A SENTIMENT-DRIVEN STRATEGY FOR CRYPTOCURRENCY PORTFOLIO DYNAMIC OPTIMIZATION

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Managing cryptocurrency portfolios is challenging due to extreme volatility, the absence of fundamental valuation metrics, sentiment-driven price movements, technological disruptions, and security risks. This study investigates whether incorporating investor sentiment into dynamic portfolio optimization improves performance. Using the Crypto Fear & Greed Index as a sentiment signal, we identify optimal rebalancing (reoptimization) timing under four portfolio strategies: maximum Sharpe ratio, minimum variance, maximum modified Sharpe ratio, and minimum Conditional Value-at-Risk (CVaR). Significant shifts in the temporal dynamics of the sentiment time series were identified as triggers for portfolio reoptimization. Empirical results demonstrate that sentiment-triggered reoptimization outperforms periodic rebalancing benchmarks—particularly during high-volatility periods—by reducing transaction costs and enhancing risk-adjusted returns. Notably, minimum variance portfolios achieved superior extreme loss mitigation compared to CVaR minimization when reoptimization timing was sentiment-driven. These findings demonstrate the value of behavioral metrics in cryptocurrency asset allocation and provide investors with an alternative portfolio optimization strategy.

Keywords: Cryptocurrency Portfolio Optimization; Market Sentiment Analysis; Dynamic Rebalancing; Behavioral Finance.

1 INTRODUCTION

Portfolio optimization is a central topic in finance, addressing how investors can dynamically adjust their strategies to achieve objectives amid changing market conditions (ZHANG *et al.*, 2023). Over the past seven decades, portfolio models have evolved significantly, reflecting the growing complexity of financial markets and the demand for more adaptive strategies (SALO *et al.*, 2023). In particular, the rise of dynamic and multi-period optimization frameworks highlights their practical relevance in addressing real-world challenges, such as shifting market regimes and transaction costs (ZHANG *et al.*, 2023).

The rapid expansion of the cryptocurrency market has introduced both new opportunities and challenges for investors (FANG *et al.*, 2021). Its decentralized architecture enhances user autonomy by reducing transaction and transfer costs (MAKRIDIS *et al.*, 2023). Furthermore, the inherent auditability of blockchain technology mitigates fraud risks and improves transactional transparency (MAESA; MORI; RICCI, 2019). However, cryptocurrencies exhibit significantly higher price volatility than traditional assets. While this volatility can enable greater returns, it also necessitates precise price monitoring and robust risk management strategies (ALMEIDA; GONÇALVES, 2023).

Sentiment analysis enhances traditional quantitative metrics by incorporating behavioral insights into asset allocation decisions, thereby improving the risk-return trade-off (YU *et al.*, 2022). Unlike purely historical price data, sentiment indicators more effectively signal impending upward or downward price movements (CAI; TANG; CHEN, 2024), as they directly capture investors' collective beliefs and expectations about future prices and cash flows (ADAM; NAGEL, 2023). The cryptocurrency market's dominance by individual investors (PILATIN; DILEK, 2023) further amplifies sentiment's role in driving price fluctuations and volatility (ALMEIDA; GONÇALVES, 2023). Consequently, integrating sentiment data with historical price information—rather than relying solely on fixed-frequency rebalancing—presents a promising avenue for developing more adaptive and robust portfolio strategies.

In this context, a critical question remains: given a set of objectives, constraints, and optimal weights, when is the right time to reoptimize a portfolio?[1] This study tackles this question by introducing a data-driven approach to determine rebalancing timing—leveraging market sentiment as a key signal for dynamic adjustments.

This study investigates whether integrating investor sentiment analysis into dynamic portfolio rebalancing timing can enhance cryptocurrency portfolio performance. While sentiment-based strategies have been explored in traditional markets, their application to

[1] In this study, the terms rebalancing and portfolio reoptimization are treated as equivalent concepts. Given a defined universe of assets, investors determine the weights that optimize their target objective (such as Sharpe ratio maximization, for instance). This optimization yields what are called optimal weights. The investor maintains this portfolio in the market and, at a given point, may choose to revise the asset weights—a process called rebalancing or reoptimization—aiming to obtain the most suitable allocation for current market conditions. The primary focus of this study is to determine the optimal timing for such reoptimization.

cryptocurrencies—a market uniquely driven by events and herd behavior—remains nascent. Current portfolio optimization models predominantly rely on fixed-interval/periodic rebalancing, which fails to adapt to the crypto market's volatility dynamic. By leveraging sentiment as a triggering mechanism for dynamic reoptimization, this work introduces a context-aware framework that aligns portfolio adjustments with real-time market conditions, offering a more responsive approach to crypto asset allocation.

This paper examines the temporal dynamics of the Crypto Fear & Greed Index to identify optimal reoptimization timing for cryptocurrency portfolios using two main criteria: (1) crossings of dynamic bands based on extreme percentiles (5th and 95th) of the sentiment indicator, signaling extreme market conditions; and (2) significant index variations defined as movements exceeding two standard deviations from its historical mean. Hence, significant shifts in the temporal dynamics of the sentiment time series were identified as triggers for portfolio reoptimization. These inflection points, characterized by statistically meaningful changes in sentiment trends or volatility patterns, serve as behavioral indicators for adjusting asset allocations in response to evolving market psychology. The study evaluates portfolios comprising the top 20 most liquid cryptocurrencies from 2018 to 2023, testing four optimization strategies—Sharpe ratio maximization, variance minimization, Conditional Value-at-Risk (CVaR) minimization, and modified Sharpe ratio maximization—with performance compared against periodic rebalancing approaches (weekly, monthly, and quarterly) through comprehensive risk-return metrics.

The results demonstrate that portfolio reallocation strategies incorporating investor sentiment consistently outperform fixed-period/periodic optimization approaches in terms of risk-adjusted returns. This superiority is particularly evident during significant market downturns, while also maintaining lower transaction costs. Among the various optimization strategies tested, risk-minimizing approaches—specifically minimum variance and minimum CVaR optimizations—proved more efficient than return-maximizing strategies such as maximum Sharpe Ratio (SR) and maximum modified Sharpe Ratio (MSR) optimizations. Furthermore, within the efficient strategies, sentiment-based approaches with higher sensitivity to minor market fluctuations were shown to be particularly suitable for risk-tolerant investors when compared to traditional benchmarks.

This study makes three key contributions to academia and market practice. First, it introduces a novel sentiment-based triggering mechanism for dynamic portfolio rebalancing in cryptocurrencies, advancing the literature on behavioral portfolio optimization. Second, it demonstrates empirically that sentiment extremes (captured through the Crypto Fear & Greed Index) serve as effective rebalancing signals than calendar-based approaches, particularly for risk-minimizing strategies. Third, for practitioners, the research provides a framework to: (i) reduce transaction costs through event-driven rebalancing, (ii) improve risk-adjusted returns during market turbulence, and (ii) tailor reoptimization sensitivity to investor risk profiles. The findings challenge conventional periodic rebalancing norms in crypto asset management while offering implementable tools for algorithmic trading systems.

The remainder of this work is organized as follows. Section 2 reviews the foundational literature, covering portfolio optimization approaches, behavioral finance principles, financial sentiment analysis applications, and existing cryptocurrency portfolio models. Section 3 presents the methodological framework, detailing both data collection procedures and analytical approaches. Section 4 reports and discusses the empirical results, comparing the performance of sentiment-driven reallocation strategies against conventional periodic rebalancing approaches, with particular attention to transaction cost implications. Section 5 concludes and proposes directions for future research.

2 LITERATURE REVIEW

This section synthesizes the studies across three foundational domains: (1) portfolio optimization, (2) behavioral finance's impact on investment decision-making, and (3) contemporary approaches to cryptocurrency portfolio management. The review establishes the theoretical framework for our sentiment-driven rebalancing methodology while identifying critical gaps in existing research.

2.1 Portfolio Optimization

The foundations of modern portfolio optimization trace back to Markowitz (1952) seminal work introducing the mean-variance (MV) model, which established a quantitative framework for selecting optimal asset combinations that maximize expected returns for given risk levels. For the purposes of this study, we focus on three critical aspects of the MV model that subsequent research has expanded upon: (1) its single-period investment horizon, (2) its simplified parametric structure, and (3) its dependence on the assumption of normally distributed returns.

Regarding the single-period portfolio, subsequent studies showed positive empirical results when proposing approximations derived from the MV model but using different types of utility functions, especially those considering a continuous-time and intertemporal model rather than a single-period one (SAMUELSON, 1969; MERTON, 1971). However, according to Atkinson and Mokkhavesa (2004), one of the main weaknesses of this theory is the zero-transaction cost assumption, as it compromises the practical application of optimization (YU *et al.*, 2022). Dynamic portfolio optimization models address these limitations by incorporating continuous or periodic portfolio rebalancing, while explicitly accounting for two critical market realities: (1) transaction costs that erode returns, and (2) time-varying market conditions that alter risk-return profiles. These models extend traditional frameworks by introducing adaptive optimization mechanisms responsive to evolving market dynamics (SALO *et al.*, 2023).

According to Bowala and Singh (2022), traditional risk measures, such as standard deviation and variance, often fail to quantify the entire complexity of risk in highly volatile markets, such as that of cryptocurrencies. These measures generally assume a normal distribution of asset returns, which tends to be a more accurate approximation for stable and low-risk portfolios. However, in highly volatile markets, returns frequently exhibit skewness and heavy tails, which deviate significantly from the assumptions underlying normal distribution models, such as the MV model. In this sense, Samuelson (1975) proposed the consideration of higher-order moments, such as skewness and kurtosis, when dealing with high-risk portfolio optimization to avoid suboptimal allocation strategies.

2.2 Behavioral Finance and Investor Sentiment

Behavioral finance incorporates psychological aspects into financial models, considering that investors' behavior can influence asset prices (BARBER; ODEAN, 2000). For example, investors often overreact to new information, causing prices to move excessively, which, combined with subsequent corrections, generates high volatility in long-term returns (HIRSHLEIFER, 2001). Current research in this domain focuses on three interconnected themes: (1) the measurement and dynamics of investor sentiment, (2) quantitative models assessing sentiment's influence on financial markets, and (3) the predictive relationship between sentiment indicators and expected stock returns. These research streams collectively advance our understanding of behavioral factors in asset pricing and portfolio management (PAULE-VIANEZ; GÓMEZ-MARTÍNEZ; PRADO-ROMÁN, 2020).

