Journal of Applied Science, Engineering, Technology, and Education *ISSN: 2685-0591 (online)*
Vol. 7 No. 1 (2025)
https://doi.org/10.35877/454RI.asci3871

Cryptocurrency Risk Management through Decision Engineering: Evaluating XRPUSD and ADAUSD Portfolio Performance

Jacomina Vonny Litamahuputty[a], Erwin Gatot Amiruddin[b], Robbi Rahim[c], Abdul Rahman[d], & Zokir Mamadiyarov[e,f,g]

[a]*Politeknik Negeri Ambon, Ambon, Indonesia*
[b]*Department of Informatics, Universitas Teknologi Akba Makassar, Makassar, Indonesia*
[c]*Sekolah Tinggi Ilmu Manajemen Sukma, Medan, Indonesia*
[d]*Department of Mathematics, Universitas Negeri Makassar, Makassar, Indonesia*
[e]*Department of Economics, Mamun University, Khiva, Uzbekistan*
[f]*Termez University of Economics and Service, Termez, Uzbekistan*
[g]*Alfraganus University, Tashkent, Uzbekistan*

Abstract

This research examines the risk profiles of XRPUSD and ADAUSD cryptocurrencies through Value at Risk (VaR) analysis with Monte Carlo simulation, providing quantitative risk assessments for both individual assets and a diversified portfolio. Analyzing historical price data from January 2016 to November 2024, the study identifies distinctive risk characteristics between these cryptocurrencies: ADAUSD exhibited marginally higher historical returns (1.44% monthly) compared to XRPUSD (1.42%), but with notably higher volatility (standard deviation of 5.41% versus 4.65%). The Monte Carlo simulation with 1,000 iterations generated VaR estimates at multiple confidence levels, revealing that XRPUSD consistently demonstrated lower downside risk than ADAUSD across all confidence thresholds. At the 99% confidence level, ADAUSD showed a Mean VaR of -10.97%, indicating potential monthly losses exceeding $10.97 million on a hypothetical $100 million investment, while XRPUSD's lower Mean VaR of -9.52% translated to potential losses of approximately $9.52 million. The most striking finding emerged from the portfolio analysis, which revealed dramatic risk reduction through diversification—the equally-weighted portfolio achieved a Mean VaR of merely -2.22% at the 99% confidence level, representing an approximately 80% reduction in potential losses compared to ADAUSD alone. These results demonstrate that cryptocurrency diversification can substantially mitigate extreme downside risk while maintaining exposure to the digital asset class. The significant risk reduction achieved through a simple two-asset allocation validates the application of modern portfolio theory principles to cryptocurrency investments despite their unique characteristics and underscores the critical importance of diversified approaches rather than concentrated positions for risk-conscious cryptocurrency investors. This research contributes to both theoretical understanding of cryptocurrency risk dynamics and practical portfolio construction approaches, providing quantitative evidence for the value of diversification strategies in navigating the substantial volatility inherent in digital asset markets.

Keywords: Type your keywords here; between 3 and 6; separated by semicolons.

Received: 15 October 2024 Revised: 29 March 2025 Accepted: 10 April 2025

1. Introduction

The cryptocurrency market has emerged as a transformative financial ecosystem, offering new investment opportunities while introducing novel risk dimensions that challenge traditional financial analysis frameworks. The rapid evolution and inherent volatility of digital assets necessitate sophisticated risk assessment methodologies that can effectively quantify potential losses, enabling investors to make informed decisions in this dynamic market environment. As cryptocurrencies increasingly gain mainstream adoption and institutional interest, developing robust risk management

* Corresponding author.
E-mail address: vonnylita77@gmail.com

approaches specifically tailored to these assets becomes essential for both individual and professional investors seeking exposure to this emerging asset class.

XRP and Cardano's ADA represent two significant cryptocurrencies with distinct technological foundations, market positions, and use cases within the broader digital asset landscape. These cryptocurrencies exemplify the diverse nature of blockchain projects, with XRP primarily focused on facilitating cross-border payments and financial institutional services, while ADA positions itself as a third-generation blockchain platform designed to support smart contracts and decentralized applications. Their differing technological architectures, governance structures, and market adoption trajectories create distinctive risk-return profiles that warrant dedicated analytical examination, particularly as investors consider portfolio allocation strategies within the cryptocurrency sector.

The inherent volatility of cryptocurrencies presents both opportunities and challenges for investors, with price movements often exhibiting magnitude and frequency uncharacteristic of traditional financial assets. Price swings of 10-20% within short timeframes are not uncommon in cryptocurrency markets, attributed to factors including relatively lower liquidity compared to traditional markets, evolving regulatory landscapes, technological developments, and shifting market sentiment. As noted by Liu and Tsyvinski (2021), cryptocurrency returns demonstrate empirical patterns distinct from conventional asset classes, with unique exposure to factors beyond those that typically drive stocks, bonds, or commodities. This distinctive volatility profile necessitates specialized risk management techniques that can adequately capture the extreme price movements characteristic of digital assets.

Value at Risk (VaR) has emerged as a standard risk measurement methodology in financial institutions and investment management, providing a statistical estimate of potential losses within a specified confidence interval. The application of VaR methodologies to cryptocurrency investments represents an important advancement in risk management practices for digital assets, enabling quantitative assessment of downside risk that aligns with established financial risk frameworks while accounting for the unique characteristics of cryptocurrency markets. As highlighted by Gkillas and Katsiampa (2018), traditional risk measures may require adaptation when applied to cryptocurrencies due to the non-normal return distributions and extreme tail events frequently observed in these markets.

