Profitability and Data-Snooping Tests of Four Technical Trade Strategies for Cryptocurrency Pair BTC/USDT and ETH/USDT in Cryptocurrency Markets During 2022–2023

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We provide a comprehensive investigation into the profitability of technical trading methods applied to the cryptocurrency pairs BTC/USDT and ETH/USDT. By employing rigorous evaluations and incremental examinations, we address the pervasive issue of data-snooping bias that often plagues the evaluation of trading strategies. Our empirical results indicate the lack of profitable technical trading strategies in both the analysis sample and prediction sample periods, even after rigorous adjustments for data snooping. These findings highlight the difficulties associated with selecting profitable technical trading strategies in the dynamic and volatile cryptocurrency market. Market participants, including individual traders, institutional investors, and regulatory bodies, should take note of our findings when making investment decisions based on technical analysis.

Keywords: *technical trading, data-snooping, reality check, cryptocurrency*

INTRODUCTION

Chartist analysis, also referred to as technical analysis, encompasses a wide variety of methodologies used to derive trading recommendations for financial instruments. These recommendations are based on the examination of the historical time series of the asset's price, using graphical or mathematical techniques. This methodology solely focuses on a thorough examination of historical price patterns and statistical information, disregarding the potential impact of fundamental factors that influence the asset's value.

Importantly, despite its deviation from fundamental principles, technical analysis continues to be widely recognized within the financial industry across numerous markets. The extensive adoption of technical analysis methodologies has been extensively documented. Market participants consistently find value in utilizing these techniques, despite their divergence from fundamentals.

Moreover, empirical evidence supports the effectiveness of trading strategies developed using technical indicators. Various studies have verified the profitability of such strategies across different markets. For example, a pioneering study conducted on technical trading rules specifically for the NYSE index from 1962 to 1996 has shown promising potential for generating profits (Kwon and Kish (2002)). Another study examines the profit potential of variable length Moving Average trading rules in emerging equity markets (Ratner and Leal (1999)). The findings of this research suggest that technical analysis techniques can indeed yield profitable trading strategies in these markets. Additionally, Tam and Cuong (2018) focused on the Vietnam stock market establishes the effectiveness of the three most popular technical indicators for investment strategies.

Overall, despite its departure from fundamental principles, technical analysis effectively demonstrates its utility in guiding trading decisions and achieving favorable financial outcomes. The widespread acceptance and effectiveness of technical analysis in financial markets underscore its value as a valuable tool in the arsenal of investors and traders.

In contemporary times, there has been significant interest in the digital currency market. It has now been established that there is a bidirectional causal relationship between the profits and quantity of digital currencies, which has implications for technical analysis and trend-following (Fousekis and Tzaferi (2021)). Detzel et al. (2019) provides evidence that trading strategies based on mean oscillations generate profits for Bitcoin. As noted by Corbet et al. (2019), strategies involving mean oscillations and breaking out of trading ranges exhibit remarkable trading performance for Bitcoin. Given the existing body of research, understanding the factors that influence the digital currency market, both from economic fundamentals and behavioral perspectives, is of great interest.

However, it is of utmost importance to conduct a thorough and up-to-date investigation into the field of technical analysis in the marketplace. Previous research in this area has been inadequate, as it has primarily concentrated on brief periods of observation, limited collections of technical trading regulations, uncomplicated performance metrics, and rudimentary testing methodologies. These limitations have significant implications for the reliability and validity of the findings, as they might be prone to the influence of data-snooping bias. Data-snooping bias, as defined in academic literature, arises when researchers persist in seeking predictive patterns or regulations but fail to conduct comprehensive collective tests for each attempt employing the same dataset. This bias can result in exaggerated conclusions and inaccurate predictions. Hence, it is crucial to acknowledge this bias and address it in future studies on technical analysis.

Consequently, the captivating question of whether technical analysis has the potential to outperform the general market demands a thorough and extensive-scale examination. To achieve this, it is essential to adopt a suitable empirical framework that considers an extensive range of variables, methodologies, and statistical analyses. This comprehensive approach will enable researchers to draw more reliable and valid conclusions regarding the effectiveness of technical analysis in achieving superior market performance.

In conclusion, the study of technical analysis in the marketplace is paramount due to the limitations of prior research. By addressing these limitations through an extensive-scale examination with an empirical framework, researchers can determine whether technical analysis has the ability to outperform the market. This will contribute valuable insights to the field of finance and aid in decision-making for market participants.

In this paper, we examine the practical profitability of technical trading strategies by incorporating performance evaluations and conducting reality verification. We also assess the presence of data snooping in the selection of these trading approaches. Initially, we divide the entire observation period (January 2022 to June 2023) into an in-sample period before January 2023. During this phase, we analyze whether the profitability of technical trading methods observed in this period continues in the subsequent out-of-sample phase after January 2023. Furthermore, we address the bias caused by data snooping in the in-sample and out-of-sample analyses, a factor often overlooked in previous studies on technical trading in the cryptocurrency market, by employing the verification of reality and consecutive evaluations, following existing literature (e.g. Neely et al. (2014)). To assess the mean yearly return and Sharpe ratio of over 200 technical trading approaches, we aggregate daily and hourly trading data for the BTC/USDT and ETH/USDT cryptocurrency pair.

This study makes a significant contribution to the existing body of research on the profitability of technical trading strategies in the cryptocurrency market, with a specific focus on the BTC/USDT and ETH/USDT pairs. We aim to shed light on the challenges faced by traders when attempting to select strategies that can consistently generate profits during the subsequent out-of-sample period.

The findings of this research suggest that the profitability of technical trading strategies is not always sustainable, as those strategies that appear successful during the in-sample period may fail to deliver positive results in the out-of-sample period. In other words, traders cannot solely rely on historical performance to predict future profitability.

The study further emphasizes that the observed profitability of technical trading strategies is highly dependent on the selection of specific parameters rather than indicating the existence of market inefficiencies. This means that the success of a strategy is more attributed to the careful tuning of its parameters rather than exploiting inherent market inefficiencies.

While it is possible to identify profitable strategies through retrospective analysis or back testing, it is considerably more challenging to learn and predict their performance prospectively or ex-ante. Traders and investors should not assume that a strategy's past success guarantees its future profitability. Therefore, careful selection and validation of strategies in real-time trading scenarios are crucial.

The implications of these findings are significant for traders and investors who rely on technical trading strategies to generate profits in the cryptocurrency market. It highlights the importance of cautious strategy selection and diligent evaluation before deploying them in live trading environments. Traders should recognize that the cryptocurrency market is dynamic and ever-changing, and historical performance alone is not sufficient to ensure profitability.

Overall, this study provides valuable insights into the challenges and limitations associated with technical trading strategies in the context of the cryptocurrency market. It serves as a reminder that successful strategies should not solely rely on historical performance but should be thoroughly evaluated to ensure their viability in real-time trading. By considering these insights, traders and investors can make more informed decisions and enhance their chances of achieving sustainable profitability in the dynamic and evolving cryptocurrency market.

The subsequent sections are organized in a coherent manner to provide a comprehensive analysis of multiple aspects of the investigation. Section 2 provides an overview of technical analysis and the efficient market hypothesis. Section 3 focuses on the trading data used in the study. Condensed statistics are included to offer a comprehensive overview of the dataset. Section 4 centers on the development of technical trading techniques. Section 5 introduces various metrics to evaluate the effectiveness of the technical trading rules. Section 6 addresses the issue of data snooping and implements reality check tests for statistical inference. Section 7 presents the pivotal empirical findings, focusing on the performance of the technical trading techniques. Section 8 reveals outcomes of various robustness checks, confirming the stability and dependability of the findings. Section 9 concludes our findings by summarizing the main discoveries and presenting concluding remarks.

THEORETICAL BACKGROUND

Technical Analysis

Quantitative equity investing is a robust investment methodology that integrates computational science, numerical econometrics, monetary finance, and related disciplines to execute investment strategies. It requires the development of investment frameworks that leverage advanced mathematical principles, efficient data manipulation techniques, and state-of-the-art technologies, such as computer algorithms, to detect lucrative trading opportunities within massive datasets. This approach offers significant advantages in mitigating the impact of emotional fluctuations that can result from subjective investor decision-making.

The main idea of this paragraph is that quantitative investment primarily focuses on using statistical probability distributions to develop trading strategies. These strategies are derived from analyzing massive historical datasets using powerful data processing capabilities of computers. Mathematical models are then employed to validate and refine these strategies, aiming to achieve higher and more stable returns while minimizing investment risk. One of the key features of quantitative investment is its ability to provide measurable, reproducible, and predictable results, which allows investors to make investment decisions within a rigorous and analytical framework. This objective approach helps reduce the impact of subjective biases and emotions on investment performance. The growing popularity of quantitative investment is attributed to advancements in technology and the availability of vast amounts of financial data.

