Data Sampling Frequency Effects on Risk-Adjusted Cryptocurrency Portfolio Construction

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ABSTRACT

The cryptocurrency market exhibits a high level of volatility, and the process of portfolio construction can be complex and highly lucrative. Issues related to portfolio construction in the cryptocurrency market are targeted in this paper through the assessment of the effect of sampling frequency on cryptocurrency portfolio optimization. A detailed analysis of the effect of three specific sampling frequencies (15 minutes, 1 hour, and 1 day) was undertaken, and the activities of eight top cryptocurrencies (ADA, BTC, DOGE, ETH, LTC, SOL, TRX, and XRP) were considered. Using price information sourced from the KuCoin exchange from 2023 to 2025, we are able to conduct a risk-adjusted optimization-based analysis to determine the optimal portfolio composition while utilizing the Sharpe Ratio measure to determine portfolio performance. The effect of sampling frequency on portfolio composition, as well as on the estimate of the risk/return profile and correlation measures, proved to be significant.

Keywords-cryptocurrency portfolio; portfolio optimization; data sampling frequency; high-frequency data; risk management; Sharpe ratio; mean-variance optimization

I. INTRODUCTION

Cryptocurrency markets attract growing attention from both investors and researchers due to their rapid expansion, decentralized structure, and high-return potential. As digital assets increasingly become integrated into diversified investment strategies, portfolio construction involving cryptocurrencies has emerged as a promising yet challenging task. However, unlike traditional financial assets, cryptocurrencies exhibit pronounced volatility, non-stationary behavior, and strong interdependencies, which significantly complicate risk management and asset allocation decisions [1-3]. Modern portfolio theory originates from the seminal work of Markowitz, who introduced the mean–variance optimization framework and the concept of the efficient frontier [4]. Despite its foundational role in portfolio management, the mean–variance approach assumes symmetric risk preferences and normally distributed returns. These assumptions are often violated in financial markets and particularly in cryptocurrency environments. To address these limitations, several extensions have been proposed, particularly in markets characterized by non-normal return distributions and high volatility. Among these, the Sortino ratio and semi-variance-based risk frameworks explicitly penalize negative deviations and offer a more realistic assessment of risk exposure [5-7].

Empirical evidence suggests that optimization-based portfolio strategies generally outperform naïve allocation rules and traditional benchmarks when risk is appropriately modeled [8]. In the context of cryptocurrency markets, diversification plays a critical role due to high correlations among assets and the presence of extreme price movements. Previous studies demonstrate that incorporating cryptocurrencies, particularly Bitcoin, into diversified portfolios can improve the overall risk–return trade-off [9, 10]. Furthermore, advances in numerical optimization and computational techniques have enabled the application of efficient constrained optimization algorithms, such as the Sequential Least Squares Programming (SLSQP), facilitating robust portfolio construction under nonlinear objectives and constraints [9, 10].

Beyond asset selection and optimization methods, the choice of historical data sampling frequency constitutes a crucial yet underexplored dimension of cryptocurrency portfolio optimization, as most existing studies rely primarily on daily price data and potentially neglect valuable intraday information. The vast majority of cryptocurrency portfolio studies are based exclusively on daily observations, thereby limiting the analysis of short-term market dynamics [11]. High-frequency data, while capable of capturing intraday fluctuations, may also introduce significant noise and estimation uncertainty, affecting volatility and correlation estimates [12].

The literature presents mixed conclusions regarding the impact of data granularity on portfolio performance. Recent benchmark studies have further emphasized the importance of frequency-aware and risk-based portfolio optimization in cryptocurrency markets [13, 14]. While some studies argue that daily data are sufficient for long-term portfolio formation and stable risk estimation [8], others highlight the advantages of higher-frequency data for short-term strategies and dynamic portfolio rebalancing, particularly during periods of elevated volatility [15]. Recent contributions further suggest that the effectiveness of data frequency may depend on market conditions, asset characteristics, and the adopted risk-adjusted optimization framework [16, 17]. The importance of global risk factors and advanced data-driven approaches in understanding cryptocurrency price dynamics and financial stability were discussed in [18]. These findings underline the need for frequency-aware portfolio optimization frameworks that can reconcile responsiveness to market movements with robustness against noise and estimation errors.

