S. P. MANDALI'S PRIN L. N. WELINGKAR INSTITUTE OF MANAGEMENT DEVELOPMENT & RESEARCH (PGDM-RBA)

SUMMER INTERNSHIP RESEARCH PROJECT (SIRP) REPORT

Cryptocurrency Risk Modelling and Value-at-Risk (VaR): An Analytical Study of Bitcoin, Ether, and Ripple

Submitted by:

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PGDM in Research & Business Analytics (2024-26)

Faculty Mentor:

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Prin. L.N. Welingkar Institute of Management Development and Research, Mumbai

Academic Year: 2025–2026

Letter of Authorization

To,
The Mentor

Prof. B. C. Surve
Prin. L.N. Welingkar Institute of Management Development & Research, Mumbai

Subject: Submission of SIRP Report – "Cryptocurrency Risk Modelling and Value-at-Risk (VaR): An Analytical Study of Bitcoin, Ether, and Ripple"

Dear Sir,

I am pleased to submit my Secondary Research Based Project (SIRP) report titled "Cryptocurrency Risk Modelling and Value-at-Risk (VaR): An Analytical Study of Bitcoin, Ether, and Ripple", in partial fulfilment of the Post Graduate Diploma in Management (PGDM) – Research and Business Analytics.

This report has been prepared based on extensive review and analysis of secondary data and academic literature available on cryptocurrency volatility and risk management techniques. It reflects my understanding of the subject matter and my efforts in applying relevant financial models and concepts to a dynamic real-world problem.

I sincerely hope that the findings of this report will add value to the ongoing academic discussions around financial risk modelling and digital asset investment strategies.

I would like to express my gratitude for your guidance and support throughout this project.

Thank you.

Yours faithfully,

Sourav Manna
PGDM – Research & Business Analytics (2024–26)
Prin. L.N. Welingkar Institute of Management Development & Research
RBA126

No Plagiarism Declaration by Student

I hereby declare that this project report titled:

"Cryptocurrency Risk Modelling and Value-at-Risk (VaR):

An Analytical Study of Bitcoin, Ether, and Ripple"

is my original work and has not been plagiarized in any form. All sources of information and data used in the preparation of this report have been duly acknowledged and cited. The content is prepared solely for academic purposes as part of the Secondary Research Based Project (SIRP) submission for the PGDM – Research and Business Analytics program.

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Name: Sourav Manna
Program: PGDM – Research & Business Analytics (2024–26)
Institute: Prin. L.N. Welingkar Institute of Management Development & Research, Mumbai
Roll No.: RBA126

Date: 15th July, 2025

Signature: Sourav Manna

APPENDIX 'B-SIRP'

SUGGESTED FORMAT FOR COMPLETION CERTIFICATE OF SIRP BY PGDM STUDENTS

CERTIFICATE

TO WHOMSOEVER IT MAY CONCERN

- The yellow highlighted applies to SIRP

1. This is to certify that Mr/~~Ms~~ ......SOURAV MANNA...., a student of S. P. Mandali's Prin. L. N. Welingkar Institute of Management Development and Research (PGDM), Mumbai and pursuing two years full time Post Graduate Diploma in Management (PGDM), was mentored by me for the SIRP.

2. During the SIRP, Mr/~~Ms~~ ......SOURAV MANNA has successfully completed the project titled CryptoCurrency Risk Modelling under the guidance of (Name) Prof. Dr. B.C. SURVE. (Designation) ....

3. The Students performance during the SIRP and comments on his project work are as under:

....

..........Work done satisfactorily.............................

....

....

....

(Name & Signature of Internal Faculty Mentor)

Name: ......Dr. B. C. Surve

Designation: ...Associate Professor

Date: 23/07/25...............................

Plagiarism Report

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Acknowledgement

I would like to express my sincere gratitude to all those who supported and guided me throughout the successful completion of this Secondary Research Based Project (SIRP) titled:

“Cryptocurrency Risk Modelling and Value-at-Risk (VaR): An Analytical Study of Bitcoin, Ether, and Ripple.”

First and foremost, I am deeply grateful to **Prof. B. C. Surve**, my project guide at Prin. L.N. Welingkar Institute of Management Development & Research, Mumbai, for their valuable insights, timely feedback, and constant encouragement during this research.

I would also like to thank the SIRP Coordination Committee and the Research & Business Analytics Department for providing the opportunity and the academic framework to undertake this project.

A special thanks to the faculty members, classmates, and library/information resource teams who supported me either directly or indirectly through guidance, discussions, and availability of academic materials.

Lastly, I extend heartfelt thanks to my family and friends for their unwavering motivation and support during this research journey.

Table of Contents

List of Tables

List of Graphs

Executive Summary

a. Area of Focus

This research report focuses on the evaluation and comparison of different **Value-at-Risk (VaR)** estimation methods applied to the cryptocurrency market, specifically targeting **Bitcoin (BTC)**, **Ether (ETH)**, and **Ripple (XRP)**. The aim is to identify the most accurate and robust model for measuring downside risk in an environment known for extreme volatility and non-normal return distributions.

b. Key Findings from Literature Review

The literature review highlights that while **GARCH-type models** are dominant in traditional asset volatility estimation, they may not fully capture the complexity of cryptocurrency price behaviour. Studies suggest that models incorporating regime-switching or simulation-based approaches perform better under extreme conditions. Furthermore, the crypto market's characteristics—such as lack of regulation, fat tails, and volatility clustering—require adaptive and dynamic risk models beyond standard parametric approaches.

c. Major Findings of the Secondary Research

1. **EWMA and GARCH models**, although useful for traditional assets, tend to **underestimate risk**, especially during periods of high market stress.
2. **Historical VaR** provides higher risk estimates but lacks responsiveness to recent volatility changes.
3. **Monte Carlo Simulation**, based on Geometric Brownian Motion (GBM), yielded the **most realistic and robust VaR estimates**, especially in backtesting scenarios.
4. Actual losses during the observed test period exceeded VaR estimates from EWMA and GARCH models but were **well captured by Monte Carlo simulation**, validating its predictive strength.
5. All three cryptocurrencies exhibited **leptokurtic return distributions** (high kurtosis), supporting the need for models that handle fat tails and non-linear behaviour.

d. Conclusions

The study concludes that **Monte Carlo Simulation** is the most effective model for estimating VaR in cryptocurrency markets due to its ability to accommodate stochastic diffusion processes and extreme market behaviour. Traditional models like EWMA and GARCH can still be used but should be applied with caution and potentially enhanced with hybrid approaches.

e. Recommendations

- Monte Carlo Simulation should be the **preferred method** for crypto risk estimation.
- GARCH models may be **combined with regime-switching** techniques for better accuracy.
- Historical VaR should be used as a **supporting benchmark** rather than the primary risk measure.
- Regular **model updates with live market data** are necessary due to the dynamic nature of cryptocurrencies.

