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A COMPARATIVE STUDY BETWEEN PRICE-DRIVEN AND MECHANISTIC MOVING AVERAGES USING CAUSAL ANALYSIS ON BITCOIN HISTORICAL DATA

The subject *of this study is the comparative analysis of price-driven and mechanistic moving averages applied to Bitcoin volume and price data, using causal analysis to assess profitability and accuracy in historical records.* ***This study aims*** *to explore the effectiveness of mechanistic versus price-driven moving averages in predicting Bitcoin price trends.* ***The objectives*** *are as follows: 1) To evaluate the performance of the traditional price-driven simple moving average (SMA) against a mechanistic simple moving average (MSMA) that incorporates trading volume as an asset "mass"; 2) Perform backtesting with fast and slow moving average crossovers to determine each method's profitability and trade accuracy across different parameter settings; 3) To calculate cause-and-effect relationships between moving average choice and observed trading outcomes, and further between Bitcoin price trend directions and returns using causal analysis; 4) To analyze the implications of these results on trading strategies within the volatile cryptocurrency market. The following* ***results*** *were obtained: 1) The price-driven SMA demonstrated higher profitability and higher volatility compared to MSMA which yielded more uniform but lower returns with significantly better trade accuracy; 2) Correlation analysis found stronger relationships between return and win rate for MSMA than for SMA, suggesting MSMA's relative stability in volatile trading environments; 3) Causal analysis confirmed a statistically significant causal relationship between MSMA use and consistent returns; 4) MSMA returns were strongly affected by market trends with uptrends yielding higher returns than downtrends by 16%.* ***Conclusions****. This research contributes to the cryptocurrency technical analysis by demonstrating the advantages and limitations of price-driven and mechanistic moving averages. While SMA is better suited for researchers prioritizing higher potential returns despite volatility, MSMA offers a stable, volume-based approach. The study provides valuable insights for researchers aiming to refine investment strategies in the fast-evolving the cryptocurrency sector.*

Keywords: *cryptocurrency; moving average; statistical analysis; causal analysis; technical indicators; econophysics.*

1. Introduction

1.1. Motivation

The rapid growth of blockchain technologies and the cryptocurrency market encourages researchers to develop novel, efficient investment and trading strategies within this domain. The foundation of cryptocurrency technical analysis entails analyzing historical pricing data and trading volumes, which are grounded in the premise that oscillations are not entirely stochastic, but rather follow particular patterns or repetitions in the supply and demand dynamics of the currencies [1]. For studying the market using technical analysis, traders and investors use different instruments to analyze historical behavior and try to predict the assets' forthcoming price trajectory [2]. Moving averages are heavily used to create investment and trading strategies [3]. By observing and studying the dynamics of cryptocurrencies, we can determine patterns in how assets behave, which can help us guess what action we should take next. A mechanistic approach to generalized technical analysis [4], primarily focused on stock market analysis, resulted in promising outcomes. This approach attempts to generalize technical analysis techniques using physical principles that encompass not only share prices but also trade volumes as a "mass" of assets. Applying causal analysis, we can understand the cause-and-effect relationships between variables or events in various fields [5] as well as in cryptocurrencies [6]. It helps researchers and analysts make informed decisions, predict outcomes, and understand the underlying mechanisms at play.

1.2. State of the art

The price-driven simple moving average (or simple moving average on price data or SMA) is extensively used by researchers to analyze assets [7]

$$M_t(i) = \frac{1}{\tau} \cdot \sum_{i=t}^{t+\tau-1} x(i-\tau), \quad i = \tau+1, \ldots, N, \quad (1)$$

where x(t) – is a time series at time t over the last data points τ.

One of the most famous trading strategies is crossover which consists of using two moving averages on the asset's price: fast and slow moving averages (or short-term and long-term moving averages) [8]. A fast-moving average has a shorter period, and a slow one has a longer one. In the case when a fast average crosses a slow average from the bottom up, it is a buy signal, and when it crosses from top to bottom, it is a sell signal.

In general, moving averages are extensively used as a backbone for many novel algorithms: dynamically adapting to nonlinear trends through novel feature extraction using a distance-based exponential moving-average [9], or compositional time series forecasting using Bayesian Dirichlet auto-regressive moving average [10].

Any cryptocurrency is characterized not only by price but also by the volume of sales. This is the amount of the asset that was traded in a certain period. The price rises when the demand for the asset increases and falls when the supply is greater than the demand. Trends in trading volume could be used to forecast future stock market trends [11], finding a tracking strategy with a volume-weighted average price [12]. One such application of volume-based analysis is a mechanistic approach, in which the idea is to rely not only on the price but also on the volume, considering it as the physical mass of the asset. Accordingly, for the price to rise or fall, it is necessary to "move" the volume (mass) of the asset.

Consider V(t) as the volume of transactions with the asset at the price x(t) at the time t. The generalized impulse for a time interval τ can be determined, as in physics, through

$$R_\tau(t) = \frac{V(t)}{\sum_{i=1}^{\tau} V(i)} \cdot \frac{x(t) - x(t-\tau)}{\tau} \quad (2)$$

or

$$R_\tau(t) = m(t) \cdot \frac{\Delta x}{\Delta t} \quad (3)$$

or

$$R_\tau(t) = m(t) \cdot v(t), \quad (4)$$

where the time-dependent analogy to "mass" m(t) is the ratio of the volume of transaction at the time t as V(t) and the total volume of transaction V(t) per time interval τ. The average rate of change per time interval τ is an analogy to "velocity" v(t).

Then, introduce the mechanistic moving average (or MSMA) through

$$M_t(i) = \frac{1}{\tau} \cdot \sum_{i=t}^{t+\tau-1} R(i-\tau), \quad i = \tau+1, \ldots, N \ . \quad (5)$$

Thus, we consider the price and the volume. This interaction can be represented as a classical force acting on the asset.

A comprehensive review of the treatment effect estimation and causal discovery tasks for time series data was provided to emphasize the importance of scientific discoveries from the causal analysis perspective [13]. Additive Noise Model (ANM), a nonlinear causal inference approach used to identify factors influencing stock price changes, offers more reliable factor selection [14]. Causal analysis was successfully used to estimate the causal relationship between Bitcoin attention (measured by the Google Trends search queries) and Bitcoin returns [15]. The Causal Feature Selection (CFS) algorithm [16] identifies direct causal influences between features, providing more representative and stable subsets for stock prediction models unlike traditional correlation-based methods like PCA, CART, and LASSO. Experiments on 13 years of Shanghai Stock Exchange data show that CFS outperforms other feature selection methods in terms of prediction accuracy, precision, and investment profitability. The algorithm consistently identifies key features, improving risk-return measures such as Sharpe and Sortino ratios, which are critical for investors.