Studies use different methods to measure investors' sentiment. Zheludev, Smith, and Aste (2014) analyzed investors' sentiment from Twitter text messages and concluded that social media sentiment offers valuable information about financial market movements, especially for assets with a strong online presence. Meanwhile, Barone-Adesi, Pisati, and Sala (2018) evaluated the predictive ability of quantitative proxies of fear and greed on market return and risk, with fear driven by uncertainty and pessimistic views, while greed is driven by optimism and low-risk aversion. The study demonstrated that these measures effectively predict market movements and volatility.

Among the researchers who explored or developed sentiment-based portfolio models, Banholzer, Heiden, and Schneller (2018) studied the use of the Copula Opinion Pooling (COP) method to incorporate sentiment information into a portfolio optimization model, showing that its inclusion improves risk-adjusted return metrics and reduces downside risk. Yu *et al*. (2022) developed dynamic portfolio rebalancing models that are optimized using CVaR and Omega Index and incorporated changes in investor sentiment to determine the weights and positions for each asset.

Regarding studies about how investors' behavior influences asset price movements, it was demonstrated that investor sentiment can be used to predict asset prices, especially on assets with high dominance of retail investors and high non-systemic risk (KUMAR; LEE, 2006). The cryptocurrency market fits into the first attribute, as it is still dominated by retail investors, who are more susceptible to misinterpreting new information than institutional investors (OZDAMAR; SENSOY; AKDENIZ, 2022). Consequently, cryptocurrencies are known for their high idiosyncratic volatility, which can be attributed to their microstructure noise, low liquidity, and high speculation (BOURI *et al*., 2022).

2.3 Cryptocurrency Portfolio Models

With the exponential growth of the cryptocurrency market, researchers have dedicated themselves to adapting and developing portfolio models capable of dealing with its unique characteristics (ZHOU *ET AL*., 2023). In this context, various strategies for cryptocurrency portfolios have emerged, incorporating approaches such as traditional mean-variance, high-order moments, investor sentiments, and dynamic optimizations.

Jing and Luis (2023) presented a network-based approach for optimizing cryptocurrency portfolios by leveraging price correlations to minimize global correlation and improve risk-adjusted returns. The results showed that portfolios constructed using this strategy outperform traditional benchmarks, especially for short-term investments. Alternatively, Khaki *et al.* (2022) compared the MV model and the higher-order moments optimization model for multi-asset portfolios with the inclusion of cryptocurrencies. The study demonstrated that the higher-order moments model better captured tail risks and return asymmetry.

In addition, He *et al.* (2023) used the Crypto Fear & Greed Index to predict Bitcoin (BTC) and Ethereum (ETH) returns, concluding that it not only increased the returns prediction effectiveness compared to the historical average returns model but also demonstrated higher economic value, especially for shorter investment horizons. Similarly, Zhou *et al.* (2023) presented a cryptocurrency portfolio optimization model based on multi-source data, including historical data and Twitter sentiment, to predict returns. Using sentiment analysis, the study predicted future price changes and incorporated these predictions into a minimum variance portfolio model, outperforming traditional strategies such as 1/N and tangency portfolios.

Lucarelli and Borrotti (2020) presented a dynamic portfolio management model based on Deep Q-Learning, a deep reinforcement learning technique, seeking to optimize asset allocation in a portfolio of cryptocurrencies based on recent market information and past actions. The model outperforms traditional methods, such as equally weighted portfolios, in maximizing risk-adjusted returns. Analogously, Nasreen, Tiwari, and Yoon (2021) evaluated how dynamic connectivity between different cryptocurrencies can create more diversified and resilient portfolios during periods of high volatility, such as the COVID-19 pandemic. By optimizing the cryptocurrency portfolio for minimum connectivity and dynamically adjusting weights based on changes in asset interdependence, the analysis demonstrated that cryptocurrencies can be used as hedging assets.

The literature broadly demonstrates that dynamic portfolio optimization techniques are crucial for capturing the complex dynamics of financial markets and improving investor outcomes in terms of risk and return. In the cryptocurrency market, investor sentiment plays a significant role in explaining price fluctuations of digital assets. Building on this evidence, this study proposes a sentiment-driven portfolio reoptimization strategy. The core premise is to monitor market sentiment dynamics to identify the timing for investors to rebalance their portfolios—by reoptimizing the target objective and obtaining the new asset allocations (portfolio weights)—given the established relationship between sentiment shifts and cryptocurrency price movements.

3 METHODOLOGY

This section outlines the methodological framework employed in this study. First, we specify the cryptocurrency dataset used for portfolio construction. Next, we present the market sentiment monitoring strategies that determine the reoptimization timing rules. Subsequently, we detail the portfolio composition strategies, followed by the performance evaluation metrics used to assess the results.

3.1 Data

The study analyzes the 20 cryptocurrencies with the highest market capitalization as of December 31, 2028[2]: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Bitcoin Cash (BCH), Litecoin (LTC), Cardano (ADA), EOS (EOS), Stellar (XLM), TRON (TRX), IOTA (MIOTA), Binance Coin (BNB), Monero (XMR), Dash (DASH), NEM (XEM), Ethereum Classic (ETC), Neo (NEO), Maker (MKR), Waves (WAVES), Zcash (ZEC), and Tezos (XTZ). This selection represents the most liquid and established digital assets in the cryptocurrency market. It is essential to highlight that stablecoins were not included.

Historical daily closing prices were extracted from Yahoo Finance, considering the period from October 3, 2018, to December 31, 2023. Investor sentiment was quantified using the Crypto Fear & Greed Index (F&G Index), a composite metric sourced from Alternative.me[3]. This index aggregates multiple behavioral and market indicators in the following weighted composition: market volatility (25%), trading volume (25%), social media activity (15%), survey data (15%), Bitcoin dominance (10%), and search trends (10%). The index outputs normalized values on a bounded scale from 0 ("Extreme Fear") to 100 ("Extreme Greed"), providing a daily sentiment benchmark for cryptocurrency markets.

Furthermore, the risk-free rate was estimated by the rate of returns on 3-month US treasury securities extracted from the Federal Reserve Economic Data (FRED)[4]. All the data were collected through their respective APIs. he quantitative analysis and portfolio optimizations were implemented in Python.

[2] The most significant cryptocurrency market capitalization values for December 31st, 2018, were obtained from the CoinMarketCap website. Available at: https://coinmarketcap.com/historical/20181231/. Accessed on: 3 Oct. 2024.
[3] Source: https://alternative.me/crypto/. Accessed on: 3 Oct. 2024.
[4] Source: https://fred.stlouisfed.org/. Accessed on: 3 Oct. 2024.

3.2 Investor Sentiment Analysis

The study employs market sentiment analysis to determine optimal portfolio rebalancing timings. Portfolio optimization is triggered upon detection of statistically significant sentiment shifts, as identified through four distinct quantitative approaches:

1) 1 Standard Deviation Threshold (1STD);
2) 2 Standard Deviation Threshold (2STD);
3) 95th Percentile Threshold (95PCTL);
4) 99th Percentile Threshold (99PCTL).

The threshold-based methods (1STD and 2STD) utilize a 90-day simple moving average (*SMA*) of the Crypto F&G Index[5] with dynamic bands calculated as:

$$Upper\ Band_t = SMA_t + (k \times \sigma_t^{F\&G})$$

$$Lower\ Band_t = SMA_t - (k \times \sigma_t^{F\&G})$$

where $Upper\ Band_t$ and $Lower\ Band_t$ are the upper and lower bands, respectively, to define the trigger for reoptimization; $\sigma_t^{F\&G}$ is the sample standard deviation of the Crypto Fear & Greed index, calculated using data up to instant t; $k \in \{1, 2\}$ depending on the strategy (1STD or 2 STD).

As illustrated in Figure 1, a trading signal is generated when: i) the absolute F&G Index value crosses either band, and ii) the minimum holding period constraint (7, 30, or 90 days) is satisfied. This dual-condition mechanism serves two purposes: focusing on extreme sentiment conditions (absolute value crossing); and preventing excessive trading through minimum rebalancing intervals. We implemented a minimum holding period constraint to account for sentiment persistence in financial markets. This prevents excessive reoptimization during periods when market sentiment remains relatively stable, ensuring portfolio adjustments only

[5] Multiple window lengths for the moving average calculation were evaluated. The 90-day period emerged as optimal, effectively balancing two critical requirements: (1) excluding stale market information while maintaining sufficient historical context, and (2) providing appropriate smoothing dynamics for the threshold bands. This configuration optimally captures persistent sentiment trends without overreacting to short-term noise, as shorter windows proved too sensitive to transient fluctuations while longer windows incorporated outdated signals.

occur when they meaningfully reflect new market conditions. The constraint serves two purposes: (1) it reduces unnecessary transaction costs from overtrading, and (2) it ensures each reoptimization decision captures substantively changed market dynamics rather than minor fluctuations. The 1STD strategy provides higher sensitivity to moderate sentiment changes, while 2STD activation requires more substantial sentiment shocks. This framework bridges behavioral finance insights with quantitative portfolio management while addressing practical implementation constraints through its minimum rebalancing period requirement.