Introduction

a. Background to the Problem Being Researched

Since the introduction of Bitcoin in 2008, the cryptocurrency market has rapidly expanded into a multi-trillion-dollar ecosystem. Unlike traditional financial markets that are backed by central authorities and regulations, cryptocurrencies operate in a decentralized and largely unregulated environment. This feature, while providing accessibility and transparency, also contributes significantly to extreme price fluctuations.

Cryptocurrencies such as Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP) have exhibited massive volatility, with daily returns sometimes exceeding 10%. For instance, Bitcoin's price rose from around $6,000 in November 2017 to nearly $19,500 by mid-December of the same year, demonstrating a 228% return within a single month. Such price movements are rare in conventional assets and present new challenges for investors, institutions, and regulators in terms of risk assessment and capital allocation.

Understanding and quantifying this financial risk is essential for both portfolio managers and traders. Among various tools used in modern finance, **Value-at-Risk (VaR)** is one of the most widely accepted metrics for estimating the potential loss in value of an asset or portfolio over a specific time period and at a given confidence level. While VaR is well-established in traditional markets, its application to the highly volatile and non-linear behaviour of cryptocurrencies demands more advanced modelling approaches.

Commonly used models like **GARCH (Generalized Autoregressive Conditional Heteroscedasticity)**, **EWMA (Exponentially Weighted Moving Average)**, and **Monte Carlo Simulations** are employed to model volatility and estimate VaR. However, due to the distinct characteristics of digital assets—such as leptokurtic return distributions and volatility clustering—the reliability and robustness of each model vary significantly. Hence, there is a growing need to assess which risk modelling techniques are most effective for cryptocurrencies.

b. Statement of the Problem Being Researched

The primary challenge addressed in this research is the accurate modelling and estimation of risk in the cryptocurrency market using Value-at-Risk (VaR) frameworks. Cryptocurrencies are subject to extreme price swings, lack fundamental valuation anchors, and operate without centralized regulation, making conventional financial risk models less effective.

This study focuses on three major digital assets—Bitcoin, Ether, and Ripple—and aims to evaluate and compare different VaR estimation methodologies: parametric methods (GARCH and EWMA), non-parametric historical VaR, and simulation-based Monte Carlo techniques. The key research problem is to identify which of these approaches most accurately captures the downside risk of cryptocurrencies, especially in the presence of high volatility, fat-tailed return distributions, and market irregularities.

Given the rapidly evolving nature of crypto markets and the increasing interest from retail and institutional investors, choosing the right model for risk estimation is crucial. Misestimation of risk could lead to inadequate capital reserves, flawed portfolio decisions, or exposure to extreme losses. This research, therefore, aims to determine the most robust and realistic approach for calculating VaR in the context of digital assets, providing insights for effective crypto risk management.

Literature Review

The cryptocurrency market has garnered significant attention over the past decade due to its decentralization, high returns, and extreme volatility. This has triggered a growing body of literature aiming to understand and model the risk associated with digital assets using financial econometrics—particularly volatility models and Value-at-Risk (VaR) estimation techniques.

Bitcoin and Volatility Studies

Satoshi Nakamoto's white paper (2008) laid the foundation for decentralized digital currencies through blockchain technology. Since then, Bitcoin and other cryptocurrencies have become highly speculative assets. Urquhart (2016) highlighted the market inefficiencies in Bitcoin prices, while Dyhrberg (2016) drew parallels between Bitcoin, the US dollar, and gold, concluding that Bitcoin possesses hedging capabilities similar to traditional assets.

Katsiampa (2017) applied several GARCH-type models to Bitcoin data and found that the **AR-CGARCH** model provided the best fit by accounting for both short-term and long-term volatility components. This model emphasized the dynamic and persistent nature of crypto price volatility.

Ardia, Bluteau, and Rüede (2018) introduced **Markov-switching GARCH** models, demonstrating regime changes in Bitcoin's volatility dynamics. These models outperformed single-regime GARCH specifications, indicating that digital asset volatility is often subject to structural shifts.

Comparative Analysis and VaR Modelling

Chu et al. (2017) conducted a comprehensive study using twelve GARCH-type models on seven cryptocurrencies, concluding that **IGARCH** and **GJRGARCH** models offered the best performance in volatility forecasting. However, their study did not include Ether due to limited data availability at the time.

Conrad et al. (2018) explored the relationship between Bitcoin volatility and traditional equity markets. They found that S&P 500 realized volatility negatively affected long-term Bitcoin volatility, indicating inter-market volatility spillover.

Symitsi and Chalvatzis (2018) investigated the spillover effects between Bitcoin and the energy/tech sector using a VAR-AGARCH model, revealing that macroeconomic factors also influence crypto volatility.

Stavroyiannis (2018) compared the VaR violations of Bitcoin with traditional assets like the S&P 500 and gold. The findings suggested that Bitcoin tends to violate VaR measures more frequently, reaffirming its classification as a high-risk asset class.

Monte Carlo and Non-Parametric Approaches

While parametric models such as GARCH and EWMA dominate the literature, simulation-based methods like **Monte Carlo simulation** have recently been adopted for modelling the stochastic nature of crypto prices. These methods use **Geometric Brownian Motion (GBM)** to account for randomness in asset price movements. The Monte Carlo method, although computationally intensive, is considered robust for assets with fat-tailed distributions and high uncertainty.