1.3. Objectives and the approach

The primary objective of this study is to conduct a comparative analysis of price-driven and mechanistic moving averages to evaluate their effectiveness in predicting profitable trading signals within the Bitcoin market.

Given the volatile and complex nature of cryptocurrency markets, particularly Bitcoin, this study aims to assess these distinct moving average methods using causal and statistical analysis.

The main objectives and stages of this research are as follows:

1. Assess the theoretical and empirical differences between the price-driven simple moving average (SMA) and the mechanistic simple moving average (MSMA), which incorporates trading volume as an additional weighting factor;

2. Implement a backtesting framework to evaluate SMA and MSMA under a dual-moving average strategywith fast and slow crossovers. This involves testing various parameter settings (such as short and long

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window periods) to generate buy and sell signals. By simulating trading outcomes across historical Bitcoin price data, this objective aims to determine the optimal parameter settings and identify which approach yields higher returns, more accurate signals, and a better risk-to-reward ratio across different market conditions;

3. Apply causal analysis to evaluate the effect of SMA and MSMA on Bitcoin trading returns and signal quality, aiming to understand the cause-and-effect dynamics in trading outcomes. This step includes calculating the Average Treatment Effect (ATE) of each moving average on trading returns, providing insights into whether using MSMA over SMA leads to statistically significant improvements in trading performance;

4. Synthesize the findings from the comparative analysis to produce actionable insights. This objective aims to inform researchers of the optimal conditions for deploying SMA and MSMA-based strategies, helping them make informed decisions about strategy selection based on the market environment, risk tolerance, and desired return profile.

2. Methods of the research

2.1. Data and backtesting

To backtest moving averages, historical Bitcoin data were collected using the CCXT library [17] via API. The 1-day timeframe is from February 2017 to July 2023, resulting in 78 months. The close-day price of the BTC/USD trade pair was used for moving averages.

During backtesting, the profitability and accuracy of the moving averages were investigated using the strategy of crossovering two moving averages: fast and slow moving averages. Profitability is measured as the sum of all relative returns. Accuracy is the win rate of the moving average, which can be computed as the sum of all trades divided by the sum of profitable trades.

For moving average combinations of two types of window sizes: fast and slow windows. In addition, one additional parameter for computing the mechanistic moving average, which takes the value of the largest parameter of the slow moving average. The parameters for the fast- and slow-moving averages are combinations from 8 to 32 days in steps of two, with the restriction that the fast window must be strictly less than the slow window. Therefore, 78 combinations of parameters for each type of moving average and conducted 156 backtests in total. The addition value for the mechanistic moving average was 32 days for all combinations.

Window parameters from 8 to 32 were selected to evaluate short-term and medium-term trading strategies on a daily timeframe.

2.2. Descriptive analysis

Descriptive analysis was used to explore the profitability, accuracy, and performance characteristics of the SMA and MSMA strategies.

1. Key statistics are calculated that summarize the central tendency, and the dispersion of a distribution: mean return, standard deviation, minimum, maximum, and percentiles (25th, median, and 75th) [18]. These metrics provided an initial overview of each strategy's performance characteristics, including volatility, average profitability, and return distribution;

2. To understand how returns and win rates are related within each moving average method, correlation matrices were created for both SMA and MSMA. These matrices measured the relationships between the mean returns, return sums, and win rates;

3. To test for statistical differences between SMA and MSMA, two t-tests [19] were performed. The first test assessed differences in mean returns, while the second evaluated win rate differences;

4. To study how market trends affect each moving average, the weekly aggregated return data for Bitcoin was categorized into uptrend and downtrend phases. This segmentation allows an analysis of the performance of SMA and MSMA under contrasting market conditions, illuminating the situational strengths and weaknesses of each approach.

2.3. Causal analysis

Causal analysis is a set of techniques used to understand the relationships between variables and events in a system by determining whether changes in one variable cause changes in another. This analysis aims to identify causal relationships, helping to explain why certain outcomes occur and uncover the underlying mechanisms that drive these relationships, rather than just revealing correlations between variables.

Causal analysis is actively used to find the factors that affect the Bitcoin price to help investors make better investment decisions [20].

In this study, causal analysis is used to identify and estimate the following:

1. The effect of SMA compared with MSMA and their corresponding returns.

2. The effect of the trend directions and their corresponding returns.

Three distinct variable categories were defined to perform the causal analysis:

1. Treatment – the variable is manipulated in an experiment to observe its effect on the dependent variable.

2. Outcome – the variable is measured to determine the effect of the independent variable.

3. Confounding variables – are not the main subject of study, but they can impact the relationship between the independent and dependent variables.

To estimate the effect of SMA compared to and their corresponding returns, the variable "method" was used as a treatment to distinguish between the two different moving average methods, and "return" was used as an outcome to measure the profitability (Fig.1). The casual relationships are expressed through

$$\frac{d}{d(\text{Method})} \cdot E(\text{Return} | \text{confounders}), \quad (6)$$

where the confounders are "slow_period", "fast_period", "year", and "month" variables.

To estimate the effect of trend directions and their corresponding returns variable "global_trend_flag" was used as a treatment to distinguish between testing during the uptrend and downtrend, and "return" was used as an outcome to measure the profitability (Fig. 2).

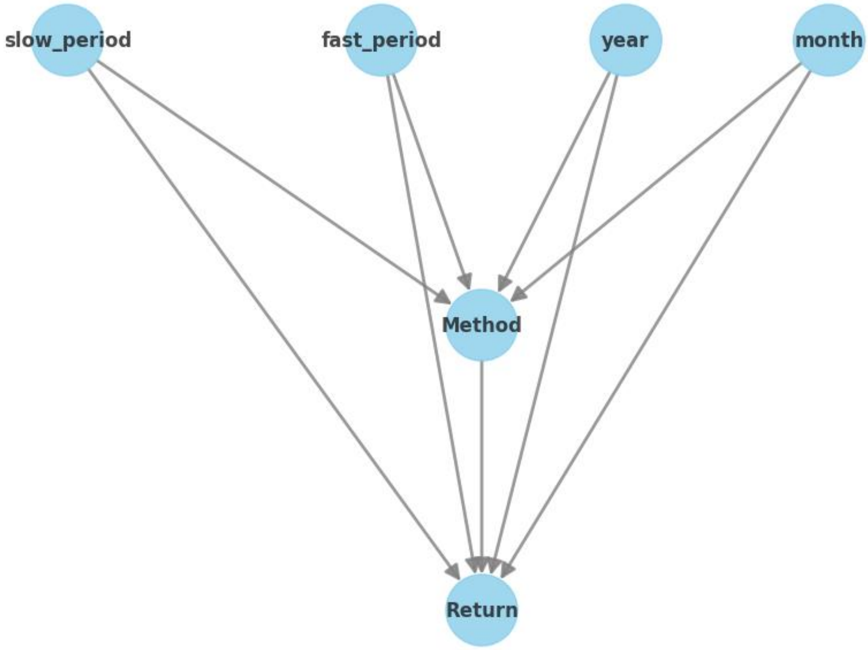

Fig. 1. Causal graph to estimate the effect of SMA compared to MSMA and their corresponding returns

Fig. 2. Causal graph to estimate the effect of trend directions and their corresponding returns

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The casual relationships are expressed through

$$\frac{d}{d(\text{global trend flag})} \cdot E(\text{Return} \mid \text{confounders}), \quad (7)$$

where the confounders are "slow_period", "fast_period", "year", and "month" variables.

