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Momentum Trading in Cryptocurrencies: A Comparative Study of Time-Series and Cross-Sectional Strategies

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Abstract. Momentum-based trading strategies are widely employed in financial markets and have become increasingly relevant within the cryptocurrency ecosystem. This study examines the profitability of momentum-based trading strategies in cryptocurrency markets using a multi-horizon exponential moving average (EMA) framework. The analysis covers eight major cryptocurrencies, Bitcoin, Ethereum, Litecoin, Ripple, Binance Coin, Cardano, Dogecoin, and Solana over the period 1 January 2020 to 31 October 2025. Momentum signals are constructed using short- and long-term Exponential Moving Average (EMAs) combined with volatility normalization to ensure comparability across assets. Two portfolio structures are evaluated: time-series momentum, which adjusts exposure for each asset individually, and cross-sectional momentum, which ranks assets by relative strength. Empirical results show that momentum effects remain economically meaningful in digital assets. Time-series momentum delivers superior performance, achieving an annual return of 31.96% and outperforming cross-sectional momentum on a risk-adjusted basis. Cross-sectional momentum exhibits higher max drawdowns of 55.0% but lower overall profitability in terms of annual returns, partly due to high correlations among cryptocurrencies. The findings confirm that trend persistence and volatility remain key drivers of momentum profitability in crypto markets.

Keywords: cryptocurrency, momentum strategy, time-series momentum, cross-sectional momentum.

JEL Code: G11, G12, G17, C58.

Introduction

Momentum trading strategies based on the principle that assets with recent positive performance tend to continue outperforming in the near term are among the most studied and applied approaches in financial economics (Jegadeesh and Titman, 1993; Moskowitz et al., 2012). Originally developed within equity and foreign exchange markets, momentum has been shown to generate statistically significant excess returns across multiple asset classes, including commodities and fixed income (Asness et al., 2013). Over the past decade, the growing maturity of cryptocurrency markets has motivated renewed interest in examining whether similar return persistence exists within digital assets (Liu and Tsyvinski, 2021; Sapkota and Grobys, 2021).

The rapid evolution of cryptocurrencies since 2020 has transformed them from speculative instruments into a distinct and complex asset class, attracting institutional investors, algorithmic traders, and quantitative funds (Chu et al., 2020). During this period, the market has witnessed substantial structural changes, including the expansion of decentralized finance (DeFi), the rise of stablecoins, and the listing of new high-liquidity assets such as Solana (SOL) and Binance Coin (BNB). These developments provide a rich environment for reassessing whether traditional momentum mechanisms derived from

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price trends and volatility dynamics remain effective in highly volatile and information-driven digital markets (Baur et al., 2022).

Momentum strategies are typically implemented using either a time-series or a cross-sectional framework. The time-series approach takes directional positions on each asset individually, going long when its own momentum signal is positive and short when it is negative. By contrast, the cross-sectional approach ranks assets relative to each other and allocates capital toward those exhibiting the strongest positive momentum while shorting those with weaker or negative signals (Baz et al., 2015; Baltas and Kosowski, 2020). Both methods rely on the same underlying premise: that price changes are not fully random and that behavioural and structural market factors cause trend persistence (Daniel and Moskowitz, 2016).

The present study applies these two momentum frameworks to a selection of eight major cryptocurrencies, Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), Binance Coin (BNB), Cardano (ADA), Dogecoin (DOGE), and Solana (SOL), using daily price data denominated in U.S. dollars over the 1 January 2020 – 31 October 2025 period. Momentum signals are constructed as combinations of exponential moving averages (EMAs) over different time horizons and normalized to account for volatility clustering and scale differences across assets. This structure captures both short-term and medium-term trend effects while maintaining comparability between assets with distinct price levels.

This study aims to contribute to the ongoing discussion on cryptocurrency market efficiency and behavioural dynamics by examining the profitability of momentum strategies during a period characterized by substantial volatility and institutional development. Through a comparative assessment of time-series and cross-sectional momentum approaches, the analysis seeks to shed light on the persistence of price trends, the influence of volatility, and the extent to which traditional momentum mechanisms may apply within contemporary cryptocurrency markets.

1. Literature review

The existence of momentum in financial markets has long been recognized in the academic literature. One of the earliest and most influential studies by Jegadeesh and Titman (1993) documented that stocks with strong past performance tend to continue generating positive returns in subsequent periods. This finding challenged the traditional efficient market hypothesis, which assumes that asset prices fully and immediately reflect all available information. Since then, numerous studies have confirmed that momentum is not confined to equity markets but also appears across a wide range of asset classes, including commodities, bonds, and foreign exchange markets (Moskowitz et al., 2012; Asness et al., 2013). These findings have established momentum trading as one of the most widely studied and practically applied quantitative strategies in modern portfolio management. From a theoretical perspective, persistent price trends are often attributed to behavioural biases such as investor underreaction to new information, delayed price adjustments, or structural market frictions that prevent prices from instantly reaching equilibrium.

With the emergence and rapid development of digital assets, researchers have increasingly examined whether similar momentum effects are present in cryptocurrency markets. Early studies investigating return predictability in cryptocurrencies produced mixed findings. Grobys and Huhta-Halkola (2019), for example, examined a broad cross-section of cryptocurrencies between 2014 and 2018 and reported only weak evidence of cross-sectional momentum once smaller and illiquid coins were excluded from the analysis. These findings suggested that the unique characteristics of cryptocurrency markets such as fragmented exchanges, limited liquidity, and highly speculative investor behaviour may weaken the persistence of conventional momentum effects. Other early studies also observed that continuation patterns during speculative market phases often reverse quickly when market sentiment changes, indicating that momentum in cryptocurrencies may be unstable or strongly dependent on specific market regimes.

More recent research provides a more refined perspective on momentum behaviour in digital asset markets. Borgards (2021) demonstrates that time-series momentum strategies can generate statistically significant returns when returns are properly adjusted for volatility. Similarly, Huang et al. (2024) show that volume-weighted momentum portfolios produce consistent profitability among liquid cryptocurrencies, highlighting the role of trading activity and liquidity in strengthening momentum signals. These findings suggest that appropriately designed momentum strategies may remain effective in cryptocurrency markets despite their extreme volatility and rapidly changing market conditions.

Additional research highlights the importance of asset characteristics in shaping the profitability of momentum strategies. Fíčura (2023) shows that momentum returns vary significantly with market capitalization and trading turnover, with large-cap cryptocurrencies exhibiting more stable and predictable return patterns than smaller and less liquid tokens. Studies by Baur et al. (2022) further emphasize the central role of volatility in determining risk-adjusted returns. Because cryptocurrency markets are characterized by extreme price fluctuations and rapid boom–bust cycles, momentum strategies may generate substantial profits during strong trend periods but can also experience large drawdowns during abrupt market reversals. In general, the literature suggests that the effectiveness of momentum strategies in digital assets depends heavily on factors such as volatility management, liquidity conditions, and portfolio construction techniques.

Several studies also emphasize the importance of signal construction and normalization in the implementation of momentum strategies. Cryptocurrency markets display high volatility and large price dispersion across assets, which can cause raw momentum signals to produce unstable portfolio allocations. As a result, volatility scaling and trend-filtering techniques are frequently used to stabilize trading signals and improve risk-adjusted performance. Moving-average-based trend indicators, particularly exponential moving averages (EMAs), are widely applied in systematic trading strategies because they allow recent price information to receive greater weight while still capturing broader trend dynamics. In this context, EMA-based signals provide a flexible approach for identifying both short-term and medium-term price trends while reducing the influence of temporary market noise. Building on this approach, the present study constructs momentum signals using combinations of exponential moving averages across multiple time horizons and applies volatility normalization to ensure comparability across cryptocurrencies with different price levels and volatility profiles.

Despite the expanding literature on cryptocurrency market efficiency and return predictability, important questions remain regarding the robustness and structure of momentum strategies in digital asset markets. Relatively few studies provide a direct comparison between time-series and cross-sectional momentum frameworks using a consistent volatility-adjusted methodology. Furthermore, much of the existing empirical evidence is based on early cryptocurrency market periods characterized by rapid speculative growth, leaving uncertainty about whether momentum effects remain economically meaningful in the more mature post-2021 market environment marked by increased institutional participation and evolving market structures. These limitations highlight the need for further empirical investigation into the performance and stability of momentum strategies under contemporary market conditions.

To address these gaps in the literature, this study investigates the effectiveness of momentum trading strategies in major cryptocurrency markets. Specifically, the analysis focuses on three research questions. First, do time-series and cross-sectional momentum strategies generate statistically and economically significant returns in major cryptocurrencies such as Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), Binance Coin (BNB), Cardano (ADA), Dogecoin (DOGE), and Solana (SOL) during the period from 1 January 2020 to 31 October 2025? Second, which momentum structure delivers superior risk-adjusted performance under conditions of high correlation among digital assets? Third, how does volatility normalization influence portfolio stability and drawdown behaviour in cryptocurrency momentum strategies?

Based on the theoretical and empirical literature on momentum trading, the study evaluates the following hypotheses:

H1: Momentum effects exist in cryptocurrency markets and can generate positive returns.

H2: Time-series momentum strategies provide higher risk-adjusted performance than cross-sectional momentum strategies.

H3: High correlations among cryptocurrencies reduce the profitability of cross-sectional momentum strategies.