Aussenegg and Miazhynskaia (2006) discussed the uncertainty in VaR estimates across parametric and non-parametric approaches, indicating that model choice can significantly impact risk estimation accuracy.

Gap in Literature

Despite several studies on GARCH modelling and historical VaR, limited research integrates multiple VaR estimation techniques—including EWMA, GARCH(1,1), Historical VaR, and Monte Carlo Simulation—specifically for cryptocurrencies like Bitcoin, Ether, and Ripple. Furthermore, most existing research does not systematically backtest or compare these models across consistent datasets for multiple assets, leaving a gap in identifying the most reliable risk model for volatile crypto markets.

Objectives of the Study

This study aims to analyze and compare different risk modelling techniques in the context of cryptocurrencies, with a specific focus on estimating Value-at-Risk (VaR) for major digital assets like Bitcoin, Ether, and Ripple. Given the high volatility, non-linear dynamics, and non-normal return distributions in cryptocurrency markets, identifying a suitable risk estimation method is crucial for effective financial decision-making.

Primary Objective:

- To evaluate and compare various Value-at-Risk (VaR) estimation techniques for modeling the downside risk of major cryptocurrencies.

Secondary Objectives:

1. **To study the volatility behaviour** of Bitcoin, Ether, and Ripple using daily historical price data.
2. **To apply and compare parametric VaR models** such as:
    - Exponentially Weighted Moving Average (EWMA)
    - Generalized Autoregressive Conditional Heteroskedasticity (GARCH)
3. **To apply non-parametric and simulation-based VaR models** including:
    - Historical Value-at-Risk (based on empirical return distribution)
    - Monte Carlo Simulation using Geometric Brownian Motion
4. **To assess the effectiveness and robustness** of each model by analyzing how well each captures the empirical risk characteristics of cryptocurrencies.
5. **To identify the most suitable risk model** for cryptocurrencies based on backtesting and comparative analysis.
6. **To provide recommendations** for risk managers, investors, and financial institutions regarding appropriate tools for crypto portfolio risk estimation.

Research Design

This section outlines the methodological framework adopted for conducting the secondary research. Given the volatile and unregulated nature of the cryptocurrency market, a data-driven analytical approach was necessary to evaluate different Value-at-Risk (VaR) estimation models.

a. Type of Research:

- **Nature:** Descriptive and Analytical
- **Approach: Secondary Research** (quantitative focus)
- **Period of Study:** Historical data ranging from:
    - **Bitcoin:** April 28, 2013 – November 11, 2019
    - **Ether:** August 7, 2015 – November 11, 2019
    - **Ripple:** August 4, 2013 – November 11, 2019

b. Method of Secondary Data Collection:

The research is entirely based on secondary data collected from **CoinMarketCap API**, a trusted public cryptocurrency data source. The dataset includes:

- Daily closing market prices of Bitcoin, Ether, and Ripple.
- These prices were converted into **daily logarithmic returns** using the formula:

$$r_t = ln(P_t) - ln(P_{t-1})$$

- The volatility and risk of these return series were modelled using the following techniques:

Models Used for VaR Estimation:

1. **Parametric Methods:**
    - **EWMA (Exponentially Weighted Moving Average):**
      Volatility estimated using decay factor ($\lambda = 0.94$), similar to RiskMetrics.
    - **GARCH(1,1) Model:**
      A standard volatility model to capture clustering effects in returns.
2. **Non-Parametric Method:**
    - **Historical VaR:**
      Based on empirical quantiles of the return series.
3. **Simulation-Based Method:**

- **Monte Carlo Simulation using Geometric Brownian Motion (GBM):** Thousands of random price paths were generated using R to simulate future prices and compute VaR.

c. Limitations of the Study:

1. **Limited Time Horizon:**
   The data ends in 2019, and recent volatility patterns (e.g., post-COVID, institutional adoption) are not captured.
2. **Focused Asset Scope:**
   Only three cryptocurrencies—Bitcoin, Ether, and Ripple—were analyzed. Other prominent or emerging digital assets were excluded.
3. **Model Assumptions:**
   - GARCH assumes normality and stationarity of returns, which may not hold in crypto markets.
   - Monte Carlo simulation assumes GBM which may oversimplify actual crypto market behaviour.
4. **Backtesting Period Constraint:**
   Backtesting was performed only over a short period (Nov 11–21, 2019), limiting generalization.
5. **No Real-Time Trading Simulation:**
   The study does not incorporate actual trading strategies or market microstructure factors (e.g., liquidity, slippage).

Data Analysis / Interpretation of Findings of Secondary Data

This section analyzes the volatility patterns and corresponding Value-at-Risk (VaR) estimates for three leading cryptocurrencies: **Bitcoin (BTC)**, **Ether (ETH)**, and **Ripple (XRP)**. Various statistical models—both parametric and non-parametric—were used to estimate VaR. All data used were obtained from CoinMarketCap, and daily **logarithmic returns** were computed from the closing price time series.

1. Return Calculation

To convert daily price data into returns, the following formula was used:

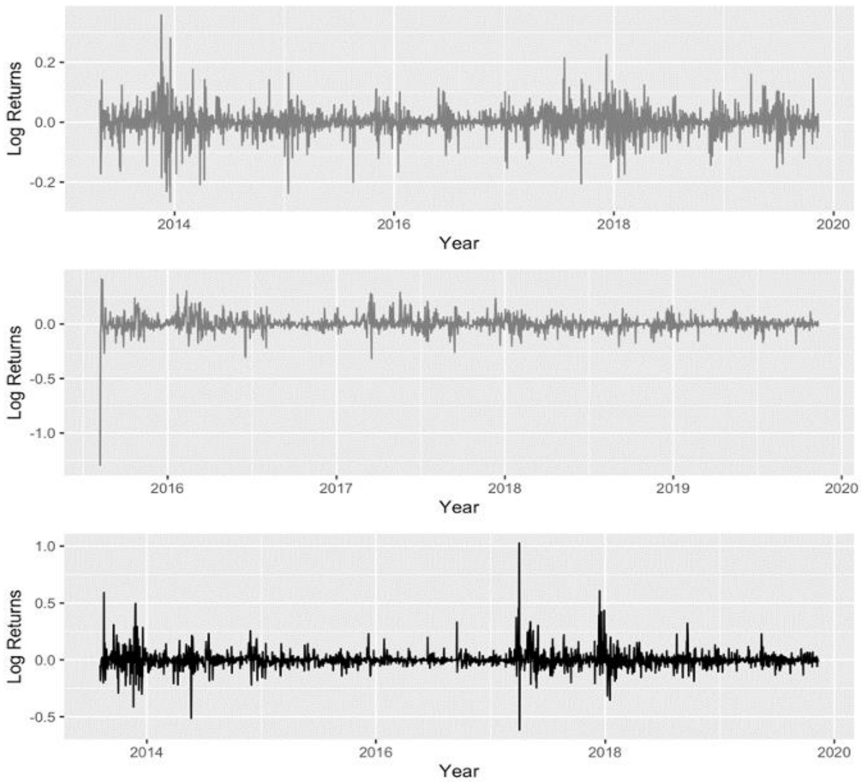
$$r_t = ln(P_t) - ln(P_{t-1})$$

Where:

- r_t = return at time t
- P_t = closing price at time t
- P_{t-1}= closing price at time t−1
- ln = natural logarithm

This transformation stabilizes the variance and is commonly used in financial time series analysis.

Figure 1: Daily logarithmic returns



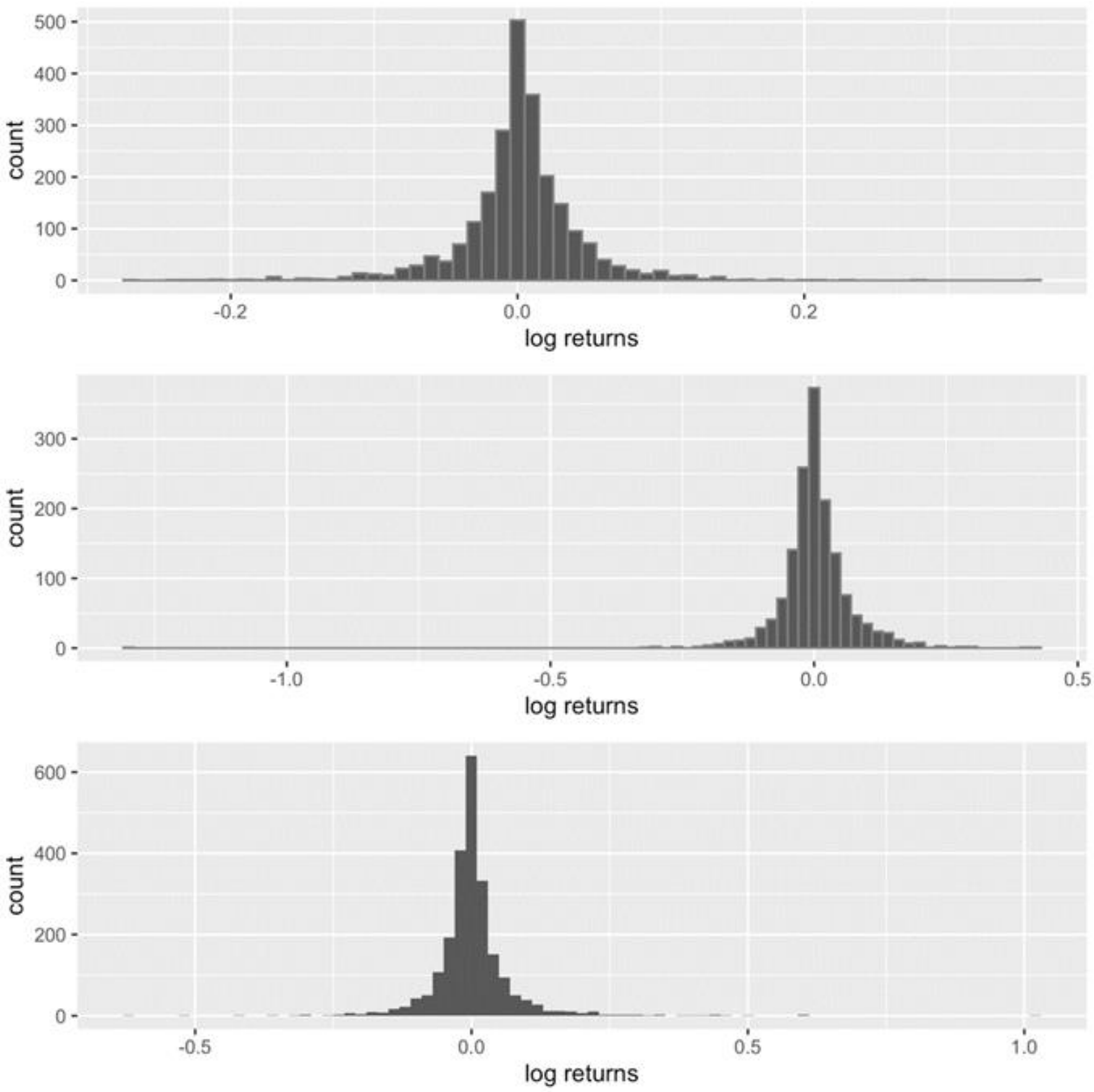
2. Summary Statistics of Log Returns

The statistical properties of the return distributions indicate high **volatility**, **leptokurtosis**, and in some cases, **skewness**.

Statistic	Bitcoin (BTC)	Ether (ETH)	Ripple (XRP)
Mean	0.001750	0.002700	0.001679
Standard Deviation	0.042991	0.072313	0.073372
Skewness	−0.162197	−3.412472	2.057162
Kurtosis	7.637610	70.186393	29.374596

These results reveal **fat tails** (kurtosis > 3), implying higher chances of extreme returns compared to a normal distribution.