To define the uptrend and downtrend the one-dimensional Gaussian filter [21] has been used through

$$g(x) = \frac{1}{\sqrt{2\pi\sigma}} \cdot e^{-\frac{x^2}{2\sigma^2}}, \quad (8)$$

where σ is the standard deviation and x is the time series value.

The following metrics are used to measure the causal effect:

1. Average Treatment Effect (ATE) – is the average difference in the outcome variable between a group that receives the treatment (treated) and a group that does not receive the treatment (control).

2. Average Treatment Effect on the Treated (ATT) – measures the average difference in the outcome variable for those who were treated compared to what their outcomes would have been if they had not been treated.

3. Average Treatment Effect on the Control (ATC) measures the average difference in the outcome variable for those in the control group compared to what their outcomes would have been if they had been treated.

To estimate the causal effect three methods have been used:

1. Propensity score matching (PSM) – was used to create a balanced comparison group by matching treated and untreated units based on their estimated probabilities of receiving the treatment (propensity scores) [22].

2. Propensity score stratification (PSS) – is a method that divides the sample into strata based on the estimated propensity scores and then analyzes the outcomes within each state [23].

3. Double ML (DML) – this method combines the strengths of machine learning and statistical methods to provide consistent estimates of causal effects [24].

To test the validity of the causal models three refutation tests were used: random common cause (RCC), placebo treatment refuter (PTR), and data subset refuter (DSR) [25].

3. Results

3.1. Returns and winning rate tendencies

Summary statistics were calculated that describe the central tendency and the dispersion of distribution for both the MSMA and the SMA returns, as shown in Table 1.

The results provide an overview of the performance characteristics of each strategy across several metrics, including trade count, mean, standard deviation, minimum and maximum returns, and several percentile markers. These metrics offer insight into how returns are distributed and the relative volatility of each approach.

The MSMA shows a lower standard deviation (21.8%) compared to the SMA (39.4%), suggesting that MSMA yields more stable returns with lower volatility. Such decreased volatility can be used by researchers seeking consistency and lower-risk deals. Furthermore, the percentile statistics reinforce this tendency: MSMA has a narrower range of returns from its 25th to 75th percentiles, highlighting that it generally yields more moderate returns compared to SMA's broader distribution.

The median return for SMA (-0.9%) is also lower than its mean (9.3%), indicating the presence of extreme positive returns that make the mean higher than the median. This higher mean is complemented by a larger maximum return (282.2%), showcasing SMA's potential to deliver high-reward trades with the higher-risk trade tendencies.

Table 1

Return of price-driven and mechanistic simple moving averages

	MSMA	SMA
Number of trades	6054	5098
Mean	5.6	9.3
Std	21.8	39.4
Min	-41.3	-39.1
25% percentile	-4.5	-6.6
50% percentile	0.4	-0.9
75% percentile	8.1	7.0
Max	151.5	282.2

The win rate, summarized in Table 2, describes the differences between these two methods in terms of trade accuracy. MSMA shows a higher win rate at 52.2%, and the SMA is slightly lower with a win rate of 43.3%. This difference implies that MSMA could be a better choice for traders who prioritize accuracy and steady gains over the larger, and more volatile returns. Potentially, a higher win rate can be particularly advantageous in trading strategies aimed at capital preservation or incremental portfolio growth, where steady gains have more priority, and risk management is key.

Table 2

Win Rate of price-driven and mechanistic simple moving averages

	Number of trades	Win Rate, %
MSMA	6054	52.2
SMA	5098	43.1

The higher win rate for MSMA indicates that, on average, it produces more successful trades relative to SMA, which can be important for risk-averse investors or those with a conservative approach to market fluctuations [26]. It is worth noting that SMA's lower win rate does not inherently imply poor performance, because it could also reflect a different risk-reward profile.

SMA appears to focus on capturing larger, more infrequent gains, which could be beneficial during strong uptrend periods or for traders with a higher risk tolerance.

In general, the choice between SMA and MSMA may depend on individual risk preferences and investment goals. SMA may attract those willing to endure higher volatility for the chance of capturing bigger returns, while MSMA's consistency and higher win rate may align better with investors prioritizing steady and predictable performance.

Visual comparison of SMA and MSMA performance across different combinations of fast and slow-moving average window sizes presented on the heatmaps. The values presented in the figure are percentages divided by 100.

The mean return heatmap (Fig. 3) illustrated for both SMA and MSMA strategies. Larger slow window sizes generally yield higher mean returns, especially for SMA. Specifically, the SMA heatmap shows higher mean returns concentrated in the upper-right region, where both the fast and slow window sizes are relatively large (around 25–30). In comparison, MSMA exhibits more moderate mean returns, with values that increase steadily but remain within a narrower range. This suggests that SMA can deliver higher average returns, having greater sensitivity to window size configurations.

The sum return heatmap (Fig. 4) shows the sum (the cumulative) return percentages for each method. Here, SMA displays an increase in the cumulative return with larger window sizes, reaching peaks in the same upper-right corner, where the cumulative return values surpass 600%. This pattern suggests that longer slow and fast windows for SMA capture more significant trends, leading to higher cumulative profits. Also, SMA has higher cumulative return patterns for smaller window sizes at the middle-bottom corner. The MSMA, by contrast, yields the sum (the cumulative) returns that are more evenly spread across the different window combinations, with a maximum cumulative return in the range of 300-500%, depending on the window size. This relative stability of MSMA reinforces its role as a more conservative strategy.