Quantitative investment in finance can be broadly classified into two principal categories: stock timing strategy and stock selection strategy. Stock timing strategy applies mathematical models and algorithms to predict market trends accurately, thus effectively generating excess returns through strategic buying or selling of financial assets. By employing mathematical tools and advanced algorithms, investors can closely analyze market patterns and tendencies, enabling them to make informed decisions and capture lucrative opportunities. Investing decisions backed by thorough data analysis allow investors to capitalize on market movements and maximize their investment returns. In contrast, the stock selection strategy involves a meticulous and comprehensive assessment of various factors to identify high-quality stocks. These factors encompass vital components such as company financial data and prevailing market conditions. Through meticulous evaluation of these elements, investors can effectively analyze the potential of different stocks and screen out those most likely to yield positive returns. The objective of this strategy is to optimize investment portfolios by carefully selecting stocks with significant growth potential and minimizing potential risks.

Both stock timing strategy and stock selection strategy play indispensable roles in quantitative investment. While the former heavily relies on mathematical models and algorithms to forecast market trends, the latter concentrates on analyzing fundamental factors such as financial data and market conditions. By combining these approaches, investors can achieve a balanced investment strategy that capitalizes on both market trends and individual stock characteristics. This integrated approach empowers investors to maximize their investment returns while effectively managing risks within their portfolios.

Stock timing is a highly profitable trading strategy that involves the analysis and prediction of market trends over a specific period using a particular approach. It provides investors with valuable guidance on when to buy and hold or when to sell and clear their positions based on the expected direction of the market. By taking advantage of anticipated market movements, investors can mitigate risks and maximize returns.

When the market trend is expected to rise, investors are advised to adopt a buy-and-hold strategy. This means they should purchase stocks and hold onto them for an extended period, allowing them to benefit from the upward movement of stock prices. On the other hand, if the market trend is anticipated to fall, it is recommended that investors sell their stocks and exit their positions to avoid potential losses. In cases where the market trend is uncertain, investors have the flexibility to engage in different strategies to minimize holding costs. They can either engage in high selling and low buying or low selling and high buying, depending on their assessment of the market. The objective is to limit the overall costs associated with holding stocks during uncertain periods, thus optimizing their investment returns.

Stock timing has proven to be a highly effective trading strategy, surpassing the simple buy-and-hold approach in terms of generating significantly higher returns. However, accurately predicting market trends can be a daunting task due to the intricate interaction of various factors. These factors include macroeconomic conditions, such as interest rates, inflation, and economic growth, as well as firm-specific performance, government policies, and international events. To overcome these challenges, stock timing relies on the use of quantitative methods. These methods involve the analysis of various macro and micro indicators to identify key information that influences market trends. By employing statistical models and sophisticated algorithms, investors can obtain insights into the underlying dynamics of the market and make informed predictions about its future direction.

In the field of stock timing, there are two primary methods used for analysis: fundamental analysis and technical analysis. Fundamental analysis involves evaluating the intrinsic value of securities based on factors such as financial statements and economic indicators. However, technical analysis takes a different approach by relying on transaction data to predict future trends of asset prices. This technique focuses on price changes and trading volume to identify patterns and signals that can inform investment decisions.

The effectiveness of technical analysis has been a subject of debate among academics and industry professionals. Critics argue that it lacks a solid theoretical foundation and may rely too heavily on past price patterns, which may not accurately reflect future movements. However, proponents of technical analysis highlight its ability to identify short-term trends and patterns that can be exploited for trading profits. They argue that through diligent analysis of transaction data and attention to market indicators, investors can improve their chances of making successful trades.

In the complex world of stock trading, investors cannot afford to ignore technical analysis. By incorporating technical analysis techniques into their decision-making process, investors can enhance their chances of achieving reasonable returns and reducing volatility risk. This can be accomplished by studying price charts, identifying support and resistance levels, and utilizing indicators and oscillators. By using these tools, investors can gain insights into potential buying or selling opportunities and make more informed trading decisions. Furthermore, understanding technical analysis can also help investors avoid emotional decision-making and reduce the impact of cognitive biases. By relying on objective analysis of transaction data rather than relying solely on gut feelings or market rumors, investors can strive for more rational and disciplined investment strategies. Consequently, while the effectiveness of technical analysis may continue to be debated, it remains a widely used method in the field of stock timing. Investors cannot afford to ignore its potential benefits, as it offers a practical approach to predicting future asset price trends. By developing a better understanding of technical analysis and incorporating its techniques into their investment strategies, investors can strive for reasonable returns and mitigate volatility risk in their portfolios.

The theoretical foundation of technical analysis in finance is based on three primary assumptions: the incorporation of all market information in prices, the importance of tendencies as a fundamental concept, and the recurrence of historical patterns and events in the market. Understanding these assumptions is critical for practitioners who wish to employ technical analysis techniques and strategies in their financial decision-making processes.

The first assumption is that all available information is reflected in the market price, indicating that price changes are influenced by both direct and indirect factors. This means that the price itself represents all market information.

The second assumption emphasizes the concept of tendencies, which refers to the speed at which the current price moves towards a rational price range. Tendencies play a crucial role in technical analysis. By observing how quickly prices move towards a rational range, analysts can determine whether the market is in an uptrend (prices rising) or a downtrend (prices falling). The duration of a tendency is influenced by the speed at which prices reach the desired range. A longer duration suggests slower movement, while a shorter duration indicates faster price fluctuations. Furthermore, tendencies can be thought of as the "inertia" of price fluctuations. Similar to objects in motion, prices tend to continue moving in the same direction until an external force affects them.

The third assumption states that historical patterns tend to repeat themselves in the market. This means that patterns and events that have occurred in the past are likely to occur again in the future. Quantitative trading heavily relies on statistical analysis of historical data to exploit this principle. By systematically analyzing large amounts of past market data, traders can identify recurring patterns and high-probability events, enabling them to make informed decisions based on statistical probabilities.

Expanding on these assumptions, it is important to understand the fundamental principles on which technical analysis is based. Technical analysts believe that the market is efficient and all relevant information is already reflected in the price. Therefore, trying to predict market movements based on fundamental analysis or insider information may not provide a significant advantage. Instead, technical analysts focus on studying price patterns and tendencies to make investment decisions.

Effective Market Hypothesis

The efficient market hypothesis (EMH) is a theory in finance that asserts the efficiency of financial markets. It states that financial markets are efficient because in a society with rapid information dissemination and perfect competition, investors can quickly and costlessly obtain specific information. This allows them to make informed decisions based on the complete knowledge they possess, maximizing their interests. As a result, security prices fully incorporate all available information, adjusting until expected returns align precisely with risk. In an efficient market, investors cannot obtain excess returns solely based on this information and can only earn risk-adjusted average market returns.

First proposed by Eugene F. Fama in 1970 (Fama (1970)), the EMH identifies two key factors contributing to the efficiency of financial markets: rapid information dissemination and perfect competition. In a society where information travels quickly and effortlessly, investors have the ability to promptly and freely access specific information. This enables them to make informed decisions based on complete knowledge, resulting in security prices reflecting the collective wisdom of market participants.

At the core of the EMH is the idea that security prices adjust until expected returns precisely compensate for the associated risks. Market prices respond to new information until expected returns accurately reflect the level of risk involved. This equilibrium ensures that investors cannot earn excess returns solely based on already reflected information. Instead, investors can only achieve risk-adjusted average market returns in an efficient market.

The efficient market hypothesis posits that financial markets are efficient due to the rapid dissemination of information and the presence of perfect competition. Investors in an efficient market can quickly and freely obtain specific information, enabling them to make informed decisions. Consequently, security prices fully reflect all available information and adjust until expected returns align precisely with risks. Investors in an efficient market cannot gain excess returns solely based on existing information and can only earn risk-adjusted average market returns. Understanding the concept of market efficiency is crucial for analyzing and comprehending the dynamics of financial markets.

The efficient market hypothesis classifies information into three categories: historical transaction records, aggregate data, and individualized data. Based on these categories, market efficiency is divided into three levels: weak-form efficiency, semi-strong form efficiency, and strong-form efficiency. In a weak-form efficient market, technical analysis is unnecessary as current security prices fully reflect all past transaction records, including both valuation and volume. In a semi-strong form efficient market, current security prices incorporate not only past data but also readily available discrete data such as financial statements, management discussions and analysis, CEO correspondence, and so on. As a result, both technical analysis and fundamental analysis lose their effectiveness. In a strong-form efficient market, current security prices fully reveal all information, including historical transaction records, aggregate data, and individualized data, making it impossible for investors to achieve excess returns.

DATA

In this study, we sourced our trading data from the highly reputable cryptocurrency data source, Binance. Binance is renowned for its reliability and comprehensive coverage of cryptocurrency markets, providing us with a robust dataset to explore the price dynamics of Bitcoin and Ethereum.

Our dataset incorporates a wide range of granular information, capturing both daily and hourly trading data. This comprehensive approach enables us to examine the intricate fluctuations in the prices of these cryptocurrencies over time. Including daily data allows us to observe the broader trends and long-term patterns, while hourly data allows us to delve into the finer details of price movements.

The collected data includes several vital components essential for understanding the behavior and performance of Bitcoin and Ethereum in the market. Opening prices, for instance, serve as valuable indicators of investors' sentiment and expectations at the start of a specific time period. These initial trading values set the tone for subsequent price movements, reflecting the market's initial reaction to various factors such as news, market sentiment, and overall economic conditions.