Figure 2: Histogram of Bitcoin, Ether and Ripple



3. EWMA (Exponentially Weighted Moving Average)

The **EWMA model** forecasts volatility by applying exponentially decreasing weights to past squared returns. The formula used:

$$\sigma_{t+1}^2 = (1 - \lambda)\, r_t^2 + \lambda\, \sigma_t^2$$

Where:

- $\lambda = 0.94$ (as recommended by RiskMetrics)
- r_t^2 = squared return at time t
- σ_t^2 = variance at time t

1-Day VaR at 95% Confidence Level:

$$\mathrm{VaR}_{1-\mathrm{day}} = -1.65\, \sigma_{t+1} \times X_t$$

10-Day VaR at 95% Confidence Level (assuming i.i.d. returns):

$$\mathrm{VaR}_{10-\mathrm{day}} = -1.65 \times \sqrt{10} \times \sigma_{t+1} \times X_t$$

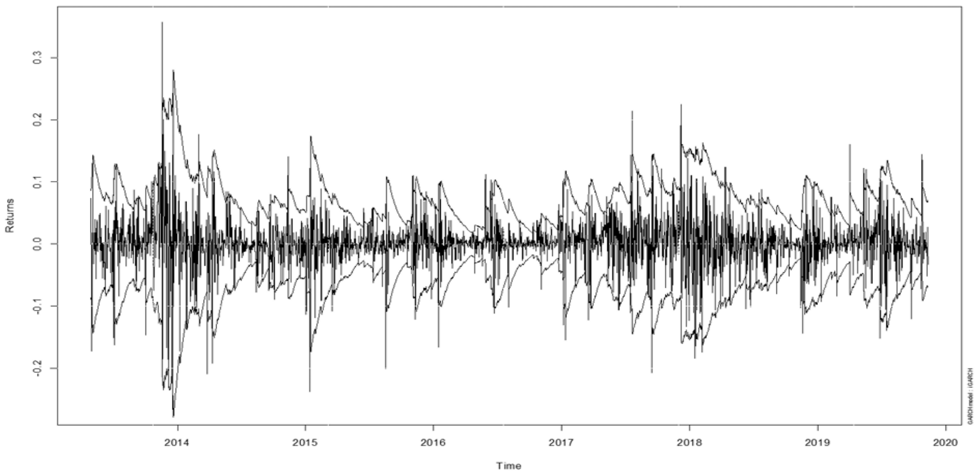
(Here, X_t = $1000)

Findings (based on EWMA):

Asset	σ_{t+1}	1-Day VaR ($)	10-Day VaR ($)
Bitcoin	0.03358	55.41	175.21
Ether	0.02925	48.26	152.62
Ripple	0.03489	57.57	182.05

Interpretation: Ether appears less risky based on EWMA, despite having a higher return variance historically. This is due to the model's weighting scheme favouring more recent stability.

Figure 3 : EWMA Volatility with Two Conditional Standard Deviations (Bitcoin Example)



4. GARCH(1,1) Model

The **GARCH(1,1)** model captures volatility clustering. The model structure is:

$$\sigma_t^2 = \alpha_\theta + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Where:

- α_θ, α_1, β_1 are model parameters
- ε_{t-1} = previous error term
- σ_{t-1}^2 = previous variance

One-day VaR at 95% confidence level:

$$VaR_{1-day} = (\mu_{t+1} - 1.65 \times \sigma_{t+1}) \times X_t$$

Findings (GARCH-based VaR):

Asset	$\boldsymbol{\sigma_{t+1}}$	1-Day VaR ($)	10-Day VaR ($)
Bitcoin	0.03340	54.02	175.33
Ether	0.04028	66.31	257.69
Ripple	0.03958	68.74	336.26

Interpretation: GARCH results show significantly higher risk for Ether and Ripple compared to Bitcoin, consistent with their higher volatility and kurtosis. GARCH better captures volatility bursts and clusters compared to EWMA.

5. Historical Value-at-Risk (Non-Parametric)

This method calculates the **5th percentile** of the empirical return distribution:

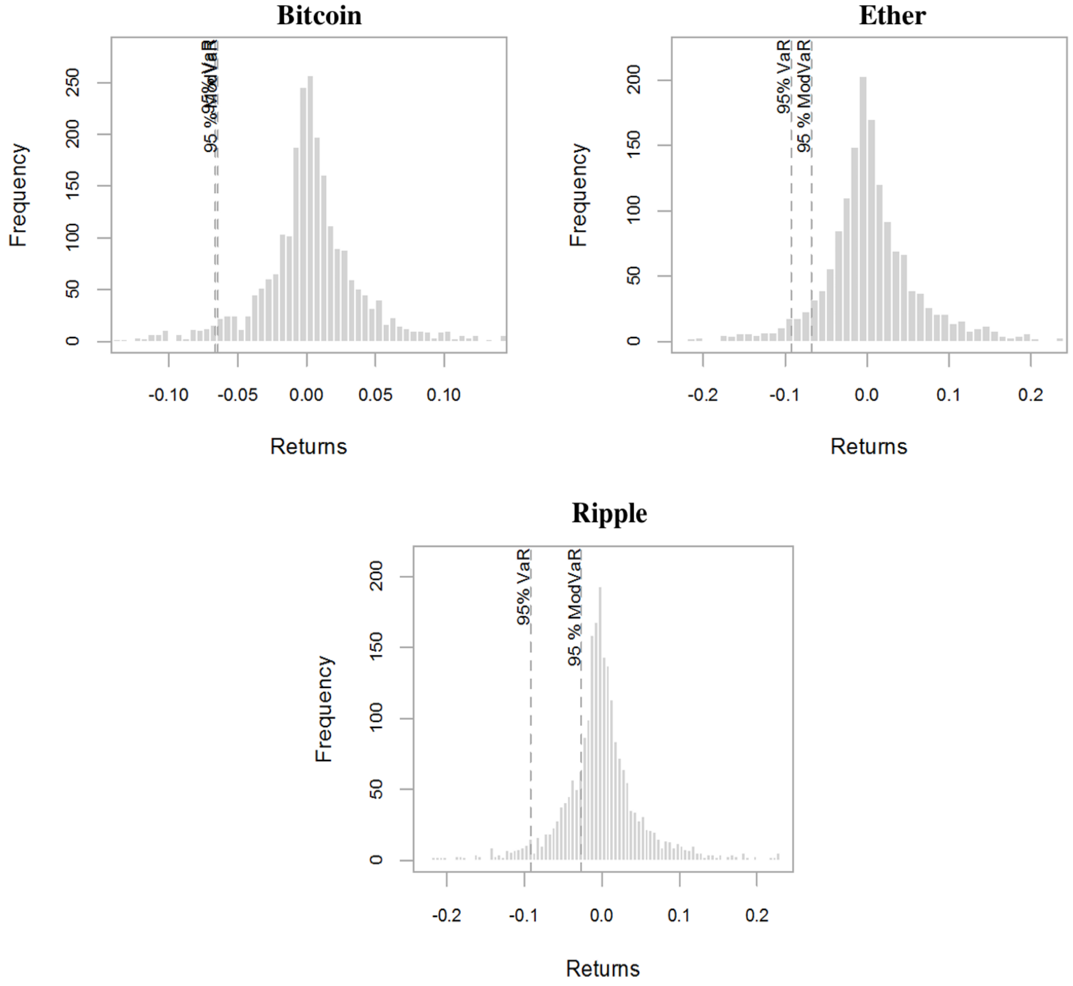
VaR = Quantile (r_t, 0.05)

