewness for BTC, ETH, BNB, USDC, ADA, and TRX indicating more frequent small gains but potential for large losses. Positive skewness for USDT (1.097), XRP (0.4695), and DOGE (0.533) suggests frequent small losses but potential for large gains. Excess kurtosis, indicating the likelihood of extreme returns, is very high for USDT (396.769) and DOGE (553.908), suggesting a higher probability of extreme values, while the rest show moderate kurtosis. JB test confirms the results of skewness and kurtosis that the data is not normally distributed. The Jarque-Bera test reveals significant JB statistics (p-value 0.000) for all cryptocurrencies, indicating non-normal return distributions.

Elliott, Rothenberg and Stock (ERS) unit root test is a modification of the augmented Dickey-Fuller (ADF) test and is also called as the ADF-GLS test. The ERS test dominates other unit root tests in terms of power. A unit root test determines whether a time series variable is non-stationary using an autoregressive model. The significant p-value results highlights that the return series for each cryptocurrencies is non-stationary. The Ljung-Box Q-test and Q^2-test checks for the null hypothesis whether the data is independently distributed collectively at the mentioned lag. The highly significant p-values for the Q-test and Q^2-test at 20 lags shows that the return distribution are heavily autocorrelated. Kendall's Tau reveals significant positive correlations among most cryptocurrencies, except for USDT and USDC, which show the least and negative correlations, indicating distinct movement patterns. These insights into statistical properties and interrelationships are crucial for understanding risk profiles and informing investment strategies in cryptocurrency markets.

4.3 Cryptocurrency correlation plot (Annexure III)

Most correlations presented are statistically significant, indicating non-random relationships. Major cryptocurrencies like BTC, ETH, BNB, XRP, ADA, TRX, and LINK exhibit strong positive correlations, suggesting they tend to move together, likely due to similar investor sentiment, market conditions, or usage patterns. In contrast, USDC and DOGE show weak correlations with most other cryptocurrencies, reflecting more independent price movements, especially for USDC as a stablecoin. USDT exhibits slight negative correlations, indicating a weak inverse relationship with other cryptocurrencies. This correlation analysis is vital for portfolio diversification, risk management, and trading strategies. Cryptocurrencies with low or negative correlations can help reduce overall portfolio risk, while high correlations suggest limited diversification benefits.

4.4 VAR calculations

4.4.1 Historical Value at Risk at different confidence levels for the cryptocurrencies (Annexure IV A):

The analysis of Historical Value at Risk (HVaR) across major cryptocurrencies reveals distinct risk profiles based on confidence levels in Table 2. DOGE consistently has the highest values, suggesting it is the most volatile and risky cryptocurrency followed by ADA and LINK. USDT and USDC have the lowest values across all confidence levels, indicating they are the least risky with minimal losses. BTC, ETH, BNB, XRP and

TRX have moderate to high values, indicating varying levels of risk, with ETH showing relatively higher risk compared to BTC and BNB.

4.4.2 Normal Value at Risk at different confidence levels for the cryptocurrencies (Annexure IV B):

The analysis of Normal Value at Risk (HVaR) across major cryptocurrencies reveals distinct risk profiles based on confidence levels in 3. XRP, ADA, DOGE and LINK consistently have the very highest values, suggesting it is a highly volatile and risky cryptocurrency. USDT and USDC have the lowest values across all confidence levels, indicating they are the least risky with minimal losses. BTC, ETH, BNB and TRX have moderate to high values, indicating varying levels of risk, with BNB and TRX showing relatively higher risk compared to BTC and ETH.