Furthermore, our dataset includes the highest and lowest prices, representing the extreme fluctuations experienced by Bitcoin and Ethereum within the given time frame. These extreme values provide insights into the volatility of these cryptocurrencies and highlight the influence of market forces and sentiment on their prices. Examining these peak values allows us to identify periods of heightened market activity and gauge the resilience of these cryptocurrencies during times of market stress.

To comprehensively analyze the price dynamics, we have also incorporated closing prices in our dataset. The closing prices signify the final traded value at the end of a specific period, encapsulating the sentiments and market views that have evolved throughout the trading day. By considering these closing values, we can gain a comprehensive understanding of the overall market sentiment and evaluate the impact of various events and announcements on the prices of Bitcoin and Ethereum. Figure 1 and Figure 2 present the trend of closing prices for the two cryptocurrency pairs respectively.

FIGURE 1
THE TREND OF CLOSING PRICE FOR BTC/USDT

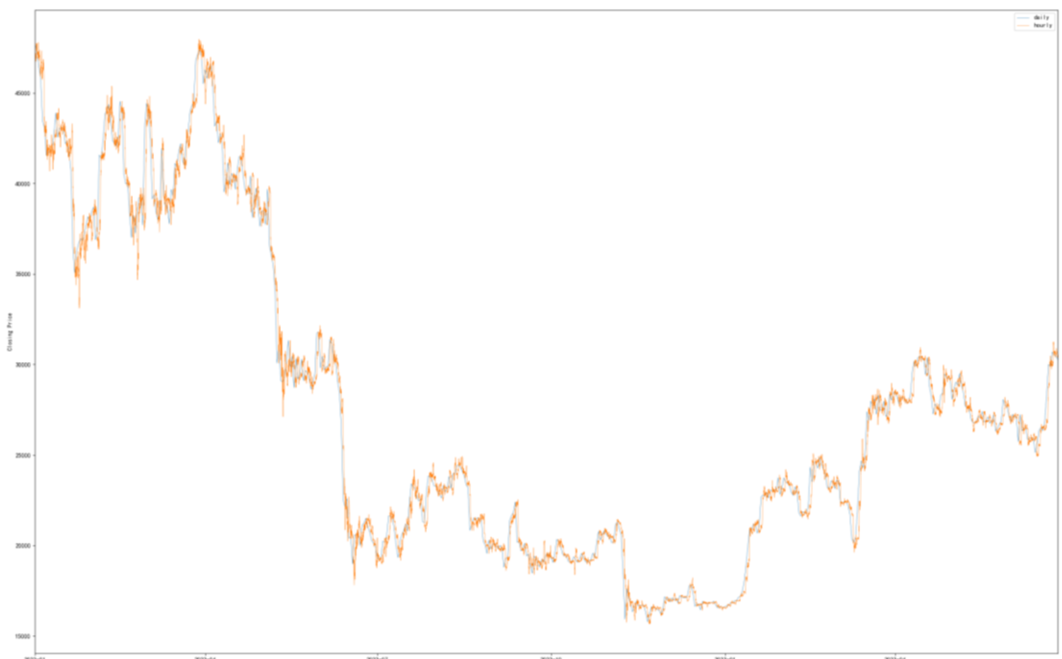


FIGURE 2
THE TREND OF CLOSING PRICE FOR ETH/USDT

Another important component of our dataset is the trading volume, which reflects the total number of shares or contracts traded during a specific period. This indicator provides valuable insights into the liquidity and interest in Bitcoin and Ethereum. Higher trading volumes suggest a greater level of investor participation and market activity, signaling increased liquidity and potentially influencing price movements.

To ensure that our analysis captures a wide range of market conditions, we have implemented a significant time frame for our data collection. The period from January 1, 2022, to June 26, 2023, spans a substantial duration, encompassing various market conditions, including periods of stability, price surges, and corrections. By analyzing this extensive dataset, we aim to uncover the complex dynamics driving the prices of Bitcoin and Ethereum, contributing to a deeper understanding of the behavior of these cryptocurrencies in the financial market.

The measurement of investment performance in Bitcoin and Ethereum trading is the daily and hourly gross return calculated by a formula, $r_t = \ln(s_t/s_{t-1})$, where s_t represents the price at time unit t. This measurement aims to assess the profitability of cryptocurrency trading, without considering transaction costs.

Table 1 provides details about the returns on the cryptocurrency pair BTC/USDT and ETH/USDT. To ensure the robustness and reliability of the findings, it is necessary to conduct an out-of-sample test. This involves dividing the dataset into two distinct periods: an in-sample period from January 1, 2022, to January 14, 2023, and an out-of-sample period from January 14, 2023, to June 26, 2023. By evaluating investment performance across these different time frames, a more comprehensive understanding of efficacy can be obtained. Examining how performance varies across these periods allows investors to assess the consistency and adaptability of their investment strategies.

TABLE 1
SUMMARY STATISTICS OF TRADING DATA

	1d				1h			
	mean	std	min	max	mean	std	min	max
BTC/ USDT								
open	27285.47	8731.39	15781.29	47722.66	27263.76	8718.67	5648.23	47970.98
high	27878.96	8939.71	16315.00	48189.84	27379.88	8762.46	5769.99	48189.84
low	26642.17	8476.10	15476.00	46950.85	27144.68	8672.63	5476.00	47811.40
close	27256.05	8694.28	15781.29	47722.65	27262.54	8717.13	5649.52	47970.99
volume	154417.24	134577.26	14434.55	760705.36	6442.58	7147.23	0.00	137207.19
returns	-0.000	0.031	-0.154	0.145	-0.000	0.006	-0.070	0.065
ETH/ USDT								
open	1903.06	660.23	995.12	3828.11	1901.61	659.06	904.26	3875.34
high	1954.89	676.22	1078.88	3900.73	1911.66	662.44	928.36	3900.73
low	1845.80	638.36	881.56	3717.30	1891.19	655.30	881.56	3851.52
close	1899.71	655.82	995.13	3828.27	1901.47	658.88	904.25	3875.34
Volume	628595.48	425969.40	117762.07	3626351.67	26205.67	27371.91	0.00	426087.79
returns	-0.000	0.040	-0.174	0.181	-0.000	0.008	-0.098	0.076

In conclusion, measuring investment performance in Bitcoin and Ethereum trading is crucial for evaluating profitability. By utilizing the formula for calculating gross return, investors can gain insights into the performance of their cryptocurrency investments. Additionally, conducting an out-of-sample test ensures the reliability of the findings by assessing performance across various time frames.

TECHNICAL TRADING STRATEGIES

EMAC Strategy

Utilizing different moving average trading strategies is prevalent among traders who employ technical trading methods. These strategies can range from simple to complex. The primary objective of these strategies is to identify trends in the market and anticipate changes or the emergence of new trends. One commonly used approach is the adoption of a basic moving average, which helps estimate the local trend.

In a basic moving average trading strategy, traders analyze the intersection of the price and the moving average to determine a trading signal. When the price crosses the moving average, it indicates a disruption in the current trend, prompting traders to either initiate a new position or close their existing position. This intersection is considered significant in technical analysis.

Traders often use short-term moving averages in place of the price to increase the accuracy of their strategies. By using a shorter moving average, traders can identify potential upward disruptions in the trend when it crosses below a longer moving average. Conversely, a downward disruption in the trend is indicated when the short moving average crosses above the longer moving average. This technique enables traders to identify potential shifts in market direction and adjust their positions accordingly.

Moving averages can be classified as short-term, medium-term, or long-term based on their calculation periods. Short-term moving averages typically have calculation periods of less than 20 days, while medium-term moving averages span from 20 to 60 days. Moving averages with calculation periods longer than 60 days are considered long-term. By using moving averages of different durations, traders can evaluate market trends across various time frames and gain valuable insights into market behavior.

There are various methods available for calculating moving averages, but the most commonly used technique is the arithmetic moving average, also known as the simple moving average. This method calculates the average of a specified number of past prices and provides a smooth representation of the underlying trend. Traders rely on this technique for its simplicity and effectiveness in capturing the essence of market fluctuations.

In conclusion, moving average trading strategies play a significant role in technical trading methods. These strategies provide a means to monitor trends and anticipate potential disruptions or the emergence of new trends. By using different types of moving averages and understanding their calculations, traders can make informed decisions about market trends across different time frames. The arithmetic moving average is favored due to its simplicity and ability to accurately represent market trends.

$$MA_t(j) = \frac{1}{j}\sum_{i=0}^{j-1} P_{t-i}, \tag{1}$$

where j represents the time interval of the moving average, MA_t represents the numerical value of the moving average on the t-th day, and P_{t-i} denotes the closing price on the $(t-i)$-th day.

A single moving average trading rule offers a systematic approach to making investment decisions using the daily closing price of an asset. This rule centers around the relationship between the current price and a moving average calculated over a specific period: If the daily closing price of the asset moves up at least x percent above $MA_t(q)$ and remains so for d days, go long the asset until its daily closing price moves down at least x percent below $MA_t(q)$ and remains so for d days, at which time go short the asset. If the daily closing price of the asset moves down at least x percent below $MA_t(q)$ and remains so for d days, go short the asset until its daily closing price moves up at least x percent above $MA_t(q)$ and remains so for d days, at which time go long the asset.