Motivated by these observations, this study conducts a comprehensive comparative analysis of cryptocurrency portfolio optimization using three different price sampling frequencies with 15-minute, 1-hour, and daily data. The analysis covers eight major cryptocurrencies, namely ADA, BTC, DOGE, ETH, LTC, SOL, TRX, and XRP, over a period expanding from January 1, 2023, to March 16, 2025. A risk-adjusted optimization framework based on the Sharpe ratio is employed, maximizing a risk-adjusted performance measure using the SLSQP algorithm. By systematically examining how data granularity influence asset allocation, correlation structures, and portfolio performance, this study aims to provide practical insights for investors and portfolio managers seeking to align portfolio strategies with their investment horizons and risk preferences.

This study contributes to the literature by providing an empirical and systematic comparison of cryptocurrency portfolio optimization outcomes under different data sampling frequencies, serving as a practical baseline for frequency-aware portfolio construction. It empirically demonstrates how sampling frequency affects asset allocation and portfolio composition in cryptocurrency markets.

II. METHODOLOGY

The proposed approach is grounded in modern portfolio theory and risk-adjusted performance evaluation, with the objective of determining optimal asset allocations under different temporal granularities. The analysis includes eight major cryptocurrencies, based on historical price data sampled at 3 different frequencies, from January 1, 2023, through March 16, 2025. The portfolio optimization problem is formulated as the maximization of a risk-adjusted performance measure based on the classical Sharpe ratio, solved using a constrained numerical optimization algorithm. All computational steps can be fully automated using Python-based scripts, ensuring that transparency, reproducibility, and consistency across experiments.

A. Asset Selection and Data Collection

The considered cryptocurrencies represent a typical group of digital assets that trade with high liquidity, huge market capitalization, and vigorous trade activity. For this reason, they can be used for portfolio studies [1, 2]. The closing OHLCV price values for the chosen digital assets are gathered from the KuCoin exchange. To incorporate various market dynamics and levels of information detail, three different sampling times were used in this study.

B. Data Preprocessing and Statistical Computation

All price indexes were aligned to Coordinated Universal Time (UTC). The missing values were replaced using forward filling, while outliers were treated to limit their impact. The logarithmic return series for each currency has been calculated for each frequency since logarithmic returns are preferred for comparison in portfolio studies to account for stationarity [3, 4]. The empirical mean return vector and the variance–covariance matrix for each frequency were calculated from the return series. To allow comparison among the different sampling rates, the measures of returns and volatility are annualized on the basis of a common scaling practice. The portfolio weights were recomputed on the basis of the frequency of the data set.

C. Portfolio Optimization Framework

The classical portfolio optimization method using total variance relies on the implicit assumption that asset return distributions are symmetric. This assumption is often violated in cryptocurrency markets, which are characterized by high volatility, heavy tails, and extreme price movements [3]. To address these challenges, the proposed model adopts a classical mean–variance-based portfolio optimization framework combined with risk-adjusted performance evaluation using the Sharpe ratio. It should be noted that the Sharpe ratio–based optimization adopted in this study follows a static mean–variance framework. While this approach is widely used and intuitive, it assumes symmetric return distributions and relatively stable volatility. These assumptions are often challenged in cryptocurrency markets, which are characterized by high volatility, heavy tails, and regime changes. Nevertheless, the use of a static framework is intentional, as the objective of this study is to isolate the impact of data sampling frequency under a consistent and widely accepted baseline.

1) Sharpe Ratio Formulation

To evaluate risk-adjusted portfolio performance, the Sharpe ratio is employed as a standard and widely accepted performance measure. The Sharpe ratio quantifies excess portfolio return per unit of total volatility and is defined by:

$$S = \frac{\mathrm{E}[R_P]-R_f}{\sigma_p} \tag{1}$$

where $\mathrm{E}[R_P]=\frac{1}{T}\sum_{t=1}^{T} R_t^P$ denotes the expected portfolio return, R_f is the risk-free rate, and σ_p represents the standard deviation of portfolio returns.