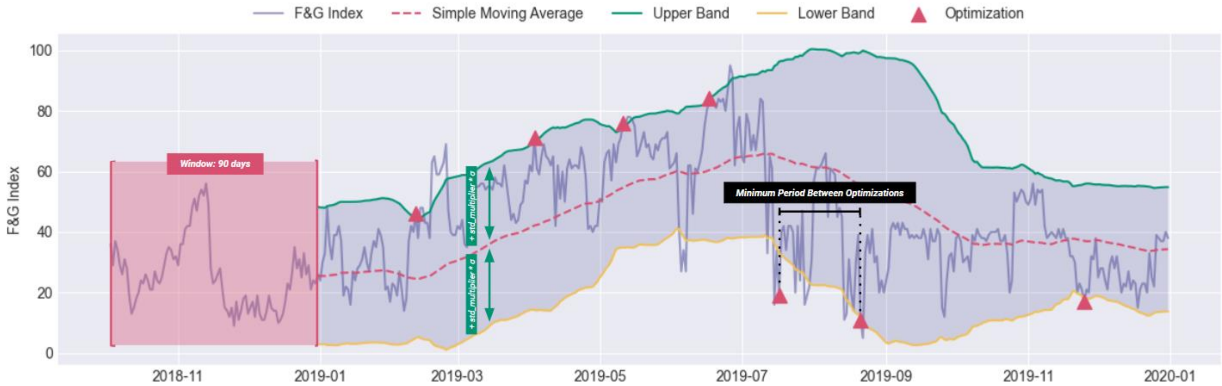

Figure 1. F&G Index Analysis for 1 Standard Deviation (1STD) Strategy.

Alternatively, the percentile-based analyses (95PCTL and 99PCTL) similarly employ a 90-day simple moving average of the Crypto F&G Index but utilize recursive percentile thresholds (95th/5th for 95PCTL; 99th/1st for 99PCTL) to define dynamic bands. For instance, for the 95PCTL strategy, the upper band is the 95th percentile and the lower band is the 5th percentile. Reoptimization triggers when the F&G Index's variance crosses these thresholds, provided the minimum holding period (7, 30, or 90 days) is satisfied—a mechanism illustrated in Figure 2. By focusing on variance rather than absolute levels, this approach better captures rapid sentiment shifts, with 95PCTL responding to moderate fluctuations and 99PCTL activating only during extreme sentiment volatility, thereby offering tiered sensitivity to market dynamics while maintaining systematic rebalancing constraints. Percentile approaches focus on the variance (rather than the level) of the F&G Index, capturing rapid sentiment shifts through second-moment dynamics, providing non-parametric thresholds that adapt to the empirical distribution, and maintaining the same minimum rebalancing constraints for comparability with the standard deviation strategy.

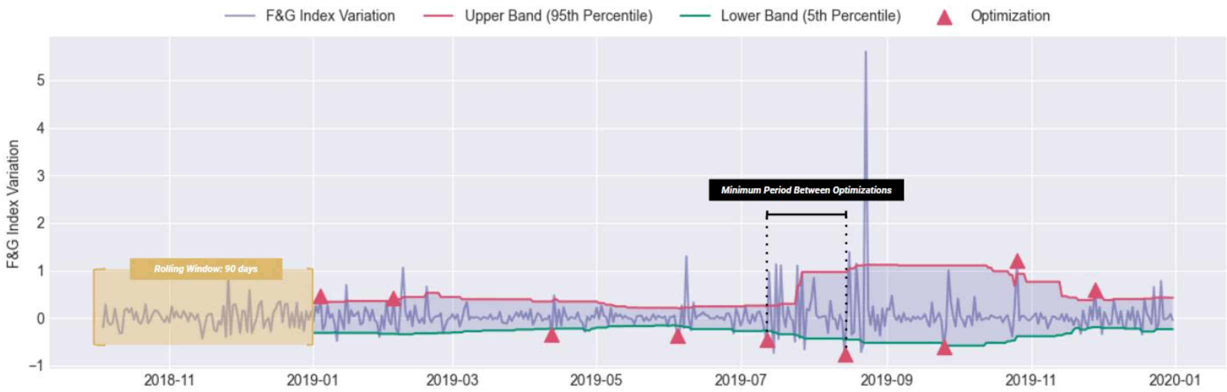

Figure 2. F&G Index Analysis for 95th Percentile (95PCTL).

3.3 Portfolio Optimization Strategies

This study incorporates both long and short positions while enforcing two key constraints: (1) the sum of all asset weights must equal 1 (full capital allocation), and (2) portfolio concentration is limited via a maximum Normalized Herfindahl-Hirschman Index (HHIN) of 0.20, ensuring diversification. The Herfindahl-Hirschman Index (HHI)—a well-established measure of market concentration—is adapted here to quantify portfolio diversification, where lower values indicate greater diversification (ARDAKANI, 2024; FULKERSON; RILEY, 2019). HHI is normalized, HHI^N, in this study to facilitate its interpretation, working as a standardized scale between 0 and 1, being defined as:

$$HHI^N = \frac{HHI - \frac{1}{n}}{1 - \frac{1}{n}}\ ,\ with\ \ HHI = \sum_{i=1}^{n} w_i^2, \tag{1}$$

where n is the total number of assets in the portfolio and w_i is the weight of each asset; thus, a higher weight for a single asset increases HHI.

Notably, all assets maintain non-zero weights during optimization, and the asset universe remains fixed (no additions/removals), forcing the strategy to reallocate rather than reconstitute holdings.

In the first part of this study, two optimizations aligned with Markowitz's MV model will be analyzed: a maximum Sharpe ratio strategy and a minimum variance strategy. The former is suitable for investors who wish to maximize the return of their portfolio relative to risk, comparing its risk premium with a risk-free rate of return. In this way, the maximum Sharpe ratio (SR) strategy objective function is the following:

$$\max_{w}[SR_p] = \max_{w}\frac{w^T\mu_p - R_F}{\sigma_p}, \tag{2}$$

$$s.t. \qquad \sum_{i=1}^{n} w_i = 1,\ HHI^N \leq 0.20\ ,\ -1 \leq\ w_i \leq 1\ ,\ \forall i \in \{1,2,\dots,n\}, \tag{3}$$

where μ_p is the portfolio's vector of assets mean returns, R_F is the risk-free interest rate, and σ_p is the portfolio returns standard deviation (historical approach).

Additionally, the minimum variance (σ^2) strategy is more adequate for investors who wish to reduce the absolute risk regardless of the portfolio's expected return. Its objective function was set as the following:

$$\min_{w}[\sigma_p^2] = \min_{w}\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \times Cov(R_i, R_j)\ , \tag{4}$$

$$s.t. \qquad \sum_{i=1}^{n} w_i = 1\ ,\ HHI^N \leq 0.20,\ -1 \leq\ w_i \leq 1\ ,\ \forall i \in \{1,2,\dots,n\}, \tag{5}$$

where $Cov(R_i, R_j)$ is the covariance between the returns of assets i and j. Here, we adopted for simplicity the historical approach to compute the covariance matrix.

Two strategies will be analyzed to evaluate the consideration of higher-order statistics or long-tailed distributions in a cryptocurrency portfolio optimization: a maximum modified Sharpe ratio (MSR) strategy and a minimum Conditional Value at Risk (CVaR) strategy. The first is a more risk-tolerant approach to achieve the highest risk-adjusted return. Introduced by Gregoriou and Gueyie (2003), the MSR replaces the standard deviation on the traditional Sharpe ratio equation with the modifier Value at Risk (MVaR), proposed by Favre and Galeano (2002) to extend its limitations regarding non-normal distributions. Its objective function is defined as the following:

$$\max_{w}[MSR_p] = \max_{w}\frac{w^T\mu_p - R_F}{MVaR}\ , \tag{6}$$

$$s.t. \qquad \sum_{i=1}^{n} w_i = 1\ ,\ HHI^N \leq 0.20,\ -1 \leq\ w_i \leq 1\ ,\ \forall i \in \{1,2,\dots,n\}, \tag{7}$$

Where $MVaR = W\left[\mu_p - \left\{z_c + \frac{1}{6}(z_c^2 - 1)S_p + \frac{1}{24}(z_c^3 - 3z_c)K_p - \frac{1}{36}(2z_c^3 - 5z_c)S^2\right\}\sigma_p\right]$, z_c is the critical value for a confidence level (α) of 95%, K_p is the portfolio excess kurtosis, and S_p is the portfolio skewness.

Finally, another optimization strategy minimizes the CvaR. It is a metric that measures the average expected loss beyond the Value at Risk (VaR) at a given α. Minimizing CVaR makes the strategy more suitable for risk-averse investors, especially those more intolerant to extreme losses. Its objective function is the following:

$$\min_{w} CVaR = \min_{w} \mathbb{E}[\, f(w, r_s) \mid f(w, r_s) \leq VaR_{\alpha}], \tag{8}$$

$$s.t. \qquad \sum_{i=1}^{n} w_i = 1, HHI^N \leq 0.20, -1 \leq w_i \leq 1, \forall i \in \{1,2,\ldots,n\}, \tag{9}$$

where $f(w, r_s)$ is the function of portfolio losses in each scenario s, considering only those in the lower tail of the distribution, at or below VaR_{α} with a 95% confidence level (α).

Portfolio weights are optimized using the Sequential Least Squares Programming (SLSQP)[6] method according to each strategy's objective function when the sentiment analysis conditions are satisfied and on the first day of the investment. The sentiment-based portfolios were also compared to Fixed-Period Optimization (FPO) portfolios, in which each optimization occurs every 7, 30, or 90 days (frequent reoptimization strategy).

3.4 Performance Analysis Procedures

To evaluate each portfolio performance, the annualized portfolio total return, the risk-adjusted measured by the MSR, and the downside risk measured by the CVaR will be used. To analyze portfolios average risk, the Exponentially Weighted Moving Standard Deviation ($\sigma_T(EWMA)$) is going to be used as the following for a time interval analysis ($t = 1, 2, \ldots, T$):

$$\sigma_T(EWMA) = \sqrt{\sum_{i=1}^{T-1} \lambda^i (1 - \lambda) R_{T-1}^2}, \; 0 \leq \lambda \leq 1, \tag{10}$$

where R_{T-1}^2 is the portfolio return on the period $T - 1$, λ is the smoothing parameter, which in this study is considered 94%, indicating a slower decay in the series.

To prevent performance overestimation and maintain practical relevance, total transaction costs (τ) are estimated by the daily turnover as:

[6] The Sequential Least Squares Programming (SLSQP) method combines sequential quadratic programming with nonlinear least squares to optimize constrained problems in which some of the constraints are nonlinear equalities or inequalities or the objective function is nonlinear (FU; LIU; GUO, 2019).

$$\tau = \frac{1}{2}\sum_{i=1}^{n}\left|w_{i,t} - w_{i,t-1} \times 1\%\right|. \tag{11}$$

Considering an initial investment of $1,000,000, the ending portfolio value and the total transaction costs will be estimated in monetary terms, finally allowing the calculation of both the annualized total return and the MSR with discounted transaction costs.