By examining these questions, the present study contributes to the literature in several ways. First, it applies a unified dual-momentum framework that evaluates both time-series and cross-sectional strategies within a consistent volatility-adjusted structure across a diversified basket of major cryptocurrencies. Second, the analysis focuses on the 1 January 2020 – 31 October 2025 market period, which represents a more mature phase of cryptocurrency development compared with the earlier high-growth periods emphasized in prior studies. Third, the study provides a transparent and replication-oriented methodological framework, enabling future researchers to reproduce and extend the analysis. Although momentum strategies are traditionally examined within the asset pricing literature, their evaluation also has important implications for financial management and investment analysis. Understanding return persistence and volatility dynamics in cryptocurrency markets is particularly relevant for institutional investors, portfolio managers, and risk analysts who increasingly incorporate digital assets into diversified portfolios.

2. Material and method

2.1 Data

The empirical analysis in this study focuses exclusively on the cryptocurrency market. Daily price data for eight major and liquid digital assets: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), Binance Coin (BNB), Cardano (ADA), Dogecoin (DOGE), and Solana (SOL) are employed. This selection captures the largest and most actively traded cryptocurrencies in terms of market capitalization, liquidity, and historical data availability. The inclusion of Solana (SOL), which was launched in 2020, ensures that the sample reflects both early-established and more recent blockchain networks that have contributed to the diversification of the digital asset market. The dataset covers the period from 1 January 2020 to 31 October 2025 and is denominated entirely in U.S. dollars (USD). All price series were obtained from Yahoo Finance using the *yfinance* Python library, which consolidates exchange-level data from multiple trading venues to produce reliable daily closing prices. This unified data source ensures consistency in quotation currency, frequency, and price reporting across all cryptocurrencies. For completeness, the stochastic simulation framework is presented in Appendix A, while the empirical analysis relies on observed market data.

Each series was examined for completeness and alignment. Occasional missing values resulting from temporary exchange outages or synchronization delays were filled using forward interpolation when gaps were shorter than three consecutive days; longer gaps were excluded from the analysis. The dataset was then synchronized across all assets to create a uniform daily trading calendar, ensuring that price observations were aligned by date.

For descriptive analysis, summary statistics including mean, median, standard deviation, minimum, and maximum were computed to characterize each asset's price behaviour over the sample period. As expected for cryptocurrencies, the distributions display high volatility and occasional extreme price fluctuations. The dataset thus provides a representative view of the structural dynamics of modern cryptocurrency markets, capturing periods of rapid appreciation, correction, and stabilization. The evaluation of portfolio risk, the study also considers maximum drawdown as a key performance metric. Maximum drawdown measures the largest peak-to-trough decline in the cumulative portfolio value over the sample period. Formally, drawdown at time tis defined as the percentage deviation of the portfolio value from its previous historical peak:

$$DD_t = \frac{P_t - \max(P_{0:t})}{\max(P_{0:t})} \quad ; \tag{1}$$

where P_t denotes the portfolio value at time t. For reporting purposes, the magnitude of the maximum drawdown is expressed as a positive percentage indicating the largest loss from a previous peak. In graphical representations, drawdowns are plotted as negative deviations from the peak to visually illustrate periods of portfolio decline. Daily returns are computed as logarithmic returns defined by:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \; ; \tag{2}$$

where P_t denotes the daily closing price. Logarithmic returns are used consistently throughout the study for descriptive statistics, volatility estimation, portfolio aggregation, Sharpe ratio calculation, drawdown measurement, and annual performance computation. All reported values are expressed in percentage terms for clarity.

2.2 Algorithm

2.2.1 Exponential Moving Average (EMA)

The exponential moving average (EMA) provides a smoothed representation of the underlying price process while retaining sensitivity to the recent changes for a stochastic price series C_t, the EMA is defined recursively as:

$$EMA_t = (1 - \lambda)C_t + \lambda EMA_{t-1} \; ; \tag{3}$$

where $0 < \lambda < 1$ is the smoothing constant.

The smoothing parameter is linked to the characteristic lookback period L through the exponential decay relation:

$$\lambda = e^{-\frac{1}{L}} \; . \tag{4}$$

Smaller value of L produce faster-reacting EMAs that follow short-term fluctuations, whereas larger values of L yield smoother curves that capture longer-term movements. The EMA, unlike a simple moving average, assigns exponentially decreasing weights to past prices, allowing it to respond more efficiently to sudden changes in highly volatile markets such as cryptocurrencies. In the next subsection, short and long horizon EMAs are computed and compared to illustrate the smoothing behaviour and the resulting crossing signals that form the basis of the momentum indicator. The EMA-based momentum structure follows established momentum literature (Jegadeesh & Titman, 1993; Moskowitz et al., 2012). The volatility normalization approach is consistent with risk-managed momentum strategies as in Barroso and Santa-Clara (2015).

2.2.2 Crossing EMAs for different time-periods

The interaction between exponential moving averages (EMAs) of differing horizons forms the core of the momentum-signal construction. A shorter-horizon EMA reacts quickly to new price information, whereas a longer-horizon EMA provides a smoother estimate of the underlying trend. The crossing of these two averages identifies shifts in market direction and therefore acts as a fundamental building block of the momentum indicator.

The EMA weighting scheme decreases exponentially with lag length, meaning that past observations contribute less to the current average. The decay rate of this weighting can be characterized by its half-life the number of periods after which the weight of a past observation declines to half its initial value. If L denotes the characteristic look-back length, the exponential decay relation:

$$\frac{1}{2} = e^{-\tau_{\frac{1}{2}}/L} ; \tag{5}$$

implies the half-life:

$$\tau_{\frac{1}{2}} = L \ln(2) . \tag{6}$$

The half-life therefore provides an intuitive interpretation of the EMA parameter such that a shorter half-life yields a rapidly reacting filter, while a longer half-life yields a sluggish, trend-following one. The decay parameter λ associated with each EMA is linked to L through $\lambda = e^{-1/L}$. Table 1 lists representative pairs of λ and $\tau_{1/2}$ corresponding to the smoothing lengths employed in this study.

Table 1. **Smoothing parameters and corresponding half-lives**

EMA length $\boldsymbol{L}$	Decay parameter $\boldsymbol{\lambda = e^{-1/L}}$	Half-life $\boldsymbol{\tau_{1/2} = L\ln(2)}$ **(days)**
8	0.8825	5.55
16	0.9394	11.09
24	0.9592	16.63
32	0.9690	22.18
48	0.9793	33.27
96	0.9896	66.55

Source: compiled by the author

In the cryptocurrency markets, shorter EMAs capture immediate momentum arising from rapid price movements, whereas longer EMAs capture persistent medium to long-term trends. For visualization, three EMA pairs (8, 24), (16, 48), and (32, 96) from (Baz et al., 2015) are computed on the simulated cryptocurrency price series from Section 2.2.2. Crossings of the shorter EMA above (below) the longer EMA are interpreted as upward (downward) momentum phases. The resulting paths are illustrated in Figures 1–3, which demonstrate how increasing the look-back length progressively smooths the underlying series and reduces the frequency of crossings.

Figure 1. **EMA with length 8 (navy blue) and 24 (magenta)**
Source: compiled by the author

Figure 2. **EMA with length 16 (light green) and 48 (dark blue)**
Source: compiled by the author

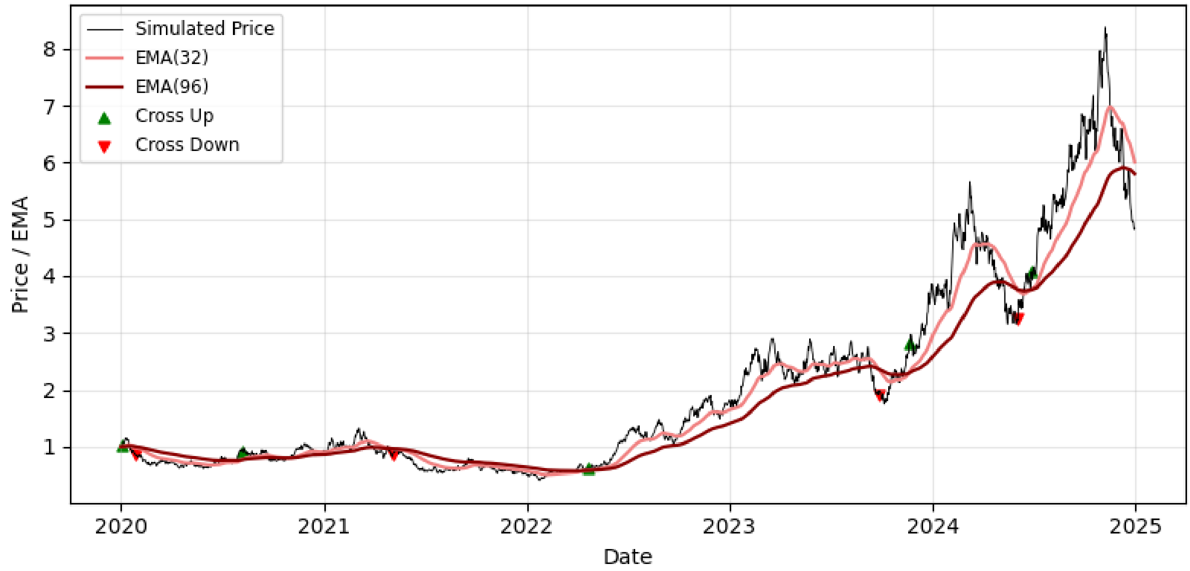

Figure 3. **EMA with length 32 (light red) and 96 (dark red)**
Source: compiled by the author

Figure 1–3 show the short and long EMAs applied to the simulated cryptocurrency price path. As the look-back length increases from the first to the third panel, the EMAs become progressively smoother, and the number of crossing points declines. These crossings correspond to the zero points of the intermediate momentum variable $x_{t,k}$ $\mathrm{EMA}_t^{(s,k)} - \mathrm{EMA}_t^{(l,k)}$, which serves as the first stage of momentum-signal computation described in the following subsections.