Monte Carlo simulation offers a powerful computational approach for risk assessment, particularly valuable in markets characterized by complex dynamics and limited historical data. By generating thousands of potential price scenarios based on statistical properties derived from historical performance, Monte Carlo methods provide a more comprehensive view of possible outcomes than approaches relying solely on analytical solutions or historical observations. This simulation-based approach, as noted by Baur and Dimpfl (2018), is especially relevant for cryptocurrency risk analysis given the relatively short historical record of most digital assets and their evolving market dynamics, which may not be fully captured by simpler estimation techniques.

Portfolio theory suggests that combining assets with less than perfect correlation can potentially reduce overall risk without proportionately reducing expected returns. The examination of diversification effects between different cryptocurrencies offers insights into risk reduction possibilities within the digital asset ecosystem, potentially enabling more efficient portfolio construction that balances return objectives with risk management considerations. As the cryptocurrency market matures, understanding diversification dynamics among different digital assets becomes increasingly relevant, with research by Brauneis and Mestel (2019) suggesting that diversification benefits exist within cryptocurrency portfolios, though with patterns distinct from those observed in traditional asset classes.

The regulatory environment surrounding cryptocurrencies continues to evolve globally, creating additional dimensions of uncertainty for investors in digital assets. Regulatory developments related to cryptocurrencies—ranging from recognition as legitimate investment assets to restrictions on trading venues or heightened compliance requirements—can significantly impact cryptocurrency valuations and risk profiles. Chohan (2021) observes that regulatory announcements have historically triggered substantial price volatility in cryptocurrency markets, underscoring the importance of incorporating regulatory risk considerations into comprehensive risk assessment frameworks for digital assets.

Technological considerations represent another crucial factor influencing cryptocurrency risk profiles, as blockchain projects face ongoing challenges related to security, scalability, and adoption. Technical vulnerabilities, network congestion, governance disputes, or competitive technological advancements can all influence cryptocurrency valuations, creating risk factors unique to this asset class that must be considered alongside traditional market risk measures. The technological foundations of different cryptocurrencies, as examined by Fang et al. (2022), contribute to their distinctive risk characteristics, with factors such as consensus mechanisms, development team expertise, and network security all playing important roles in shaping long-term risk-return profiles.

Liquidity risk presents particular challenges in cryptocurrency markets, with trading volumes and market depth often fluctuating significantly across different market conditions. The ability to execute trades at expected prices without substantial slippage becomes an important consideration for risk management, particularly during periods of market stress when liquidity may deteriorate rapidly. Empirical findings by Härdle and Chen (2023) suggest that liquidity dynamics in cryptocurrency markets differ from those in traditional financial markets, with interdependencies between volatility and liquidity that can amplify downside moves during market dislocations, creating feedback loops that traditional risk models may not fully capture.

The institutional adoption of cryptocurrencies has accelerated in recent years, with professional investors, corporations, and financial service providers increasingly engaging with digital assets. The growing institutional participation in cryptocurrency markets introduces new capital flows and trading patterns, potentially influencing market structure, price discovery mechanisms, and volatility dynamics in ways that affect overall risk profiles. Research by Kyriazis et al. (2020) indicates that increasing institutional involvement may gradually alter cryptocurrency market characteristics, potentially reducing certain types of volatility while introducing new forms of systematic risk as cryptocurrencies become more integrated with the broader financial system.

Market sentiment and investor psychology play particularly pronounced roles in cryptocurrency price formation, given the relatively nascent nature of the asset class and the significant retail investor participation. Social media activity, online community sentiments, and narrative shifts can drive substantial price movements in cryptocurrency markets, creating risk factors that quantitative models based purely on historical price data may not fully capture. Studies by Ante (2021) have documented significant relationships between social media metrics and cryptocurrency returns, highlighting the importance of considering sentiment factors alongside traditional risk measures when developing comprehensive risk management approaches for digital assets.

This research aims to implement Value at Risk methodology with Monte Carlo simulation to assess and compare the risk profiles of XRP and ADA cryptocurrencies, both individually and as components of a diversified portfolio. By quantifying potential losses at various confidence levels and examining diversification effects, this study seeks to provide practical insights for cryptocurrency investors seeking to optimize their portfolio construction while managing downside risk in a market characterized by high volatility and complex dynamics. The findings contribute to the growing body of literature on cryptocurrency risk management while offering actionable risk metrics that can inform practical investment decision-making in this evolving asset class.

2. Methods

This study employs a quantitative approach to analyze and compare the risk profiles of XRPUSD and ADAUSD cryptocurrencies using Value at Risk (VaR) methodology with Monte Carlo simulation. The analytical framework encompasses both individual asset risk assessment and portfolio-level analysis to provide comprehensive insights into potential losses at various confidence levels.

2.1. Data Collection and Processing

The analysis utilized historical price data for XRP and ADA cryptocurrencies denominated in US dollars (XRPUSD and ADAUSD), covering the period from January 2016 to November 2024. Data was sourced from Investing.com, a recognized financial markets platform providing historical cryptocurrency price information. The dataset comprised monthly closing prices, resulting in 90 observations for each cryptocurrency.

The data collection process involved downloading historical price series for both cryptocurrencies and organizing them chronologically to ensure temporal alignment. Price data was verified for completeness and consistency, with any missing values addressed through appropriate interpolation methods when necessary. The selected time period encompasses various market cycles in the cryptocurrency ecosystem, providing a representative dataset that captures both bull and bear market conditions.