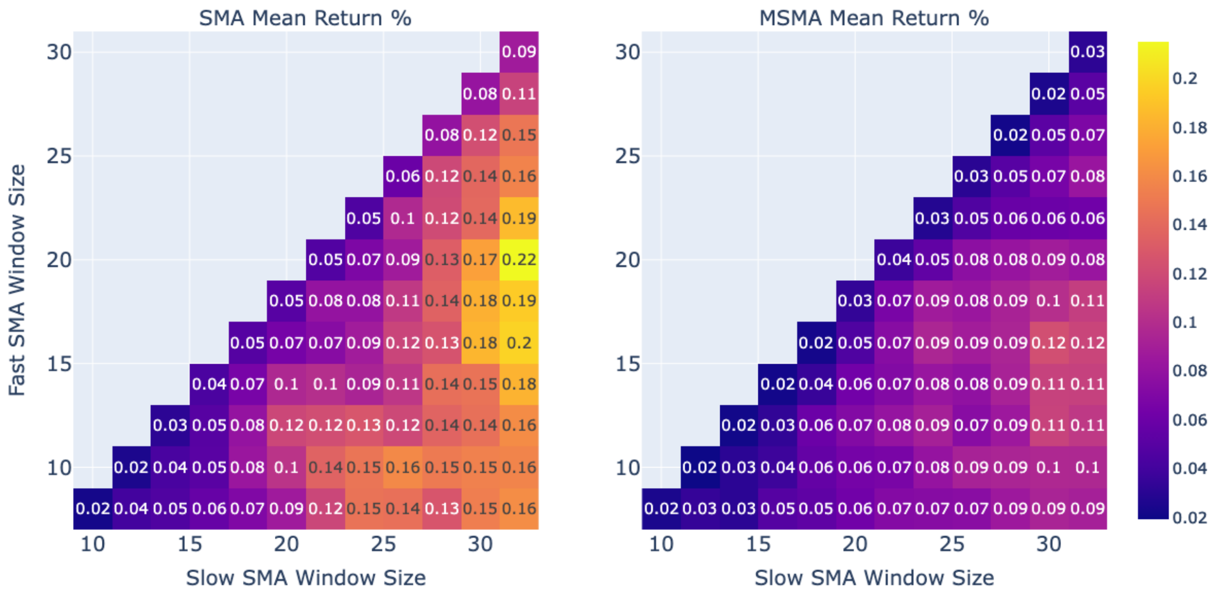

Fig. 3. SMA and MSMA mean return heatmaps

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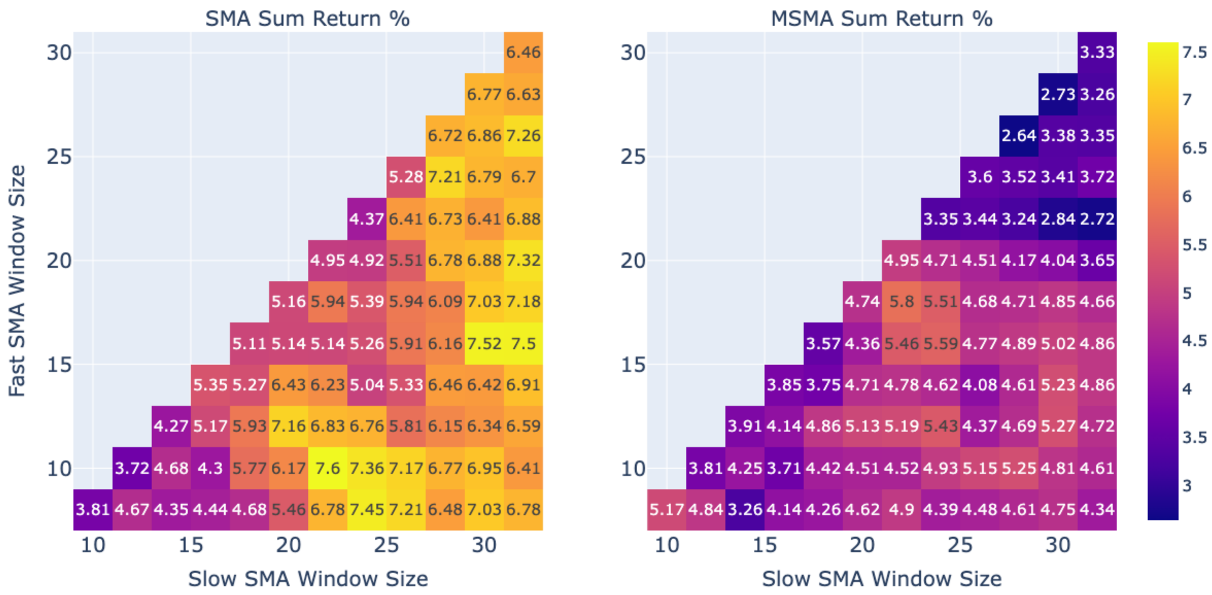

Fig. 4. SMA and MSMA sum return heatmaps

The win rate heatmap (Fig. 5) presents the win rates for both strategies. The SMA win rate heatmap shows that its performance is most accurate when the slow and fast windows are near each other, specifically in the 20–25 range. Conversely, MSMA demonstrates higher win rates across a broader range of window sizes, with peak win rates near 63% in the right corner. This finding aligns with earlier observations that MSMA has a higher overall accuracy, having a win rate advantage over SMA across different configurations.

The SMA correlation data (Table 3) indicate a strong positive correlation (0.87) between the mean return and the sum (cumulative) return. This high value suggests that as individual trade returns increase on average, the total cumulative return also grows substantially. However, the correlation between the mean return and the win rate is very low (0.1), implying that the winning percentage of trades is largely independent of the size of the returns achieved per trade. Similarly, the correlation between cumulative return and win rate is modest (0.21), indicating that while higher win rates contribute slightly to cumulative profitability, they are not the main drivers of SMA's overall return profile.

