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Sharpe Ratio-Based Dynamic Crypto Asset Allocation with Trend Filtering Using Simple Moving Average

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ABSTRACT

This paper proposes a dynamic cryptocurrency asset allocation strategy combining Sharpe ratio-based weighting with simple moving average (SMA) trend filtering of Bitcoin (BTC). The Sharpe ratio evaluated risk-adjusted returns, while SMA provided robust trend signals, enabling adaptive portfolio management in volatile crypto markets. The model reallocated capital among seven major cryptocurrencies, namely BTC, Ethereum (ETH), Binance coin (BNB), Solana (SOL), Toncoin (TON), TRON (TRX), and ripple (XRP), every three days. If BTC traded below its SMA threshold (50-day, 100-day, or 200-day), the strategy shifted to tether USD (USDT) to minimize downside risk. Using historical data from January 1, 2024, to January 1, 2025, the SMA-50 strategy achieved the highest cumulative return of +231.51% and Sharpe ratio of 2.51, significantly outperforming longer SMA models and a buy-and-hold baseline (+132.14%). A Sharpe ratio of 2.51 indicates 2.51 units of excess return per unit of risk. Risk analysis suggests shorter SMA windows offer responsive exposure but increase short-term volatility. Findings support hybrid strategies for active crypto portfolio management and suggest future research into advanced trend detection.

1. Introduction

Cryptocurrencies have emerged as a distinct asset class, characterized by high volatility and unique risk–return profiles. Empirical evidence suggests that cryptocurrency returns are primarily driven by market-specific factors such as investor attention and momentum [1], rather than traditional macroeconomic indicators. Furthermore, prior studies document market inefficiencies in early cryptocurrency markets, indicating potential predictability in returns and creating opportunities for active trading strategies [2], [3]. This distinct behavior challenges conventional portfolio optimization methods, necessitating the development of tailored strategies for crypto assets. Technical analysis tools, particularly moving average (MA) strategies, have gained prominence in navigating the volatile crypto markets. Studies have demonstrated the effectiveness of MA-based trading rules in generating excess returns, especially in assets with privacy features [4], [5]. These findings suggest that integrating technical indicators can enhance trading performance in the crypto domain.

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The existing literature strongly supports the individual efficacy of both risk-adjusted performance metrics like the Sharpe Ratio and trend-following indicators such as simple moving averages (SMA) in financial markets, including cryptocurrencies. Empirical evidence from studies like [4], [5], and [6] demonstrates the profitability of technical trading rules, while theoretical foundations of portfolio optimization [7], [8] highlight the importance of risk-adjusted returns.

Specifically, a previous study has identified that cryptocurrency returns are primarily driven by market-specific factors, such as investor attention and momentum, rather than conventional economic indicators [1]. A systematic analysis in [9] has concluded that cryptocurrencies exhibit unique characteristics, positioning them as a separate asset class with distinct risk-return profiles.

Technical analysis, particularly MA strategies, has shown strong effectiveness in cryptocurrency trading. The findings in [4] has demonstrated that simple MA trading rules can yield substantial returns in crypto markets, while [5] has revealed that these strategies are especially profitable for privacy-focused cryptocurrencies. In addition, [6] has affirmed the effectiveness of technical trading rules, including MA oscillators and trading-range breakouts, within cryptocurrency markets.

Conventional portfolio optimization approaches often underperform in the cryptocurrency domain due to extreme volatility and non-normal return distributions. Cryptocurrency markets are highly sensitive to global shocks and contagion effects, as evidenced during the COVID-19 pandemic [10], further emphasizing the importance of dynamic risk management. To address these issues, [7] has proposed a robust optimization framework that integrates conditional value-at-risk (CVaR) constraints and advanced covariance estimation techniques. Furthermore, the integrated covariance estimation approach introduced in [8] enhances the performance of risk-based portfolio optimization under such conditions.

Machine learning approaches have also been explored for asset allocation. Previous study employed machine learning models to predict bond risk premiums and demonstrates improved forecasting accuracy [11]. In [12], a dynamic asset allocation framework was developed using asset-specific regime forecasts that integrate both unsupervised and supervised learning techniques.