4.4.3 Historical value at risk at different confidence levels across time (Annexure V A):

The "Returns" column in Figure 4 depicts daily returns for each cryptocurrency, revealing significant variability and high volatility, especially during market shocks such as the 2020 pandemic. Notable spikes and dips indicate impactful market events. High volatility is particularly evident in all cryptocurrencies except DOGE show more stability. The HVaR values across all confidence levels reflect market volatility, with noticeable spikes during periods of high market stress, such as the COVID-19 pandemic. From 2020 to 2024, a general decline in HVaR values for some cryptocurrencies suggests reduced volatility and potentially more stable market conditions. While most cryptocurrencies exhibit relatively stable HVaR values over time, occasional spikes correspond to market turbulence. Few cryptocurrencies show persistently high HVaR values, indicating ongoing high risk.

4.4.4 Normal value at risk at different confidence levels across time (Annexure V B):

Figure 5 shows that NVaR follows same returns trend as HVaR. From 2020 to 2024, NVaR values for most cryptocurrencies exhibit a declining trend, suggesting reduced volatility and risk over time. During market stress periods, such as the COVID-19 pandemic in early 2020, there are noticeable spikes in NVaR values across all confidence levels, reflecting heightened risk. The general stability of NVaR values indicates effective risk management practices, with occasional spikes marking periods of market turbulence. NVaR, which assumes a normal distribution of returns, offers a distinct perspective on risk compared to Historical VaR, which is based on actual historical data.

4.5 Kupiec's POF-test (Annexure VI A):

Backtest Historical and Normal VaR Kupiec Test p-values (Table 4) results: For Historical and Normal VaR, the p-values of 0.00 indicate for all cryptocurrencies at all confidence levels. This means that both VaR models are not accurately predicting the number of exceptions, suggesting it is not performing well.

4.6 . Christoffersen Independence test (Annexure VI B):

Backtest Historical and Normal VaR Christoffersen Test p-values (Table 5) results: For Historical and Normal VaR Christoffersen, the p-values of 0.00 for all cryptocurrencies at all confidence levels. This indicates that the exceptions are not independently distributed for the normal VaR model either, making it unreliable for these cryptocurrencies at the tested confidence levels.

4.7 Dynamic Quantile (DQ) test (Annexure VI A):

Backtest Historical and Normal VaR Dynamic Quantile Test p-values (Table 6) results: The DQ test assesses whether the violations (or exceedances) of the VaR model are independent and uncorrelated with past values and other explanatory variables. The null hypothesis is that the violations are uncorrelated (i.e., the model is correctly specified).

For Historical and Normal VaR dynamic quantiles, the p-values of 0.00 indicate for all cryptocurrencies at all confidence levels. Both models show significant inadequacies in capturing the risk for most cryptocurrencies, as evidenced by the low p-values. These results suggest that for most cases, the models need improvement to better capture the risk and address the clustering of violations.

5. FINDINGS AND SUGGESTIONS

Our analysis of VaR performance for major cryptocurrencies from 2018 to 2023 highlights significant variations in risk profiles and volatility. Using Historical VaR (HVaR) and Normal VaR (NVaR) methods, we found that DOGE, ADA, and LINK exhibit the highest risk, while stablecoins like USDT and USDC show minimal risk.

The decline in NVaR values from 2020 to 2024 suggests reduced volatility, possibly due to improved market stability.

During market stress periods, such as the COVID-19 pandemic, both HVaR and NVaR values spiked, indicating increased risk. Descriptive statistics reveal non-normal return distributions for most cryptocurrencies. Additionally, the correlation analysis shows strong positive correlations among major cryptocurrencies like BTC, ETH, and BNB, suggesting they tend to move together, influenced by similar market conditions and investor sentiment. Conversely, stablecoins like USDC and USDT exhibit weak or negative correlations with other cryptocurrencies, indicating more independent price movements. Backtesting results, including Kupiec's Proportion of Failures (POF) test, Christoffersen's Independence Test, and the Dynamic Quantile (DQ) test, indicate significant inadequacies in both HVaR and NVaR models. The tests revealed that neither model accurately predicts the number of exceptions or their independence, with low p-values across all tests suggesting a failure to capture the clustering of violations effectively. The failures indicate a lack of reliable risk assessment, as evidenced by the clustering of exceptions and the inability to account for extreme market conditions.