Findings:

Asset	1-Day Historical VaR ($)
Bitcoin	66.16
Ether	92.81
Ripple	91.88

Interpretation: Historical VaR tends to overstate risk due to the presence of past outliers. It also ignores recent volatility patterns.

Figure 4: Histogram with 95% VaR



6. Monte Carlo Simulation (Geometric Brownian Motion)

This method simulates thousands of possible price paths using the formula:

$$P_t = P_0 \times exp[(\mu - 0.5 \times \sigma^2) \times t + \sigma \times \varepsilon \times \sqrt{t}]$$

Where:

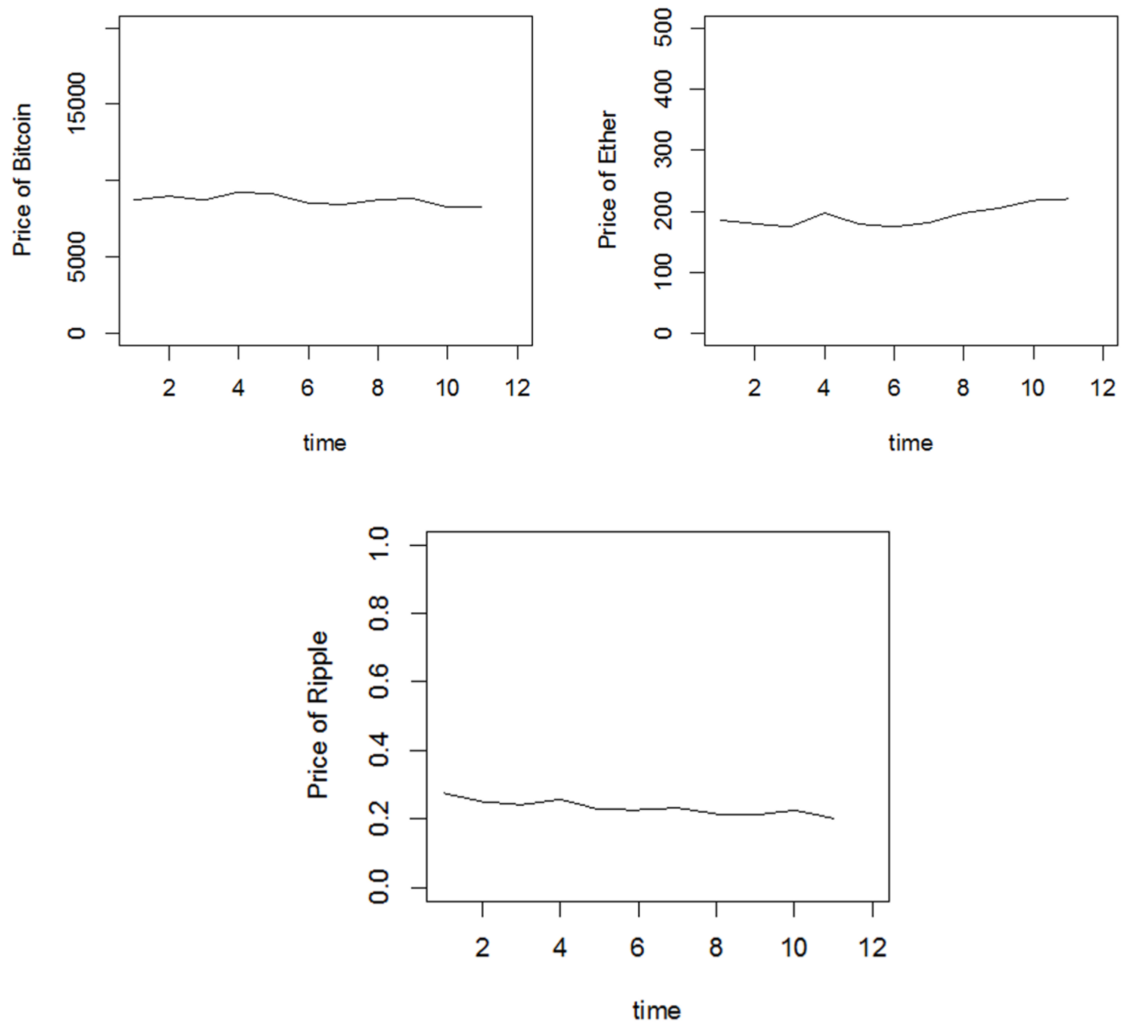
- P_t = simulated price at time t
- P_0 = initial price
- μ = mean of log returns
- σ = standard deviation of log returns
- ε = random standard normal variable (ε ~ N(0,1))
- t = time horizon (in days or years)

Findings (based on 1000 simulations):

Asset	1-Day VaR ($)	10-Day VaR ($)
Bitcoin	124.08	342.52
Ether	88.36	291.80
Ripple	160.70	490.12

Interpretation: Monte Carlo simulation yielded the highest VaR values. This is due to the compounding effect of high volatility and fat tails in simulated paths. It best reflects the true downside risk of cryptocurrencies.