Recent studies have also examined the fusion of technical indicators with machine learning to enhance trading strategies. A study combined deep learning-based price forecasting with technical indicators to improve cryptocurrency trading performance [13]. Additionally, [14] utilized artificial intelligence (AI)-generated sentiment data alongside traditional models to forecast cryptocurrency market volatility, demonstrating the potential of hybrid approaches. These developments highlight the importance of integrating technical analysis with modern computational techniques to effectively address the complexities of cryptocurrency markets.

Recent literature highlights the growing relevance of momentum and trend-following strategies in speculative and high-volatility markets. Empirical findings indicate that momentum-based allocation can enhance risk-adjusted performance, although such strategies may remain vulnerable to crash risk during regime shifts [15]. Classical portfolio frameworks, including Markowitz's mean–variance optimization and the Black–Litterman model, provide the theoretical foundation for constructing efficient risk-aware portfolios [16], [17]. In parallel, modern volatility modeling approaches emphasize the time-varying and clustered nature of cryptocurrency risk, underscoring the importance of dynamic allocation mechanisms [18], [19].

Traditional asset pricing theories further stress the role of systematic risk factors in explaining asset returns, thereby supporting the application of performance measures such as the Sharpe ratio in portfolio evaluation [20]. More recently, studies on risk-managed momentum strategies in cryptocurrency markets have demonstrated that incorporating volatility controls can improve both return stability and Sharpe performance relative to conventional momentum models [21]. Additionally, research examining Bitcoin's hedge and safe-haven properties, as well as its characterization as a speculative asset, reinforces the need for adaptive and regime-sensitive portfolio strategies [22], [23]. Collectively, these findings suggest that combining risk-based weighting with

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trend-confirmation signals may reduce downside exposure while preserving participation in momentum-driven upside movements.

This paper builds upon this established knowledge by proposing a novel hybrid strategy that synergistically combines these two powerful approaches. While previous research has explored advanced optimization techniques [7], [8] and machine learning integration [11]–[14], there is a discernible gap in studies that systematically evaluate a dynamic asset allocation strategy explicitly driven by Sharpe ratio optimization conditioned on a SMA trend filter within the context of recent crypto market dynamics (2024-2025). This paper addresses this gap by proposing and evaluating such a hybrid strategy, offering a novel approach to navigating the unique challenges of cryptocurrency portfolio management.

2. Method

2.1. Data Collection

This study utilizes historical daily closing price data for seven major cryptocurrencies: Ethereum (ETH), Binance coin (BNB), Solana (SOL), Toncoin (TON), TRON (TRX), and ripple (XRP). The data were obtained from the Yahoo Finance API, with the corresponding ticker symbols listed in Table 1.

Table 1. Mapping of Selected Cryptocurrencies to Yahoo Finance Ticker Codes

Ticker	Yahoo Finance Code
BTC	BTC-USD
ETH	ETH-USD
BNB	BNB-USD
SOL	SOL-USD
TON	TON11419-USD
TRX	TRX-USD
XRP	XRP-USD

The study covered the period from January 1, 2024, to January 1, 2025, ensuring a complete year of data suitable for short-term and trend-based strategy evaluation. Before analysis, the raw data underwent a cleaning process to handle missing values (e.g., through forward-fill or interpolation for short gaps) and ensure data consistency, particularly for closing prices and dates.

2.2. Signal Generation

For each asset, 3-day return and volatility were calculated using the formulas presented in (1) and (2). The computation of returns and volatility followed standard financial econometrics practices as discussed in classical literature [24].

Return over a 3-day period:

$$R_{i,t}^{(3D)} = \frac{P_{i,t} - P_{i,t-3}}{P_{i,t-3}} \quad (1)$$

Volatility over a 3-day period (sample standard deviation of daily returns):

$$\sigma_{i,t}^{(3D)} = \sqrt{\frac{1}{n-1}\sum_{j=1}^{3}\left(r_{i,t-j} - \bar{r}_{i,t}\right)^2} \quad (2)$$

where:

- $R_{i,t}^{(3D)}$: is the cumulative return for asset *i* over 3 days ending at time *t*.
- $P_{i,t}$: is the closing price of asset *i* at time *t*.
- $P_{i,t-3}$: is the closing price of asset *i* three days prior to time *t*.
- $\sigma_{i,t}^{(3D)}$: is the standard deviation of daily returns for asset *i* over the 3-day window.