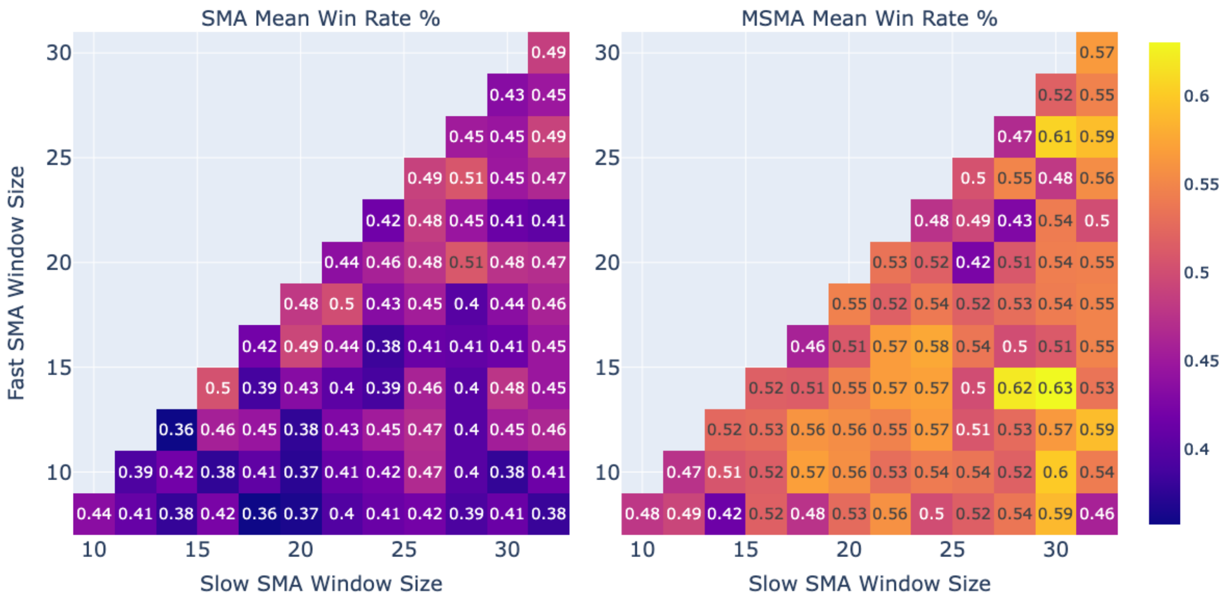

Fig. 5. SMA and MSMA mean win rate heatmaps

Table 3

Return and winning rate correlation of SMA

	Return mean	Return sum	Win rate mean
Return mean	1	0.87	0.1
Return sum	0.87	1	0.21
Win rate mean	0.1	0.21	1

The relationship between the mean and cumulative returns for MSMA (Table 4) is weaker than that for the SMA, with a correlation of 0.57, suggesting a more tempered link between individual trade profitability and total cumulative gains. This indicates that MSMA's cumulative return is less dependent on consistently high mean returns.

Also, the MSMA demonstrates a stronger correlation between the mean return and the win rate (0.43), as well as between the cumulative return and the win rate (0.35). These higher values imply that, for MSMA, higher returns are more closely associated with a higher winning rate.

Comparing these tables, we can see that SMA, with its strong correlation between mean and cumulative return, behaves in a way that is more reliant on capturing substantial trends to achieve profitability. This aligns with earlier observations that SMA has higher volatility and can deliver extreme returns. MSMA, on the other hand, demonstrates a balanced approach where the win rate plays a more important role in its performance, reflecting its focus on consistent, stable returns rather than large gains.

Table 4

Return and winning rate correlation of MSMA

	Return mean	Return sum	Win rate mean
Return mean	1	0.57	0.43
Return sum	0.57	1	0.35
Win rate mean	0.43	0.35	1

3.2. Distributions analysis

The return distributions for SMA and MSMA (Fig. 6) show differences for each moving average method in terms of return volatility. The overlay of the return distributions for both strategies highlights a more compressed, tightly clustered distribution for MSMA compared to the wider and more stretched distribution for SMA.

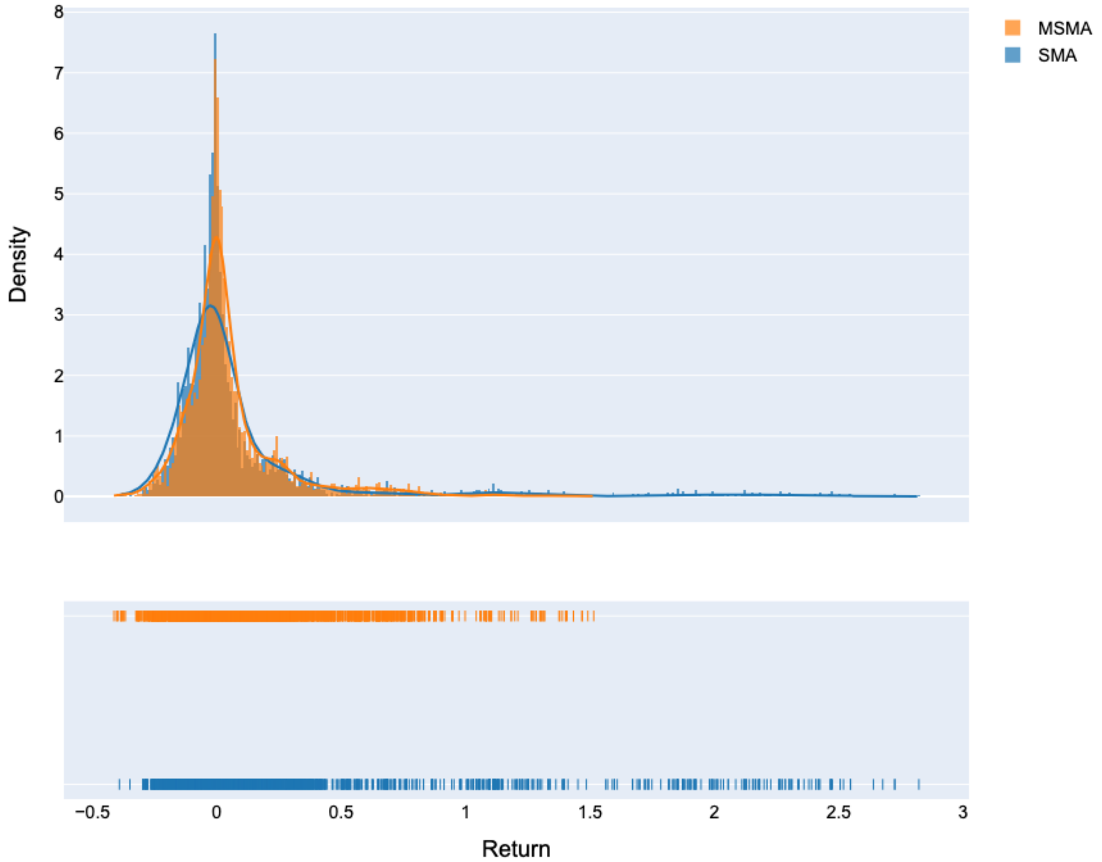

Fig. 6. SMA and MSMA return distributions

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The MSMA's compressed distribution aligns with its lower standard deviation, emphasizing accuracy and stability rather than large gains. In contrast, SMA's stretched distribution, which includes a notable portion of outliers, suggests a strategy with greater potential for high returns but also higher risk. This finding is consistent with earlier observations of SMA's reliance on capturing substantial trends to achieve profitability, in contrast to MSMA's focus on consistent, smaller gains.

To statistically validate the difference in performance between SMA and MSMA, two independent-sample t-tests were conducted to compare both the mean returns and win rates of each strategy (Table 5).