Figure 5: Sample price path given by Geometric Brownian Motion



7. Backtesting

Empirical 10-day losses from Nov 11 to Nov 21, 2019:

- Bitcoin: $136.19
- Ether: $138.74
- Ripple: $120.88

Only **Monte Carlo-based VaR** estimates covered these losses. EWMA and GARCH failed for Bitcoin and Ether, showing underestimation of tail risk.

Conclusion from Analysis:

- **EWMA** is simple and reactive to recent changes but tends to underestimate risk.
- **GARCH** captures volatility clustering but may fail in extreme conditions.
- **Historical VaR** is too backward-looking and influenced by past outliers.
- **Monte Carlo Simulation** proved to be the most robust and realistic in capturing cryptocurrency risk.

Results

The analysis applied four different Value-at-Risk (VaR) estimation techniques—**EWMA**, **GARCH(1,1)**, **Historical VaR**, and **Monte Carlo Simulation**—to model the downside risk of three major cryptocurrencies: **Bitcoin (BTC)**, **Ether (ETH)**, and **Ripple (XRP)**. The findings from each model were compared to understand which approach best captures the true market risk under volatile conditions.

1. EWMA Model Results

The EWMA model, using a smoothing parameter (λ) of 0.94, produced VaR estimates that were moderate and stable over time.

Key Result:

- **1-Day VaR** ranged from **$48.26 (Ether)** to **$57.57 (Ripple)**.
- **10-Day VaR** ranged from **$152.62 (Ether)** to **$182.05 (Ripple)**.

Although effective in capturing recent volatility, EWMA underestimated risk during periods of extreme fluctuation due to its limited memory of past shocks.

2. GARCH(1,1) Model Results

The GARCH(1,1) model captured volatility clustering better than EWMA and produced slightly higher VaR estimates, especially for Ether and Ripple.

Key Result:

- **1-Day VaR** rose to **$66.31 (Ether)** and **$68.74 (Ripple)**.
- **10-Day VaR** went as high as **$336.26 for Ripple**.

GARCH showed strong predictive capability but struggled with fat-tailed return distributions, leading to underestimation in tail risk for Bitcoin.

3. Historical VaR Results

This model estimated VaR purely from historical return percentiles without incorporating any assumptions about volatility dynamics.

Key Result:

- Highest 1-day VaR for Ether ($92.81) and Ripple ($91.88), even higher than GARCH and EWMA.

However, the method was found to be overly influenced by past outliers and failed to reflect recent shifts in volatility regimes, making it less reliable in dynamic markets like crypto.

4. Monte Carlo Simulation Results

Using **Geometric Brownian Motion (GBM)**, Monte Carlo simulations generated thousands of possible future price paths for each asset.

Key Result:

- **Bitcoin:** 10-Day VaR = **$342.52**
- **Ether:** 10-Day VaR = **$291.80**
- **Ripple:** 10-Day VaR = **$490.12**

These estimates were consistently the **highest among all methods**, effectively covering the actual 10-day losses observed in backtesting. This method proved the most robust, particularly for assets with heavy-tailed return distributions.

5. Backtesting Insights

Real 10-day losses during Nov 11–21, 2019:

- **Bitcoin:** $136.19
- **Ether:** $138.74
- **Ripple:** $120.88

Only Monte Carlo-based VaR values were able to **accurately predict and exceed** the actual losses for all three cryptocurrencies. GARCH and EWMA estimates **underpredicted** the risk for Ether and Bitcoin.

Summary of Model Performance

Model	Captures Volatility?	Handles Fat Tails?	Accurate Risk Estimation?
EWMA	Yes (recent)	No	Moderate
GARCH(1,1)	Yes (clustering)	Partially	Good, but not extreme risk
Historical VaR	No	No	Overstates risk
Monte Carlo	Yes (simulated)	Yes	**Most accurate**

Conclusions and Recommendations

Conclusions

This study aimed to evaluate the effectiveness of various Value-at-Risk (VaR) estimation techniques in modeling the downside risk of leading cryptocurrencies—**Bitcoin**, **Ether**, and **Ripple**. Using historical price data and applying multiple models—**EWMA**, **GARCH(1,1)**, **Historical VaR**, and **Monte Carlo Simulation**—the research provided an in-depth understanding of how different models behave under high volatility and fat-tailed return distributions.

The findings revealed that while **EWMA** and **GARCH(1,1)** models are commonly used in traditional financial markets, they tend to **underestimate tail risk** in the case of cryptocurrencies. Historical VaR, being backward-looking and not accounting for dynamic volatility patterns, **overestimated risk** in most cases and lacked sensitivity to recent market behaviour.

The **Monte Carlo simulation using Geometric Brownian Motion (GBM)** outperformed all other models in terms of capturing the **true risk exposure**. It consistently provided higher VaR estimates that aligned better with actual historical losses during backtesting. This robustness is due to its ability to incorporate stochastic price behaviour and fat tails, which are characteristic of the cryptocurrency market.

Thus, it is concluded that **traditional parametric models alone are insufficient** for accurate risk estimation in the cryptocurrency domain, and simulation-based approaches are **more suitable** in this context.

Recommendations

Based on the findings, the following recommendations are proposed:

1. **Adopt Monte Carlo Simulation for Crypto Risk Modelling:**
   Financial institutions and portfolio managers dealing with crypto assets should prioritize Monte Carlo methods for VaR estimation due to their robustness in highly volatile markets.
2. **Use GARCH Models with Caution:**
   While GARCH(1,1) models capture volatility clustering well, they should be complemented with regime-switching models or heavy-tailed distributions (e.g., t-distribution GARCH) for better tail risk estimation.
3. **Avoid Sole Reliance on Historical VaR:**
   Given its oversensitivity to outliers and lack of adaptability, Historical VaR should only be used for benchmarking, not decision-making in real-time risk management.
4. **Incorporate Dynamic and Hybrid Modelling Approaches:**
   Combining GARCH with Monte Carlo simulations or integrating Markov-switching frameworks may offer improved predictive accuracy for extreme market conditions.