2.2.3 Raw momentum variable x_k

The next stage in the momentum algorithm involves transforming the pairwise EMA information into a single quantitative measure of directional pressure. For each smoothing-pair k consisting of a short and a long EMA horizon, the raw momentum variable $x_k(t)$ is given below:

$$x_k(t) = EMA\left(C_t, \frac{1}{n_{ks}}\right) - EMA\left(C_t, \frac{1}{n_{kl}}\right); \tag{7}$$

where n_{ks} and n_{kl} denote the short and long characteristic look-back lengths, respectively. When the short EMA exceeds the long EMA, $x_k > 0$ signals positive momentum; when it falls below, $x_k < 0$ reflects negative momentum. This variable therefore provides a continuous measure of trend direction and magnitude prior to normalization. Because cryptocurrencies exhibit higher volatility than fiat currencies, $x_k(t)$ fluctuates more sharply, producing larger positive and negative swings around zero. To illustrate the behaviour of the raw momentum variable across different time horizons, three $x_k(t)$ series corresponding to EMA pairs (8, 24), (16, 48), and (32, 96) are computed from the simulated cryptocurrency price and shown in figure 4.

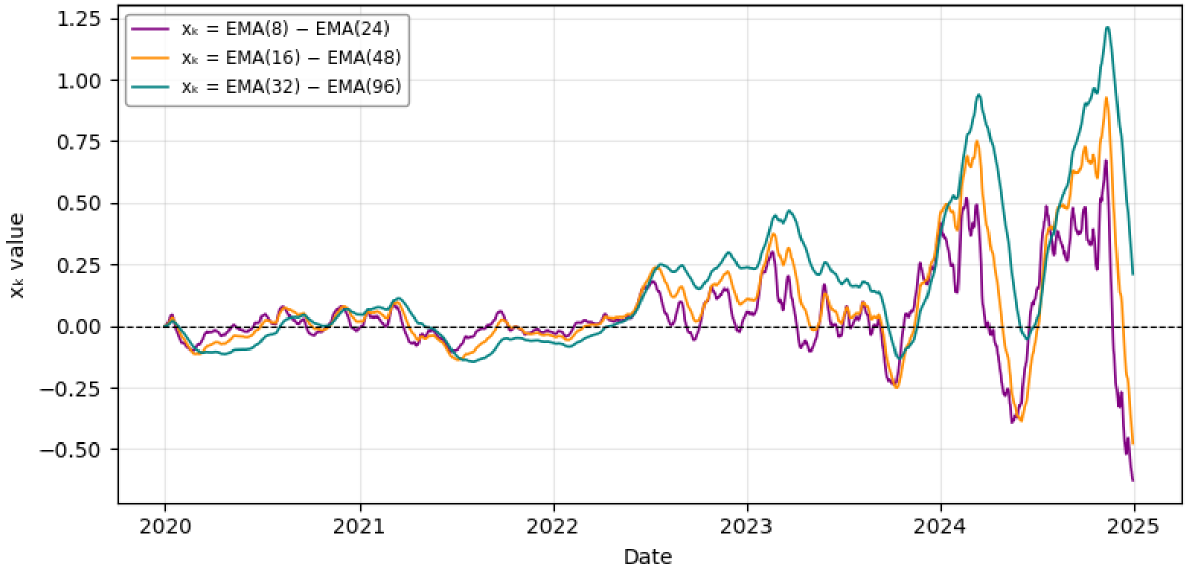

Figure 4. x_k **Comparison of time-series momentum signals**
Source: compiled by the author

As expected, the shortest-horizon variable fluctuates most rapidly, reflecting short-term noise sensitivity, while longer-horizon measures are progressively smoother and more persistent. The sign of $x_k(t)$ indicates the prevailing trend direction, whereas its magnitude reflects the strength of the divergent between shot and long-term price component. These unnormalized momentum series form the inputs for the normalization step.

2.3 Normalisation

The raw momentum variable $x_k(t)$ derived in the previous subsection exhibit horizon dependent magnitudes short-term EMAs fluctuate widely, while long-term EMAs vary more smoothly. To ensure comparability across horizons and prevent volatility clustering from dominating the signal, each $x_k(t)$ is normalised by its recent variability using a rolling standard deviation. The normalized momentum variable $y_k(t)$ is defined as:

$$y_k(t) = \frac{x_k}{\eta_k}, \text{ where } \eta_k(t) = std[x_k(t-L:t)] \; ; \tag{8}$$

where $\eta_k(t)$ denotes the moving standard deviation of x_k computed over a lookback window L. This scaling step produces a dimensionless series with approximately unit variance, allowing fair aggregation across different time scales. In cryptocurrency markets known for heteroskedastic behaviour, this normalisation is particular important for stabilizing signal amplitude during volatility spikes.

The effect of normalization on $x_k(t)$ shown in Figure 5 demonstrates how the normalization procedure rescales the raw momentum variables $x_k(t)$ into volatility-adjusted series $y_k(t)$. The standardized signals oscillate around zero with relatively uniform amplitude, ensuring that short-term and long-term momentum components contribute comparably to subsequent signal generation. This transformation mitigates the disproportionate influence of high-volatility periods, which is crucial in cryptocurrency markets characterized by abrupt price shocks.

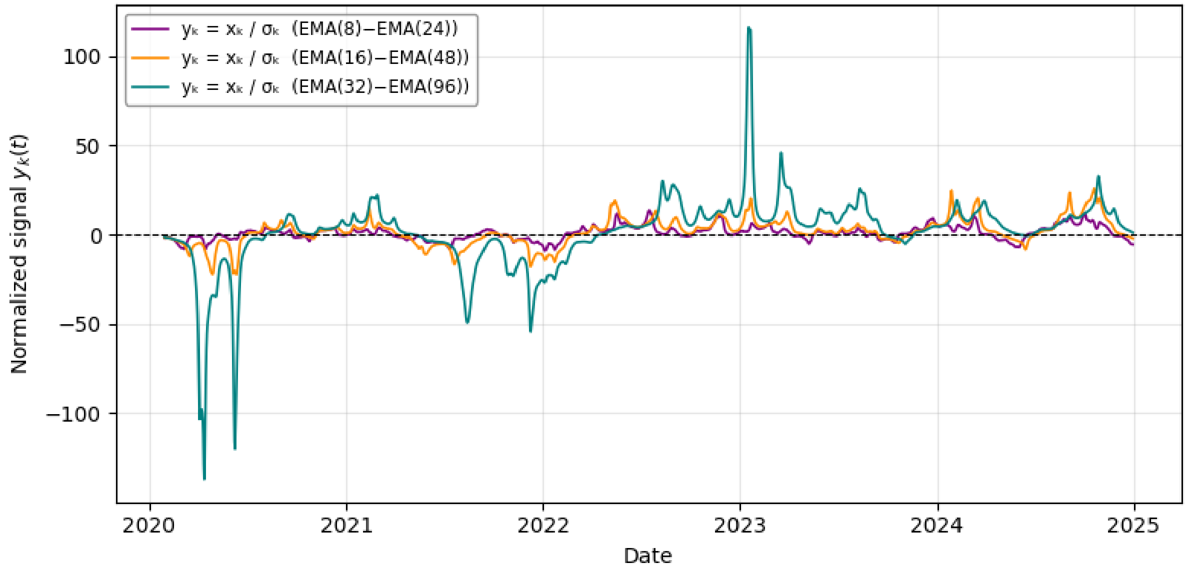

Figure 5. **Effect of normalization on $x_k(t)$**
Source: compiled by the author

After obtaining the normalized momentum variables $y_k(t)$, an additional smoothing transformation is applied to reduce short-term noise and emphasize persistent trends. Following the structure of the original algorithm, each $y_k(t)$is exponentially averaged again to yield a smoothed signal $z_k(t)$:

$$z_k(t) = EMA\left(y_k(t), \frac{1}{n_k}\right) \; ; \tag{9}$$

where n_k represents the characteristic smoothing length for each momentum component. This secondary exponential filter acts as a low-pass transformation, mitigating erratic fluctuations in the normalized signal while preserving its overall directional structure. In volatile markets such as cryptocurrencies, this step stabilizes the momentum measure before constructing the final composite trading signal. Figure 6, the effect of normalization on $z_k(t)$, shows the smoothed normalized signals $z_k(t)$ derived from the volatility adjuste d series $y_k(t)$. As expected, the shorter-term component (8,24) remains the most responsive, while longer horizons (32, 96) evolve more smoothly. The additional exponential smoothing reduces transient spikes, yielding cleaner and more persistent momentum indicators suitable for final signal construction.