4 RESULTS ANALYSIS

This section presents the empirical results. First, we analyze the statistical properties of the sentiment time series and cryptocurrency price returns. Next, we evaluate portfolio performance for each investment strategy considered: Sharpe ratio maximization, modified Sharpe ratio maximization, variance minimization, and CVaR minimization. The analysis aims to verify whether using sentiment as a timing indicator for portfolio reoptimization outperforms a naive periodic rebalancing strategy. Finally, we compare the strategies to identify cases where sentiment-driven reoptimization provides superior risk-return benefits.

4.1 Descriptive Analysis of the Data

Figure 3 illustrates the temporal dynamics of the Crypto Fear & Greed Index from 2019 to 2023. The index exhibits substantial volatility during this period, with pronounced fluctuations corresponding to major market events. This historical perspective is crucial for analyzing the relationship between investor sentiment, price movements, and market volatility in cryptocurrency markets. For instance, it is possible to identify the same year peaks of greed above 80 and abrupt drops in periods of extreme fear, such as in 2020. This year was highly influenced by the COVID-19 pandemic, so that in the same week that the World Health Organization (WHO) declared it, Bitcoin's price dropped nearly 50%, indicating extreme fear of the Crypto F&G index.

In February 2021, Tesla announced that it had bought about $1.5 billion of Bitcoins, making investors believe that the cryptocurrency would become a mainstream financial asset, according to BBC News (BITCOIN [...], 2021), and consequently increasing the Crypto F&G Index (see Figure 3). After that, in November 2021, the Bitcoin price hit an all-time high of more than $68,000 as investors kept buying it as a hedge of gold to protect themselves from rising inflation (KOLLEWE, 2021), leading to another extreme greed moment. On the other hand, in May 2022, the cryptocurrency LUNA crash brought fear to investors regarding the volatility of the crypto market, making them express their panic through tons of messages on Twitter and Reddit and negatively impacting the price of other cryptocurrencies, such as Bitcoin (SÁNCHEZ, 2022)–see Figure 3.

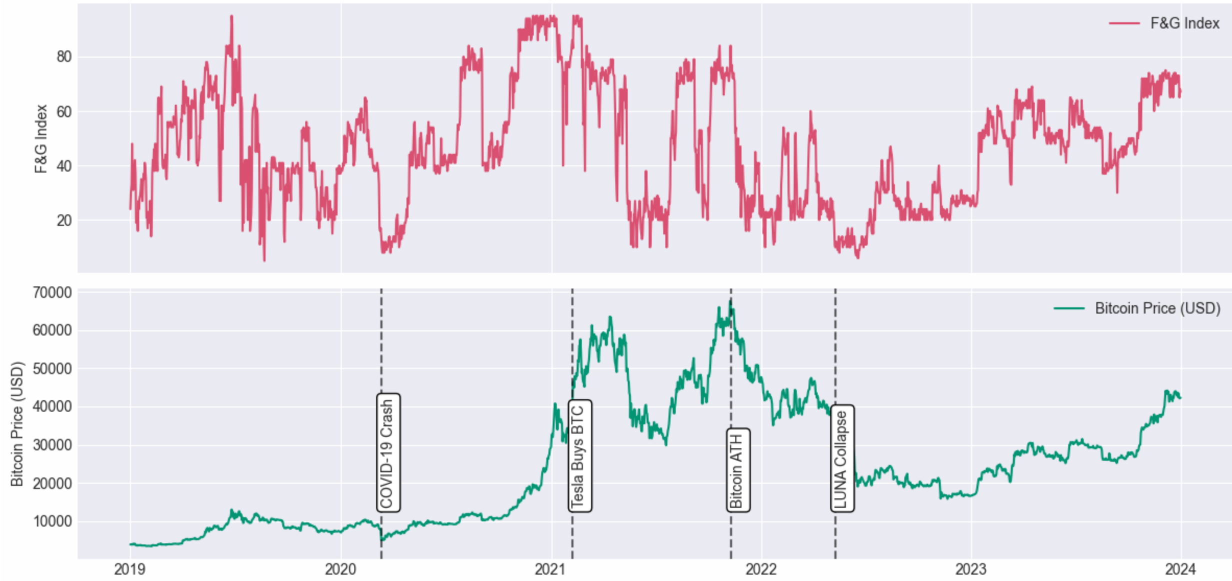

Figure 3. Time Evolution of Crypto F&G Index and Bitcoin Price.

As this study will compare the use of higher and lower-order moments in the optimizations' objective functions, analyzing the logarithmic returns distribution of assets is essential. As it can be seen in Figure 4, cryptocurrencies like XRP (0.45), WAVES (0.60), and XLM (0.97) presented skewness above zero, indicating a slightly higher tendency to present extreme positive returns than negative ones. In contrast, XMR (-1.38), ETH (-1.18), and BTC (-1.18) demonstrated a significant negative skewness, indicating that extreme negative returns were more frequent than positive ones.

Most cryptocurrencies have kurtosis above 3, which is the kurtosis of a normal distribution, indicating the existence of heavy tails. MKR (27.98), XRP (21.03), and BNB (20.60) show a high concentration of returns close to the mean but with wider fluctuations, resulting in more significant potential for extreme variations. This suggests the need to evaluate risk based on the first and second moments and include metrics like skewness, kurtosis, and CVaR to assess the frequency and impact of extreme events on a portfolio's performance.

The Kolmogorov-Smirnov test[7] was used to test the hypothesis of normal distribution and the hypothesis of t-Student distribution afterward in the sample of logarithmic returns. Considering that kurtosis and skewness of assets consistently deviate from normal ones, a non-parametric test was chosen, not requiring the distributions to meet any assumptions about their shape, being the hypothesis of normality and t-Student rejected if the *p-value* is less than or equal to 0.05. The results in Figure 4 show that the null hypothesis is rejected for normality. After that, a second test shows no evidence to reject the null hypothesis for the t-student distribution with degrees of freedom (df) equal to or lower than 3.10, so the daily logarithmic returns distributions have heavier tails and a higher frequency of extreme events.

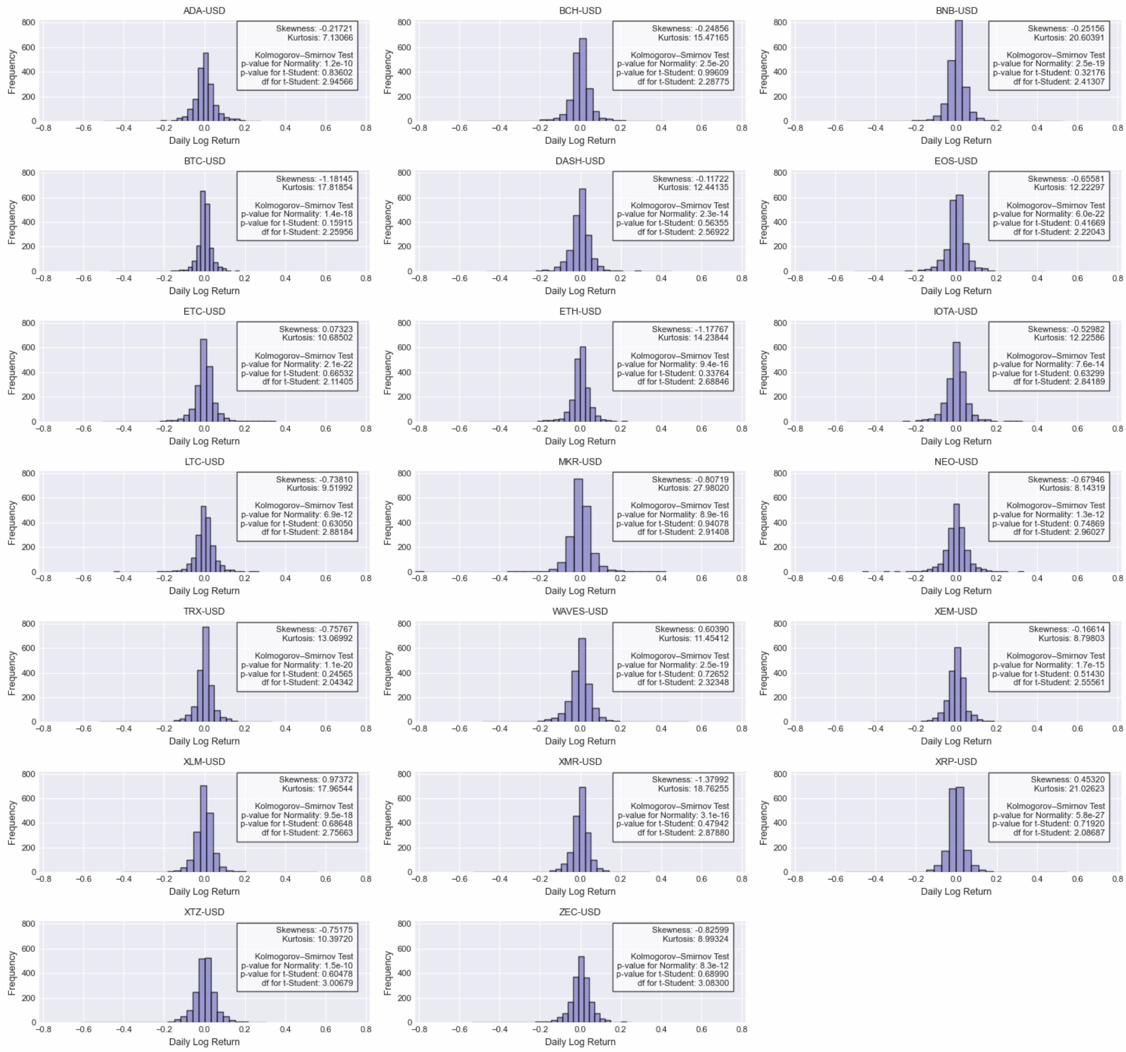

Figure 4. Histograms of Daily Logarithmic Returns of Cryptocurrencies.