The trading rule emphasizes the significance of both upward and downward movements in the daily closing price relative to the moving average. By considering these price dynamics, investors and traders can capitalize on potential trends and reversals in the asset's price, with the objective of maximizing their investment returns.

A modification to a trading strategy aimed at identifying the most optimal holding period for an asset. This modification disregards all other signals and concentrates solely on the movement of the asset's daily closing price during the holding period: If the daily closing price of the asset moves up at least x percent above $MA_t(q)$ and remains so for d days, go long the asset for k days and then neutralize the position. If the daily closing price of the asset moves down at least x percent below $MA_t(q)$ and remains so for d days, go short the asset for k days and then neutralize the position.

By pre-determining the holding period and focusing solely on the price movement relative to the moving average, this straightforward variation aims to capture profitable opportunities in the market. The strategy's essence lies in its ability to identify potential upward or downward trends through the asset's deviation from the moving average. The predetermined holding period ensures a disciplined approach to trading, enabling investors to capitalize on short-term price movements without succumbing to impulsive decision-making.

A double moving average trading rule entails observing the behavior of two moving averages, namely $MA_t(p)$ and $MA_t(q)$, and using their relationship to guide investment decisions. The rule outlines conditions for taking long or short positions, the duration of these positions, and the required percentage move in the moving averages: If $MA_t(p)$ moves up at least x percent above $MA_t(q)$ and remains so for d days, go long the asset until $MA_t(p)$ moves down at least x percent below $MA_t(q)$ and remains so for d days, at which time go short the asset. If $MA_t(p)$ moves down at least x percent below $MA_t(q)$ and remains so for d days, go short the asset until $MA_t(p)$ moves up at least x percent above $MA_t(q)$ and remains so for d days, at which time go long the asset. p is less than q.

After a brief introduction, the focus shifts to the selection of the Exponential Moving Average Crossover (EMAC) approach and the determination of its effectiveness. To achieve this objective, a range of numerical quantities is examined. Specifically, the study examines the fast span, which ranges from 10 to 30, with an increment of 2. Similarly, the slow span is examined, ranging from 35 to 60, with an increment of 3. Through the exploration of these various numerical quantities, we aim to comprehensively evaluate the performance of the EMAC tactic. This analysis will enhance our understanding of the usefulness and effectiveness of employing the EMAC tactic in financial decision-making and trading strategies. Our findings will provide valuable insights for investors and market participants seeking to optimize their trading decisions using the EMAC approach.

RSI Strategy

An often utilized technical tool in finance is the "overbought/oversold" indicator, also known as an oscillating contraption. Despite its infrequent mention in scholarly writings, these oscillating contraptions are metrics designed to signal that recent price fluctuations in a certain direction have been excessively rapid, indicating an imminent change in the opposite direction. These indicators can be configured in multiple precise ways. One widely used configuration is the relative strength index (RSI) (Levy (1967); Wilder (1978)), which is characterized as follows:

$$RSI_t(h) = 100\left[\frac{U_t(h)}{U_t(h)+D_t(h)}\right], \tag{2}$$

where $U_t(h)$ represents the total increase in value from one day to the next, when the closing value of the following day exceeds the closing value of the previous day, over a period of h days. Conversely, $D_t(h)$ represents the total decrease in value from one day to the next, when the closing value of the following day is lower than the closing value of the previous day, within the same time period.

The RSI is widely used in finance as a momentum oscillation indicator to assess the speed and magnitude of value fluctuations. It allows for an understanding of the strength of an asset's price movement and facilitates the identification of potential overbought or oversold conditions.

It is important to note that some versions of the RSI define $U_t(h)$ and $D_t(h)$ in relation to averages rather than cumulative values. However, these explanations are considered equivalent, as dividing the cumulative values by the total number of days cancels out the effect when calculating the RSI.

$$U_t(h) = \sum_{j=1}^{h} \iota\left(P_{t-j} - P_{t-1-j} > 0\right)\left(P_{t-j} - P_{t-1-j}\right) \tag{3}$$

$$D_t(h) = \sum_{j=1}^{h} \iota\left(P_{t-j} - P_{t-1-j} < 0\right)\left|P_{t-j} - P_{t-1-j}\right|, \tag{4}$$

where $\iota(\cdot)$ is an indicator variable that takes the value one when the statement in parentheses is true and zero otherwise.

Furthermore, the RSI is normalized within a range of 0 to 100, enhancing its interpretability. If the RSI reads zero, it indicates that all observed price movements are downward, implying a strong bearish sentiment. Conversely, a value of 100 signifies that all observed movements are upward, reflecting a strong bullish sentiment. Values between 0 and 100 represent varying levels of strength for both bullish and bearish movements.

By providing a quantified measure of market trend strength, the RSI equips market participants with a reliable tool for making well-informed decisions. Traders can use the RSI to identify potential entry or exit points, evaluate the likelihood of trend reversals, or confirm the continuation of existing market trends. This technical indicator stands as a valuable resource in the field of finance, empowering investors to navigate the intricacies of the market with confidence.

The RSI measurement scale ranges from 0 to 100, with the equilibrium point considered to be 50. A range between 30 and 70 on the RSI scale indicates a standard trading condition. This implies that there is neither excessive buying nor selling pressure, resulting in relatively stable prices. However, when the RSI exceeds 80, it signals an overbought market with a higher likelihood of a price reversal or correction. Conversely, an RSI falling below 20 indicates an oversold market, suggesting a higher probability of a price rebound.

To thoroughly analyze the market using the RSI, it is essential to consider different time durations. The most commonly utilized durations are the 6-day, 12-day, and 24-day periods, which are selected according to the desired timeframe for market analysis. The 6-day RSI is suitable for immediate short-term analysis, while the 12-day and 24-day RSIs are ideal for intermediate and long-term analysis, respectively. By studying the RSI values across these durations, traders can gain valuable insights into the overall market trend and make well-informed trading decisions.

Additionally, the RSI measurement is also an effective tool for evaluating the strength of long and short positions. If the RSI remains above 50 for an extended period, it indicates a robust long position, implying that the market favors buyers and prices are expected to rise. Conversely, if the RSI remains below 50 for an extended duration, it signifies a pronounced short position, indicating that the market favors sellers, and prices are likely to decline. By monitoring the pattern of the RSI trace, traders can accurately assess the vigor of these positions and adjust their strategies accordingly.

In conclusion, the RSI is a highly valuable tool for evaluating market conditions and making well-informed trading decisions. By carefully considering the RSI measurement, its various durations, and the patterns in the RSI trace, traders can gain crucial insights into the state of the market, identify overbought or oversold conditions, and accurately determine the strength of long and short positions. This information is instrumental in developing effective trading strategies and managing investment portfolios.

A conventional oscillatory trading principle based on the relative strength index (RSI) can be described as follows: If the $RSI_t(h)$ surpasses a threshold of 50 + v for a duration of d days and subsequently drops below 50 + v, initiate a short position on the asset. Conversely, if the $RSI_t(h)$ falls below 50 - v for at least d days and then rises above 50 - v, take a long position on the asset.

A modification to the conventional RSI trading regulation that aims to improve trading outcomes. The modification involves imposing a previously determined retention duration for a specific trading stance: If $RSI_t(h)$ moves above 50 + v for at least d days and then subsequently moves below 50 + v, go short the asset for k days and then neutralize the position. If $RSI_t(h)$ moves below 50 - v for at least d days and then subsequently moves above 50 - v, go long the asset for k days and then neutralize the position.

The trading indication strategy based on the analysis of the RSI in financial markets requires careful consideration to avoid false signals. It is crucial to note that the initiation of a trading indication should not occur when the RSI enters the overbought or oversold area. Instead, the signal should be triggered as the RSI departs from this region. The overbought area is determined when the RSI surpasses the threshold of 50 plus a certain value denoted as v, while the oversold area is indicated when the RSI falls below 50 minus the value v.

The primary reason for this cautious approach is the potential for an asset to persistently remain in an overbought or oversold state for a considerable period. In fact, in some cases, these extreme conditions may intensify momentarily. It is essential to ensure that the asset's price movement is not prematurely interpreted as a definitive trend reversal. By waiting for the RSI to cross 50 + v from above or 50 - v from below, a more reliable confirmation of the trend reversal can be obtained. This approach allows the asset price to continue moving in the expected direction until a clear shift in the trend becomes perceptible.

The oscillation trading regulation, which incorporates this cautious approach, serves to prevent premature trading decisions based on temporary aberrations in the RSI values. By waiting for a confirmed departure from the overbought or oversold region, investors and traders can ride the asset price movement in the anticipated direction for longer durations. This prolonged exposure to favorable price movements maximizes potential profits and reduces the likelihood of entering positions that are quickly reversed. It is important to emphasize that the oscillation trading regulation is designed to provide sufficient flexibility to capture substantial price movements while remaining cautious enough to avoid false signals.

In conclusion, when utilizing the RSI as a tool for trading indications, focusing on the departure from the overbought or oversold areas is crucial rather than their entry. By exercising patience and waiting for the RSI to cross the predetermined thresholds, investors can navigate the market more effectively, avoiding false trends and optimizing their investment strategies. The oscillation trading regulation encapsulates this approach, allowing for the persistence of favorable price movements until a noticeable shift in the trend occurs.