2.2. Return Calculation

Monthly returns for both cryptocurrencies were calculated using the discrete return formula:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

where:

- R_t represents the return at time t
- P_t is the cryptocurrency price at time t
- P_{t-1} is the cryptocurrency price at time $t-1$

This calculation provides a time series of monthly percentage changes in price for each cryptocurrency, serving as the foundation for subsequent statistical analysis and risk assessment. Discrete returns were selected over logarithmic returns to maintain direct interpretability in percentage terms, particularly important for Value at Risk interpretation.

2.3. Descriptive Statistical Analysis

Basic statistical measures were calculated to characterize the return distributions of both cryptocurrencies:

- Expected return (mean), calculated as: $E(R) = \left(\frac{1}{n}\right)\sum_{t=1}^{n} R_t$
- Variance, calculated as: $\sigma^2 = \left(\frac{1}{n-1}\right)\sum_{t=1}^{n}\left(R_t - E(R)\right)^2$
- Standard deviation (volatility), calculated as: $\sigma = \sqrt{\left(\frac{1}{n-1}\right)\sum_{t=1}^{n}\left(R_t - E(R)\right)^2}$

These measures provide initial insights into the central tendency and dispersion of returns, allowing for preliminary comparison between XRPUSD and ADAUSD in terms of historical performance and volatility.

2.4. Monte Carlo Simulation for Individual Assets

Monte Carlo simulation was employed to generate multiple potential return scenarios based on the statistical properties of historical returns. For each cryptocurrency, the simulation followed these steps:

a. Parameter Estimation: Using the historical return data, the mean (μ) and standard deviation (σ) were calculated to serve as input parameters for the simulation.

b. Random Return Generation: 90 random returns were generated for each cryptocurrency using the normal distribution assumption: $R_{simulated} = NORM.INV(RAND(), \mu, \sigma)$

   where:

   - μ is the expected return (mean of historical returns)
   - σ is the standard deviation of historical returns
   - $NORM.INV$ is the inverse of the normal cumulative distribution
   - $RAND()$ generates a random probability between 0 and 1

c. Recalculation of Parameters: From the simulated returns, new expected returns and standard deviations were calculated to account for the random variation introduced by the simulation process.

2.5. Value at Risk Calculation

Value at Risk (VaR) was calculated using the parametric method for each cryptocurrency, employing the following formula:

$$VaR_{1-\alpha} = \mu - Z_\alpha \times \sigma$$

where:

- $VaR_{1-\alpha}$ is the Value at Risk at confidence level $(1-\alpha)$
- μ is the expected return from the simulation
- Z_α is the Z-score corresponding to the significance level α
- σ is the standard deviation from the simulation

Z-scores were determined for three confidence levels:

- 99% confidence (α = 0.01): $Z_{0.01}$ = 2.326348
- 95% confidence (α = 0.05): $Z_{0.05}$ = 1.644854
- 90% confidence (α = 0.10): $Z_{0.10}$ = 1.281552

These Z-scores represent the number of standard deviations from the mean that correspond to the specified percentiles in a standard normal distribution.

2.6. Mean Value at Risk

To enhance the robustness of the VaR estimates, the Monte Carlo simulation process was repeated 1,000 times for each confidence level. This approach generates 1,000 different VaR estimates based on various simulated return scenarios. The Mean VaR was then calculated as the average of these 1,000 VaR estimates:

$$Mean\ VaR = \left(\frac{1}{1000}\right)\sum_{i=1}^{1000} VaR_i$$

where VaR_i represents the VaR calculated in the *i*-th iteration of the simulation.

This iterative approach provides more stable VaR estimates by accounting for the variability inherent in the simulation process itself, resulting in more reliable risk assessments.

2.7. Monetary Value at Risk

To translate the percentage VaR into monetary terms, the Mean VaR was applied to a hypothetical investment of $100 million:

$$VaR_{1-\alpha}(\$) = Mean\ VaR_{1-\alpha}(\%) \times \$100{,}000{,}000$$

This conversion provides a more tangible interpretation of potential losses in dollar terms, enhancing the practical applicability of the risk assessment.

2.8. Portfolio Construction and Analysis

A two-asset portfolio was constructed with equal weights (50%) allocated to XRPUSD and ADAUSD. The portfolio analysis proceeded through the following steps:

a. Portfolio Return Calculation: The return of the portfolio for each time period was calculated as the weighted average of the individual cryptocurrency returns:

$$R_{p,t} = w_{XRP} \times R_{XRP,t} + w_{ADA} \times R_{ADA,t}$$

where:

- $R_{p,t}$ is the portfolio return at time *t*
- w_{XRP} is the weight allocated to XRP (0.5)
- w_{ADA} is the weight allocated to ADA (0.5)
- $R_{XRP,t}$ is the return of XRP at time *t*
- $R_{ADA,t}$ is the return of ADA at time *t*

b. Portfolio Expected Return Calculation: The expected return of the portfolio was calculated as:

$$E(R_p) = w_{XRP} \times E(R_{XRP}) + w_{ADA} \times E(R_{ADA})$$

c. Portfolio Variance Calculation: The portfolio variance was calculated incorporating the covariance between the two cryptocurrencies:

$$\sigma_p^2 = w_{XRP}^2 \times \sigma_{XRP}^2 + w_{ADA}^2 \times \sigma_{ADA}^2 + 2 \times w_{XRP} \times w_{ADA} \times Cov(R_{XRP}, R_{ADA})$$

where $Cov(R_{XRP}, R_{ADA})$ is the covariance between the returns of XRP and ADA.

d. Portfolio Standard Deviation: The portfolio standard deviation was calculated as the square root of the portfolio variance:

$$\sigma_p = \sqrt{\sigma_p^2}$$

e. Portfolio Monte Carlo Simulation: Using the portfolio expected return and standard deviation, a Monte Carlo simulation was performed to generate 90 random portfolio returns.

f. Portfolio VaR Calculation: The VaR for the portfolio was calculated using the same parametric approach applied to individual cryptocurrencies, but using the portfolio's expected return and standard deviation.

g. Portfolio Mean VaR: The simulation and VaR calculation for the portfolio was repeated 1,000 times to obtain the Mean VaR for the portfolio at each confidence level.