[7] The Kolmogorov-Smirnov (KS) test is distribution-free and independent of the sample size. It is a goodness-of-fit test used to evaluate whether the sample's distribution follows a specific referenced distribution, such as the normal or the s-Student distributions (CARDOSO; GALENO, 2023).

4.2 Maximum Sharpe Ratio Optimization

At the minimum Sharpe ratio optimization, the results presented at Table 1 show that in portfolios considering 7 or 90 days between optimizations, all the sentiment-based ones had a higher risk-adjusted return than the FPO. Also, 95PCTL and 1STD strategies consistently had lower general volatilities and lower CVaR than the FPO in all horizons, whereas 1STD, 2STD, and 99PCTL strategies had higher annualized total returns than the benchmark, except for the minimum of 7 days between optimizations scenarios. Notably, the sentiment-based portfolios presented lower daily mean turnover and transaction costs; even so, it was not significant enough to make their ending portfolio higher, as the differences between the sentiment-based portfolios' annualized total returns and the benchmark one is higher.

Table 1. Maximum SR Optimization Performance from 2019 to 2023.

Portfolio	**Min. Days**	**Annualized Total Return**	**Annualized $\sigma_n(EWMA)$**	**95% CVaR**	**MSR**	**Daily Mean Turnover**	**Transaction Costs**	**Ending Portfolio Value**
1STD	7 days	0.5176	0.7363	0.0986	**0.1682**	0.0313	$570,670	$7,724,995
2STD	7 days	0.4108	0.7785	0.1026	0.1396	0.0146	$267,501	$5,461,192
95PCTL	7 days	0.4649	0.7304	0.0988	0.1204	0.0231	$421,892	$6,512,085
99PCTL	7 days	0.3042	**0.7128**	**0.0983**	0.1191	**0.0106**	**$193,214**	$3,653,546
FPO	7 days	**0.5832**	0.7477	0.0996	0.1002	0.0412	$752,724	**$9,528,646**
1STD	30 days	**0.4140**	0.7258	0.0988	0.1221	0.0174	$316,941	**$5,478,749**
2STD	30 days	0.4004	0.7498	0.0993	0.1379	**0.0091**	**$166,532**	$5,351,133
95PCTL	30 days	0.3562	0.7199	**0.0978**	0.1406	0.0164	$299,206	$4,390,147
99PCTL	30 days	0.2542	**0.7134**	0.0979	0.1307	0.0092	$168,777	$2,985,187
FPO	30 days	0.3200	0.7389	0.1002	**0.1861**	0.0192	$350,969	$3,738,261
1STD	90 days	0.3312	0.7311	**0.0976**	0.1598	0.0102	$186,221	$4,082,081
2STD	90 days	**0.3438**	0.7308	0.0984	0.1250	0.0073	$134,105	**$4,341,916**
95PCTL	90 days	0.3129	**0.7176**	0.0981	**0.2019**	0.0096	$175,927	$3,802,657
99PCTL	90 days	0.3247	0.7267	0.0999	0.1184	**0.0065**	**$118,088**	$4,045,482
FPO	90 days	0.1875	0.7295	0.0988	0.0653	0.0112	$205,329	$2,185,101

Note: Final portfolio values were estimated based on a $1,000,000 initial investment, considering cumulative returns from Jan 2019 to Dec 2023, minus transaction costs. Best results are highlighted in bold.

The same insights regarding the overall annualized total returns can be applied to the cumulative daily returns evolution over the period, as it can be seen at Figure 5. However, analyzing the higher disparity between the portfolios' cumulative returns during highly volatile years such as 2021 and 2022 is essential. In this case, the 2STD portfolio outperformed the others during most of this period. This suggests that this sentiment-based portfolio can achieve higher returns while managing extremely risky scenarios.

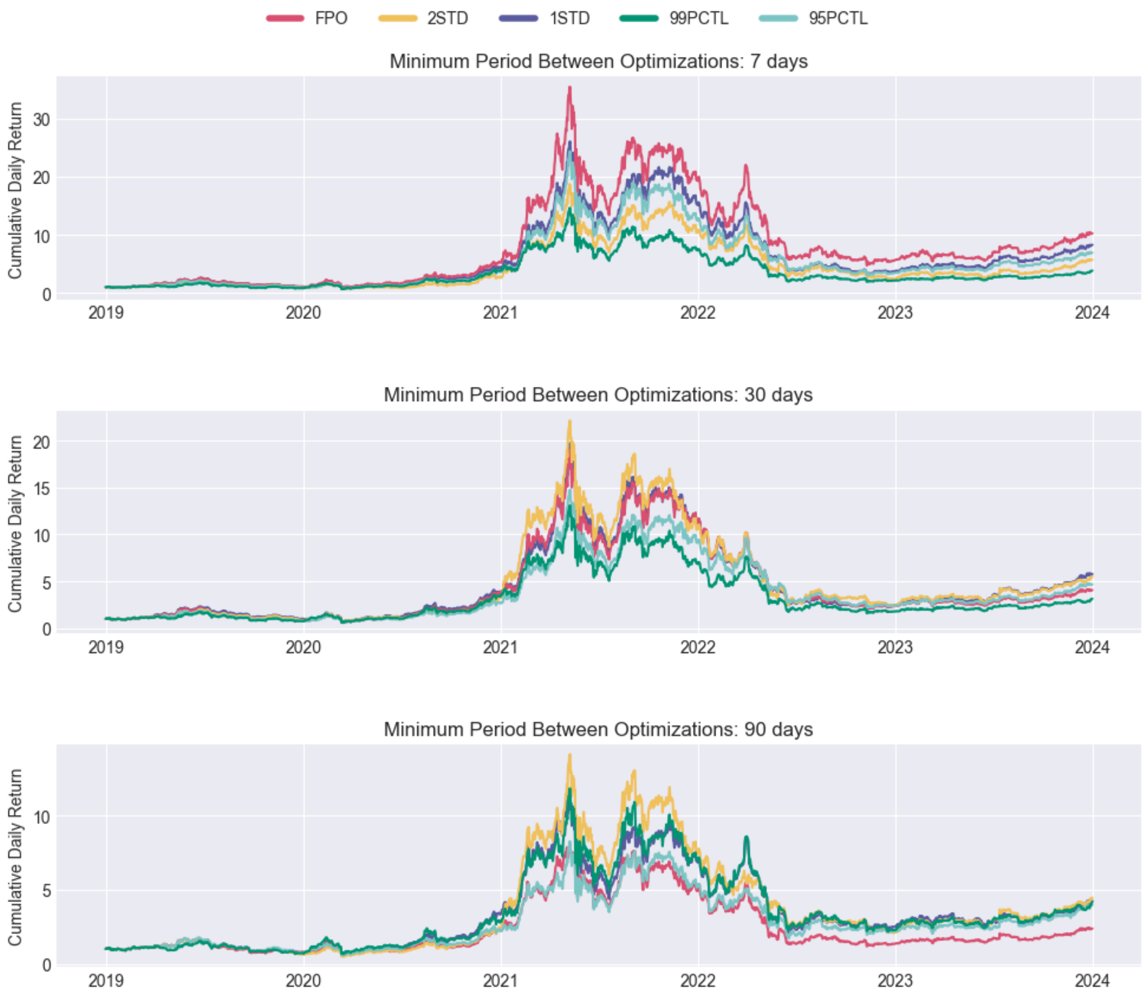

Figure 5. Maximum SR Optimization's Cumulate Daily Returns.

4.3 Minimum Variance Optimization

Analysing the minimum variance optimization performance at Table 2, the sentiment-based strategies presented higher annualized total returns and risk-adjusted returns. Still, the fixed period optimization had lower annualized volatilities and CVaR on the minimum of 7 and 30 days between optimizations. The only scenario in which the sentiment-based portfolio had a lower volatility than the benchmark is at the 90-day horizon, as the 95PCTL had not only the lowest volatility (0.6630) but also the highest annualized total return (0.9959), risk-adjusted returns (0.3233) and ending portfolio value ($33,167,798).

In the same manner, as the results are shown at Table 2 and at the chart of cumulative daily returns at Figure 6, when compared to the fixed period optimization, at least one of the sentiment-based portfolios had higher returns in all scenarios of the minimum period between consecutive optimizations. Among them, 1STD and 95PCTL portfolios had the highest cumulative daily returns at the end of the period of the minimum of 7 and 30-day scenarios. At the 90-day horizon, all the sentiment-based portfolios outperformed the benchmark regarding cumulative return, especially in 2021, when the cryptocurrency market volatility was high.

Table 2. Minimum Variance Optimization Performance from 2019 to 2023.

Portfolio	**Min. Days**	**Annualized Total Return**	**Annualized $\sigma_n(EWMA)$**	**CVaR**	**MSR**	**Daily Mean Turnover**	**Transaction Costs**	**Ending Portfolio Value**
1STD	7 days	**0.8165**	0.6518	0.0881	**0.2926**	0.0101	$184,459	**$20,466,829**
2STD	7 days	0.6808	0.6608	0.0902	0.2532	0.0069	$125,238	$13,801,677
95PCTL	7 days	0.7760	0.6475	0.0876	0.2902	0.0090	$163,787	$18,256,175
99PCTL	7 days	0.7533	0.6739	0.0899	0.2638	**0.0062**	**$114,065**	$17,139,666
FPO	7 days	0.7199	**0.6339**	**0.0868**	0.2825	0.0104	$189,730	$15,461,607
1STD	30 days	**0.8745**	0.6649	0.0884	0.2934	0.0093	$169,884	**$24,044,877**
2STD	30 days	0.7971	0.6534	0.0885	0.2864	**0.0055**	**$100,418**	$19,456,286
95PCTL	30 days	0.8697	0.6577	0.0876	**0.2978**	0.0084	$152,669	$23,752,995
99PCTL	30 days	0.7496	0.6748	0.0899	0.2614	0.0060	$110,302	$16,958,664
FPO	30 days	0.7978	**0.6482**	**0.0874**	0.2962	0.0088	$160,890	$19,429,596
1STD	90 days	0.7243	0.6655	0.0898	0.2698	0.0066	$119,689	$15,732,726
2STD	90 days	0.8340	0.6632	0.0890	0.2911	0.0043	$78,233	$21,597,741
95PCTL	90 days	**0.9959**	**0.6630**	**0.0874**	**0.3233**	0.0068	$123,273	**$33,167,798**
99PCTL	90 days	0.8044	0.6681	0.0890	0.2787	**0.0040**	**$73,451**	$19,889,020
FPO	90 days	0.7106	0.6632	0.0893	0.2640	0.0069	$126,395	$15,099,717

Note: Final portfolio values were estimated based on a $1,000,000 initial investment, considering cumulative returns from Jan 2019 to Dec 2023, minus transaction costs. Best results are highlighted in bold.