In the context of our research, we have deliberately chosen to focus on a specific Relative Strength Index (RSI) strategy and thoroughly evaluate its performance using a robust backtesting approach. The selected RSI strategy involves setting the RSI period to 14, which aligns with the prevailing practice in the field. To comprehensively assess the effectiveness of this strategy, we employ a systematic grid search methodology, where we systematically vary the upper values of the RSI within the range of 70 to 90, incrementing by 2 units. Similarly, we specify a range for the lower values of the RSI, ranging from 20 to 40, also incrementing by 2 units. By following this meticulous and well-defined approach, we are able to thoroughly investigate various RSI settings and determine the potential of this strategy as a valuable tool for making well-informed financial decisions.

Bollinger Bands Strategy

Support-resistance trading rules aim to identify specific price levels known as resistance and support levels, where the price encounters difficulty in either rising or falling. When the price surpasses these levels by a certain percentage, it triggers significant price movement in the same direction. Support-resistance trading rules are frequently used to predict potential turning points in the market. Traders utilize these rules to determine moments when the price is likely to experience difficulty continuing its upward or downward movement. Resistance levels indicate when the price may struggle to rise further, providing a selling or short position opportunity. Similarly, support levels indicate areas where the price may find support and reverse its trend, presenting a buying or long position opportunity. These trading rules differ from filter rules, which rely on the price exceeding recent highs or lows to initiate a trade. Support-resistance trading rules consider the breach of support or resistance levels by a certain percentage as the trigger for a trading signal. This percentage is often determined based on historical data and market conditions.

The rationale behind support-resistance trading rules lies in the concept of price dynamics. When the price surpasses a resistance level, it signifies increasing buying pressure and implies the potential for further upward movement. Conversely, when the price falls below a support level, it indicates increasing selling pressure and suggests continued downward movement. Traders take advantage of these dynamics by entering trades when support or resistance levels are breached, expecting significant price momentum in the same direction.

In summary, support-resistance trading rules are a valuable approach for identifying potential price turning points in financial markets. By recognizing levels where the price struggles to continue rising or falling, traders can generate trading signals when these levels are breached. These rules complement filter rules by focusing on support and resistance levels rather than recent highs or lows. The application of support-resistance trading rules requires the use of technical analysis tools to pinpoint these levels accurately and increase the probability of successful trades.

Support and resistance levels play a crucial role in informed investment decision-making within financial trading. These levels offer valuable insights into the bounds of an asset's price and facilitate the determination of optimal trading strategies. One method of defining these levels involves examining the highest closing price among the previous j closing prices as the resistance level and considering the lowest closing price among the previous j closing prices as the support level. By accurately identifying these levels, traders can gain a better understanding of an asset's price movements.

Once the support and resistance levels have been determined, traders can utilize them to guide their trading decisions. For instance, if an asset's daily closing price increases by at least x percent above the highest closing price among the previous j closing prices and maintains that level for d days, traders may opt to go long on the asset. This condition acts as a trigger, indicating a potential upward movement in the asset's price. Moreover, the price must remain above the resistance level for a consecutive period of d days to confirm the sustained upward movement.

In contrast, if an asset's daily closing price declines by at least x percent below the lowest closing price among the previous j closing prices and continues at that level for d days, traders may consider going short on the asset. This condition suggests a potential downward trend in the asset's price. To validate this descending movement, the price must persist below the support level for a continuous period of d days.

By adhering to these criteria, traders can capitalize on price movements and enhance the precision of their trading strategies. Accurately determining support and resistance levels based on previous closing prices enables traders to identify potential entry and exit points for their positions. Furthermore, incorporating percentage thresholds and consecutive-day requirements provides a systematic approach to trading, reducing the impact of short-term fluctuations. Ultimately, the inclusion of these methods enhances the effectiveness of financial trading strategies.

The pre-specified holding period version of the support-resistance rule bears a resemblance to a similar filter rule used in financial analysis. This rule serves as a guiding principle for traders and investors when making decisions about trading assets, specifically based on their daily closing prices. By closely monitoring the daily closing price of an asset, market participants can identify significant price movements that signal potential position changes. The rule is expressed as follows: If the daily closing price of the asset moves up at least x percent above the highest closing of the j previous closing prices and remains so for d days, go long the asset for k days and then neutralize the position. If the daily closing price of the asset moves down at least x percent below the lowest closing of the j previous closing prices and remains so for d days, go short the asset for k days and then neutralize the position.

One widely used support-resistance trading rule is the Bollinger Band, which was developed by technical trader John Bollinger. It is used in technical analysis to predict the levels of resistance and support for the price of a security. These levels are determined by calculating the specific number of standard deviations from the mean price. The trading rules associated with Bollinger Bands are similar to those that have been discussed earlier.

Having outlined above, we explore the careful selection of the Bollinger Bands strategy. An extensive and thorough backtesting analysis will be conducted to effectively evaluate its true potential. In regard to the Bollinger Bands strategy itself, a wide range of values will be meticulously examined for the period parameter, spanning from a minimum of 15 to a maximum of 30, with a consistent and precise step size of 3. This diligent exploration intends to encompass and capture a comprehensive understanding of the strategy's performance across different time horizons. Additionally, attention will be given to examining the devfactor, where a distinct set of values, specifically 1.0, 2.0, and 3.0, will be evaluated. This limited range of devfactor values will be scrutinized meticulously and precisely to assess their impact on the overall effectiveness of the Bollinger Bands strategy. By conducting such a comprehensive analysis, our aim is to ascertain the true potential and viability of the Bollinger Bands strategy in the realm of financial economics.

MACD Strategy

The moving average trading approach is a commonly used method in financial markets that calculates the mathematical average of prices over a specific time period. However, this approach has certain limitations. One of the main drawbacks of the moving average method is its inherent delay. Regardless of its proximity to the present, each value is given equal weight. This means that historical data has the same impact on the calculated average as recent data, which may not be optimal for responding to current market conditions.

To address these limitations, the Moving Average Convergence Divergence (MACD) indicator was developed. The MACD is a smoothed moving average indicator that is a significant improvement over the traditional simple moving average. By using exponential moving averages (EMA) instead of simple moving averages, the MACD mitigates the latency issue associated with the original moving average method.

The exponential moving averages used by the MACD assign more weight to recent data points, giving greater importance to the most recent market conditions. This helps provide a more accurate representation of the current state of the market and reduces the impact of outdated information. As a result, the MACD generates more timely trading signals, which are crucial for successful trading strategies. Another advantage of the MACD indicator is its ability to address the problem of frequent trading signals that may arise from short backtesting periods. The use of exponential moving averages helps smooth the signals and filter out noise that could lead to excessive trading. This feature makes the MACD particularly suitable for long-term analysis, as it is less susceptible to being influenced by short-term market fluctuations.

In its calculation, the MACD subtracts a long-term EMA, typically calculated over a period of 26 days, from a short-term EMA, usually calculated over 12 days. The result of this subtraction is referred to as the DIF. Additionally, the MACD Signal Line, also known as DEA, is calculated using the MACD's own exponential moving average.

$$EMA_t j = \frac{2}{1+j} P_t + \left(1 - \frac{2}{1+j}\right) EMA_{t-1}(j), \tag{5}$$

$$MACD_t(n) = DIF_t(n) = EMA_t(p) - EMA_t(q), \tag{6}$$

$$DEA_t(n) = EMA_t(n)(\text{the EMA of DIF}), \tag{7}$$

where n denotes the exponential moving average period of DIF, and p is less than q.

The location of the MACD bar serves to evaluate the difference between the MACD and its signal line. When there is a positive difference between the DIF and DEA, the MACD bar assumes a positive value, indicating a bullish market. Conversely, when there is a negative difference between the DIF and DEA, the MACD bar takes on a negative value, indicating a bearish market. Additionally, the decrease and change in direction of the MACD bar can be used as a method for identifying trading opportunities.

A traditional principle for MACD trading can be defined as follows: If the DIF rises by at least *x* percent, exceeding the DEA, and continues to do so for a duration of *d* days, initiate a prolonged position in the resource. This stance should be maintained until the DIF descends by at least *x* percent below the DEA and persists for *d* days. At this point, shift to a concise position in the resource. In the event that the DIF descends by at least *x* percent below the DEA and endures for *d* days, continue with a concise position in the resource until the DIF rises by at least *x* percent, surpassing the DEA, and maintains this condition for *d* days. At that moment, adopt a prolonged position in the resource.

In financial analysis, the candlestick chart is a widely-used tool for analyzing price patterns. However, it is not the sole indicator for predicting market reversals. An additional factor to consider is the DEA line, which stands for "detrended exponential moving average". The DEA line can provide crucial insights into potential market reversals.

When observing the relationship between the DEA line and the candlestick chart, a deviation can indicate a prospective market reversal. If the DEA line establishes a fresh peak while prices do not, it suggests a possible reversal in the market. Conversely, if prices establish a new peak while the DEA line does not, this also signifies a potential market reversal. It is important to note that market reversals do not always follow a V-shaped or inverted V-shaped configuration. While these patterns are commonly associated with reversals, they are not the only possibilities. A market reversal can also manifest as a more extensive trend reversal, indicating a shift in the overall market direction.