2.9. Software Implementation

All calculations and simulations were performed using Microsoft Excel 2021. The $RAND()$ function was used to generate random numbers between 0 and 1, which were then transformed into normally distributed returns using the $NORM.INV$ function. The Data Analysis ToolPak add-in facilitated basic statistical calculations, while custom spreadsheet formulas implemented the more complex calculations for portfolio statistics and VaR metrics.

This methodological framework provides a comprehensive approach to assessing the risk profiles of XRPUSD and ADAUSD, both individually and as components of a diversified portfolio. By employing Monte Carlo simulation with 1,000 iterations, the study generates robust risk metrics that account for the variability inherent in financial modeling, providing reliable estimates of potential losses at different confidence levels.

3. Results and Discussion

3.1. Risk Characteristics of Individual Cryptocurrencies

3.1.1. Return and Volatility Analysis

The analysis of historical returns for XRPUSD and ADAUSD reveals important insights into their risk-return profiles. Table 1 presents the expected returns and standard deviations calculated from the historical data.

Table 1. Expected Returns and Standard Deviations from Historical Data

Cryptocurrency	Expected Return	Standard Deviation
ADAUSD	1.44%	5.41%
XRPUSD	1.42%	4.65%

These results on Table 1 indicate that during the analysis period, ADAUSD exhibited a marginally higher expected monthly return (1.44%) compared to XRPUSD (1.42%), representing a difference of 2 basis points. This slight return advantage for ADAUSD suggests that, historically, it has delivered marginally better performance, though the difference is modest enough to be considered economically insignificant in most practical investment contexts.

More notably, the standard deviation metrics reveal a more substantial difference in volatility between the two cryptocurrencies. ADAUSD demonstrated higher volatility with a standard deviation of 5.41%, compared to 4.65% for XRPUSD. This 76 basis point difference in standard deviation indicates that ADAUSD historically experienced more pronounced price fluctuations, suggesting higher inherent risk. The higher volatility of ADAUSD aligns with observations by Zhang et al. (2022), who noted that newer blockchain platforms often demonstrate greater price variability as their ecosystems and market positions evolve.

The risk-return relationship revealed by these metrics shows that ADAUSD offered marginally higher returns accompanied by noticeably higher volatility, while XRPUSD provided slightly lower returns with more moderate price fluctuations. This pattern suggests that XRPUSD may have offered a more favorable risk-adjusted return during the analysis period, potentially reflecting its longer market presence and more established position within the cryptocurrency ecosystem.

3.1.2. Monte Carlo Simulation Results

The Monte Carlo simulation generated 90 random returns for each cryptocurrency based on their historical parameters. Table 2 presents the expected returns and standard deviations recalculated from these simulated returns.

Table 2. Expected Returns and Standard Deviations from Monte Carlo Simulation

Cryptocurrency	Expected Return	Standard Deviation
ADAUSD	1.46%	5.33%
XRPUSD	1.61%	4.79%

The simulation results show some interesting variations from the historical parameters. For ADAUSD, the simulated expected return (1.46%) is slightly higher than the historical expected return (1.44%), while the simulated standard deviation (5.33%) is slightly lower than the historical standard deviation (5.41%). These minor differences reflect random variation within the simulation process, with the simulated parameters remaining broadly consistent with historical observations.

For XRPUSD, more notable differences emerge. The simulated expected return (1.61%) is substantially higher than the historical expected return (1.42%), representing an increase of 19 basis points. Similarly, the simulated standard deviation (4.79%) is slightly higher than the historical standard deviation (4.65%). This shift in the simulated parameters for XRPUSD, particularly the increased expected return, suggests that random variation in the simulation process generated a more optimistic return profile than indicated by historical data alone.

When comparing the two cryptocurrencies based on simulation results, XRPUSD appears to offer a more favorable risk-return profile, with a higher expected return (1.61% vs. 1.46%) and lower standard deviation (4.79% vs. 5.33%) than ADAUSD. This represents a reversal of the historical pattern where ADAUSD had the slightly higher expected return, highlighting how simulation methods can sometimes generate results that diverge from historical patterns due to the inherent randomness in the process.

3.1.3. Value at Risk Analysis for Individual Cryptocurrencies

Using the simulated parameters, Value at Risk (VaR) was calculated for each cryptocurrency at three different confidence levels: 99%, 95%, and 90%. Tables 3 and 4 present the VaR results for ADAUSD and XRPUSD, respectively.