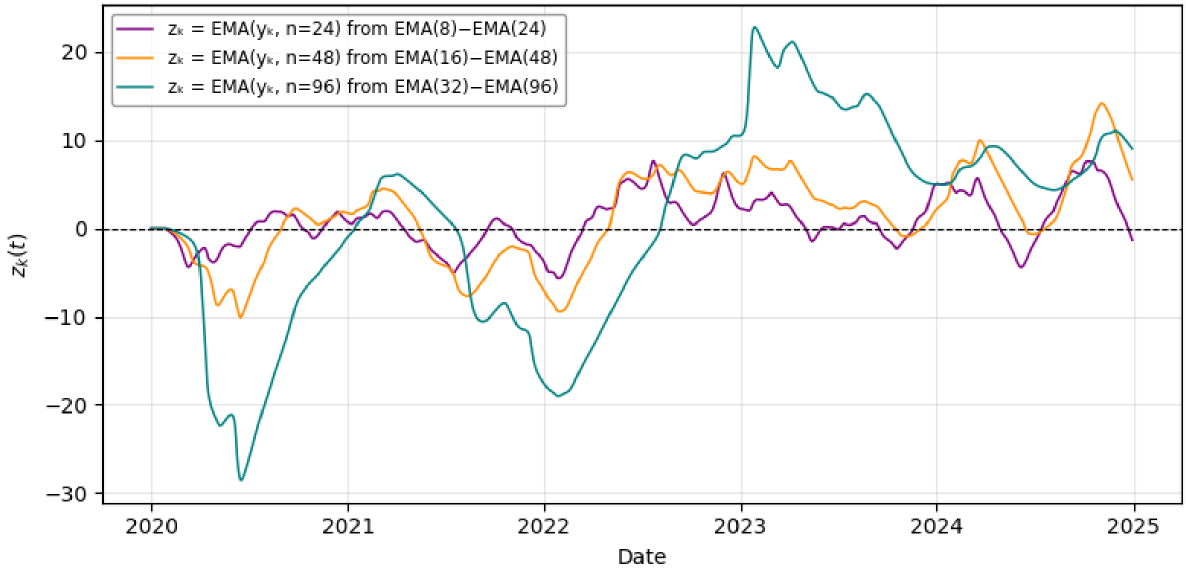

Figure 6. **Effect of normalization on $z_k(t)$**
Source: compiled by the author

2.3.1 Signal generation

After obtaining the smoothed normalized momentum signals $z_k(t)$, the next step transforms them into bounded trading indicators. This transformation ensures that large movements in volatility-adjusted returns do not lead to excessive or unstable position sizes. The nonlinear response function is defined as:

$$u_k(t) = \tanh\big(\alpha\, z_k(t)\big)\,; \tag{10}$$

where the hyperparameter $\alpha > 0$ controls sensitivity. The hyperbolic tangent ensures that signals remain within $[-1,1]$, producing a stable and continuous mapping that avoids excessive position sizes during periods of high volatility. The tanh transformation is widely adopted in contemporary quantitative finance due to its smoothness, numerical robustness, and suitability for the extreme return distributions characteristic of cryptocurrency markets.

Each bounded signal $u_k(t)$is then aggregated across all smoothing horizons $k = 1, \dots, K$ to obtain the composite momentum signal:

$$u(t) = \sum_{k=1}^{K} b_k\ u_k(t)\,; \tag{11}$$

where b_k denotes the weighting coefficient associated with each EMA pair. Unless otherwise stated, equal weights $(b_k = 1/K)$ are assigned across horizons. To maintain comparability through time, the composite signal is re-standardized using its moving standard deviation:

$$S(t) = \frac{u(t)}{\sigma_u(t)}\,; \tag{12}$$

where $\sigma_u(t)$ is computed over a rolling 30-day window. This step ensures that the strength of the composite momentum signal remains scale-invariant even under changing market volatility conditions. Finally, trading positions are determined by the sign of the standardized signal:

$$\text{Position } (t) = \begin{cases} +1, & \mathrm{S(t)} > 0 \\ -1, & \mathrm{S(t)} < 0 \end{cases};$$

which corresponds to a long-short momentum rule: a positive $S(t)$indicates bullish momentum (long position), while a negative $S(t)$ implies bearish momentum (short position) captured through Figures 7–9.

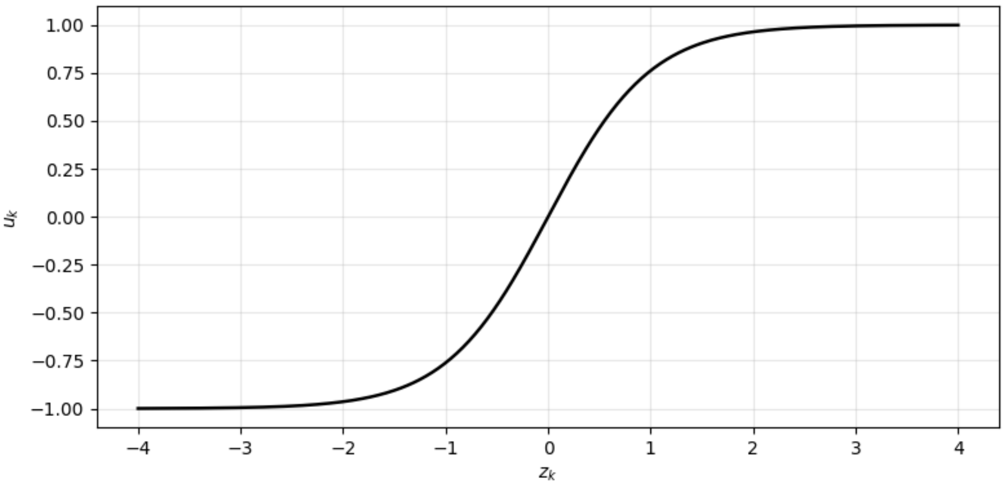

Figure 7. **Response function $u_k(t)$**
Source: compiled by the author

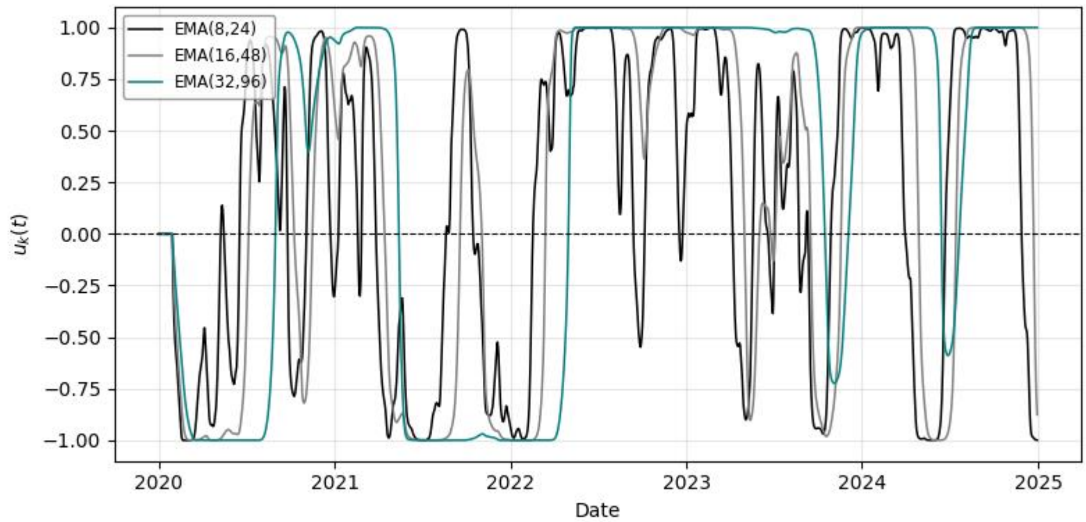

Figure 8. **Bounded momentum signals $u_k(t)$**
Source: compiled by the author

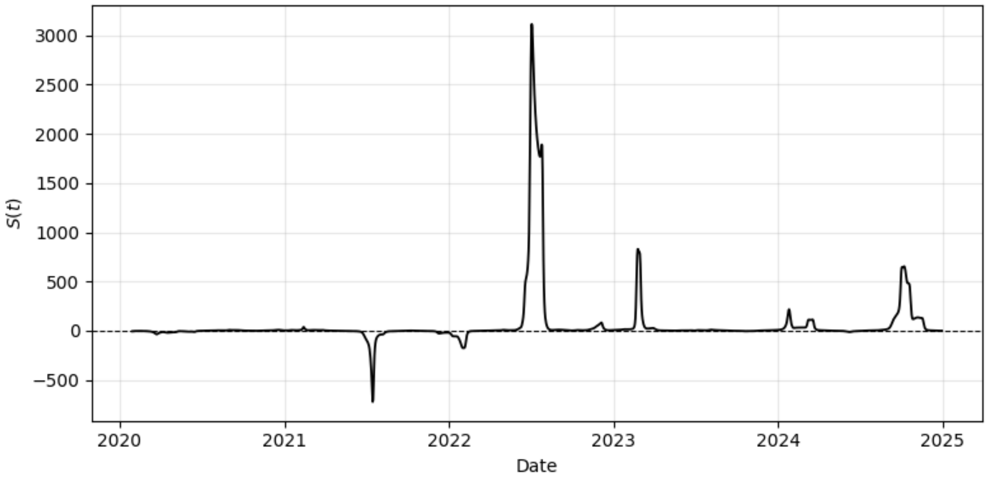

Figure 9. **Standardized composite momentum signal $S(t)$**
Source: compiled by the author

3. Portfolio types

3.1 Time series momentum portfolio

The time-series momentum portfolio allocates capital to each cryptocurrency purely based on its own standardized momentum signal. On each rebalancing date, the position in asset i is proportional to the value of its signal $S_i(t)$, scaled by the number of assets N:

$$w_i(t) = \frac{S_i(t)}{N} . \quad (13)$$

Because the signal is bounded within $[-1,1]$, the portfolio allocates at most $1/N$ units of capital to any single asset, either long or short. A positive signal leads to a long position, a negative signal results in a short position, and a signal close to zero yields minimal exposure.