Understanding and interpreting the relationship between the DEA line and the candlestick chart is crucial for identifying potential market reversals. By considering these indicators together, investors and analysts can gain valuable insights into the future direction of the market. It is essential to remain vigilant and not solely rely on a single indicator, as a comprehensive analysis requires considering multiple factors and technical indicators.

In this paper, we delve into the variety and evaluation of the MACD strategy by conducting an exhaustive backtesting analysis. Through a grid search, we systematically examine a range of parameter values for the fast length, slow length, signal length, simple moving average length, and direction length to determine the most effective configuration. To begin, we examine the fast length values ranging from 10 to 20, considering a step size of 5. Furthermore, we extend our analysis to the slow length, examining values between 20 and 30 using a step size of 5. We also analyze the signal length, examining values from 6 to 12 with increments of 2. Moreover, we carefully select a value of 30 for the simple moving average length. Lastly, we designate the direction length as 10, finalizing the configuration of our chosen MACD strategy. By thoughtfully determining the direction length, we further refine the strategy's capability to identify and capitalize on directional trends in the financial markets.

RETURNS AND PERFORMANCE METRICS

Logarithmic Returns

Logarithmic returns are a valuable tool for measuring the pace of exponential advancement in the financial market. Instead of simply evaluating the proportion of price fluctuation for each specific period, a more comprehensive approach is adopted. We focus on appraising the exponent of the inherent advancement throughout that interval. This approach enables us to understand the growth potential of a financial instrument or asset more accurately.

The essence of logarithmic returns lies in their ability to capture the inherent advancement of a financial instrument during a specific duration. This intrinsic advancement factor helps us uncover the underlying trend and potential growth prospects, which may not be evident when only focusing on price fluctuations. By appraising the exponent of this advancement, we gain valuable insights into the compounding effect that drives exponential growth.

By utilizing logarithmic returns, we shift our attention from the proportion of price fluctuation to the exponent of inherent advancement over a defined interval. This enables us to grasp the true pace of exponential growth in the financial market and better assess the growth potential of various assets or derivatives. Adopting such a methodology allows for a more accurate evaluation and understanding of financial trends and their inherent complexities.

The comprehensive aggregate return is evaluated as follows:

$$R_{tot} = \ln(P_T) - \ln(P_0) = \sum_{t=1}^{T}[\ln(P_t) - \ln(P_{t-1})]. \tag{8}$$

The arithmetic mean of logarithmic returns functions as a powerful tool, offering a comprehensive and precise representation of the complete accumulated return, facilitating both theoretical research and practical applications:

$$\overline{\mathrm{R}} = \frac{R_{tot}}{T}. \tag{9}$$

In practical scenarios, it would be beneficial for this indicator to manifest as the widely comprehensible annual growth rate. To achieve this goal, we standardize our earnings assessment by calculating the average annual growth in the following manner:

$$R_{norm} = \left(e^{\bar{R}T_{ann}} - 1\right) * 100, \tag{10}$$

where T_{ann} denotes number of sub-periods in one year (monthly=12, weekly=52, daily=252). The flexibility of measuring T_{annual} on different time intervals allows researchers to adapt their analysis to specific needs and time horizons. When evaluating long-term investment strategies, measuring T_{annual} on a monthly or weekly basis provides a broader perspective while capturing meaningful variations. On the other hand, measuring it on a daily basis allows for a more detailed analysis, which can be valuable for short-term trading or intraday market analysis.

Sharpe Ratio

The Sharpe ratio, a prevalent performance indicator in the financial sector, plays a crucial role in assessing the merits of investment strategies. This extensively utilized measure evaluates the relationship between the mean surplus gain and uncertainty, taking into account the dispersion of surplus gains. By quantifying the risk-normalized function of an investment, the Sharpe ratio provides valuable insights into the performance of an investment strategy.

In our study, we specifically focus on the post-event Sharpe ratio (SR) as our gauge of performance. The post-event SR considers the actual outcome and reflects the performance of an investment strategy after a specific event or period. This measure is particularly useful for evaluating the performance of investment strategies in real-world scenarios where market conditions may change over time.

$$SharpeRatio = \frac{R_{norm} - R_f}{\sigma_P}, \tag{11}$$

where R_{norm} denotes total annualized returns of the strategy, R_f refers to the risk-free rate, and σ_P denotes the algorithm volatility of the strategy.

By considering both the mean surplus gain and the uncertainty associated with an investment, the Sharpe ratio allows for a comprehensive assessment of risk-adjusted returns. Practically speaking, a higher Sharpe ratio indicates a more appealing risk-adjusted return profile. Investors and financial professionals often employ this measure to compare and select investment strategies that offer a higher potential for returns relative to the level of risk involved.

In conclusion, the Sharpe ratio serves as a valuable tool for evaluating the performance of investment strategies in the financial sector. Specifically, the post-event Sharpe ratio provides a comprehensive measure of risk-adjusted returns by considering both the mean surplus gain and the uncertainty associated with an investment strategy. This measure enables investors and financial professionals to make informed decisions and select investment strategies that offer optimal risk-adjusted returns.

Max Drawdown

Maximum drawdown is a crucial metric in the field of investment analysis as it quantifies the extent of the downward movement in the valuation of a portfolio. This measure specifically focuses on the most severe proportion of the decline, considering the potential loss that an investor could have faced. It quantifies the darkest possible scenario that an investment method might have entailed.

$$MaxDrawdown = Max\left(\left(P_i - P_j\right)/P_i\right), \tag{12}$$

where P_i, P_j are the total value of the portfolio on day *i* and day *j*, respectively, and $j > i$. Here we use the length of the period and value in percentage of max drawdown as metrics.

The concept of maximum drawdown revolves around the idea of purchasing stocks or assets at their highest value and subsequently selling them when they have reached their lowest point. It serves as an indicator of the risk associated with a specific investment strategy, offering valuable insights into the potential losses that investors may experience.

By examining the maximum drawdown, investors can gain a deeper understanding of the negative exposure associated with their chosen investment approach. This metric effectively captures the largest deficit that an investor could have incurred by purchasing assets at their peak and subsequently selling them at their lowest point. It acts as a historical marker, representing the highest possible loss that could have been suffered if the investor’s timing had been impeccable.

Therefore, maximum drawdown plays a significant role in evaluating the downside risk of an investment strategy. By considering the worst-case scenario, investors can make more informed decisions and adjust their investment approaches accordingly. This metric should be carefully assessed alongside other risk measures to develop a comprehensive understanding of the potential pitfalls associated with an investment methodology.

REALITY CHECK AND STEPWISE TEST

To accurately evaluate the predictive superiority of technical trading strategies, it is crucial to address the issue of data snooping, which arises due to the absence of theoretical restrictions on their construction. This lack of constraints allows for the selection of various parameters, resulting in the existence of multiple alternative hypotheses for statistical inferences. Therefore, it is essential to determine whether the identified profitable trading strategies, discovered through specification search, truly exhibit predictive superiority over a given benchmark model. However, accomplishing this within the traditional framework of classical statistical inference is no easy task.

Classical statistical inference relies on rejecting the null hypothesis when the observed data's likelihood under the null hypothesis is low. When searching among trading strategies, this process inherently involves testing and discarding underperforming models or rules, leading to an increase in the number of hypotheses being evaluated. This proliferation of hypotheses tested gives rise to the problem of multiplicity.

Multiplicity arises because the likelihood of a rare event and the probability of incorrectly rejecting the null hypothesis (Type I error) for each competing model or trading rule increase exponentially as the number of tested hypotheses grows. Therefore, the apparent superior performance observed in specific searches through the rejection of individual null hypotheses may not necessarily indicate true predictive superiority over a benchmark model. Instead, it could be a result of extensive specification searches that maximize a given model's performance.

In our research, we face the challenge of searching through a substantial number of variants (up to 217) of technical trading strategies. Given the large number of strategies tested, skepticism regarding the findings is justified, as it is possible for some strategies to perform well solely by chance. Thus, it becomes crucial to rigorously assess the predictive superiority of the identified models while accounting for the implications of data snooping and the problem of multiplicity.

The phenomenon of information extraction, or more commonly referred to as information prying due to the emergence of "big data" analysis, has been extensively studied in the realms of applied economics and finance. Scholars have devoted considerable attention to understanding the challenges associated with extracting valuable information from available data. The extensive chronicle of research on this topic includes influential works such as Leamer (1978) and the references cited therein. These studies have laid the foundation for the contemporary advancement in the field of information extraction.

Nowadays, with the advent of sophisticated data analytical techniques and the proliferation of vast data sets, the issue of information extraction has gained even greater significance. Researchers and practitioners alike are increasingly concerned with effectively appropriating the information contained within these datasets to gain valuable insights into economic and financial phenomena. The heightened utilization of the term "information prying" reflects the growing recognition of the complexities involved in extracting meaningful information from the ever-expanding pool of available data.

In the field of applied economics and finance, the exploration of information extraction techniques has seen significant advancements. Scholars have developed novel methodologies and approaches to tackle the challenges posed by the abundance of data. These advancements encompass not only the development of statistical models and algorithms but also the integration of machine learning and artificial intelligence techniques. As a result, the field of information extraction has experienced substantial contemporary progress, leading to a deeper understanding of economic and financial dynamics.