Table 5

T-test statistical hypothesis test for return and the winning rate

	p-values
Return mean	4.05×10^{-10}
Win rate	1.13×10^{-21}

The t-test results yielded exceptionally low p-values for the mean return and win rate, indicating a statistically significant difference between the SMA and MSMA in both profitability and accuracy. This rejection of the null hypothesis confirms that the observed differences in mean returns and win rates are unlikely to have occurred by chance and are indeed reflective of distinct behavioral patterns for each moving average strategy.

These statistical findings, combined with the distributional analysis, reinforce the assumption that SMA is suited for traders willing to accept more risk in pursuit of larger gains, and MSMA is more appropriate for traders seeking a less volatile approach.

3.3. Trend directions and returns

The analysis of SMA (Fig. 7) and MSMA (Fig. 8) weekly mean returns highlights how each moving average strategy performs in Bitcoin's trend directions: during uptrends and downtrends.

The returns for both SMA and MSMA are not evenly distributed across different market conditions, with both strategies generally showing higher profitability and win rates during uptrend periods compared to downtrends. This uneven distribution underscores the influence of broader market movements on the effectiveness of each moving average approach.

The SMA produced more extreme returns capitalizing on significant price shifts during pronounced trends. This aligns with the general finding that SMA is capable of yielding higher returns but with greater volatility and less accuracy.

The MSMA appears to deliver more stable returns across both market conditions, with lower profitability but greater accuracy than the SMA.

This consistency is particularly evident in the way MSMA dampens the impact of extreme price shifts, yielding a more uniform return profile regardless of trend direction.

MSMA's performance during downtrends, while less profitable, remains relatively stable and predictable, reflecting its conservative design.

However, MSMA has more severe negative returns than SMA, which leads to a significant decrease in the account balance. This finding should be carefully researched in further studies.

The uptrend before 2019 is characterized by higher and more stable returns for MSMA compared to the following uptrends in 2020 and 2021 years. This could indicate how specific market formation impacts the returns and win rates. Comparing the performance of the adapted MSMA [27] and not adapted MSMA may provide more insight into the large negative returns during downtrends, which seems to be the consequence of a slow reaction to market changes.

These findings indicate that SMA is better suited for traders seeking to maximize gains in strongly trending markets, where capturing larger price shifts is advantageous. MSMA, on the other hand, appeals to traders who prioritize stability and accuracy, especially during uncertain or volatile market periods.

However, there are obvious return and win rate differences during uptrends in 2018-2019 and in 2020-2021 years for MSMA that should be considered accordingly.

3.4. The causal effect of MSMA use on returns

The causal analysis of the SMA and MSMA methods was performed to determine whether a causal effect exists between the choice of the method and the observed trade returns.

This analysis models the relationships among three main categories of variables: the outcome variable (Return), the treatment variable (Method), and several confounding variables, including the slow and fast window periods, year, and month. Considering these confounders, the analysis isolates the effect of using either SMA or MSMA on returns, performing a more precise estimation of the causal effect.