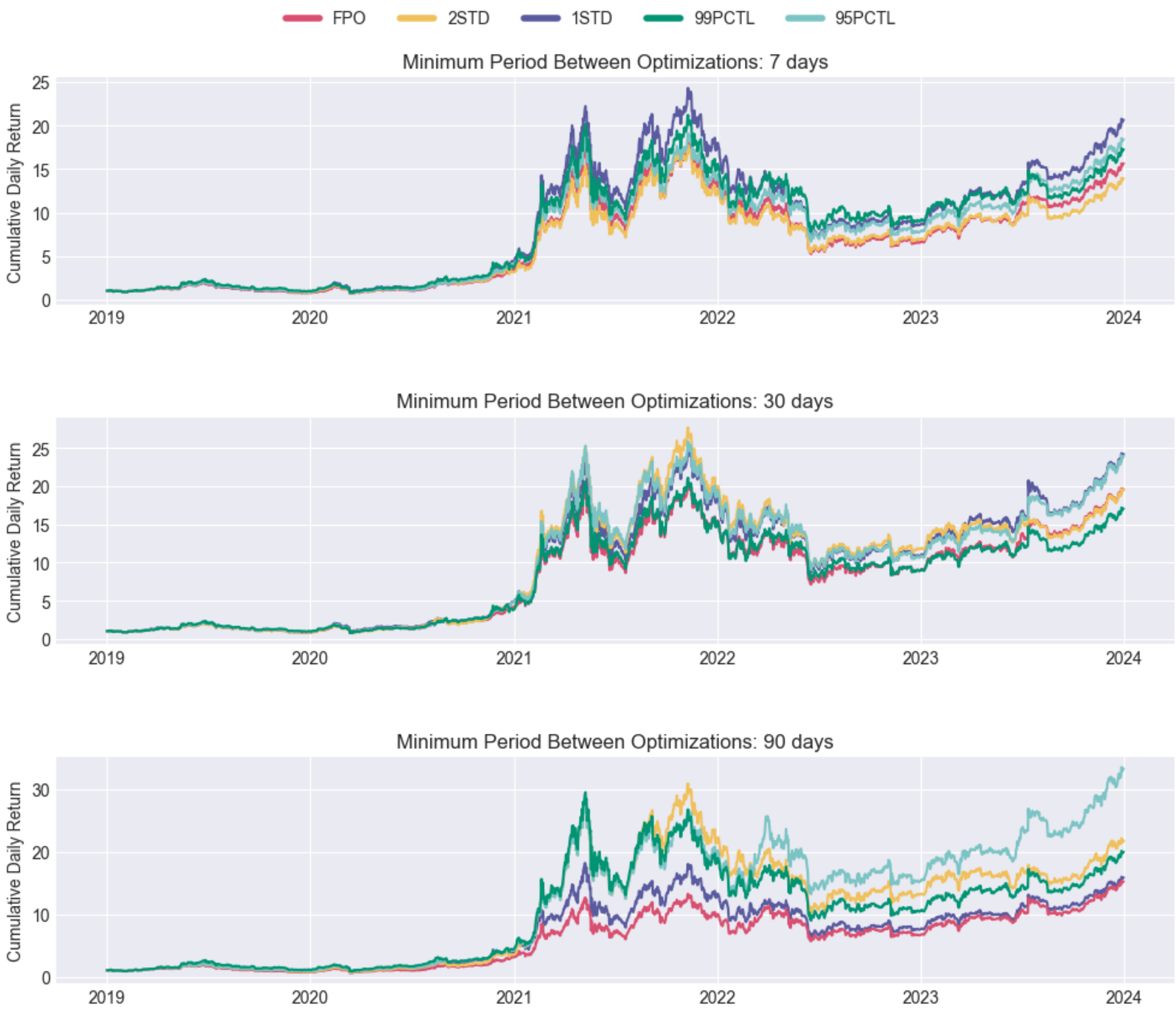

Figure 6. Minimum Variance Optimization's Cumulative Daily Returns.

4.4 Maximum Modified Sharpe Ratio Optimization

Table 3 provides portfolio performances considering the maximization of the modified Sharpe ratio. It is worth to note that sentiment-based portfolios (1STD, 2STD, 95PCTL, and 99PCTL) had higher annualized total returns than the FPO, except in the 7-day horizon, when the FPO presented a slightly higher return than the 1STD portfolio. Even so, this former portfolio consistently outperformed the benchmark on the long-term periods (considering a minimum of 30 or 90 days between optimizations) in terms of efficiency by presenting lower downside risk and general volatility and higher returns even with a lower mean turnover.

Table 3. Maximum MSR Optimization Performance from 2019 to 2023.

Portfolio	Min. Days	Annualized Total Return	Annualized $\sigma_n(EWMA)$	CVaR	MSR	Daily Mean Turnover	Transaction Costs	Ending Portfolio Value
1STD	7 days	0.5722	0.7270	**0.0970**	0.2040	0.0331	$604,342	$9,319,807
2STD	7 days	0.3933	0.7581	0.1006	0.1396	0.0152	$278,428	$5,098,795
95PCTL	7 days	0.5086	0.7221	0.0978	0.1851	0.0242	$441,329	$7,608,494
99PCTL	7 days	0.3483	**0.7108**	0.0978	0.1372	**0.0105**	**$192,019**	$4,360,339
FPO	7 days	**0.5911**	0.7349	0.0981	**0.2099**	0.0439	$801,739	**$9,745,031**
1STD	30 days	**0.4859**	0.7190	**0.0971**	**0.1845**	0.0180	$329,531	**$7,124,758**
2STD	30 days	0.3918	0.7397	0.0987	0.1447	**0.0095**	**$173,143**	$5,175,006
95PCTL	30 days	0.4149	0.7182	**0.0971**	0.1603	0.0168	$307,575	$5,507,910
99PCTL	30 days	0.3038	**0.7135**	0.0979	0.1204	0.0093	$169,668	$3,671,109
FPO	30 days	0.3598	0.7270	0.0982	0.1368	0.0200	$364,362	$4,388,562
1STD	90 days	**0.4620**	0.7237	**0.0965**	**0.1711**	0.0101	$184,083	**$6,681,920**
2STD	90 days	0.3800	0.7287	0.0984	0.1463	**0.0074**	**$135,416**	$4,987,700
95PCTL	90 days	0.4251	**0.7150**	0.0972	0.1633	0.0095	$173,103	$5,857,536
99PCTL	90 days	0.4452	0.7223	0.0987	0.1640	0.0062	$113,666	$6,359,832
FPO	90 days	0.2830	0.7190	0.0972	0.1100	0.0113	$206,762	$3,332,485

Note: Final portfolio values were estimated based on a $1,000,000 initial investment, considering cumulative returns from Jan 2019 to Dec 2023, minus transaction costs. Best results are highlighted in bold.

The 95PCTL portfolio also outperformed the benchmark on the long-term horizons regarding efficiency. It modified risk-adjusted returns, suggesting that strategies more sensitive to minor changes in the market sentiment might be more suitable to determine the optimization timing in a cryptocurrency portfolio optimized to maximize the MSR. Additionally, the chart of each portfolio's cumulative daily returns on Figure 7 is consistent with the results shown in Table 3 the FPO portfolio presented higher cumulative returns throughout the period analyzed on the 7-day horizon, whereas the 1STD, 95PCTL, and 2STD outperformed the benchmark on the other two minimum periods between optimizations.

It is also important to highlight from Figure 7 that the 1STD, 95PCTL, and 2STD portfolios reacted to the upturns before November 2021 and at the end of 2022 quicker than the fixed period optimizations in the minimum of 30 days between asset weights reallocation, which is why their returns ended up being higher, suggesting the predictive power of investors sentiment over the assets price changes, as stated before.