More precisely, let $\mathrm{H} = \{H_1, H_2, \cdots, H_K\}$ represent a series of K values, where each component H_k represents the mean gain or Sharpe ratio of the k_{th} method. Here, K denotes the total number of different technical trading strategies considered in each analysis. Data snooping occurs when an investigator selects the highest value from the series, denoted as $H_j = max(\mathrm{H})$, and evaluates this strategy under the assumption of zero profit generation.

$$H_0: H_j = 0. \tag{13}$$

The focus of an "individual test" is to determine the statistical significance of the null hypothesis, as represented by Equation (13). In order to obtain the results of this individual test, researchers employ the nominal t-statistic. This statistical measure enables the quantification of the discrepancy between the sample data and the null hypothesis, allowing for the assessment of significance and the evaluation of the likelihood that the observed results are merely due to chance. The calculation of the nominal t-statistic furnishes researchers with substantial statistical evidence, enabling them to make informed decisions based on the outcome of the individual test.

$$t_{H_j} = \frac{H_j}{Std(H_j)\sqrt{n}}, \tag{14}$$

where $Std(H_j)$ is the standard deviation of H_j and n is the sample size. Then the nominal p-value can be calculated based on the cumulative distribution function.

Nevertheless, the individual testing is inadequate for assessing the profitability of technical trading strategies. This is because it fails to account for the possibility that the strategy being tested is already the best among a group of strategies. Consequently, the statistical significance is overestimated, and there is a higher chance of Type I error. According to White (2000), this approach disregards the fact that the performance of a specific strategy may represent the best performance among a group of strategies, an outcome that researchers often aim to demonstrate. In other words, individual testing does not accurately reflect the true distribution of statistics, rendering the assumed significance levels inadequate.

When considering a large number of strategies, relying solely on individual testing can lead to an artificially low probability of Type I error for technical trading profitability. This occurs because the strategy being tested has already been selected as the top performer within the set, introducing a bias known as data snooping. As a consequence, the null hypothesis is frequently excessively rejected, leading to an overestimation of the statistical significance associated with the profitability of technical trading strategies.

To thoroughly investigate the data-snooping issue, White (2000) suggests an "empirical scrutiny" trial that utilizes bootstrapping. This trial aims to determine the experimental setup for H and assess a composite null hypothesis by considering all components of H.

$$H_0: \max_{k=1,\cdots,K} H_k \leq 0, \tag{15}$$

where H_k represents the mean return or Sharpe ratio of each individual trading strategy.

It is important to employ a multiple-testing method to evaluate the composite null hypothesis regarding multiple technical trading strategies and determine the appropriate significance levels for the profits. We utilize the bootstrap reality check implementation, which was introduced by White (2000), to compute the p-value for the reality check (take daily data as an example):

1. We compute the daily return matrix G, in which each element G_{kt} denotes the daily return of the k_{th} strategy in each day ($k = 1, \cdots, K; t = 1, \cdots, T$).
2. We resample G using the stationary bootstrap method of Politis and Romano (1994), with pre-specified parameter set X, for B times, and label each resample as $\mathrm{G}_b, b = 1, \cdots, B$.
3. For each strategy k, we compute its performance metric (mean return or Sharpe ratio), H_k, based on G and H_{kb} based on G_b.
4. Now set $\overline{\Lambda}_1 = \mathrm{T}^{1/2}\mathrm{H}_1$ and $\overline{\Lambda}_{1b}{}^* = \mathrm{T}^{1/2}(\mathrm{H}_{1\mathrm{b}} - \mathrm{H}_1)$, and set $\overline{\Lambda}_k = max\{\mathrm{T}^{1/2}\mathrm{H}_k, \mathrm{T}^{1/2}\mathrm{H}_{k-1}\}$ and $\overline{\Lambda}_{kb}{}^* = \max\{\mathrm{T}^{1/2}(\mathrm{H}_{\mathrm{kb}} - \mathrm{H}_{\mathrm{k}}), \overline{\Lambda}_{k-1,b}{}^*\}$ for $k > 1$.
5. Denote the sorted values of $\overline{\Lambda}_{kb}{}^*$ as $\overline{\Lambda}_{k(1)}{}^*, \cdots, \overline{\Lambda}_{k(B)}{}^*$. Find N such that $\overline{\Lambda}_{k(N)}{}^* < \overline{\Lambda}_k < \overline{\Lambda}_{k(N+1)}{}^*$. The bootstrap reality check p-value can be calculated as $p_{rc} = 1 - N/B$.

Hansen (2005) suggests that the reality check is sensitive to poor and irrelevant alternatives. Including irrelevant alternatives can erode the power of reality check to reject the false null hypothesis. This problem can be alleviated by studentizing the test statistic and by incorporating an additional sample-dependent null distribution to identify the relevant alternatives. We thus adopt a stepwise test that is based on a series of methodologies based on White's reality check test, including Hansen (2005); Romano and Wolf (2005); Hsu, Hsu, and Kuan (2010). We first specify the alternative hypotheses for the null hypothesis by Equation (15) as:

$$H_A^k: H_k \geq 0, \text{ for } k = 1, \cdots, K. \tag{16}$$

The rejection of the k_{th} individual null hypotheses in finance research holds great importance as it plays a critical role in determining the profitability of various technical strategies. These null hypotheses are carefully tested while considering all alternative hypotheses to ensure that the selected strategy is genuinely profitable and not influenced by the data snooping bias. This bias refers to the tendency to mistakenly identify ineffective strategies as profitable ones due to the exploitation of multiple testing.

To address and mitigate the issue of data snooping bias, a stepwise test is specified with a certain Type I error level within a defined period ($t = 1, \cdots, T$). The main objective of this test is to effectively control the family-wise error, which represents the probability of rejecting at least one correct null hypothesis. By establishing a predefined significance level, such as 5%, in the testing process, researchers can minimize the chances of erroneously identifying any ineffective strategy as a profitable one.

Maintaining rigorous control over the rejection of null hypotheses is vital in finance research to ensure the validity and reliability of the findings. By implementing the stepwise test and carefully considering the family-wise error, we can effectively mitigate the risks associated with data snooping bias. This methodological approach enhances the integrity and robustness of finance studies, providing valuable insights for investors and decision-makers in the field.

1-3. The first three steps are the same as that of calculating reality check p-values.

4. We construct an empirical null distribution for the test statistics as follows:
   (a) For each b, compute

$$\Omega_{bi} = \mathrm{T}^{1/2} \max_{k=1,\cdots,K} \{H_{kb} - H_k + H_k \mathbb{1}(\mathrm{T}^{1/2}\mathrm{H}_k \leq -\sigma_k[2\log(\log(\mathrm{T}))]^{1/2})\}, \tag{17}$$

where $\mathbb{1}(\Psi)$ denotes the indicator function of the event Ψ and σ_k denotes the standard deviation of the original daily return series of the k_{th} strategy. The bound $\mathbb{1}(\mathrm{T}^{1/2}\mathrm{H}_k \leq -\sigma_k[2\log(\log(\mathrm{T}))]^{1/2})$ is proposed by Hansen (2005) to re-center the distribution for H to avoid the bias driven by too many "bad" strategies.

   (b) Collect all $\{\Omega_{bi}\}_{b=1,\cdots,B}$, rank them in descending order and then collect its $(1-\alpha_0)_{th}$ quantile as $q_i(\alpha_0)$.

5. We compare each strategy's $T^{1/2}H_k$ to $q_i(\alpha_0)$, and treat the k_{th} null hypothesis as rejected at the i_{th} step if $T^{1/2}H_k > q_i(\alpha_0)$, following Romano and Wolf (2005). We record all information of these rejected strategies and label then rejected at the i_{th} step. Then, restart from Step 5, let $H_k = 0$ and $H_{kb} = 0$ for all rejected hypotheses k, and change the loop indicator from i to $i+1$. However, if no strategy is rejected given $q_i(\alpha_0)$, i.e. $T^{1/2}H_k \leq q_j(\alpha_0)$ for remaining j, then stop and go to Step 7.
6. Finally, restore the original H_k from G and estimate each technical rule's marginal p-value, p_k, as the percentile of $T^{1/2}H_k$ in the last $\{\Omega_{bi}\}_{b=1,\cdots,B}$ as an empirical null distribution.
7. Compare each technical rule's p_k to α_0. If $p_k < \alpha_0$, we claim that k_{th} strategy is profitable in the sample period at the significance level of α_0. When there exists at least one profitable strategy in the sample period, we claim that technical trading is profitable at the significance level of α_0 and the stepwise test p-value is $1-\alpha_0$.

In our empirical experiments, we determine α_0 to be 0.05 and establish the statistical significance at the 5% threshold. In addition, we set Q as a value of 0.9 and B as a size of 1000 based on previous research. If a strategy yields positive profits but fails to demonstrate success in the data-snooping tests, its outcomes may have been coincidentally achieved rather than truly commendable.

THE EMPIRICAL PERFORMANCE OF TRADING STRATEGY

In this section, our objective is to assess the overall profitability of technical trading techniques during both the in-sample and out-of-sample periods. This analysis presents a comprehensive examination of several crucial considerations that significantly impact the success of these strategies. Initially, we evaluate the initial capital amount, which has been set at a substantial value of 100,000. This assessment allows us to evaluate the potential returns and effectiveness of the selected trading methodologies.