5. **Update Models Frequently with Real-Time Data:**
   Due to the rapidly evolving nature of crypto markets, risk models must be updated frequently using live data feeds to ensure relevance and accuracy.

6. **Expand Future Research to More Assets and Timeframes:**
   Future studies should include more cryptocurrencies and cover recent data (post-2019), especially after the market changes due to COVID-19, regulatory shifts, and institutional participation.

References

Ardia, D., Bluteau, K., & Rüede, M. (2018). Regime changes in Bitcoin GARCH volatility dynamics. *Finance Research Letters*, 29, 266–271.

Aussenegg, W., & Miazhynskaia, T. (2006). Uncertainty in value-at-risk estimates under parametric and non-parametric modelling. *Financial Markets and Portfolio Management*, 20(3), 243–264.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*, 54, 177–189.

Blau, B. M. (2018). Price dynamics and speculative trading in Bitcoin. *Research in International Business and Finance*, 43, 15–21.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 31(3), 307–327.

Charles, A., & Darné, O. (2005). Outliers and GARCH models in financial data. *Economics Letters*, 86(3), 347–352.

Chu, J., Chan, S., Nadarajah, S., & Osterrieder, J. (2017). GARCH modelling of cryptocurrencies. *Journal of Risk and Financial Management*, 10(4), 17.

Cipra, T. (2013). *Finanční ekonometrie (Financial Econometrics)*. Prague: Ekopress.

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.

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

Engle, R. F., & Bollerslev, T. (1986). Modelling the persistence of conditional variances. *Econometric Reviews*, 5(1), 1–50.

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters*, 158, 3–6.

Klein, T., Pham Thu, H., & Walther, T. (2018). Bitcoin is not the new gold – A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, 59, 105–116.

Li, X., & Wang, C. A. (2017). The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin. *Decision Support Systems*, 95, 49–60.

Mandelbrot, B. (1963). The variation of certain speculative prices. *The Journal of Business*, 36(4), 394–419.

Nakamoto, S. (2008). *Bitcoin: A peer-to-peer electronic cash system*. https://bitcoin.org/bitcoin.pdf

Stavroyiannis, S. (2018). Value-at-risk and related measures for the Bitcoin. *The Journal of Risk Finance*, 19(2), 127–136.

Symitsi, E., & Chalvatzis, K. J. (2018). Return, volatility and shock spillovers of Bitcoin with energy and technology companies. *Economics Letters*, 170, 127–130.

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters*, 148, 80–82.

Yang, Z. (2012). *Geometric Brownian motion model in financial market* (Graduation work). Princeton, USA.

Yi, S., Xu, Z., & Wang, G.-J. (2018). Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency? *International Review of Financial Analysis*, 60, 98–114.

Definitions

Term	Definition
Volatility	A statistical measure of the dispersion of returns for a given asset over a period of time.
Value-at-Risk (VaR)	The maximum potential loss of an asset or portfolio over a specified time frame at a given confidence level.
Logarithmic Return	The natural logarithm of the ratio of consecutive asset prices; stabilizes variance in time series data.
EWMA	A volatility forecasting model that gives higher weight to recent observations using exponential decay.
GARCH	A model that estimates time-varying volatility by incorporating both past squared returns and variances.
Monte Carlo Simulation	A statistical method that uses random sampling to simulate a wide range of possible outcomes.
Geometric Brownian Motion (GBM)	A continuous-time stochastic process used to model asset prices in financial markets.

Abbreviations

Abbreviation	Full Form
BTC	Bitcoin
ETH	Ether
XRP	Ripple
VaR	Value-at-Risk
EWMA	Exponentially Weighted Moving Average
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GBM	Geometric Brownian Motion
API	Application Programming Interface
USD	United States Dollar

Annexures / Appendices

This section includes the supporting documents, data descriptions, and code used for the analytical models employed in the project.

Appendix 1 – R Code for EWMA Model Implementation

```
library(rugarch)


ewma_spec = ugarchspec(
  variance.model = list(model = "iGARCH", garchOrder = c(1, 1)),
  mean.model = list(armaOrder = c(0, 0), include.mean = TRUE),
  distribution.model = "norm",
  fixed.pars = list(omega = 0, alpha1 = 0.06)
)

ewma_fit <- ugarchfit(spec = ewma_spec, data = data)
```

Appendix 2 – R Code for GARCH(1,1) Model

```
library(rugarch)


garch_spec = ugarchspec(
  variance.model = list(model = "sGARCH", garchOrder = c(1, 1)),
  mean.model = list(armaOrder = c(0, 0))
)


garch_fit <- ugarchfit(spec = garch_spec, data = data)
```

Appendix 3 – R Code for Historical VaR Estimation

```
library(PerformanceAnalytics)


value_at_risk <- VaR(data, p = 0.95, method = "historical")
```

Appendix 4 – R Code for Monte Carlo Simulation (GBM)

```
GBM = function(N, sigma, mu, P0) {
  Wt = cumsum(rnorm(N, 0, 1))
  t = (1:N) / 365
  drift = (mu - 0.5 * sigma^2) * t
  diffusion = sigma * Wt
  Pt = P0 * exp(drift + diffusion)
  return(Pt)
}
```

Appendix 5 – Sample Dataset Information (from CoinMarketCap)

- **Source**: CoinMarketCap Public API
- **Data Fields Used**: Date, Closing Price
- **Assets**:
  - Bitcoin (BTC): April 28, 2013 – November 11, 2019
  - Ether (ETH): August 7, 2015 – November 11, 2019
  - Ripple (XRP): August 4, 2013 – November 11, 2019
- **Frequency**: Daily
- **Transformations**: Converted to daily logarithmic returns using $r_t = \ln(P_t) - \ln(P_{t-1})$