The portfolio return at time t is given by:

$$R_t^P = \sum_{i=1}^{n} \omega_i R_t^i \tag{2}$$

where ω_i is the weight of asset *i*, R_t^i is the return of asset *i*, and *n* is the number of assets.

2) Optimization via Sequential Least Squares Quadratic Programming (SLSQP)

The non-linear optimization problem is formulated by:

$$\begin{cases} max_{\omega} \dfrac{\mathrm{E}[R_P]-R_f}{\sigma_p} \\ \sum_{i=1}^{n} \omega_i = 1 \;\; \omega_i \geq 0\,,\; i = 1,2,\dots\dots\dots,n \end{cases} \tag{3}$$

where $\boldsymbol{\omega} = [\omega_1, \omega_2, \dots\dots\dots, \omega_n]^T$ is the vector of portfolio weights.

The optimization problem is solved using the SLSQP algorithm, which is well suited for handling nonlinear objective functions with linear equality and inequality constraints.

3) Performance Metrics

Optimized portfolios are evaluated using the metrics defined below:

$$\text{Mean Daily portfolio Return: } \bar{R}_p = \frac{1}{T}\sum_{i=1}^{T} R_t^P \tag{4}$$

$$\text{Daily Volatility: } \sigma_P=\sqrt{\frac{1}{T} \;\; \sum_{i=1}^{T}\left(R_t^P - \bar{R}_p\right)^2} \tag{5}$$

$$\text{Sharpe Ratio: } s_{\omega} = \frac{\bar{R}_p-R_f}{\sigma_p} \tag{6}$$

These metrics enable robust comparisons of portfolio performance across different sampling frequencies and market conditions [8, 16, 17].

III. RESULTS AND DISCUSSION

A. Data Collection and Preparation

Daily, hourly, and 15-minute closing prices for eight major cryptocurrencies (ADA, BTC, DOGE, ETH, LTC, SOL, TRX, and XRP) were retrieved from the KuCoin Exchange API over the period from January 1, 2023, to March 16, 2025. The daily dataset contains 806 observations, while the hourly and 15-minute datasets comprise 20,084 and 80,333 observations, respectively. These datasets were used to compute return, risk, correlation, and portfolio performance metrics across different sampling frequencies.

B. Impact of Data Frequency on Risk-Return

Table I reports the estimated annualized returns and volatility for each cryptocurrency and sample interval. Despite covering the same time period, return and risk estimates vary substantially across frequencies, indicating that sampling frequency significantly affects portfolio input parameters. Overall, higher-frequency data tend to produce higher volatility estimates, reflecting increased sensitivity to short-term price fluctuations. These results confirm that data granularity plays a critical role in the evaluation of cryptocurrency risk–return characteristics and directly influences portfolio optimization outcomes.

TABLE I. ESTIMATION OF CRYPTOCURRENCY RISK AND RETURN

Asset	Hourly Return (%)	Hourly Risk (%)	15-min Return (%)	15-min Risk (%)	Daily Return (%)	Daily Risk (%)
ADA/USDT	0.0102	0.9715	0.2457	4.7527	0.2388	4.9188
BTC/USDT	0.0094	0.5140	0.2268	2.5395	0.2322	2.5768
DOGE/USDT	0.0096	1.0057	0.2390	5.0739	0.2108	4.5696
ETH/USDT	0.0043	0.6257	0.1053	3.0945	0.1038	3.1006
LTC/USDT	0.0048	0.8272	0.1213	4.1744	0.1054	3.8998
SOL/USDT	0.0181	1.0142	0.4453	5.1520	0.4336	4.9296
TRX/USDT	0.0084	0.5468	0.1989	2.5144	0.2360	4.2123
XRP/USDT	0.0139	0.9192	0.3434	6.6870	0.3431	4.8782