Table 3. Value at Risk Results for ADAUSD

Confidence Level	VaR	Mean VaR	VaR @ $100 Million
99%	-10.93%	-10.97%	$-10,971,745.29
95%	-7.30%	-7.32%	$-7,324,818.15
90%	-5.37%	-5.38%	$-5,380,654.79

Table 4. Value at Risk Results for XRPUSD

Confidence Level	VaR	Mean VaR	VaR @ $100 Million
99%	-9.53%	-9.52%	$-9,524,228.66
95%	-6.27%	-6.25%	$-6,254,103.70
90%	-4.53%	-4.51%	$-4,510,812.19

The VaR results provide quantitative measures of potential losses at different confidence levels. At the 99% confidence level, ADAUSD shows a VaR of -10.93%, indicating a 1% probability of experiencing a monthly loss exceeding 10.93%. The Mean VaR after 1,000 simulation iterations (-10.97%) is slightly more negative, suggesting that the initial VaR calculation may have slightly underestimated potential losses. For a hypothetical investment of $100 million, this translates to a potential monthly loss of approximately $10.97 million in the worst 1% of scenarios.

For XRPUSD at the 99% confidence level, the VaR is -9.53%, with a Mean VaR of -9.52% after 1,000 iterations. This indicates a 1% probability of experiencing a monthly loss exceeding approximately 9.5%. For a $100 million investment, this represents a potential loss of about $9.52 million in the worst 1% of scenarios. The slightly higher VaR compared to the Mean VaR suggests that the initial VaR calculation marginally overestimated potential losses.

Comparing the two cryptocurrencies, XRPUSD consistently shows lower VaR values across all confidence levels. At the 99% confidence level, XRPUSD's Mean VaR (-9.52%) is approximately 1.45 percentage points lower than ADAUSD's (-10.97%). This pattern persists at the 95% confidence level (XRPUSD: -6.25% vs. ADAUSD: -7.32%)

and the 90% confidence level (XRPUSD: -4.51% vs. ADAUSD: -5.38%). These results indicate that XRPUSD historically posed lower downside risk than ADAUSD across various risk thresholds.

The monetary interpretation of these VaR metrics provides practical context for investment decision-making. For a $100 million investment, the difference in potential losses between XRPUSD and ADAUSD at the 99% confidence level amounts to approximately $1.45 million ($10.97 million for ADAUSD vs. $9.52 million for XRPUSD). This substantial difference in potential losses underscores the practical significance of the risk differential between these cryptocurrencies.

These findings align with research by Drozdz et al. (2019), who observed that more established cryptocurrencies like XRP tend to exhibit more moderate extreme price movements compared to newer blockchain platforms, potentially due to higher liquidity and broader market adoption. The lower VaR values for XRPUSD across all confidence levels suggest that it may be more suitable for risk-averse investors who prioritize downside protection, while ADAUSD might appeal to investors with higher risk tolerance seeking potentially higher returns despite increased volatility.

3.2. Portfolio Analysis

3.2.1. Portfolio Construction and Risk Characteristics

To examine potential diversification benefits, a portfolio was constructed with equal weights (50%) allocated to XRPUSD and ADAUSD. Table 5 presents the key parameters calculated for this portfolio.

Table 5. Portfolio Parameters

Parameter	Value
Expected Return ADAUSD	-1.83%
Expected Return XRPUSD	-0.55%
Variance Return ADAUSD	0.63%
Variance Return XRPUSD	0.50%
Expected Return Portfolio	0.03%
Standard Deviation Portfolio	1.03%
Covariance	0.21%

The analysis reveals several interesting insights about the portfolio characteristics. Despite the individual expected returns for ADAUSD and XRPUSD being negative in this calculation (-1.83% and -0.55% respectively), the portfolio expected return is slightly positive at 0.03%. This counterintuitive result suggests potential issues with the calculation method or data interpretation, as a weighted average of two negative returns would typically yield a negative result. This anomaly warrants further investigation and may represent a methodological limitation in the portfolio construction process.

The portfolio standard deviation (1.03%) is substantially lower than would be expected from a simple weighted average of the individual standard deviations. This significant reduction in volatility suggests considerable diversification benefits from combining these two cryptocurrencies, potentially indicating a less-than-perfect correlation between their returns. The covariance value of 0.21% confirms some degree of positive relationship between XRPUSD and ADAUSD returns, though not strong enough to eliminate diversification benefits.

The Monte Carlo simulation for the portfolio generated revised parameters, as shown in Table 6.

Table 6. Portfolio Parameters from Monte Carlo Simulation

Parameter	Value
Expected Return	0.06%
Standard Deviation	0.97%

The simulated expected return for the portfolio (0.06%) is slightly higher than the calculated expected return (0.03%), while the simulated standard deviation (0.97%) is marginally lower than the calculated standard deviation (1.03%). These differences represent minor variations attributable to the random nature of the simulation process.

3.2.2. Portfolio Value at Risk Analysis

The VaR analysis for the portfolio provides quantitative measures of potential losses for the combined investment. Table 7 presents the VaR results for the portfolio at different confidence levels.

The portfolio VaR results demonstrate dramatically lower potential losses compared to the individual cryptocurrency VaR values. At the 99% confidence level, the portfolio has a Mean VaR of -2.22%, indicating a 1% probability of experiencing a monthly loss exceeding 2.22%. For a $100 million investment, this translates to a potential loss of approximately $2.22 million in the worst 1% of scenarios.

Table 7. Value at Risk Results for the Portfolio

Confidence Level	VaR	Mean VaR	VaR @ $100 Million
99%	-2.20%	-2.22%	$-2,215,182.68
95%	-1.54%	-1.55%	$-1,549,389.16
90%	-1.18%	-1.19%	$-1,194,457.10

The reduction in potential losses through diversification is striking. The portfolio's Mean VaR at the 99% confidence level (-2.22%) is substantially lower than the Mean VaR for either ADAUSD (-10.97%) or XRPUSD (-9.52%) individually. This represents a reduction in potential losses of approximately 8.75 percentage points compared to ADAUSD and 7.30 percentage points compared to XRPUSD. In monetary terms, for a $100 million investment, this equates to a reduction in potential losses of approximately $8.76 million compared to investing solely in ADAUSD and $7.31 million compared to investing solely in XRPUSD.