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- $r_{i,t-j}$: is the daily return for asset *i* at time *t-j*.
- $\overline{r}_{i,t}$: is the average daily return for asset *i* over the 3-day window ending at time *t*.
- *n*: refers to the number of data points in the calculation (here, 3 for the 3-day volatility).
- *D*: represents a period in days (e.g., 3D for 3-day period).
- *P*: represents price.
- *R*: represents return.
- *SR*: represents Sharpe Ratio.
- *i*: refers to a specific asset (e.g., *i* = 1, 2, ..., 7 for the seven cryptocurrencies).
- *t*: refers to a specific time point or date.
- *j*: refers to a specific day within a window (e.g., *j* = 1, 2, 3 for the 3-day window)

Ratio over 3-day window (assuming risk-free rate r_f=0):

$$SR_{i,t}^{(3D)} = \frac{R_{i,t}^{(3D)}}{\sigma_{i,t}^{(3D)}} \quad (3)$$

The assumption of a zero risk-free rate (r_f=0) is made for simplicity and is common in studies of highly volatile asset classes like cryptocurrencies where the excess return over a typical risk-free asset (e.g., T-bills) is often negligible compared to the asset's own volatility and returns.

In parallel, a trend filter was computed using the SMA of BTC prices. Three SMA parameters were tested: 50-day, 100-day, and 200-day SMA. The SMA was computed in (4):

$$SMA_n(t) = \frac{1}{n}\sum_{j=0}^{n-1} P_{BTC,t-j} \quad (4)$$

where *n* in {50, 100, 200} represents the number of days for the SMA calculation, and $P_{BTC,t}$, is the closing price of BTC at time *t*. The index *j* iterates from 0 to *n*-1, summing up the closing prices over the specified period.

2.3. Allocation Strategy

At every 3-day interval, a rebalancing decision was made based on the SMA condition. The choice of a 3-day rebalancing horizon is a critical design decision aimed at balancing responsiveness to market changes with the minimization of transaction costs and computational overhead. In highly volatile markets like cryptocurrencies, a shorter rebalancing period allows the strategy to quickly adapt to emerging trends and capitalize on momentum, as opposed to longer intervals which might miss significant price movements. This frequency is also chosen to align with typical short-term trading cycles observed in crypto markets.

2.3.1. Trend Filter Condition:

- If $P_{BTC,t} < SMA_n(t)$: Allocate 100% of capital to Tether USD (USDT) (no crypto exposure).
- If $P_{BTC,t} > SMA_n(t)$: Allocate capital proportionally based on the positive Sharpe Ratios of the available crypto assets.

2.3.2. Sharpe Ratio-Based Allocation

For assets with $SR_{i,t}^{(3D)}$ >0, weights are calculated as shown in (5):

$$w_{i,t} = \frac{SR_{i,t}^{(3D)}}{\sum_{j \in A_t} SR_{j,t}^{(3D)}} \quad (5)$$

where A_t is the set of all assets with positive Sharpe ratios at time *t*.

Capital is rebalanced every 3 days, and returns are compounded over time to simulate portfolio growth.

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2.4. Baseline Strategy

To evaluate the effectiveness of the dynamic strategy, a buy-and-hold baseline model is implemented using the total return of each asset over the study period. The baseline return is defined as shown in (6):

$$R^{baseline} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{P_{i,end}-P_{i,start}}{P_{i,start}}\right) \tag{6}$$

where $N = 7$ is the number of crypto assets, while $P_{i,start}$ and $P_{i,end}$ are the initial and final prices of asset i, respectively. The calculated returns of each individual asset and the average portfolio return are shown in Table 2.

Table 2. Buy-and-Hold Returns of Individual Crypto Assets from January 1, 2024 to January 1, 2025

Asset	Ticker	Return (%)
BTC	BTC-USD	118.05%
ETH	ETH-USD	50.74%
BNB	BNB-USD	121.37%
SOL	SOL-USD	91.96%
TON	TON11419-USD	147.87%
TRX	TRX-USD	137.96%
XRP	XRP-USD	257.05%

The average return (buy-and-hold baseline) was 132.14%. This result served as the benchmark for comparing the performance of each dynamic allocation scenario (SMA-50, SMA-100, and SMA-200).