To mitigate potential losses, investors should diversify portfolios, use stop-loss orders, and monitor statistical indicators. Given the limitations of VaR models, caution is advised. Diversification strategies should consider the distinct risk profiles and correlation patterns, particularly the stability provided by stablecoins. Regulatory bodies can use these insights to develop guidelines for market stability. The study emphasizes the need for robust risk management practices and continuous market analysis to navigate the volatile cryptocurrency market effectively.

6. CONCLUSION

Firstly, this research is aimed to evaluate the performance of Value at Risk (VaR) measures for the top twelve cryptocurrencies by market capitalization, employing both Historical VaR (HVaR) and Normal VaR (NVaR) methodologies. Through comprehensive analysis, including descriptive statistics, correlation assessments, and backtesting using Kupiec's Proportion of Failures (POF) test, Christoffersen's Independence Test, and the Dynamic Quantile (DQ) test, the study sought to provide insights into the risk profiles of these cryptocurrencies and the accuracy of VaR models.

Secondly, our findings reveal substantial variations in risk profiles among the analyzed cryptocurrencies. Specifically, DOGE, ADA, and LINK exhibit the highest levels of risk, whereas stablecoins like USDT and USDC show minimal risk exposure. Both HVaR and NVaR models demonstrated significant limitations, with backtesting results indicating inadequate performance in predicting and capturing risk accurately. The clustering of exceptions and non-normal distribution of returns highlight the models' deficiencies in accounting for extreme market conditions and the dynamic nature of cryptocurrency volatility.

Lastly, to address these limitations, we suggest implementing robust risk management strategies such as portfolio diversification, stop-loss orders, and continuous monitoring of statistical indicators. Investors and financial institutions should exercise caution and consider the distinct risk profiles of cryptocurrencies when developing investment strategies. Future research should focus on refining VaR models to better capture the complexities and unique characteristics of cryptocurrency markets, exploring alternative risk measurement techniques such as Extreme Value Theory (EVT) and Copula-based VaR, and examining the impact of emerging market trends and regulatory changes on cryptocurrency risk dynamics.

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ANNEXURE

Annexure I A:

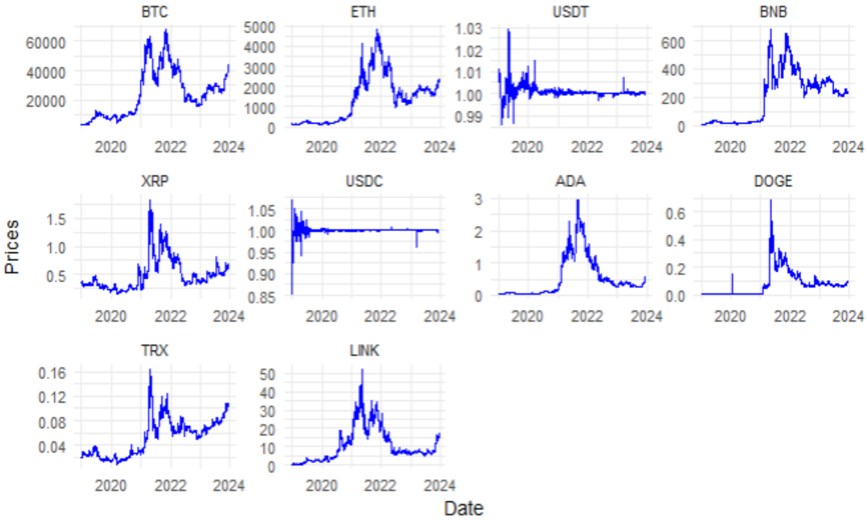

Figure 1: Cryptocurrency Price Charts

Annexure I B:

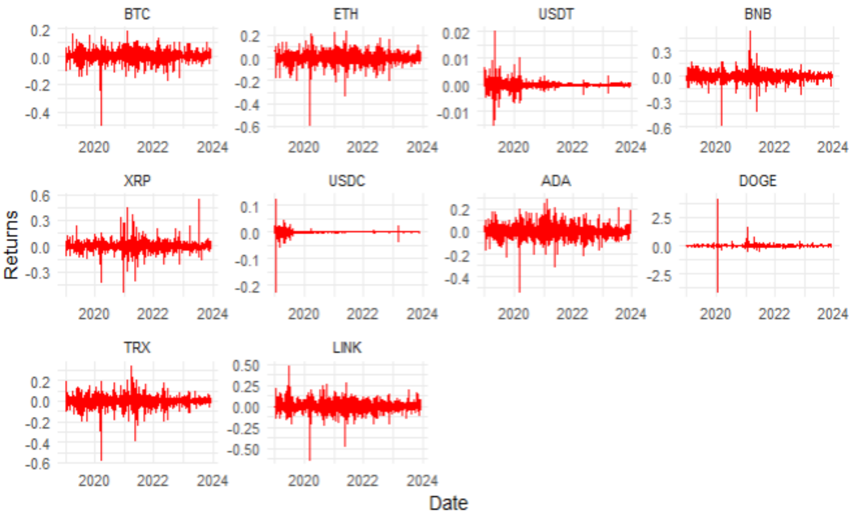

Figure 2: Cryptocurrency Returns Charts

Annexure II *Table 1: Descriptive Statistics Table*

Statistics	BTC	ETH	USDT	BNB	XRP	USDC	ADA	DOGE	TRX	LINK
Mean	0	0	0	0.00*	0	0	0	0	0	0
	-0.11	-0.15	-0.99	-0.08	-0.79	-0.96	-0.24	-0.57	-0.4	-0.14
Variance	0	0	0	0	0	0	0	0.02	0	0
Skewness	-1.42***	-1.38***	1.10***	-0.42***	0.47***	-10.53***	-0.32***	0.53***	-0.98***	-0.43***
	0	0	0	0	0	0	0	0	0	0
Ex.Kurtosis	22.17***	17.89***	45.44***	23.38***	20.77***	396.77***	8.66***	553.91***	16.19***	10.98***
	0	0	0	0	0	0	0	0	0	0
JB	37572.40***	24639.32***	155673.10***	41149.48***	32503.78***	11873071.47***	5665.26***	23075070.29***	20003.81***	9131.28***
	0	0	0	0	0	0	0	0	0	0
ERS	-9.17	-5.95	-1.47	-12.46	-10.09	-5.46	-9.76	-22.49	-10.44	-18.72
	0	0	-0.14	0	0	0	0	0	0	0
Q.20.	20.99***	41.27***	293.06***	50.17***	15.43*	459.18***	32.18***	283.36***	45.83***	29.19***
	-0.01	0	0	0	-0.1	0	0	0	0	0
Q2.20.	27.21***	58.12***	1475.28***	169.06***	78.44***	208.70***	100.08***	441.73***	86.96***	77.89***
	0	0	0	0	0	0	0	0	0	0
kendall	BTC	ETH	USDT	BNB	XRP	USDC	ADA	DOGE	TRX	LINK
BTC	1.00***	0.64***	0.03**	0.51***	0.52***	-0.13***	0.52***	0.47***	0.47***	0.44***
ETH	0.64***	1.00***	0.04**	0.54***	0.56***	-0.10***	0.58***	0.47***	0.52***	0.51***
USDT	0.03**	0.04**	1.00***	0.01	0.01	-0.27***	0.03**	0.02	0.03	0.01
BNB	0.51***	0.54***	0.01	1.00***	0.46***	-0.08***	0.50***	0.41***	0.45***	0.43***
RP	0.52***	0.56***	0.01	0.46***	1.00***	-0.09***	0.55***	0.45***	0.51***	0.45***
USDC	-0.13***	-0.10***	-0.27***	-0.08***	-0.09***	1.00***	-0.11***	-0.08***	-0.10***	-0.10***
ADA	0.52***	0.58***	0.03**	0.50***	0.55***	-0.11***	1.00***	0.46***	0.51***	0.49***
DOGE	0.47***	0.47***	0.02	0.41***	0.45***	-0.08***	0.46***	1.00***	0.39***	0.40***
TRX	0.47***	0.52***	0.03	0.45***	0.51***	-0.10***	0.51***	0.39***	1.00***	0.41***
LINK	0.44***	0.51***	0.01	0.43***	0.45***	-0.10***	0.49***	0.40***	0.41***	1.00***