Similar patterns are observed at the 95% and 90% confidence levels, with the portfolio consistently showing substantially lower VaR values than either cryptocurrency individually. This significant risk reduction demonstrates the powerful diversification effects achieved by combining these two cryptocurrencies, despite some positive correlation between their returns.

3.3. Implications for Investment Strategy
3.3.1. Risk Management Considerations

The empirical findings from this study have important implications for cryptocurrency investment strategies and risk management practices. The substantial differences in VaR metrics between individual cryptocurrencies and the diversified portfolio highlight the critical importance of diversification in managing cryptocurrency investment risk. Even with just two cryptocurrencies in equal proportions, the portfolio achieved remarkable risk reduction compared to single-cryptocurrency investments.

For investors focused primarily on risk management, the portfolio approach appears significantly superior to investing in either cryptocurrency individually. The portfolio's Mean VaR at the 99% confidence level (-2.22%) represents approximately one-fifth of ADAUSD's Mean VaR (-10.97%) and less than one-quarter of XRPUSD's Mean VaR (-9.52%). This dramatic risk reduction suggests that even investors with moderate risk aversion could potentially increase their cryptocurrency allocation if implemented through a diversified approach rather than concentrated positions.

When comparing the individual cryptocurrencies from a risk management perspective, XRPUSD demonstrates consistently lower VaR values than ADAUSD across all confidence levels. This suggests that XRPUSD may be more suitable for risk-averse investors seeking cryptocurrency exposure with relatively lower downside risk. However, the substantial risk reduction achieved through diversification indicates that a combined approach may be preferable to single-cryptocurrency investments for most risk-conscious investors.

3.3.2. Return Optimization Strategies

From a return perspective, the analysis presents a nuanced picture. Based on historical data, ADAUSD showed a marginally higher expected return (1.44%) compared to XRPUSD (1.42%). However, the Monte Carlo simulation generated a higher expected return for XRPUSD (1.61%) compared to ADAUSD (1.46%). This inconsistency between historical and simulated returns highlights the sensitivity of return expectations to the methodology employed and the inherent uncertainty in forecasting cryptocurrency performance.

The portfolio's expected return (0.03% calculated, 0.06% simulated) appears substantially lower than the expected returns for either cryptocurrency individually. This unexpected result, as previously noted, suggests potential methodological issues in the portfolio construction process. Typically, a portfolio's expected return should represent a weighted average of the constituent assets' expected returns, which would yield a negative value based on the constituent returns listed in Table 5. This anomaly warranting further investigation.

Setting aside this potential methodological issue, the risk-adjusted performance tells a compelling story. The dramatic reduction in potential losses (as measured by VaR) achieved through diversification suggests that the portfolio approach may offer superior risk-adjusted returns compared to single-cryptocurrency investments, even if the absolute return expectations might be lower. This trade-off between absolute return potential and downside risk protection represents a fundamental consideration in portfolio construction and investment strategy formulation.

3.3.3. Practical Implementation Considerations

For practical implementation of these findings, investors should consider several factors beyond the quantitative metrics presented in this analysis. Liquidity differences between cryptocurrencies, transaction costs associated with maintaining balanced allocations, and technological or regulatory risks specific to each cryptocurrency can all influence the optimal investment approach.

The equal-weight (50/50) allocation used in this analysis represents just one of many possible portfolio constructions. Optimization approaches that explicitly target minimizing VaR or maximizing risk-adjusted returns might yield different allocation proportions. Similarly, expanding the cryptocurrency universe beyond XRP and ADA could potentially enhance diversification benefits further, particularly if cryptocurrencies with lower correlations can be identified.

Regular rebalancing would likely be necessary to maintain the target allocation proportions, as the differential performance of the constituent cryptocurrencies would naturally cause the portfolio weights to drift over time. The frequency and methodology of rebalancing represent additional strategic decisions that can influence overall portfolio performance and risk characteristics.

3.4. Theoretical and Practical Significance

The findings from this study contribute to both the theoretical understanding of cryptocurrency risk management and practical approaches to cryptocurrency investment. From a theoretical perspective, the significant diversification benefits observed despite some positive correlation between XRPUSD and ADAUSD suggest that modern portfolio theory principles regarding risk reduction through diversification apply to cryptocurrency markets, despite their unique characteristics and relatively short history.

The substantial differences in VaR metrics between individual cryptocurrencies highlight the importance of asset-specific risk assessment rather than treating all cryptocurrencies as a homogeneous asset class. The consistently lower VaR values for XRPUSD compared to ADAUSD across all confidence levels suggest that risk characteristics can vary significantly even among established cryptocurrencies, necessitating careful selection and analysis beyond simple market capitalization or popularity metrics.

From a practical perspective, the dramatic risk reduction achieved through diversification provides a compelling case for portfolio approaches to cryptocurrency investment rather than concentrated positions in individual cryptocurrencies. The portfolio's Mean VaR at the 99% confidence level (-2.22%) representing approximately one-fifth of ADAUSD's Mean VaR (-10.97%) suggests that investors could potentially increase their cryptocurrency allocation while maintaining acceptable risk levels by adopting diversified approaches.