3. Results and Discussion

3.1. Performance Evaluation Metrics

To evaluate the effectiveness of the dynamic allocation strategies using SMA-based trend filters, this study compares three models: SMA-50, applying Sharpe ratio-based allocation with a 50-day SMA filter; SMA-100, applying a 100-day SMA filter; and SMA-200, incorporating a 200-day SMA filter. Each model simulated capital growth with 3-day rebalancing intervals from January 1, 2024, to January 1, 2025, starting with an initial investment of USD10,000. The performance of these models was assessed against a baseline buy-and-hold strategy, in which an equal-weighted portfolio of the seven crypto assets was maintained throughout the year.

3.2. Final Portfolio Values

At the end of the evaluation period, the cumulative portfolio values for each strategy are shown in Table 3.

Table 3. Final Portfolio Value and Cumulative Return of SMA-Based Strategies vs. Buy-and-Hold Baseline

Strategy	Final Value (USD)	Growth (%)
SMA-50	33,150.87	+231.51%
SMA-100	26,268.68	+162.69%
SMA-200	26,311.40	+163.11%
Baseline	-	+132.14% (avg)

The baseline was based on average annual return across assets: BTC, ETH, BNB, SOL, TON, TRX, and XRP, with a calculated mean return of +132.14%. The SMA-50 model significantly outperformed SMA-100, SMA-200, and the static baseline, indicating that a shorter trend window allows for more responsive market positioning and higher compounding effects during bullish phases, as illustrated in Fig. 1.

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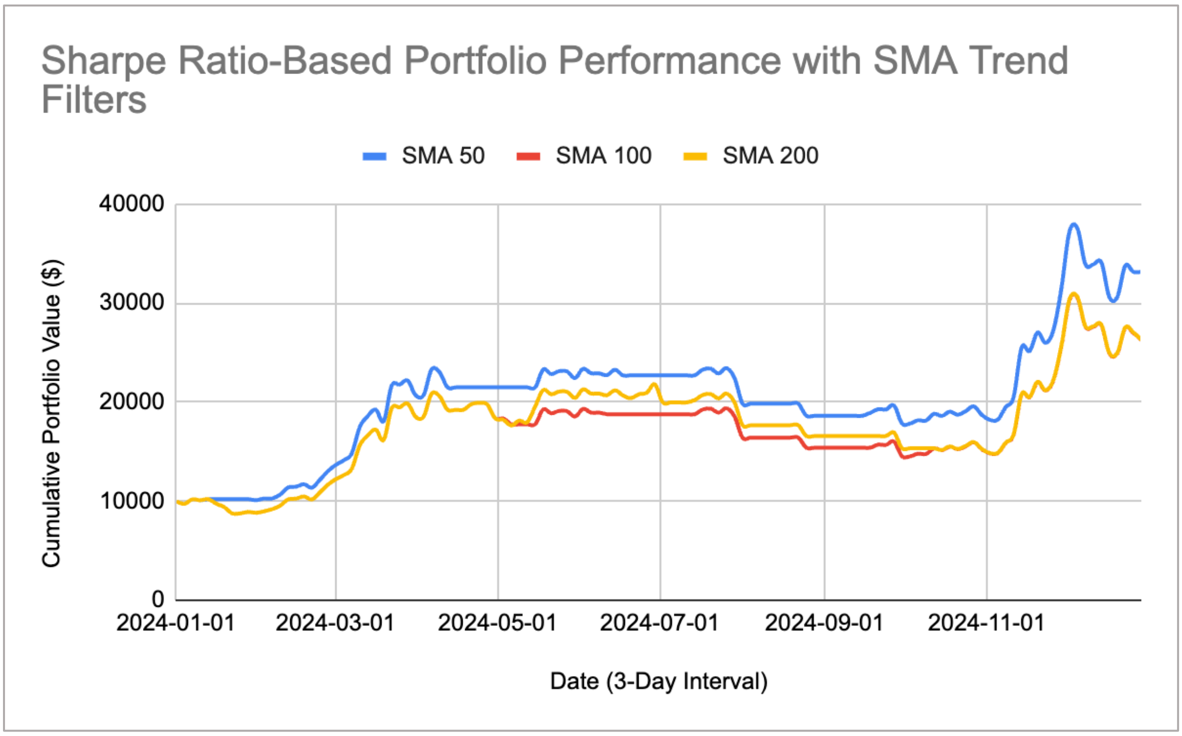

Fig. 1 Sharpe ratio-based portfolio performance with SMA trend filters.