C. Impact of Data Frequency on Optimal Asset Allocation

The obtained optimal portfolio weights are presented in Table II. The results show that sampling frequency has a pronounced effect on portfolio composition, with each frequency yielding a distinct allocation structure. Only four assets—BTC, SOL, TRX, and XRP—receive non-zero weights across the different frequencies, reflecting strong correlations among cryptocurrencies and limited diversification benefits for redundant assets. High-frequency data lead to increased allocations toward more volatile assets. For instance, TRX's weight increases from 26.45% using daily data to 39.23% using 15-minute data, while BTC's allocation also rises under higher-frequency sampling. These findings indicate that data frequency influences not only risk and return estimation but also asset inclusion and exclusion decisions in optimal portfolios. High-frequency strategies may therefore favor more reactive allocations, whereas daily data promote more stable portfolio structures.

TABLE II. OPTIMAL ASSET ALLOCATION

Asset	Daily Data Weight (%)	Hourly Data Weight (%)	15-Min Data Weight (%)
BTC/USDT	21.63	29.58	32.19
SOL/USDT	28.74	40.12	25.78
TRX/USDT	26.45	30.30	39.23
XRP/USDT	23.18	0.00	2.80
Others	0.00	0.00	0.00

D. Portfolio Performance Across Sampling Frequencies

Table III compares the performance of the constructed optimized portfolios. The portfolio based on daily data achieves the highest Sharpe ratio (6.86), outperforming both hourly (6.21) and 15-minute (6.17) portfolios. It should be noted that all Sharpe ratios reported in this study are annualized and computed over the 2023–2025 period, which corresponds to a particularly favorable market phase for cryptocurrencies, characterized by strong upward price movements and elevated returns. As a result, higher risk-adjusted performance values are observed. These Sharpe ratios should therefore be interpreted in a relative sense for comparing sampling frequencies rather than as absolute indicators of long-term portfolio performance. Although high-frequency portfolios exhibit slightly lower volatility, this advantage does not translate into superior risk-adjusted performance. Increased sensitivity to market noise and short-term fluctuations limits the effectiveness of high-frequency data within a static portfolio optimization framework. These results suggest that daily data provide a more favorable balance between risk and return for long-term portfolio optimization.

TABLE III. OPTIMAL PORTFOLIO PERFORMANCE

Metric	15-Minute Frequency	Hourly Frequency	Daily Frequency
Daily Return (%)	0.21	0.22	0.25
Daily Volatility (%)	3.46	3.57	3.60
Sharpe Ratio	6.17	6.21	6.86

E. Impact of Data Frequency on Return Correlation Structure

Correlation matrices were computed using the considered data (Figures 1–3). They reveal that asset correlations are strongly influenced by sampling frequency. Daily data produce stable and economically interpretable correlation patterns, characterized by high correlations among major cryptocurrencies such as BTC, ETH, and DOGE, and weaker correlations for assets such as TRX and XRP, indicating potential diversification benefits. In contrast, higher-frequency data capture short-term market noise, leading to less stable correlation estimates. This effect may create an illusion of enhanced diversification and result in an underestimation of systemic risk.

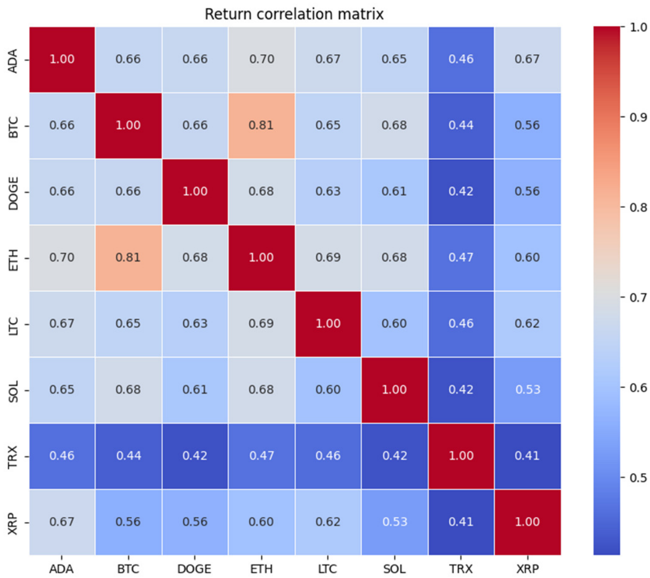

Fig. 1. Correlation matrix of cryptocurrency returns using 15-minute data.