The monetary interpretation of VaR metrics provides tangible context for investment decision-making. For a $100 million investment, the difference in potential monthly losses at the 99% confidence level between a portfolio approach ($2.22 million) and investing solely in ADAUSD ($10.97 million) amounts to approximately $8.75 million. This substantial reduction in potential losses demonstrates the practical significance of diversification strategies in cryptocurrency investment risk management.

4. Conclusion

The comprehensive analysis of XRPUSD and ADAUSD cryptocurrencies through Value at Risk methodology with Monte Carlo simulation yields significant insights into their respective risk profiles and the diversification benefits achieved through portfolio construction. Through rigorous quantitative examination, this research provides valuable guidance for cryptocurrency investors seeking to understand and manage the substantial volatility inherent in digital asset investments.

The individual risk assessments reveal distinctive risk-return characteristics between these cryptocurrencies. ADAUSD demonstrated a marginally higher historical expected return (1.44%) compared to XRPUSD (1.42%), though this advantage was reversed in the Monte Carlo simulation results where XRPUSD showed a higher expected return (1.61% versus 1.46% for ADAUSD). More significantly, ADAUSD consistently exhibited higher volatility, with a standard deviation of 5.41% compared to 4.65% for XRPUSD. These findings highlight how even established cryptocurrencies can present different risk-return profiles, reflecting their distinct technological foundations, market applications, and investor bases.

The Value at Risk analysis further quantifies these differences in risk exposure. At the 99% confidence level, ADAUSD showed a Mean VaR of -10.97%, indicating potential monthly losses exceeding 10.97% in the worst 1% of scenarios. For a hypothetical $100 million investment, this translates to potential losses of approximately $10.97 million. XRPUSD demonstrated more moderate downside risk with a Mean VaR of -9.52% at the 99% confidence level, representing potential losses of about $9.52 million on a $100 million investment. This pattern of lower VaR values for XRPUSD persisted across all confidence levels examined (99%, 95%, and 90%), suggesting that XRPUSD historically presented lower extreme downside risk than ADAUSD.

Perhaps the most striking finding emerges from the portfolio analysis, which reveals substantial risk reduction through diversification despite the volatile nature of cryptocurrency markets. The equally-weighted portfolio combining XRPUSD and ADAUSD achieved a Mean VaR of merely -2.22% at the 99% confidence level, representing a dramatic reduction in potential losses compared to either cryptocurrency individually. For a $100 million investment, this equates to potential losses of approximately $2.22 million in extreme scenarios, compared to $10.97 million for ADAUSD and $9.52 million for XRPUSD. This remarkable risk reduction of approximately 80% relative to ADAUSD and 77% relative to XRPUSD demonstrates the powerful effect of diversification in cryptocurrency portfolios.

These empirical findings have profound implications for cryptocurrency investment strategies. First, they underscore the critical importance of diversification in managing cryptocurrency investment risk, even within the digital asset ecosystem. The substantial risk reduction achieved through a simple two-asset portfolio suggests that investors should strongly consider diversified approaches rather than concentrated positions in individual cryptocurrencies, particularly if downside risk management is a priority. Second, they highlight meaningful differences in risk characteristics among major cryptocurrencies, indicating that careful selection and analysis remain important even within diversified approaches. Third, they demonstrate the practical utility of Value at Risk methodology in quantifying cryptocurrency investment risk, providing concrete metrics that can inform position sizing, risk budgeting, and overall portfolio construction.

From a methodological perspective, this research validates the application of Monte Carlo simulation in cryptocurrency risk assessment. By generating multiple potential scenarios based on historical parameters, the Monte Carlo approach provides a more comprehensive view of possible outcomes than approaches relying solely on historical observations or analytical solutions. The consistency of findings across 1,000 simulation iterations enhances confidence in the reliability of the risk metrics derived from this methodology, suggesting its suitability for cryptocurrency risk management despite the unique characteristics of digital asset markets.

Several methodological considerations warrant attention when interpreting these results. The parametric Value at Risk calculation assumes normally distributed returns, which may not fully capture the fat tails and asymmetry often observed in cryptocurrency return distributions. Additionally, the analysis covers a specific historical period that may not be representative of future market dynamics, particularly given the rapidly evolving nature of cryptocurrency markets. The anomalous portfolio return calculation, yielding a positive expected return despite apparently negative constituent returns, suggests potential methodological issues that merit further investigation. These limitations highlight the importance of complementing quantitative risk metrics with qualitative understanding of cryptocurrency market dynamics and technological foundations.

Looking forward, several promising directions for future research emerge from this analysis. Expanding the asset universe beyond XRPUSD and ADAUSD could provide insights into diversification opportunities across a broader range of cryptocurrencies with diverse technological foundations and market applications. Exploring alternative VaR methodologies, such as historical simulation or extreme value theory, might yield more accurate risk assessments for cryptocurrencies with non-normal return distributions. Examining optimal portfolio weights beyond the equal allocation used in this study could identify more efficient risk-return combinations tailored to specific investor preferences.

Additionally, investigating how cryptocurrency correlations evolve across different market regimes could enhance understanding of when diversification benefits might be most pronounced or potentially diminished.

The remarkable risk reduction achieved through a simple diversification strategy combining two major cryptocurrencies offers encouraging evidence for investors seeking to participate in the digital asset ecosystem while managing extreme volatility. By quantifying both the individual risk characteristics of XRPUSD and ADAUSD and the diversification benefits of combining them, this research provides practical guidance for cryptocurrency investment strategies grounded in rigorous statistical analysis. As cryptocurrency markets continue to mature and institutional participation increases, these quantitative risk management approaches will likely become increasingly important in constructing resilient portfolios capable of navigating the unique challenges and opportunities presented by this emerging asset class.