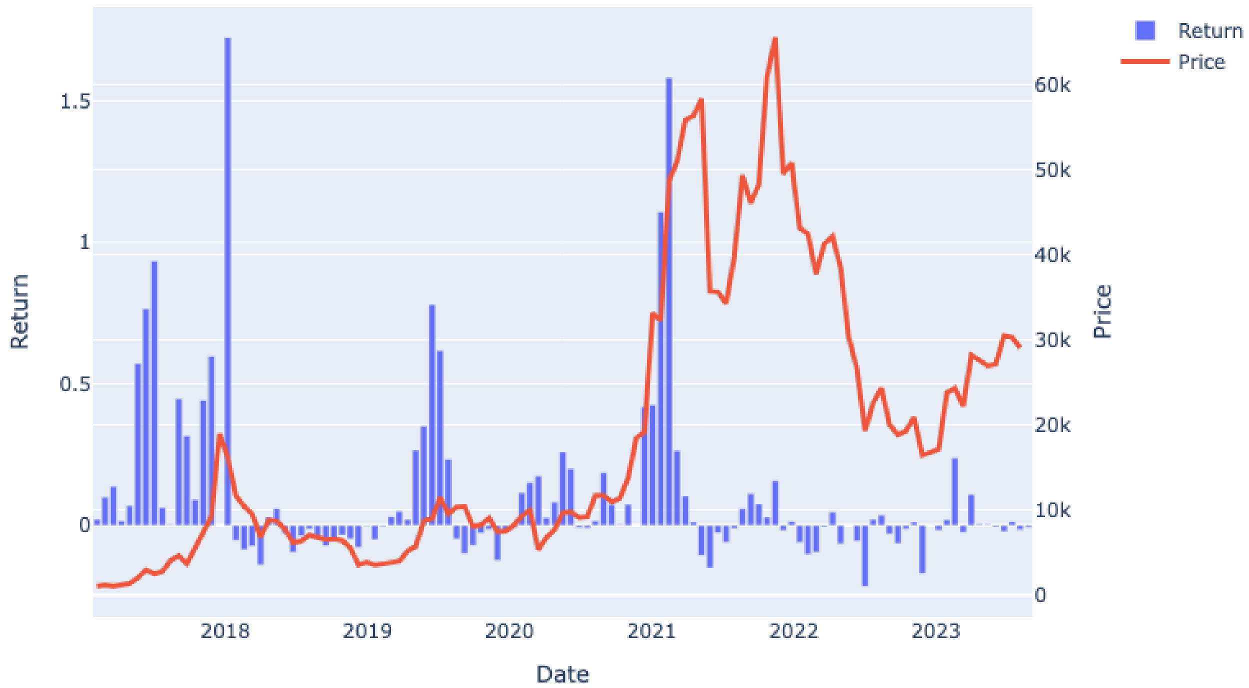

Fig. 7. SMA weekly mean return on Bitcoin uptrends and downtrends

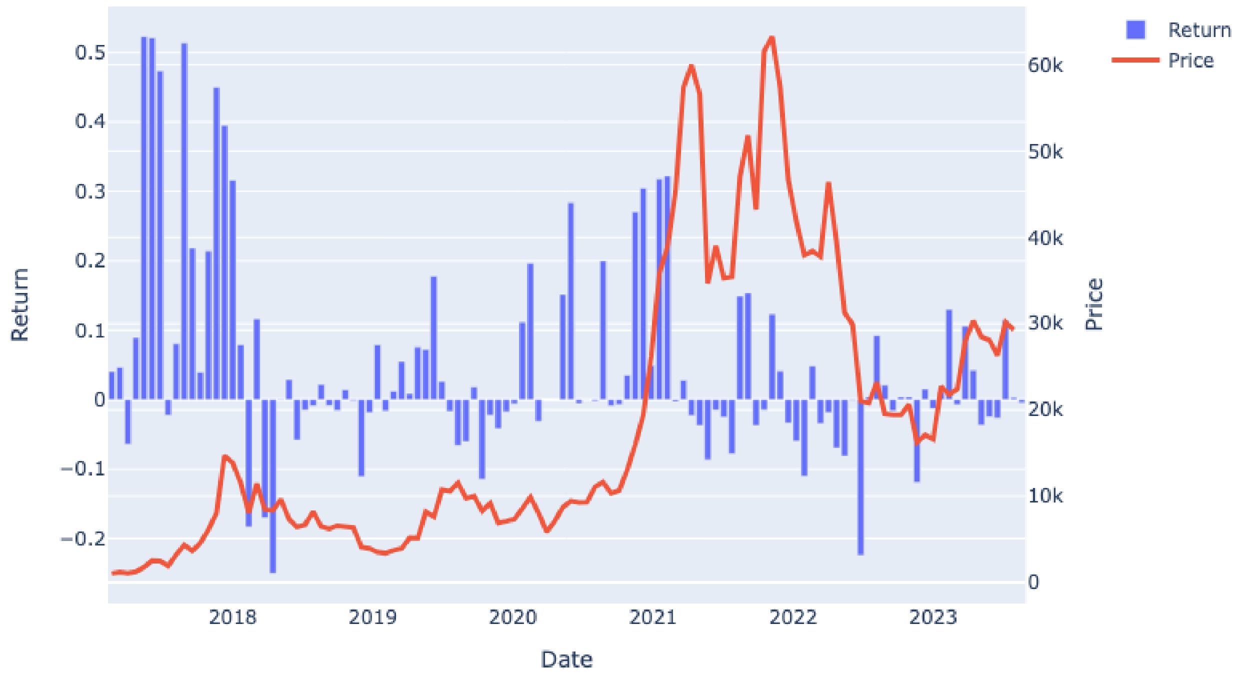

Fig. 8. MSMA weekly mean return on Bitcoin uptrends and downtrends

In summary, the results in Table 6 reveal that all three methods suggest a negative causal effect of using MSMA compared to SMA, with the estimated ATE values ranging from -3.5% to -6.0%. This range suggests that, on average, MSMA results in lower returns, aligning closely with the observed differences in mean returns between SMA and MSMA.

The negative ATT and ATC values further confirm this trend across both treated and untreated groups, meaning that, whether focusing on traders who typically use MSMA or those who do not, MSMA tends to yield lower returns than SMA.

To validate these estimates, several refutation tests were performed, including random common cause (RCC), placebo treatment refuter (PTR), and data subset

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refuter (DSR), as shown in Table 7. Two models passed each of these tests, except DML which failed on the placebo refuter.

Table 6

Estimated ATE, ATT, and ATC of using MSMA

Method	ATE, %	ATT, %	ATC, %
PSM	-5.9	-5.7	-6.0
PSS	-3.5	-3.5	-3.6
DML	-4.0	-4.0	-3.9

Table 7

Refutation test of the causal models

Model	RCC	PTR	DSR
PSM	Passed	Passed	Passed
PSS	Passed	Passed	Passed
DML	Passed	Failed	Passed

The application of causal analysis methods revealed a consistent and significant relationship between the use of MSMA and slightly lower returns. These findings suggest that the choice of the moving average method could indeed have a causal impact on trading outcomes, with SMA potentially offering superior profitability compared to MSMA in the observed dataset.

3.5. The causal effect of trend direction on MSMA returns

The casual analysis of trend direction on MSMA returns aims to understand whether the uptrend or downtrend has a causal impact on the profitability of MSMA.

The results shown in Table 8 indicate, indicate that the use of MSMA is positively correlated with higher returns during uptrends, suggesting a causal relationship between trend direction and profitability. The ATT and ATC values also support this conclusion, highlighting that MSMA performs better in the uptrends across both the treated and untreated groups.

Table 8

Estimated ATE, ATT, and ATC of using MSMA on the uptrend

Method	ATE, %	ATT, %	ATC, %
PSM	17.5	16.7	18.3
PSS	16.4	15.8	17.2
DML	16.3	16.2	16.1

To validate the robustness of these causal estimates, three refutation tests were applied (Table 9). Two models passed each of these tests, except DML which failed on the placebo refuter.

The analysis indicates that MSMA yields substantially higher returns in the uptrends, with an estimated average increase of approximately 16% compared to the downtrends.

Table 9

Refutation test of the causal models

Model	RCC	PTR	DSR
PSM	Passed	Passed	Passed
PSS	Passed	Passed	Passed
DML	Passed	Failed	Passed

4. Discussion

The findings of this study provide important insights into the comparative performance of simple moving averages (SMA) and mechanistic simple moving averages (MSMA) on Bitcoin data. While both approaches demonstrate unique strengths and weaknesses, their performance is shaped by factors such as market trends, volatility, and strategy design.

One of the key observations is the trade-off between profitability and stability. The SMA strategy demonstrated higher returns, with a maximum return of 282.2%, but also exhibited significantly greater volatility (standard deviation of 39.4%). This suggests that SMA is more reactive to strong market trends, capturing larger price movements at the cost of increased risk. On the other hand, MSMA produced more consistent returns with a lower standard deviation (21.8%), showing its ability to smooth out fluctuations and provide stability. For researchers prioritizing steady gains and lower volatility, MSMA appears to be a more appropriate choice.

The accuracy of the two methods also shows notable differences. ’s higher win rate of 52.2%, compared to SMA’s 43.1%, indicates that generates a higher ratio of successful trades. This accuracy could be attributed to MSMA’s consideration of trading volume as an additional factor, providing a more robust signal during periods of market noise. In contrast, relies solely on price data, making it more prone to false signals in volatile or trendless markets. The correlation analysis supports this distinction, as MSMA’s cumulative returns showed a stronger dependency on the win rate, while SMA’s performance hinged on capturing extreme gains.

The impact of market trends adds another layer of complexity. Both SMA and MSMA performed better during the uptrends, but their behaviors diverged. SMA excelled in strong uptrend phases by amplifying returns from pronounced price movements, aligning with its higher-risk, higher-reward profile. MSMA, while less profitable, delivered more uniform performance across market conditions. However, MSMA faced challenges during downtrends, where returns were not only lower but also occasionally severe. This could indicate a slower response to market declines, a potential weakness in the current implementation of MSMA that warrants further investigation.

Causal analysis further reinforced these observations, revealing statistically significant effects of moving average choice on returns. SMA, despite its volatility, consistently outperformed MSMA in terms of average returns, with causal estimates indicating a 3.5%–6.0% advantage. However, when market conditions were considered, MSMA demonstrated a notable causal effect during uptrends, with returns increasing by approximately 16%. This suggests that MSMA is more sensitive to positive market momentum, while SMA benefits more from its ability to capitalize on larger trends, regardless of direction.