Fig. 2. Correlation matrix of cryptocurrency returns using hourly data.

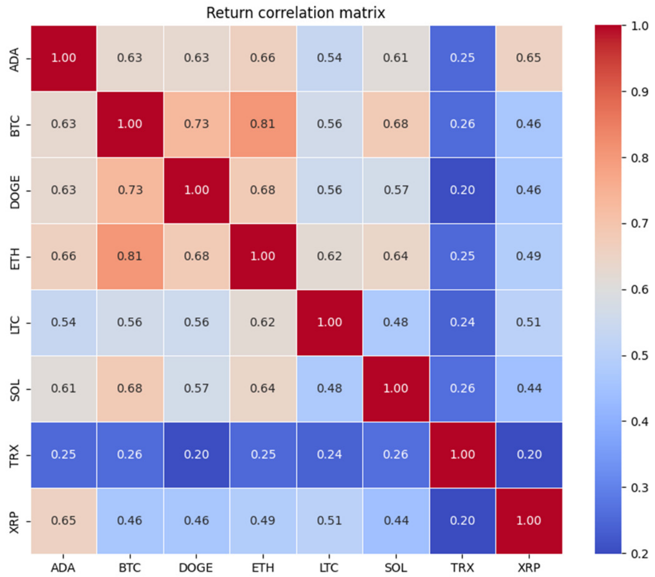

Fig. 3. Correlation matrix of cryptocurrency returns using daily data.

F. Comparative Analysis and Portfolio Implications

The comparative analysis across sampling frequencies highlights a fundamental noise–signal trade-off in cryptocurrency portfolio optimization. High-frequency data capture intraday market dynamics and enable rapid responsiveness, but they also introduce significant estimation noise that can distort risk, correlation, and diversification assessments. As data are aggregated to lower frequencies, noise is progressively reduced, resulting in more robust portfolio inputs and improved risk-adjusted performance. To evaluate the robustness of the results, additional checks were conducted by examining the stability of portfolio allocations and Sharpe ratios across different sub-periods and alternative assumptions regarding the risk-free rate. The relative ranking between daily, hourly, and 15-minute sampling frequencies remained unchanged, indicating that the main conclusions are robust and not driven by specific parameter choices. From a practical perspective, high-frequency data are more suitable for short-term or actively rebalanced strategies, whereas daily data are better aligned with long-term and institutional investment objectives that prioritize stability and robustness.

The analysis is restricted to Sharpe ratio–based optimization as a baseline framework, and comparisons with alternative approaches such as minimum variance or CVaR optimization are left for future research. A limitation of this study is the absence of explicit out-of-sample or walk-forward validation, and the results should therefore be interpreted as full-sample empirical benchmarks rather than deployable trading strategies.

IV. CONCLUSION

It is clear from this study that sampling frequency is an important determinant in implementing portfolio optimization for cryptocurrencies. There are variations identified in estimating returns, volatility, and correlation, depending on the data sampling rate.

The acquired results indicate a trade-off between responsiveness and stability. High-frequency data may capture the short-run dynamics in markets and allow for more responsive portfolios, but they are associated with more estimation errors, which can be harmful to the quality of inputs for portfolio construction. Daily data are more stable, resulting in better risk-adjusted returns, as measured by the Sharpe ratio.

The significance of this study lies in the combination of the concept of multivariate frequency data in a risk-adjusted portfolio optimization technique utilizing the Sharpe satio principle with the SLSQP optimization algorithm. The implications of this frequency-based perspective are informative for investors aiming for risk-oriented alignment of portfolio strategies with their respective investment time horizons in volatile digital markets.

DATA AVAILABILITY

All Python scripts used for data preprocessing, portfolio optimization, and performance evaluation can be available from the authors upon reasonable request.

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