This ensures that the portfolio is fully self-scaled as total gross exposure never exceeds one unit of capital. Intuitively, the strategy assigns more weight to cryptocurrencies exhibiting stronger trend persistence, while reducing or reversing exposure during periods of negative momentum. The time-series momentum returns on day t is therefore:

$$r^{TS}(t) = \sum_{i=1}^{N} w_i\,(t-1)\, r_i(t)\,; \quad (14)$$

where $r_i(t)$ is the daily return of cryptocurrency i. This portfolio structure directly reflects the classical intrinsic-momentum (trend-following) framework and has been widely applied in equities, commodities, futures markets, and, more recently, digital assets.

3.2 Cross sectional momentum portfolio

The cross-sectional momentum portfolio compares momentum signals across cryptocurrencies and allocates capital based on relative performance rather than absolute trends. On each rebalancing date, all assets are ranked according to their signals $S_i(t)$. The top-performing group (winners) is bought, while the bottom-performing group (losers) is sold.

Following the cryptocurrency market dynamics, this study long the three cryptocurrencies with the highest signals and short the three with the lowest signals:

- *long positions*: 3 strongest momentum assets;

- *short positions*: 3 weakest momentum assets.

Each selected asset receives an equal weight of 1/6, regardless of the magnitude of its signal. This approach ensures that the strategy maintains a constant exposure of one unit of capital, with long and short positions perfectly balanced.

The cross-sectional momentum return is therefore:

$$r^{XS}(t) = \frac{1}{3} \sum_{i \in L(t-1)} r_i(t) \quad - \; \frac{1}{3} \sum_{j \in S(t-1)} r_j(t) \ ; \tag{15}$$

where $L(t-1)$ contains the three cryptocurrencies with the highest signals (long portfolio) and $S(t-1)$ contains the three with the lowest signals (short portfolio).

Unlike the time-series approach, cross-sectional momentum may assign a long position to an asset even when its signal is negative, provided it is less negative than others. Similarly, it may short an asset with a positive signal if its momentum is relatively weak. This highlights the fundamentally comparative nature of the cross-sectional strategy exploiting relative strength rather than directional trends.

4. Back-test

The back-test evaluates the performance of the momentum signals described in Section 2 when applied to a portfolio of eight major cryptocurrencies over the period 1 January 2020 – 31 October 2025. The start date of the back-test is determined by the earliest point at which all required signals can be reliably computed. Because the construction of the momentum indicator involves multiple layers of smoothing and volatility normalization, a warm-up period is necessary before trading can begin. The back-testing framework assumes execution at the next-day closing price following signal generation. Transaction costs, slippage, and funding costs are not included; therefore, reported returns represent gross performance. Short positions are assumed feasible through cryptocurrency derivative markets. Portfolio positions are rebalanced using daily data to maintain alignment with updated momentum signals. Within both the time-series and cross-sectional strategies, assets are assigned equal capital weights within the long and short portfolios in order to avoid concentration risk and maintain comparability across assets. Portfolio returns are calculated as the weighted average of individual asset returns, assuming continuous reinvestment of profits. These assumptions are explicitly stated to ensure transparency and reproducibility of results.

The computation of the signal requires the short and long exponential moving averages of prices, the rolling standard deviation of the EMA spread, and an additional smoothing step applied to the normalized signals. Based on the longest EMA horizon (96 days), the 30-day rolling volatility window, and the second 96-day smoothing EMA, the total warm-up period amounts to approximately: $96 + 30 + 96 = 222$ days, an additional day for return computation. Accordingly, a 223-day warm-up *window* is required before the first reliable value of the composite momentum signal $S(t)$ becomes available. During this initial period, the signals are unstable and do not generate tradeable positions.

The back-test therefore excludes the warm-up window from all performance calculations, portfolio returns, and graphical results. Trading begins only after valid signals exist for all eight cryptocurrencies simultaneously.

Once the warm-up period has elapsed, the portfolio is rebalanced daily. At each rebalancing date, momentum signals are computed using information up to $t-1$, and portfolio positions for day $t$are determined according to the rules described in Section 4:

- in the *time-series momentum portfolio*, each cryptocurrency's position is proportional to the value of its own momentum signal;

- in the *cross-sectional momentum portfolio*, the three strongest cryptocurrencies are held long and the three weakest are held short, each with equal weight.

Daily portfolio returns are then computed as the weighted sum of next-day asset returns. All performance measures average return, volatility, sharp ratio, drawdowns, and cumulative wealth exclude the warm-up period and cover only the active trading window. This framework follows the structure of the original momentum methodology while adapting it to the continuous, 24/7 nature and higher volatility environment of cryptocurrency markets.

5. Empirical analysis and results

This section presents the empirical performance of the momentum strategy when applied to the selected set of eight major cryptocurrencies BTC, ETH, BNB, XRP, ADA, DOGE, SOL, and LTC. Daily USD prices from 1 January 2020 to 31 October 2025 serve as the underlying dataset, reflecting the continuous 24/7 trading nature of cryptocurrency markets. Consistent with this market structure, the empirical analysis relies on daily observations, resulting in approximately 365 data points per year.

After removing the required 223-day warm-up period described in Section 4, the back-test is performed over the remaining sample. The momentum signal is constructed as outlined in Section 3, incorporating price-based EMAs, volatility normalization, and smoothing of the standardized signal components. The strategy is evaluated using both time-series and cross-sectional portfolio formations.

The time-series portfolio allocates exposure to each asset according to its own momentum signal, capturing trend persistence at the individual cryptocurrency level. In contrast, the cross-sectional portfolio takes long positions in the strongest cryptocurrencies and short positions in the weakest based on relative signal rankings. Both portfolios are rebalanced daily using information available at the close of the preceding day.

In evaluating the performance of the momentum strategies, it is important to distinguish between statistical significance and economic significance. Statistical significance refers to whether observed returns differ from zero in a manner that is unlikely to occur by random chance, typically assessed through standard inferential tests. Economic significance, by contrast, evaluates whether the magnitude of the returns is sufficiently large to be meaningful from an investment perspective after accounting for trading costs, volatility, and drawdown risk. In highly volatile markets such as cryptocurrencies, strategies may produce statistically significant signals while still delivering limited economic value if the associated risks or transaction costs are substantial. Therefore, the results presented in this study are interpreted not only in terms of statistical measures but also with respect to their practical implications for portfolio performance and risk-adjusted returns. Below is the presentation of the back-test results, including daily returns, cumulative performance, volatility estimates, Sharpe ratios, and drawdown profiles. These results provide insight into the profitability, risk characteristics, and comparative behaviour of the two momentum formulations within the volatile and rapidly evolving cryptocurrency market.

The Sharpe ratio is computed using daily returns as:

$$SR = \frac{\bar{r}_d - r_f}{\sigma_d} \quad ; \tag{16}$$

where $\bar{r}_d$ denotes the average daily return and σ_d denotes daily volatility. The risk-free rate r_f is assumed to be 0% given the cryptocurrency market context. Annualized Sharpe ratios are obtained by multiplying the daily Sharpe ratio by $\sqrt{252}$.

Maximum drawdown is defined as the largest peak-to-trough decline in cumulative portfolio value and is calculated as:

$$MDD = \max_t \left(\frac{Peak_t - Trough_t}{Peak_t}\right). \tag{17}$$

It is reported as a positive percentage bounded between 0% and 100%.

Table 2a and 2b present the descriptive statistics and statistical significance tests for the daily returns of selected cryptocurrencies from 1 January 2020 to 31 October 2025. The descriptive results indicate that all cryptocurrencies exhibit positive mean returns, with Solana and XRP recording the highest averages, while Dogecoin shows the lowest. However, the large standard deviations and extreme minimum and maximum values highlight substantial volatility across the assets, reflecting the highly risky nature of cryptocurrency markets. The statistical inference results further reveal that only Bitcoin and Binance Coin display statistically significant mean returns at the 5% level, whereas Ethereum and Solana are marginally significant at the 10% level. For the remaining cryptocurrencies, the confidence intervals include zero, suggesting that their average returns are not statistically different from zero. Overall, although most cryptocurrencies demonstrate positive average performance, only a limited number provide statistically reliable returns, emphasizing the importance of adopting systematic trading strategies such as momentum approaches.

Table 2a. **Descriptive statistics of daily cryptocurrency returns (1 January 2020 – 31 October 2025)**

Index	Mean	Median	Std	Min	Max
BTC	0.115	-0.007	5.093	-30.123	53.841
ETH	0.198	0.148	4.214	-40.445	52.922
BNB	0.123	0.062	3.047	-17.405	17.182
XRP	0.201	-0.038	7.109	-51.512	151.633
ADA	0.141	0.104	4.133	-31.746	23.070
DOGE	0.028	0.107	4.547	-44.119	24.843
SOL	0.234	-0.027	6.416	-54.958	38.718
LTC	0.111	0.048	5.319	-55.050	54.855

Source: compiled by the author

Table 2b. **Statistical significance of mean daily cryptocurrency returns (1 January 2020 – 31 October 2025)**

Index	t-stat	p-value	95% CI Lower	95% CI Upper
BTC	1.9679	0.0492	0.0000	0.0027
ETH	1.6514	0.0988	-0.0003	0.0033
BNB	2.2184	0.0266	0.0002	0.0039
XRP	1.0466	0.2954	-0.0011	0.0036
ADA	1.2152	0.2244	-0.0008	0.0036
DOGE	1.3753	0.1692	-0.0009	0.0053
SOL	1.7637	0.0779	-0.0003	0.0053
LTC	0.3653	0.7149	-0.0016	0.0023

Source: compiled by the author

[Note: Daily returns are computed as logarithmic returns: $r_t = \ln(P_t/P_{t-1})$. All reported values are expressed in percentage terms. The same return definition is used consistently for descriptive statistics, volatility estimation, Sharpe ratios, drawdowns, and annualized performance calculations.]