This work did not research the trades in the real market. The market is a complex system where your actions can be considered by other market players forcing them to change their actions. Small-volume trading deals can be less impactful on the entire market but still could make a play as a butterfly effect. Conversely, large-volume trades could significantly impact the market, forcing a competitive environment to adapt to your actions, resulting in an advantage or in a failure due to liquidity shortage. Regarding this fact, the higher winning rate of MSMA could be different in a real market environment as well as the higher profitability of SMA could be lower or even higher.

5. Conclusions

This study presents an analysis of the mechanistic simple moving average (MSMA) and the traditional simple moving average (SMA), focusing on their performance metrics, distribution characteristics, causal relationships, and dependence on market trends.

The comparative analysis of MSMA and SMA returns shows that MSMA tends to provide more consistent returns, with lower volatility and a higher win rate (52.2%) compared to SMA (43.1%). While SMA shows potential for higher returns in certain instances (maximum return of 282.2% vs. MSMA's 151.5%).

The t-tests in mean returns and win rates reinforce the unique distributional behaviors of each method.

SMA's strategy, with its strong correlation between mean and cumulative returns, shows its dependency on sustained positive trends, while MSMA's weaker correlation suggests a more balanced and consistentapproach, influenced heavily by its win rate.

The analysis of returns relative to Bitcoin's market trends showed that both SMA and MSMA are influenced by trend directions but in different ways. SMA showed a tendency for more extreme returns during strong uptrends, which aligns with its higher volatility profile. MSMA, in contrast, demonstrated more stable performance across both uptrends and downtrends although its returns were generally lower. However, MSMA faced significant negative returns during the downtrend periods, which could lead to notable decreases in account balance.

The causal analysis confirmed a negative effect of using MSMA compared to SMA, with an estimated ATE indicating that MSMA yields, on average, 3.5% to 6.0% lower returns than SMA. These findings were consistent across the three different causal inference methods (PSM, PSS, and DML), which were further validated by refutation tests. Only the DML model failed in the placebo test, which should be investigated in detail further.

The analysis of the trend direction's causal effect on MSMA returns showed a positive effect during uptrends, with an average increase in returns of approximately 16% compared to downtrends. This effect was observed consistently across various causal inference models.

Experimenting with adaptive versions of MSMA that can better respond to market shifts, particularly during downtrends, may be a promising area for further research. Additionally, further investigation into hybrid strategies that combine the stability of MSMA with the profitability potential of SMA could produce methods optimized for different market cycles. Exploring machine learning approaches to dynamically adjust moving average parameters based on trend strength and volatility could also improve strategy resilience.

Future research should explore the use of varying parameters for MSMA, not the only fixed 32 period, to explore the flexibility and accuracy of the method.

For further research, exploring other time intervals such as 4 h, 1 h, 15 min, and 5 min where the number and frequency of random processes increases would be desirable.

Investigation of the effect of using MSMA on real market conditions, such as the effect of liquidity or the behavior of other participants, should be addressed in further research.

The study shows that SMA may be more suitable for capturing large gains and are willing to accept higher risk. Meanwhile, MSMA may be more suitable in strategies focused on risk management and incremental gains.

As the study shows, SMA may be more suitable for capturing large gains and are willing to accept higher risk. Meanwhile, MSMA may be more suitable in strategies focused on risk management and incremental gains.

Conflict of Interest

The author declares that he has no conflict of interest concerning this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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This study was conducted without financial support.

Data Availability

The manuscript has no associated data.

Use of Artificial Intelligence

The author confirms that he did not use artificial intelligence technologies when creating the current work.

The author has read and agreed to the published version of this manuscript.

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ПОРІВНЯЛЬНЕ ДОСЛІДЖЕННЯ ЦІНОВОЇ ТА МЕХАНІСТИЧНОЇ КОВЗНИХ СЕРЕДНІХ З ВИКОРИСТАННЯМ ПРИЧИННО-НАСЛІДКОВОГО АНАЛІЗУ НА ІСТОРИЧНИХ ДАНИХ БІТКОЇНА

І. В. Цапро

Предметом цього дослідження є порівняльний аналіз цінової та механістичної ковзних середніх, застосованих на даних про обсяг і ціну біткоїна, використовуючи причинно-наслідковий аналіз для оцінки прибутковості та точності на історичних записах. **Мета** цього дослідження полягає в тому, щоб дослідити ефективність цінової та механістичної ковзних середніх, у прогнозуванні тенденцій цін на біткоїн. **Завдання** полягають у наступному: 1) оцінити ефективність традиційної простої ковзної середньої (SMA), орієнтованої на ціну, проти механічної простої ковзної середньої (MSMA), яка включає обсяг торгів як "масу" активу; 2) провести симуляції за допомогою швидкої та повільної ковзних середніх, щоб визначити прибутковість кожного методу та точність торгових угод за різними параметрами; 3) проаналізувати причинно-наслідкові зв'язки при виборі ковзної середньої та результатами торгівлі, а також між напрямками тренду ціни біткоїна та доходами за допомогою причинно-наслідкового аналізу; 4) проаналізувати вплив результатів на торгові стратегії на нестабільному ринку криптовалют. Були отримані наступні **результати**: 1) SMA, орієнтована на ціну, продемонструвала вищу прибутковість і вищу волатильність порівняно з MSMA, яка дала більш рівномірний, але нижчий прибуток зі значно кращою точністю торгівлі; 2) кореляційний аналіз виявив більш сильний зв'язок між доходністю та коефіцієнтом виграшу для MSMA, ніж для SMA, що свідчить про відносну стабільність MSMA у нестабільному торговому середовищі; 3) причинно-наслідковий аналіз підтвердив статистично значущий причинно-наслідковий зв'язок між використанням MSMA та стабільними результатами; 4) на прибутковість MSMA сильно вплинули ринкові тенденції, причому висхідні тренди принесли вищу прибутковість, ніж спадні на 16%. **Висновки**. Це дослідження робить внесок у технічний аналіз криптовалют, демонструючи переваги та обмеження цінової та механічної ковзних середніх. У той час як SMA краще підходить для дослідників, які віддають перевагу вищим потенційним доходам, незважаючи на волатильність, MSMA пропонує стабільний підхід, заснований на обсягах. Дослідження дає цінну інформацію для дослідників, які прагнуть удосконалити інвестиційні стратегії в динамічному секторі криптовалют.

Ключові слова: криптовалюта; ковзна середня; статистичний аналіз; причинно-наслідковий аналіз; технічні індикатори; еконофізика.

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