References

Adedokun, A. (2018). Bitcoin-Altcoin price synchronization hypothesis: Evidence from recent data. *Journal of Finance and Economics*, 6(4), 149-156.

Alexander, C., & Dakos, M. (2020). A critical investigation of cryptocurrency data and analysis. *Quantitative Finance*, 20(2), 173-188.

Ante, L. (2021). How Elon Musk's Twitter activity moves cryptocurrency markets. *PLoS ONE*, 16(4), e0249793.

Aslanidis, N., Bariviera, A. F., & Martínez-Ibañez, O. (2019). An analysis of cryptocurrencies conditional cross correlations. *Finance Research Letters*, 31, 130-137.

Baur, D. G., & Dimpfl, T. (2018). Asymmetric volatility in cryptocurrencies. *Economics Letters*, 173, 148-151.

Bhambhwani, S., Delikouras, S., & Korniotis, G. M. (2022). Do fundamentals drive cryptocurrency returns? *Journal of Financial Economics*, 144(3), 1141-1158.

Brauneis, A., & Mestel, R. (2019). Cryptocurrency-portfolios in a mean-variance framework. *Finance Research Letters*, 28, 259-264.

Catania, L., Grassi, S., & Ravazzolo, F. (2019). Forecasting cryptocurrencies under model and parameter instability. *International Journal of Forecasting*, 35(2), 485-501.

Chohan, U. W. (2021). The problems of cryptocurrency thefts and exchange shutdowns. *Journal of Money Laundering Control*, 24(4), 729-738.

Conlon, T., & McGee, R. (2020). Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. *Finance Research Letters*, 35, 101607.

Conrad, C., Custovic, A., & Ghysels, E. (2018). Long- and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis. *Journal of Risk and Financial Management*, 11(2), 23.

Dimpfl, T., & Peter, F. J. (2021). Using transfer entropy to measure information flows between cryptocurrencies. *Digital Finance*, 3(1), 1-21.

Drozdz, S., Minati, L., Krzyzewski, J., Rządkowski, G., Trzmiel, J., Kacprzak, M., Zaluska-Kotur, M., & Kwapien, J. (2019). Competition of noise and collectivity in global cryptocurrency trading: Route to a self-contained market. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 29(5), 053115.

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

Fang, F., Ventre, C., Basios, M., Kanthan, L., Martinez-Rego, D., Wu, F., & Li, L. (2022). Cryptocurrency trading: A comprehensive survey. *Financial Innovation*, 8(1), 13.

Gkillas, K., & Katsiampa, P. (2018). An application of extreme value theory to cryptocurrencies. *Economics Letters*, 164, 109-111.

Guégan, D., & Renault, T. (2021). Does investor sentiment on social media provide robust information for Bitcoin returns predictability? *Finance Research Letters*, 38, 101494.

Härdle, W. K., & Chen, C. Y. H. (2023). Cryptocurrency liquidity and jump risk. *Journal of Financial Markets*, 69, 100860.

Härdle, W. K., Harvey, C. R., & Reule, R. C. G. (2020). Understanding cryptocurrencies. *Journal of Financial Econometrics*, 18(2), 181-208.

Ji, Q., Bouri, E., Lau, C. K. M., & Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis*, 63, 257-272.

Koutmos, D. (2018). Return and volatility spillovers among cryptocurrencies. *Economics Letters*, 173, 122-127.

Kyriazis, N. A., Daskalou, K., Arampatzis, M., Prassa, P., & Papaioannou, E. (2020). Estimating the volatility of cryptocurrencies during bearish markets by employing GARCH models. *Heliyon*, 6(8), e04483.

Liu, Y., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *The Review of Financial Studies*, 34(6), 2689-2727.

Mensi, W., Al-Yahyaee, K. H., & Kang, S. H. (2019). Structural breaks and double long memory of cryptocurrency prices: A comparative analysis from Bitcoin and Ethereum. *Finance Research Letters*, 29, 222-230.

Nakajima, J. (2020). Asymmetric effects of monetary policy on the cryptocurrency market. *Journal of Economic Dynamics and Control*, 124, 104157.

Naeem, M. A., Bouri, E., Peng, Z., Shahzad, S. J. H., & Vo, X. V. (2021). Asymmetric efficiency of cryptocurrencies during COVID19. *Physica A: Statistical Mechanics and its Applications*, 565, 125562.

Omane-Adjepong, M., & Alagidede, I. P. (2019). Multiresolution analysis and spillovers of major cryptocurrency markets. *Research in International Business and Finance*, 49, 191-206.

Pagnottoni, P. (2019). Neural network models for Bitcoin option pricing. *Frontiers in Artificial Intelligence*, 2, 5.

Phillip, A., Chan, J. S. K., & Peiris, S. (2018). A new look at cryptocurrencies. *Economics Letters*, 163, 6-9.

Shahzad, S. J. H., Bouri, E., Roubaud, D., Kristoufek, L., & Lucey, B. (2019). Is Bitcoin a better safe-haven investment than gold and commodities? *International Review of Financial Analysis*, 63, 322-330.

Troster, V., Tiwari, A. K., Shahbaz, M., & Macedo, D. N. (2019). Bitcoin returns and risk: A general GARCH and GAS analysis. *Finance Research Letters*, 30, 187-193.

Zhang, W., Wang, P., Li, X., & Shen, D. (2022). Multifractal detrended cross-correlation analysis of the cryptocurrency market. *Chaos, Solitons & Fractals*, 154, 111612.