The performance comparison of TS and CS momentum is presented in Table 3. It reveals that the Time-Series Momentum (TS) outperforms Cross-Sectional Momentum (CS) across the sample, delivering 31.96% annual returns compared to 14.59% for CS. TS also achieves more than double the Sharpe ratio, showing that its higher returns come from stronger and more efficient trend capture rather than additional risk-taking. Although TS experiences slightly smaller drawdowns, it remains the more profitable strategy overall. While the reported Sharpe ratios and cumulative returns suggest stronger performance for the time-series momentum strategy, the economic significance of this difference is also reflected in its relatively lower drawdown and more stable return path, indicating improved practical usability for portfolio management.

Table 3. **Performance comparison table (TS & CS Momentum)**

Metric	Time-Series Momentum	Cross-Sectional Momentum
Mean Daily Return	0.000741	0.000371
Volatility	0.026301	0.029104
Sharpe Ratio	0.028174	0.012757
Cumulative Return	3.912523	1.980864
Max drawdown (%)	45.5%	55.0%
Annual	31.96%	14.59%

Source: compiled by the author

Maximum drawdown represents the largest percentage decline from a previous portfolio peak during the sample period. While drawdowns are plotted as negative values in the figures to illustrate downward deviations from peak portfolio value, the reported maximum drawdown statistics are expressed as positive percentages.

The TS-Momentum Cumulative Performance in Figure 10 shows that the time-series momentum strategy captures the strong directional trends that characterized cryptocurrency markets, particularly during 1 January 2020 – 31 October 2021. The strategy scales into persistent up-moves, generating rapid growth in cumulative wealth during bullish phases. The steep rise in early 2021 illustrates this trend-following behaviour, once prices begin to accelerate, the momentum signal quickly strengthens, allowing the strategy to ride the trend until market conditions reverse. After mid-2021, however, cumulative performance stabilises and gradually declines, highlighting the sensitivity of TS momentum to trend exhaustion. In periods where price directions become choppy or range-bound, the strategy naturally loses its edge as signals oscillate around zero.

Figure 11, the daily returns of TS-Momentum, provides a clearer view of the volatility inherent in the TS approach. Return spikes both positive and negative correspond closely to major cryptocurrency price swings, since the strategy is fully exposed to directional risk. The extreme observations around 2021 reflect the sharp rallies and subsequent corrections that typified that period. As the market transitions into quieter conditions from 2022 onward, daily return fluctuations tighten considerably, indicating that the strategy's active risk decreases when volatility compresses and price trends weaken. This contraction is consistent with the behaviour of volatility-scaled momentum, where exposures fall when signals flatten.

Figure 12 illustrates the drawdown dynamics of the time-series momentum portfolio over the sample period. The plot shows the percentage decline of the portfolio from its previous peak value at each point in time. Negative values represent temporary losses relative to the historical maximum portfolio level. The figure indicates that the TS momentum strategy experiences periods of substantial decline, particularly during major cryptocurrency market corrections around 2021 and 2022. The deepest drawdown reaches approximately 45%, reflecting the high volatility characteristic of digital asset markets. Nevertheless, the strategy demonstrates a gradual recovery after major downturns, suggesting that trend-following signals allow the portfolio to adjust to changing market conditions and eventually regain lost value.

Generally, figure 10 to figure 12 of the TS-Momentum collectively depict a strategy that performs exceptionally well during clear and persistent uptrends but becomes vulnerable during regime shifts and prolonged sideways conditions. This behaviour is fully aligned with theoretical expectations of time-series momentum and highlights both its potential and its structural risks within the highly volatile cryptocurrency environment.

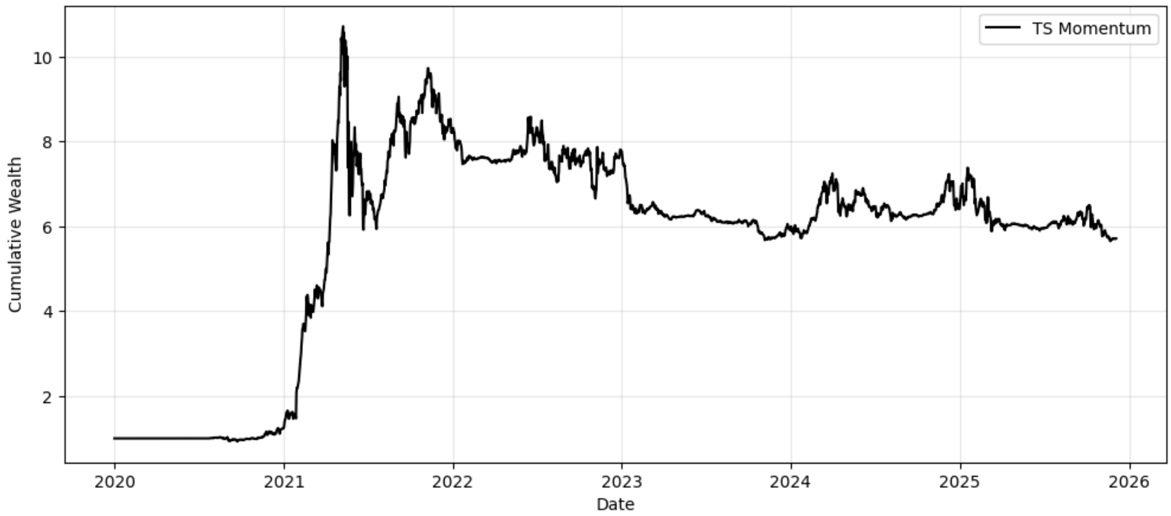

Figure 10. **TS-Momentum cumulative performance**
Source: compiled by the author

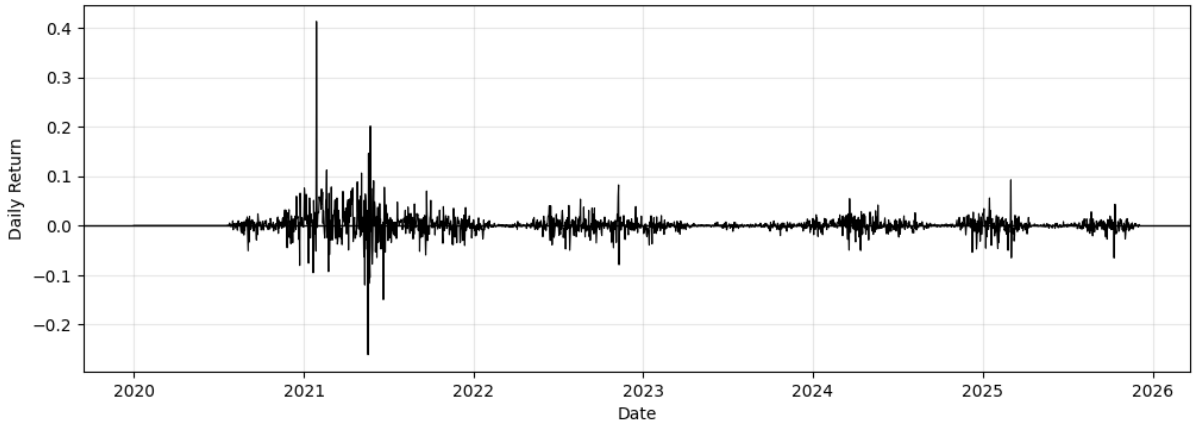

Figure 11. **TS-Momentum daily returns**
Source: compiled by the author

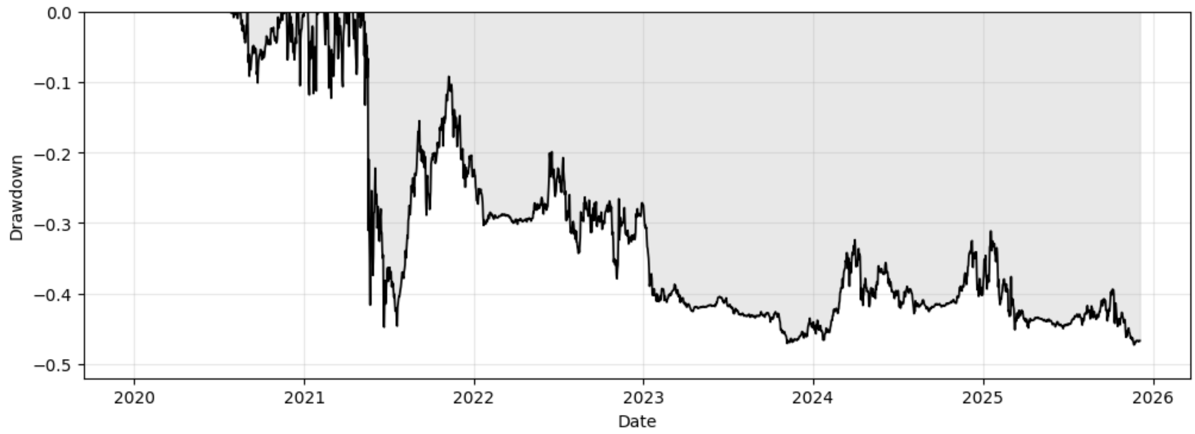

Figure 12. **TS-Momentum drawdown**
Source: compiled by the author

The cross-sectional momentum strategy exhibits a markedly different performance profile from its time-series counterpart, reflecting the distinct mechanics of relative strength selection. The cumulative performance in Figure 13 shows that CS momentum delivers only modest long-term profitability over 1 January 2020 – 31 October 2025. Short-term rallies, particularly in early 2021 and early 2025, indicate that the strategy occasionally captures strong dispersion between outperforming and underperforming cryptocurrencies. However, these gains tend to be reversed during broad market corrections, where cross-sectional spreads compress and relative strength signals weaken. Overall, the strategy behaves closer to mean reversion during major market downturns, limiting its ability to compound returns consistently.