Annexure III:

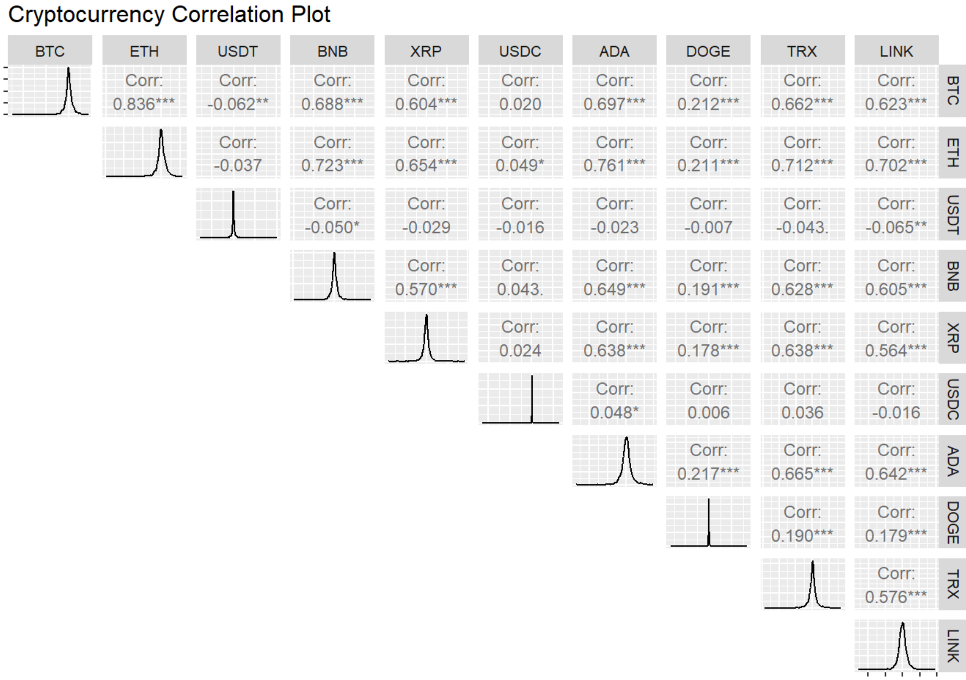

Figure 3: Cryptocurrency Correlation Plot

Significance Levels:
*** Correlation is significant at the (p < 0.001)
** Correlation is significant at the (p < 0.01)
* Correlation is significant at the (p < 0.05)
Correlation is significant at the (p < 0.1)

Annexure IV A:

Table 2: Historical Value at Risk (HVaR) at Different Confidence Levels

Crypto	HVaR_99	HVaR_95	HVaR_90
BTC	0.1020	0.0540	0.0343
ETH	0.1374	0.0708	0.0442
USDT	0.0044	0.0017	0.0009
BNB	0.1350	0.0688	0.0455
XRP	0.1356	0.0753	0.0491
USDC	0.0180	0.0022	0.0008
ADA	0.1301	0.0783	0.0558
DOGE	0.1598	0.0770	0.0516
TRX	0.1379	0.0729	0.0462
LINK	0.1510	0.0928	0.0636

Annexure IV B:

Table 3: Normal Value at Risk (NVaR) at different confidence levels

Crypto	NVaR_99	NVaR_95	NVaR_90
BTC	0.6770	0.4426	0.3177
ETH	0.8826	0.5821	0.4219
USDT	0.0328	0.0231	0.0180
BNB	0.9122	0.5914	0.4204
XRP	1.1895	0.8319	0.6413
USDC	0.1783	0.1263	0.0986
ADA	1.0386	0.6956	0.5127
DOGE	3.2634	2.2528	1.7140
TRX	0.9889	0.6736	0.5056
LINK	1.1758	0.7742	0.5601

Annexure V A:

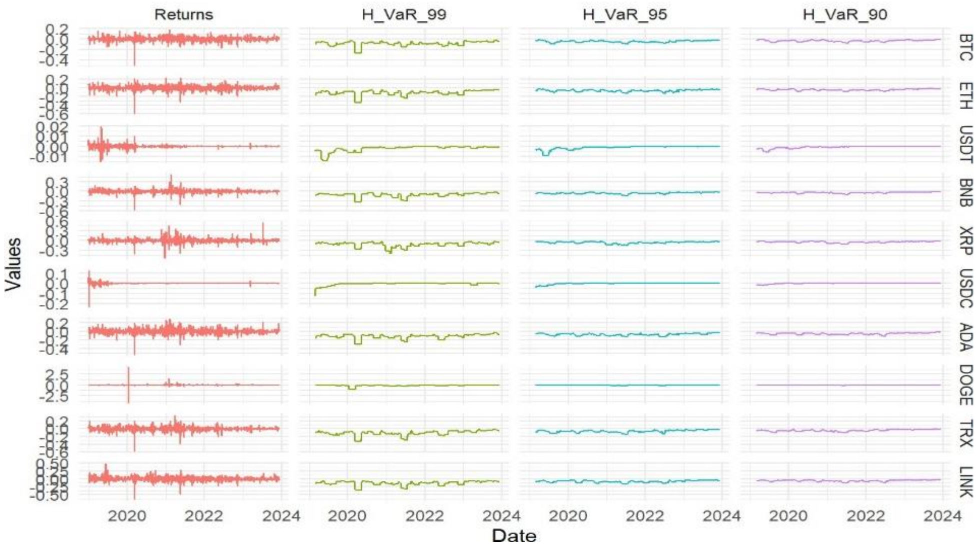

Figure 4: Historical value at risk at different confidence levels across time

Annexure V B:

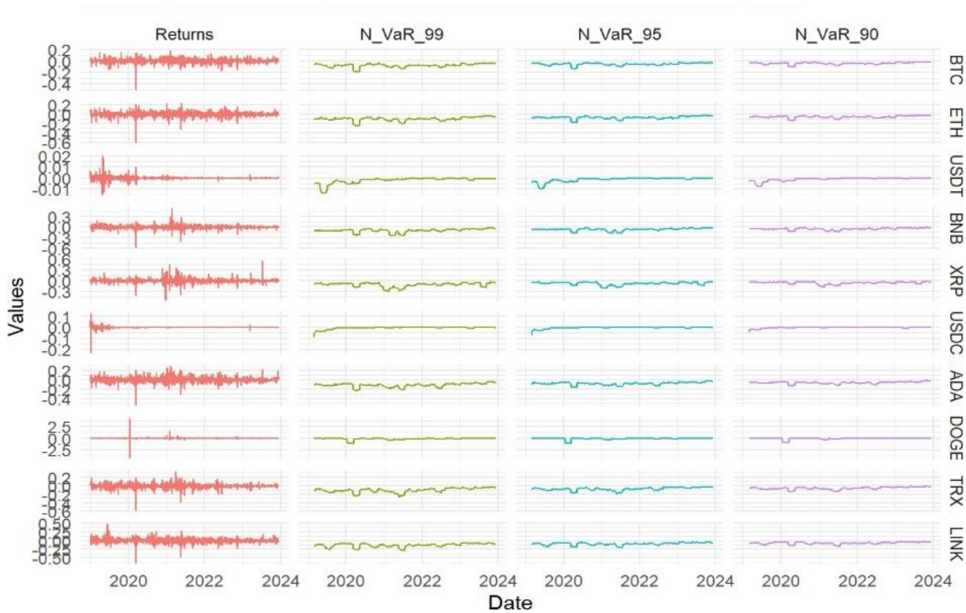

Figure 5: Normal value at risk at different confidence levels across time

Annexure VI A:

Table 4: Kupiec's PoF test for HVaR and NVaR at different confidence levels

Backtest Normal VaR Kupiec Test p-values

Crypto	Kupiec_N99	Kupiec_N95	Kupiec_N90
BTC	0.00	0.00	0.00
ETH	0.00	0.00	0.00
USDT	0.00	0.00	0.00
BNB	0.00	0.00	0.00
XRP	0.00	0.00	0.00
USDC	0.00	0.00	0.00
ADA	0.00	0.00	0.00
DOGE	0.00	0.00	0.00
TRX	0.00	0.00	0.00
LINK	0.00	0.00	0.00

Backtest Historical VaR Kupiec Test p-values

Crypto	Kupiec_H99	Kupiec_H95	Kupiec_H90
BTC	0.00	0.00	0.00
ETH	0.00	0.00	0.00
USDT	0.00	0.00	0.00
BNB	0.00	0.00	0.00
XRP	0.00	0.00	0.00
USDC	0.00	0.00	0.00
ADA	0.00	0.00	0.00
DOGE	0.00	0.00	0.00
TRX	0.00	0.00	0.00
LINK	0.00	0.00	0.00

Annexure VI B:

Table 5: Christoffersen Independence test for HVaR & NVaR at different confidence level

Backtest Normal VaR Christoffesen Test p-values			
Crypto	Christoffesen_N99	Christoffesen_N95	Christoffesen_N90
BTC	0.00	0.00	0.00
ETH	0.00	0.00	0.00
USDT	0.00	0.00	0.00
BNB	0.00	0.00	0.00
XRP	0.00	0.00	0.00
USDC	0.00	0.00	0.00
ADA	0.00	0.00	0.00
DOGE	0.00	0.00	0.00
TRX	0.00	0.00	0.00
LINK	0.00	0.00	0.00

Backtest Historical VaR Christoffesen Test p-values			
Crypto	Christoffesen_H99	Christoffesen_H95	Christoffesen_H90
BTC	0.00	0.00	0.00
ETH	0.00	0.00	0.00
USDT	0.00	0.00	0.00
BNB	0.00	0.00	0.00
XRP	0.00	0.00	0.00
USDC	0.00	0.00	0.00
ADA	0.00	0.00	0.00
DOGE	0.00	0.00	0.00
TRX	0.00	0.00	0.00
LINK	0.00	0.00	0.00

Annexure VI C:

Table 4: Dynamic Quantile test for HVaR and NVaR at different confidence levels

Backtest Normal VaR Dynamic Quantile Test p-values

Crypto	Dyn_Quantile_N99	Dyn_Quantile_N95	Dyn_Quantile_N90
BTC	0.00	0.00	0.00
ETH	0.00	0.00	0.00
USDT	0.00	0.00	0.00
BNB	0.00	0.00	0.00
XRP	0.00	0.00	0.00
USDC	0.00	0.00	0.00
ADA	0.00	0.00	0.00
DOGE	0.00	0.00	0.00
TRX	0.00	0.00	0.00
LINK	0.00	0.00	0.00

Backtest Historical VaR Dynamic Quantile Test p-values

Crypto	Dyn_Quantile_H99	Dyn_Quantile_H95	Dyn_Quantile_H90
BTC	0.00	0.00	0.00
ETH	0.00	0.00	0.00
USDT	0.00	0.00	0.00
BNB	0.00	0.00	0.00
XRP	0.00	0.00	0.00
USDC	0.00	0.00	0.00
ADA	0.00	0.00	0.00
DOGE	0.00	0.00	0.00
TRX	0.00	0.00	0.00
LINK	0.00	0.00	0.00