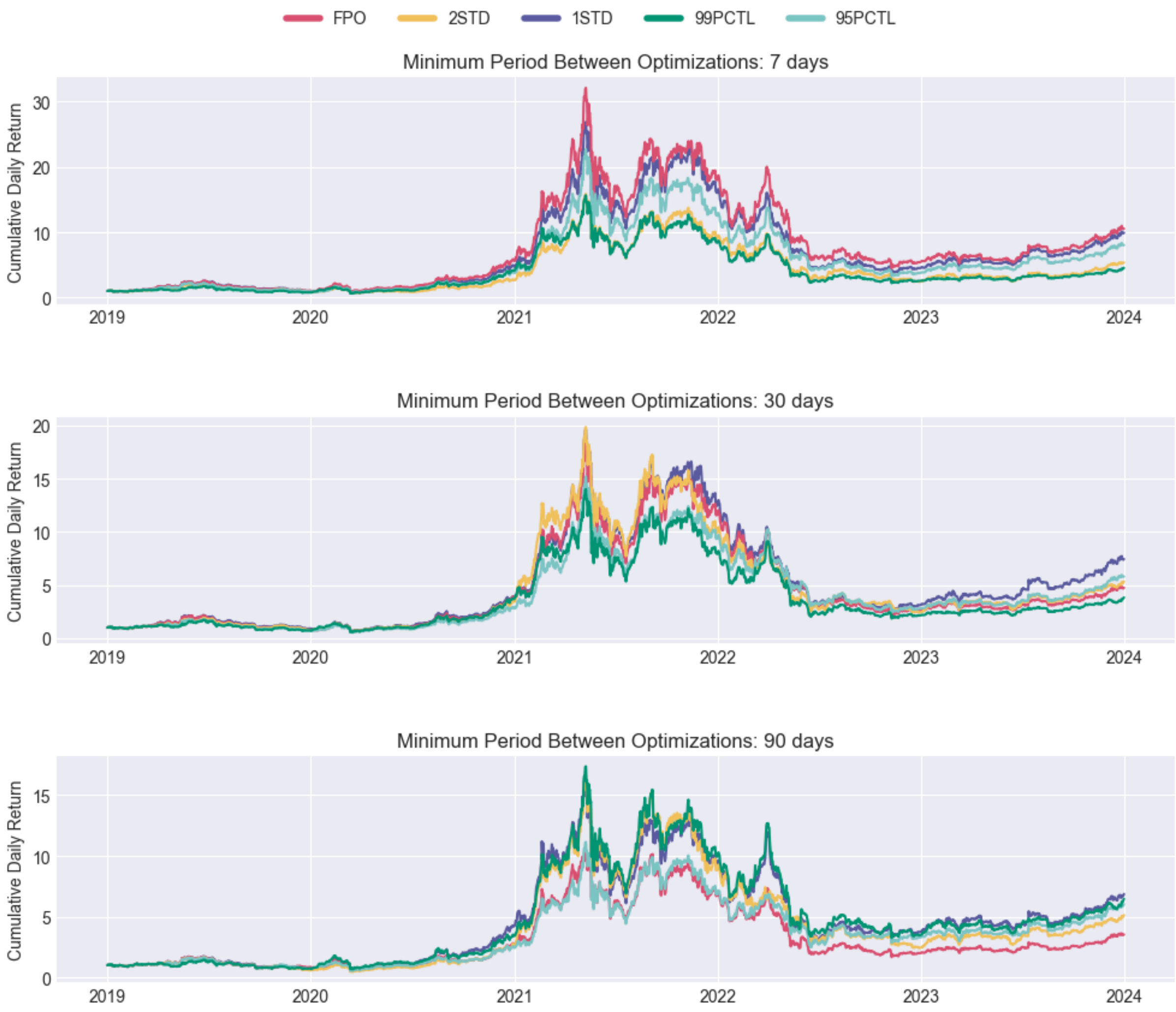

Figure 7. Maximum MSR Optimization's Cumulative Daily Returns.

4.5 Minimum Conditional Value-at-Risk Optimization

Using the minimization of CVaR as objective function, portfolios performance are described in Table 4. Results indicated that the benchmark only presented a lower expected shortfall than the 2STD portfolio on the 7-day horizon. However, both are still efficient in this scenario, with the latter being more suitable for risk-averse investors and the former for risk-tolerant ones. Also, the 2STD portfolio consistently had a higher MSR and ending value than the FPO along the three minimum days between two consecutive optimizations, even with a lower daily mean turnover and, consequently, a lower transaction cost.

Table 4. Minimum CVaR Optimization Performance from 2019 to 2023.

Portfolio	Min. Days	Annualized Total Return	Annualized $\sigma_n(EWMA)$	CVaR	MSR	Daily Mean Turnover	Transaction Costs	Ending Portfolio Value
1STD	7 days	0.7489	0.6740	0.0904	0.2629	0.0211	$385,701	$16,651,881
2STD	7 days	**0.8102**	0.6775	0.0918	**0.2802**	0.0112	$204,453	**$20,086,586**
95PCTL	7 days	0.7530	0.6776	0.0909	0.2620	0.0167	$305,279	$16,931,401
99PCTL	7 days	0.6267	0.6899	0.0917	0.2298	**0.0081**	**$147,589**	$11,650,124
FPO	7 days	0.7549	**0.6657**	**0.0897**	0.2704	0.0253	$461,604	$16,872,923
1STD	30 days	0.6341	0.6729	0.0909	0.2413	0.0151	$275,734	$11,796,507
2STD	30 days	**0.8886**	**0.6716**	**0.0897**	**0.3043**	0.0077	$141,102	**$25,017,885**
95PCTL	30 days	0.6272	0.6780	0.0901	0.2327	0.0133	$242,340	$11,572,252
99PCTL	30 days	0.6474	0.6922	0.0914	0.2355	**0.0075**	**$136,310**	$12,442,056
FPO	30 days	0.6421	0.6763	0.0912	0.2386	0.0159	$290,087	$12,083,414
1STD	90 days	0.3807	0.6917	0.0926	0.1580	0.0083	$151,717	$4,983,635
2STD	90 days	**0.8399**	**0.6783**	**0.0906**	**0.2913**	0.0061	$110,956	**$21,922,455**
95PCTL	90 days	0.6279	0.6971	0.0908	0.2254	0.0077	$141,181	$11,701,378
99PCTL	90 days	0.6577	0.7066	0.0924	0.2312	**0.0054**	**$98,752**	$12,883,540
FPO	90 days	0.5472	0.6838	0.0916	0.2151	0.0093	$169,415	$8,979,180

Note: Final portfolio values were estimated based on a $1,000,000 initial investment, considering cumulative returns from Jan 2019 to Dec 2023, minus transaction costs. Best results are highlighted in bold.

Analyzing the cumulative daily returns per minimum days on Figure 8, it can be seen that the 2STD consistently outperformed the benchmark in all the time horizons considered, which can suggest that a strategy focused on more extreme changes in the Fear & Greed Index when analyzing the market sentiment to determine a cryptocurrency portfolio weights reallocation timing brings higher returns when aligned with a minimum CVaR optimization, allowing the portfolio to capitalize on extreme sentiment-driven price movements while preserving capital during downturns.

In addition, it is relevant to point out that at the minimum of 7 days between portfolio weights reallocation scenario, the FPO alternative outperformed all the sentiment-based strategies until 2022, when the 2STD portfolio reacted quickly to the cryptocurrency prices downturn and avoided extreme losses in a more effective way than the benchmark. In this way, the 2STD portfolio's higher flexibility when adjusting weights based on the sentiment provided a proactive defence against the downside risk, whereas the FPO portfolio could only react to losses after they had already occurred.

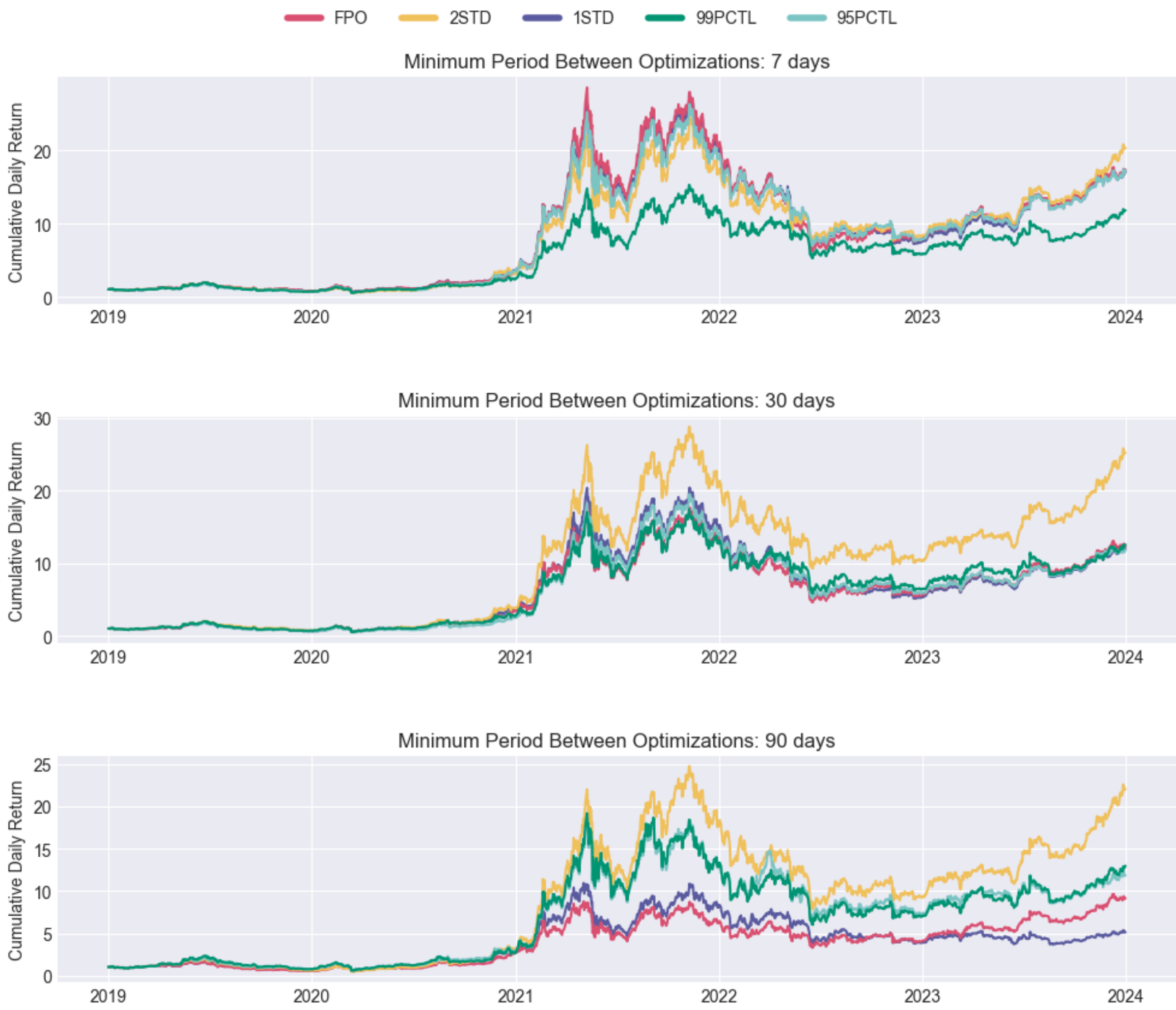

Figure 8. Minimum CVaR Optimization's Cumulative Daily Returns.

4.6 Comparison of Strategies Performance

Table 5 provides a comparison among all portfolio strategies in terms of transaction costs. It can be seen that sentiment-based strategies consistently had lower transaction costs and turnovers than the FPO, except for the 1STD portfolio strategy which considered a minimum of 30 days between two consecutive optimizations. Transaction costs depend on the optimization frequency and the volume traded, which is why one of the sentiment-based portfolios presented a higher transaction cost than the benchmark. However, despite this variation, sentiment-driven strategies generally demonstrated greater efficiency in managing trading expenses while dynamically adjusting to market conditions.