Figure 14, the daily return series, highlights why this occurs. The distribution is tightly concentrated around zero with frequent small fluctuations, reflecting the equal-weight long-short construction across the strongest and weakest assets. Although occasional spikes appear especially around major crypto events as these shocks are far smaller than those observed in the time-series strategy. This indicates that CS momentum naturally diversifies market-level volatility by holding simultaneous long and short positions, but it also reduces exposure to sustained directional trends, which limits upside potential during strong bull markets.

Figure 15 presents the drawdown profile of the cross-sectional momentum strategy. Similar to the time-series portfolio, the graph plots the deviation of the portfolio value from its historical peak. The results show that the CS strategy experiences prolonged periods of decline, with the maximum drawdown reaching approximately 55%. This deeper drawdown reflects the difficulty of exploiting relative-strength differences in cryptocurrency markets where assets often move together due to high market-wide correlations. Although the strategy occasionally benefits from cross-asset performance dispersion, large market-wide downturns tend to affect most cryptocurrencies simultaneously, resulting in sustained portfolio declines.

The CS momentum strategy offers volatility dampening and partial protection from extreme directional swings, but this comes at the expense of long-run performance. Its effectiveness depends strongly on the presence of cross-sectional return dispersion periods when certain cryptocurrencies trend significantly differently from others. During market-wide selloffs or synchronized rallies, the strategy tends to underperform, leading to extended drawdowns and relatively low cumulative returns. This practical behaviour aligns with well-documented cross-sectional momentum limitations in highly correlated markets such as cryptocurrencies. Generally, the drawdown analysis confirms that both strategies are exposed to substantial downside risk typical of cryptocurrency markets; however, the time-series momentum strategy demonstrates a slightly more resilient recovery pattern compared with the cross-sectional approach.

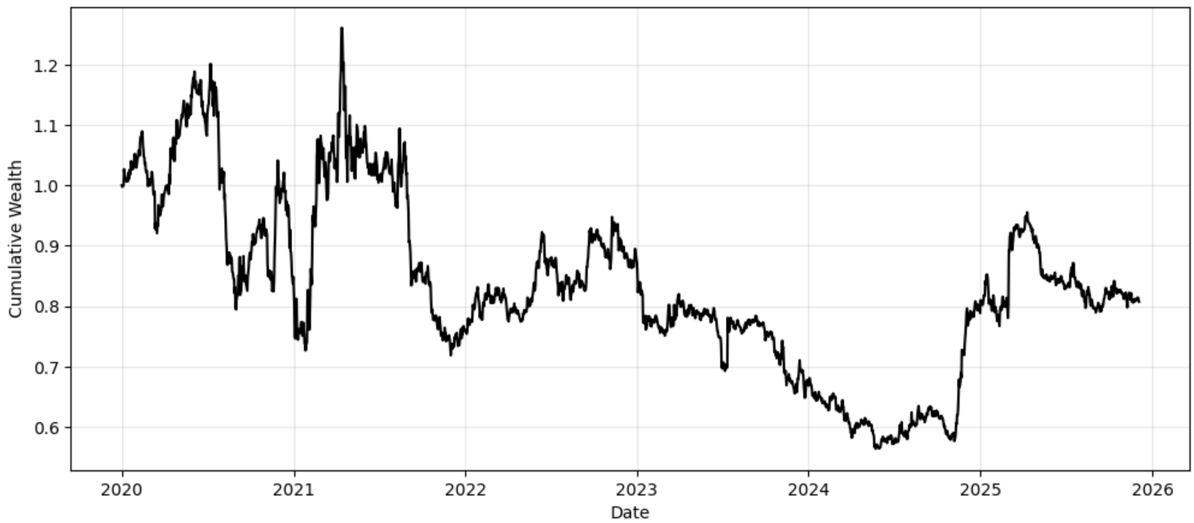

Figure 13. **CS-Momentum cumulative performance**
Source: compiled by the author

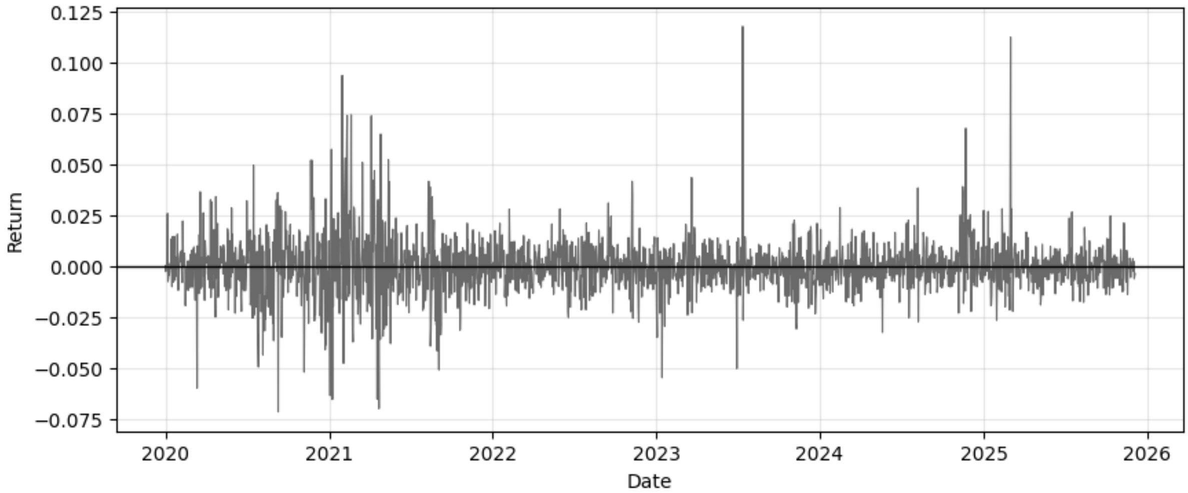

Figure 14. **CS-Momentum daily returns**
Source: compiled by the author

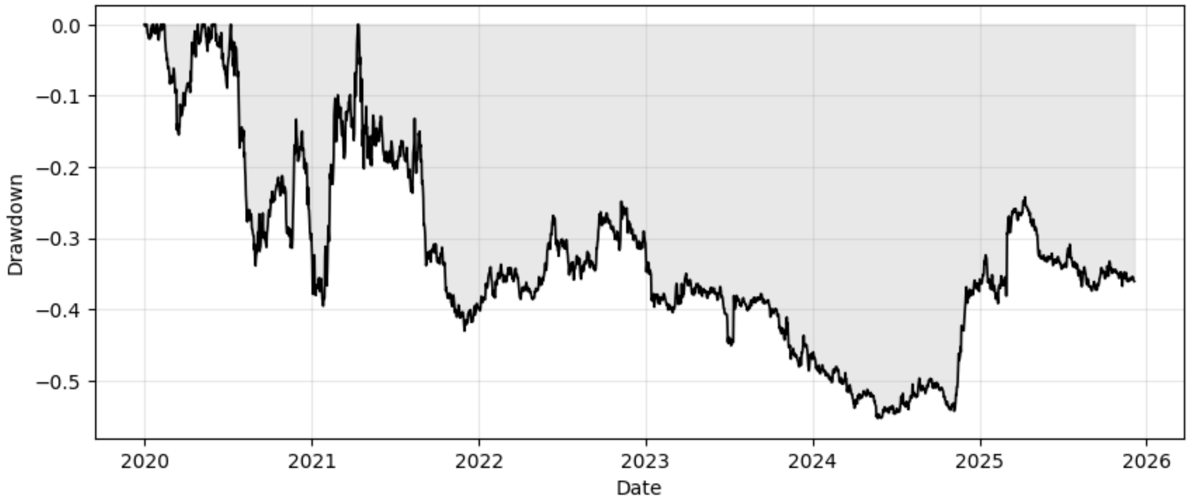

Figure 15: **CS-Momentum drawdown**
Source: compiled by the author

Figure 16, the cumulative performance plot shows that TS momentum significantly outperforms CS momentum over the full sample. The explosive rise in TS returns during late 2020-2021 reflects its ability to exploit strong persistent trends in individual cryptocurrencies, especially the large bull run led by BTC, ETH, and altcoins. CS momentum also rises during trending periods but to a lesser degree, yielding a flatter performance curve overall. After 2021, TS continues to generate higher cumulative wealth even in more volatile, sideways market conditions, although with occasional deeper pullbacks than CS. This confirms that cryptocurrencies reward trend following behaviour more strongly than relative strength ranking across assets. Following the daily return comparison of Figure 17, TS momentum exhibits frequent large positive and negative jumps, especially around 2020-2021. This reflects the sensitivity of TS to abrupt trend reversals and strong directional moves. In contrast, CS returns cluster around zero more tightly, with fewer extreme outliers. The narrower distribution of CS daily returns suggests that spreading exposure across long-short relative positions reduces volatility but also limits upside potential. In practice, TS offers higher growth but requires a more robust risk-management buffer due to sharper daily swings.