For publication, a high-resolution chart showing the cumulative portfolio value over time for SMA 50, SMA 100, and SMA 200 would be included. This chart would visually demonstrate the growth trajectories and divergence of the strategies, similar to the one described in the original paper.

The portfolio growth comparison for SMA-50, SMA-100, and SMA-200 models using Sharpe ratio-based dynamic allocation from January 1, 2024, to January 1, 2025, clearly illustrates the superior performance of the SMA-50 model, particularly during the Q4 2024 market rally.

3.3. Portfolio Trajectory Comparison

The growth trajectory of the SMA-50 strategy showed a steeper upward trend beginning around March 2024, coinciding with multiple favorable Sharpe ratio signals and BTC trading consistently above its 50-day SMA. In contrast, the SMA-100 and SMA-200 strategies demonstrated more conservative entry points, causing delayed exposure to rising markets and lower cumulative gains. SMA-100 and SMA-200 strategies began to diverge notably from SMA-50 during Q2 2024, with SMA-200 maintaining the most defensive posture (frequently staying in Tether USD) due to its longer trend confirmation window. While this reduced downside exposure in volatile periods, it also limited upside potential during sustained bull runs.

3.4. Comparative Risk and Volatility Insights

While this study prioritize return as the primary metric, the volatility implications are noteworthy. The SMA-50 model exhibited the highest exposure and drawdown potential but captured momentum early, whereas SMA-100 provided a more balanced profile by entering trends later and avoiding some short-term noise. SMA-200 represented the most conservative approach, emphasizing trend confirmation over early participation, which resulted in missed opportunities during fast-paced rallies. These findings align with established theory that shorter SMAs offer higher responsiveness but may generate more false signals, while longer SMAs reduce signal frequency at the cost of responsiveness.

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3.5. Practical Implications

The results suggest that in highly volatile and momentum-driven markets like crypto, shorter-term trend filters (e.g., SMA-50) can enhance returns when paired with dynamic, Sharpe-based allocation. However, investors seeking more stable growth may prefer longer SMA windows to minimize exposure during uncertain conditions. Furthermore, compared to the static buy-and-hold baseline, all three SMA-based models delivered superior returns, validating the core hypothesis that combining Sharpe Ratio optimization with trend filtering can outperform passive crypto investment strategies.

3.6. Statistical Summary and Risk Analysis

To complement the cumulative return evaluation, Table 4 presents a statistical summary of the three dynamic strategies, including final portfolio value, total return, annualized volatility, downside deviation, and Sharpe Ratio. These metrics were computed using 3-day returns across the 1-year simulation period from January 1, 2024, to January 1, 2025.

Table 4. Performance Summary of SMA-Based Strategies (3-Day Rebalancing)

Strategy	Final Value (USD)	Total Return (%)	Annualized Volatility (%)	Downside Deviation (%)	Annualized Sharpe Ratio
SMA-50	33,150.87	231.51%	61.12%	35.53%	2.51
SMA-100	26,268.68	162.69%	61.34%	33.86%	1.98
SMA-200	26,311.40	162.69%	61.34%	33.86%	1.98

The SMA-50 strategy outperformed the other models in both absolute and risk-adjusted terms. It produced a final portfolio value of $33,150.87, equivalent to a +231.51% return, with an annualized Sharpe ratio of 2.51. This superior performance was accompanied by slightly higher volatility (61.12%) and downside risk (35.53%) compared to the SMA-100 and SMA-200 models.