Table 5. Portfolios Transaction Costs (2019-2023).

Strategy	Min. Days	Max. SR	Min. Variance	Max. MSR	Min. CVaR
1STD	7 days	**$570,670**	**$184,459**	**$604,342**	**$385,701**
2STD	7 days	**$267,501**	**$125,238**	**$278,428**	**$204,453**
95PCTL	7 days	**$421,892**	**$163,787**	**$441,329**	**$305,279**
99PCTL	7 days	**$193,214**	**$114,065**	**$192,019**	**$147,589**
FPO	7 days	$752,724	$189,730	$801,739	$461,604
1STD	30 days	**$316,941**	$169,884	**$329,531**	**$275,734**
2STD	30 days	**$166,532**	**$100,418**	**$173,143**	**$141,102**
95PCTL	30 days	**$299,206**	**$152,669**	**$307,575**	**$242,340**
99PCTL	30 days	**$168,777**	**$110,302**	**$169,668**	**$136,310**
FPO	30 days	$350,969	$160,890	$364,362	$290,087
1STD	90 days	**$186,221**	**$119,689**	**$184,083**	**$151,717**
2STD	90 days	**$134,105**	**$78,233**	**$135,416**	**$110,956**
95PCTL	90 days	**$175,927**	**$123,273**	**$173,103**	**$141,181**
99PCTL	90 days	**$118,088**	**$73,451**	**$113,666**	**$98,752**
FPO	90 days	$205,329	$126,395	$206,762	$169,415

Note: Final portfolio values were estimated based on a $1,000,000 initial investment, considering cumulative returns from Jan 2019 to Dec 2023, minus transaction costs. Best results are highlighted in bold.

Additionally, sentiment-based strategies majorly performed better in bull markets such as 2019 and 2022 than the FPO, especially the 1STD and 99PCTL portfolios, which are more sensitive to minor and drastic sentiment changes, respectively (see Table 5). This suggests that incorporating sentiment analysis into portfolio optimization can enhance adaptability in trending markets, allowing for more responsive allocation adjustments and providing an advantage in anticipating market movements.

Table 6 compares the performance of different strategies in terms of transaction cost-adjusted Sharpe ratios, using a 90-day minimum holding period as a representative case. The results demonstrate that minimum variance strategies consistently delivered superior risk-return outcomes across all evaluated years, adapting effectively to varying market conditions. Notably, sentiment-triggered reoptimization strategies outperformed the naive periodic rebalancing benchmark, revealing that market sentiment monitoring provides more informative signals for cryptocurrency portfolio adjustments than calendar-based approaches. This evidence supports the use of behavioral metrics as dynamic triggers for portfolio rebalancing decisions in volatile crypto markets.

Table 6. Sharpe Ratio with Discounted Transaction Costs and a Minimum Holding Period of 90 Days.

Optimization	**Strategy**	**2019**	**2020**	**2021**	**2022**	**2023**
Max. MSR	1STD	-0.3356	0.4389	0.2784	-1.0108	0.3430
Max. MSR	2STD	-0.4682	0.4900	0.2635	-1.5050	0.3870
Max. MSR	95PCTL	-0.3022	0.4542	0.3001	-0.7092	0.2833
Max. MSR	99PCTL	-0.2891	0.4415	0.2826	-1.1473	0.3232
Max. MSR	FPO	-0.1710	0.4429	0.3132	-1.2328	0.3238
Max. SR	1STD	-0.3243	0.4035	0.2549	-0.6920	0.3659
Max. SR	2STD	-0.4284	0.4564	0.2233	-1.4835	0.3037
Max. SR	95PCTL	-0.2593	0.4124	0.2733	-0.6469	0.2389
Max. SR	99PCTL	-0.3108	0.3819	0.2570	-1.0436	0.3360
Max. SR	FPO	-0.2246	0.4009	0.2656	-0.7050	0.2966
Min. CVaR	1STD	-0.4956	0.4972	0.4083	-0.4723	0.4418
Min. CVaR	2STD	-0.4598	0.5451	0.4038	-0.5612	**0.5231**
Min. CVaR	95PCTL	-0.2273	0.4830	0.3656	-0.4901	0.1519
Min. CVaR	99PCTL	-0.2071	0.4707	0.3598	-0.7560	0.4505
Min. CVaR	FPO	-0.6354	0.4874	0.3423	-0.4458	0.4214
Min. Variance	1STD	-0.1901	0.4693	0.4192	**-0.2514**	0.4498
Min. Variance	2STD	-0.2686	0.5381	**0.4228**	-0.3500	0.4205
Min. Variance	95PCTL	-0.1244	0.5102	0.4014	-0.3404	0.4329
Min. Variance	99PCTL	**0.0599**	**0.5501**	0.3781	-0.7348	0.4207
Min. Variance	FPO	-0.3628	0.5298	0.3952	-0.2981	0.4661

Note: Best results are highlighted in bold.

Analyzing the Mean-CVaR framework[8] in Figure 9, it is noteworthy that minimum variance and CVaR strategies had the only efficient portfolios among all the scenarios of minimum days between two consecutive optimizations. Minimum variance portfolios, such as 1STD, 95PCTL, and the FPO, had a lower mean return and a lower downside risk, more suitable for risk-averse investors. The 2STD minimum CVaR portfolio had a higher mean return and downside risk, which is more adequate for risk-tolerant investors.

[8] The Mean-CVaR framework is an efficient frontier model that considers a new approach to measuring risk without assuming a normal distribution of returns, as the variance-covariance method does (BANIHASHEMI; NAVIDI, 2017).

Figure 9. Relationship between average return and risk (CVaR) of portfolios across different minimum holding periods between reoptimizations.

Furthermore, considering the efficient portfolios on the cases in which the minimum period between two consecutive optimizations is 7 or 30 days, the sentiment-based portfolios (1STD and 95PCTL) are more on the right side of the upper left corner of the scatter plots, thus being interesting for investors willing to trade off a higher risk for the possibility of higher returns. Correspondingly, the FPO portfolios are located on the far-left side of the upper left corner, thus being more suitable for investors who prefer to minimize risk, even if it means accepting lower returns. Also, the only efficient portfolio in the cases where the period between two consecutive optimizations is extended (minimum of 90 days) is the 95PCTL, outperforming the other strategies in terms of efficiency, as shown in Figure 9.

Besides, it is valid to bring back one aspect highlighted in Section 2: traditional risk measures, such as variance, would fail to measure the complexity of risk in highly volatile markets by assuming a normal distribution of returns. The null hypothesis for normality was rejected at the beginning of the current section. However, the empirical results showed that the minimum variance optimization outperformed other optimizations that do not consider the same assumption, such as the CVaR one, which would implicitly decrease the portfolio's negative skewness, or even the MSR one, which calculates the risk-adjusted return considering both skewness and kurtosis.

Chai and Zhou (2018) also discussed a similar result in their study in which they analyzed the applications of a minimum CVaR strategy using semi-parametric estimates to solve hedging problems in the carbon market, which is also considered a highly volatile market, comparing its effectiveness with the minimum variance strategy. They observed that the minimum variance strategy on out-of-sample data performed better when the criterion was the reduction of CVaR than the minimum CVaR strategy itself, stating that, although designed to minimize the overall variability of returns considering the covariance matrix, the minimum variance strategy tends to produce more stable portfolios that are less dependent and less exposed to extreme events, making it more robust in out-of-sample applications, where the behavior of the tails may differ from the in-sample data.

The same analysis can be applied to this study's results, considering analogously the in-sample data as the days when the sentiment analysis conditions are satisfied. Thus, the optimization is implemented, and the out-of-sample is the daily returns of the last 90 days. The returns on the optimization day are not guaranteed to perform like the previous 90 days, especially in a highly volatile environment such as the cryptocurrency market. Thus, the stability produced by the minimum variance strategy outperformed the minimum CVaR in terms of general and downside risk. Even so, among the efficient portfolios, the 2STD minimum CVaR portfolio produced a higher return for a more risk-tolerant investor, which can be explained by the fact that the minimum CVaR only penalizes extreme losses. In contrast, the minimum variance model can indirectly penalize extreme gains and losses.

5 CONCLUSION

Determining optimal portfolio reoptimization strategies is particularly crucial for cryptocurrency investments, given their inherent volatility and sensitivity to market sentiment. This study addressed this challenge by developing and evaluating dynamic rebalancing approaches that use investor sentiment as a timing indicator, with three key objectives: (1) to compare sentiment-driven strategies against fixed-period rebalancing, (2) to assess the performance of different optimization objectives (risk-minimizing versus return-maximizing) under sentiment triggers, and (3) to quantify the transaction cost efficiency of behavioral timing models.

Empirical results demonstrate that incorporating investor sentiment into cryptocurrency portfolio reoptimization timing offers significant advantages over traditional periodic rebalancing approaches. The empirical results reveal that sentiment-based portfolios, particularly the 1STD and 99PCTL strategies, showed superior risk-adjusted returns and lower transaction costs during high-volatility periods such as 2019 and 2022. These strategies responded quickly to market changes, with the 95PCTL and 1STD approaches proving more suitable for risk-tolerant investors.

Risk-minimizing strategies (minimum variance and minimum CVaR) consistently outperformed those focused on maximizing the Sharpe and modified Sharpe ratios, reflecting the frequent extreme losses and high volatility typical of this market. Among them, the minimum variance approach produced more stable portfolios with lower downside risk, while the 2STD minimum CVaR strategy showed a better trade-off between mean return and CVaR during the analyzed period.

Although sentiment-based portfolios exhibited lower turnover and reduced transaction costs, their impact on final portfolio value was insufficient to outperform the benchmark based solely on cost reduction. Among the study's limitations is the use of the Bitcoin-focused Fear and Greed Index as a single market sentiment proxy. Future research could explore asset-specific sentiment metrics and incorporate more detailed transaction cost modeling that accounts for variations across assets and market conditions. Additionally, including traditional assets and accounting for cryptocurrency failure risk could enhance the robustness and practical applicability of dynamic optimization strategies.

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