In Figure 18, the correlation matrix reveals that most large cap cryptocurrencies move together, with correlations frequently in the 0.5 - 0.8 range. When assets are this highly correlated, cross-sectional differentiation becomes weak as few coins consistently outperform or underperform their peers in a way CS can exploit. This structural characteristic of crypto markets explains why CS momentum underperformed: the strategy depends on dispersion, but dispersion in major crypto assets is limited. Conversely, TS momentum benefits from these shared trends, since strong market-wide directionality amplifies the profitability of trend-following rules. The yearly return comparison, Figure 19, clearly shows the contrast between both strategies. TS momentum captures exceptional gains in 2021 reflecting the strongest crypto bull market in the sample leading to the outsized positive bar for that year. CS momentum, by comparison, shows much smaller positive contributions in the same period. During downturn or choppy years (2022-2023), TS produces negative annual returns as trends collapse, while CS does a better job limiting losses due to its built-in market-neutral structure. In calmer periods such as 2024-2025, both strategies converge toward modest, similar positive returns. Overall, the findings suggest that the observed momentum effects are not only statistically detectable but also economically meaningful within the context of cryptocurrency portfolio management.

Figure 16. **TS Vs CS momentum cumulative performance**
Source: compiled by the author

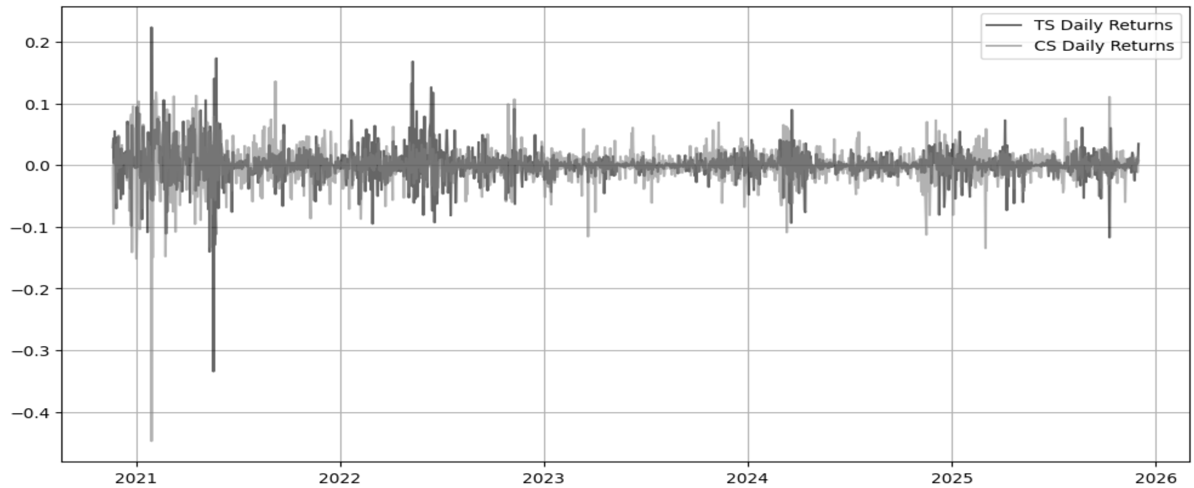

Figure 17. **TS Vs CS momentum daily returns**
Source: compiled by the author

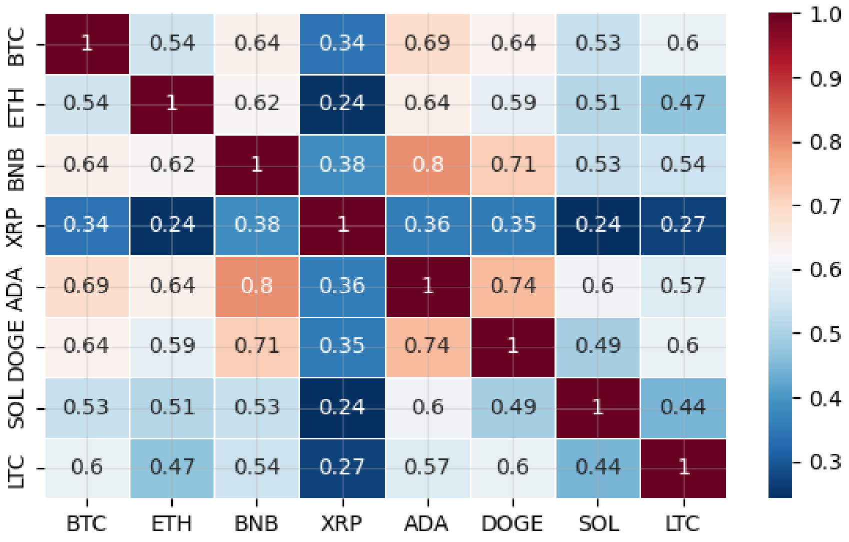

Figure 18. **Correlation heatmap of cryptocurrency return**
Source: compiled by the author

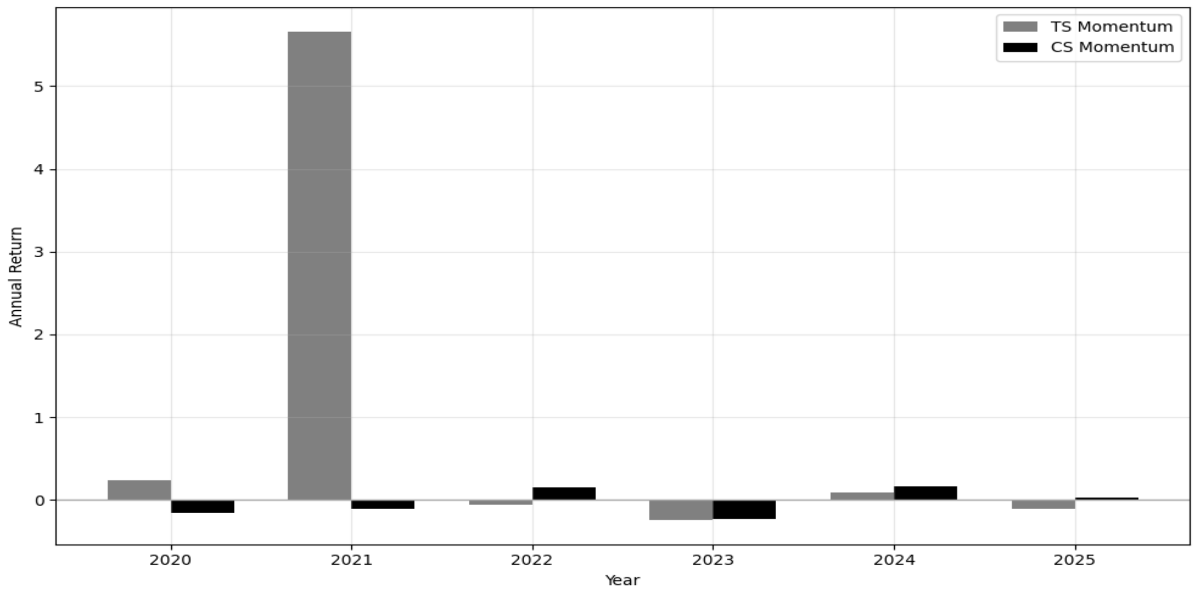

Figure 19. **TS Vs CS yearly returns**
Source: compiled by the author

Conclusions

This study evaluates time-series and cross-sectional momentum strategies applied to eight major cryptocurrencies between 1 January 2020 and 31 October 2025 using a multi-horizon EMA-based framework. By testing both absolute (TS) and relative (CS) momentum within a unified methodology, the analysis contributes additional empirical evidence to the growing literature on systematic cryptocurrency trading.

The results provide empirical evidence that momentum remains economically meaningful in digital asset markets over the sample period. Time-series momentum delivers stronger performance, achieving an annual return of 31.96% and outperforming cross-sectional momentum across the reported risk-adjusted metrics. This outcome is consistent with the persistent trending behaviour observed in cryptocurrency markets during the post-2021 period characterised by evolving market structure and heightened macroeconomic uncertainty. Cross-sectional momentum exhibits comparatively stronger downside control due to its market-neutral orientation; however, high correlations among major cryptocurrencies appear to limit its ability to exploit relative-strength differences, resulting in weaker overall returns.

While these findings suggest that momentum, particularly in its time-series form, may represent an effective systematic trading approach under similar market conditions, several limitations should be acknowledged. The analysis is based on daily data covering 1 January 2020 to 31 October 2025 and does not incorporate transaction costs, slippage, funding rates, or liquidity constraints. Short-selling feasibility is assumed, and reported performance reflects gross returns. These methodological assumptions may influence real-world implementation and limit the generalisability of the results across alternative market regimes or cost structures.

The findings also have implications for accounting practices, financial reporting, and decision-making processes. The presence of statistically significant momentum effects in selected cryptocurrencies suggests that digital assets may exhibit systematic return patterns rather than purely random price movements, which is relevant for fair value measurement and impairment assessments of cryptocurrency holdings. The substantial volatility observed across assets further highlights the importance of transparent disclosures regarding valuation assumptions, measurement uncertainty, and risk exposure in financial statements. From a financial analysis and risk assessment perspective, the results indicate that only a subset of cryptocurrencies provides statistically reliable returns, emphasizing the need for robust portfolio evaluation and risk management. Consequently, momentum-based insights may assist financial analysts, auditors, and corporate treasury managers in performance evaluation, investment decision-making, and the assessment of valuation risk associated with cryptocurrency-related financial activities.

For practitioners, the evidence indicates that volatility-adjusted trend-following signals may capture sustained directional movements in cryptocurrency markets more effectively than purely cross-sectional ranking approaches, although implementation considerations remain important. Future research may extend this framework by incorporating transaction cost modelling, alternative risk-free rate assumptions, parameter robustness tests, and sub-period analysis to evaluate regime dependence. Further investigation using higher-frequency data, derivatives-based implementations, or machine-learning-enhanced signal construction could also enhance understanding of momentum dynamics in rapidly evolving digital asset markets.

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