In contrast, both the SMA-100 and SMA-200 strategies ended with identical final values of $26,268.68 and returns of +162.69%. While these models exhibited comparable annualized volatility (~61.34%) and downside deviation (~33.86%), their lower Sharpe ratios (1.98) indicated less efficient return generation per unit of risk. This likely stems from their longer trend confirmation windows, which caused slower re-entries into favorable market conditions, reducing exposure during key rally phases.

All dynamic models outperformed the buy-and-hold baseline return of +132.14%, reinforcing the effectiveness of combining Sharpe ratio-based dynamic allocation with trend filtering. The results further suggest that shorter SMA periods (e.g., 50-day) can be more responsive in fast-moving markets like cryptocurrency, providing superior capital growth despite elevated volatility. For a more rigorous comparison and to confirm the statistical significance of these performance differences, future work would ideally include statistical tests such as t-tests or Wilcoxon rank-sum tests comparing the daily returns of the SMA strategies against the baseline.

4. Discussion

This study showed that integrating Sharpe ratio-based allocation with SMA trend filters could enhance crypto portfolio performance. Among the three strategies tested, SMA-50 delivered the highest return (+231.51%) and Sharpe ratio (2.51), highlighting the advantage of shorter trend windows in fast-moving markets. Its responsiveness allowed early entry during bullish phases, especially in Q1 and Q4 2024, which were characterized by significant market rallies driven by factors such as increasing institutional adoption and positive regulatory developments. However, this came with slightly higher volatility and downside risk compared to more conservative configurations.

Both SMA-100 and SMA-200 achieved lower returns (+162.69%) and identical Sharpe ratios (1.98), reflecting their delayed market entries due to longer trend confirmation. Despite offering better downside protection, they underperformed in capturing early rallies—indicating a trade-off

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between signal reliability and opportunity capture. For instance, during periods of rapid price recovery, their delayed signals meant missing out on the initial upward momentum.

All three models outperformed the buy-and-hold baseline (+132.14%), validating the use of adaptive, trend-aware allocation in volatile markets. Overall, the results suggest that shorter SMA filters can improve performance when paired with dynamic Sharpe-based weighting, though at the cost of increased exposure to short-term risk. It is important to acknowledge a limitation of using the Sharpe ratio in highly volatile and non-normally distributed asset classes like cryptocurrencies: the Sharpe ratio assumes that returns are normally distributed, which is often not the case for crypto assets. This can potentially misrepresent the true risk-adjusted performance, especially during extreme market events. Future research could explore alternative risk-adjusted metrics that are less sensitive to non-normality, such as the Sortino ratio or conditional CVaR.

From a theoretical perspective, the superior performance of the SMA-50 configuration aligns with momentum finance literature, which suggests that shorter-term trend signals are more effective in high-volatility environments [15]. Additionally, the findings are consistent with modern portfolio theory [17], where dynamic rebalancing improves capital efficiency when asset correlations and volatility are time-varying [18]. The integration of a trend filter acts as a regime-detection mechanism, implicitly reducing exposure during unfavorable market states, a behavior conceptually related to volatility clustering models in financial econometrics [19]. This theoretical alignment strengthens the robustness of the proposed hybrid framework.

5. Conclusion

This paper presented a dynamic crypto asset allocation strategy that combines Sharpe ratio-based weighting with SMA trend filtering. Using 3-day rebalancing and historical data from January 2024 to January 2025, we tested three configurations: SMA-50, SMA-100, and SMA-200. All models outperformed a static buy-and-hold benchmark, with SMA-50 achieving the highest return (+231.51%) and risk-adjusted performance (Sharpe ratio: 2.51).

The results demonstrate that shorter-term trend filters can significantly enhance portfolio growth in volatile markets like crypto, allowing timely entry into bullish trends. However, they also introduce higher short-term volatility. Conversely, longer SMAs offer more stable exposure but may underperform during rapid market rallies due to delayed responsiveness.

Overall, the findings support the effectiveness of combining statistical risk measures with trend-following techniques for crypto portfolio management. This approach offers a balance between return optimization and downside protection, making it suitable for investors navigating high-volatility environments. Future research could explore testing this strategy in multi-regime markets, applying more advanced machine learning models like long short-term memory (LSTM) networks for trend detection, or integrating on-chain indicators to provide additional market insights for allocation decisions.

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