It is essential to note that our analysis does not include short selling. By deliberately excluding short selling from our evaluation, we focus solely on the profitability of long positions. This provides a comprehensive evaluation of technical trading strategies without considering the potential gains derived from shorting assets.

Moreover, determining the maximum position size for both buying and selling activities is of utmost importance. Throughout this research, we adopt a conservative approach by imposing a limit on the maximum position size for both buying and selling, setting it at a value of 1. This measure ensures that the trading strategies are protected from excessive risks or market volatility, leading to a more accurate assessment of their profitability.

To ensure meticulous execution of the trading strategies, we adopt a methodology that prohibits fractional trading. Consequently, all trading takes place in whole units rather than fractions, ensuring a standardized approach to the evaluation process. Additionally, we account for the impact of slippage, which we quantify at a value of 0.001. This value represents the potential difference between the expected price and the actual execution price, incorporating a realistic measure of transaction costs and market fluctuations.

Furthermore, our comprehensive investigation considers the commission involved in executing these technical trading methodologies. To accurately reflect real-world scenarios, we assign a value of 0.0003 to this commission, aligning its magnitude with industry standards. This integral commission factor plays a crucial role in determining the profitability of the trading techniques, as it directly influences the overall returns generated.

Lastly, we base our trading decisions solely on the closing price of the previous trading day. This approach safeguards the strategies against reliance on potentially unreliable or exclusive information, as the closing price serves as a central reference point for market analysis and decision-making.

BTC/USDT

Profitability Over the Whole Sample

Table 2 presents the test results considering the whole sample period. The left and right panels are based on annualized return and Sharpe ratio as performance criteria, respectively. Within each panel, we have 2 columns for different groups of technical trading strategies based on daily, and hourly trading data we considered. We focus on two sets of indicators generated from the data snooping test: 1) performance metrics and associated p-values of the best strategy, and 2) the number of profitable strategies that produce significantly positive performance metrics. We use 5% as the nominal significance level of our tests. The "Description" row displays the best strategy based on daily, and hourly trading data. To make our results comparable to prior studies, we provide the nominal p-value generate from the simple individual test in the next row. In the next two rows, we report the p-values based on the reality check test and the stepwise test. For instance, column (1) demonstrates that emac(28, 59), based on EMAC strategy with parameters of fast period of 28, slow period of 59, outperforms all other strategies, resulting in an annualized return of 9.767%, a Sharpe ratio of 0.379, and a maximum drawdown of 17.028%. The strategy does not have outstanding performance in the whole sample period as its average annualized return is insignificant and can not reject the null hypothesis (nominal p-value = 0.322, reality check test p-value = 0.911, and stepwise test p-value = 0.857). Figure 3 shows the cumulative log returns of the best-performing technical trading strategies based on daily, and hourly trading data.

TABLE 2
THE PERFORMANCE OF TECHNICAL TRADE STRATEGIES IN THE WHOLE SAMPLE - BTC/USDT

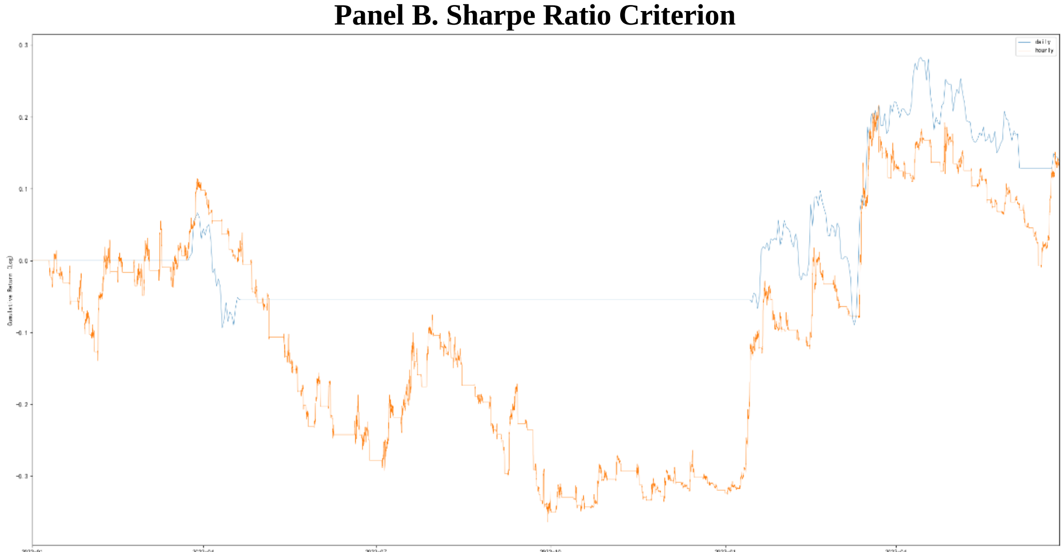
Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	217	217	217	217
Best Strategy				
Description	emac(28, 59)	emac(20, 35)	emac(28, 59)	emac(20, 35)
Annualized Return	9.767%	9.042%	9.767%	9.042%
Sharpe Ratio	0.379	0.261	0.379	0.261
Max Drawdown	17.028%	38.023%	17.028%	38.023%
P-Value (Nominal)	0.322	0.375	0.000	0.000
P-Value (Reality Check)	0.911	0.871	1.000	1.000
P-Value (Stepwise Check)	0.857	0.867	0.939	0.525
All Profitable Strategies (500 Tests)				
Minimum Number	0	0	2	0
Maximum Number	0	0	4	0
Average Number	0.000	0.000	2.928	0.000
Average Number / Number of Strategies	0.0%	0.0%	1.349%	0.0%

This table presents the profitability of technical trading strategies in the whole sample period. The left and right panels are based on the annualized return criterion and Sharpe ratio criterion, respectively. Within each panel, we have 2 columns for different groups of technical trading strategies based on daily, and hourly trading data we considered. In the panel titled "Best Strategy", we list the description, annualized return, Sharpe ratio, maximum drawdown, nominal p-value, reality check p-value, and stepwise test p-value of the best-performing strategy. In the panel titled "All Profitable Strategies", we list the average, minimum, and maximum number of profitable technical trading strategies from 500 stepwise tests. In the bottom row, we provide the ratio of the average number of profitable technical trading strategies to the total number of technical trading strategies considered. We use 5% significance level in our tests.

FIGURE 3
PERFORMANCE OF THE BEST TECHNICAL TRADE STRATEGY IN THE WHOLE SAMPLE - BTC/USDT

Panel A. Annualized Return Criterion

Panel B. Sharpe Ratio Criterion



This figure plots the performances of the best technical trade strategies of daily, and hourly trading data from Jan 01 2022 to Jun 26 2023. Panel A and B plot the results based on the annualized return criterion and Sharpe ratio criterion, and we use Jan 14 2023 as the cutoff of the in-/out-of-sample period.

Profitability in In-Sample and Out-of-Sample Periods

Table 3 presents the examination findings of the EMAC approach in both the in-sample and out-of-sample intervals, using the indicators of annualized profit and Sharpe ratio. In the panel titled "Best Strategy (In-Sample)", we enumerate the depiction, annualized profit, Sharpe ratio, maximum drawdown, and the p-values of the nominal, actual inquiry assessment, and gradual inquiry assessment for the most superior approach in-sample. Similarly, in the panel titled "Best Strategy (Out-of-Sample)", we list the annualized profit, Sharpe ratio, and the p-values of the nominal, actual inquiry assessment, and gradual inquiry assessment for the most superior approach out-of-sample. To address sampling bias in bootstrapping, we execute the data munching assessments 500 times in the lower panel entitled "All Profitable Strategies (In-Sample, 500 Tests)". In the bottom panel named "Performance of Profitable Strategies (Out-of-Sample, 500 Tests)", we list the mean figure and proportion of approaches that remain advantageous in the out-of-sample interval.

TABLE 3
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH EMAC STRATEGIES - BTC/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	90	90	90	90
Best Strategy (In-Sample)				
Description	emac(28, 59)	emac(20, 35)	emac(28, 59)	emac(20, 35)
Annualized Return	-5.126%	-11.27%	-5.126%	-11.27%
Sharpe Ratio	-0.476	-0.374	-0.476	-0.374
Max Drawdown	14.794%	38.023%	14.794%	38.023%
P-Value (Nominal)	0.314	0.352	0.000	0.000
P-Value (Reality Check)	0.920	0.812	0.010	0.000
P-Value (Stepwise Check)	0.825	0.695	0.008	0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	34.06%	97.663%	34.06%	97.663%
Sharpe Ratio	1.074	1.975	1.074	1.975
Max Drawdown	10.278%	21.212%	10.278%	21.212%
P-Value (Nominal)	0.408	0.128	0.000	0.000
P-Value (Reality Check)	0.541	0.271	0.010	0.000
P-Value (Stepwise Check)	0.545	0.286	0.008	0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	86.000	90.000
Average Number / Number of Strategies	0.0%	0.0%	95.556%	100.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	0.000	0.000	86.000	90.000
Average Number / Number of Strategies (In-Sample)	0.0%	0.0%	95.556%	100.0%

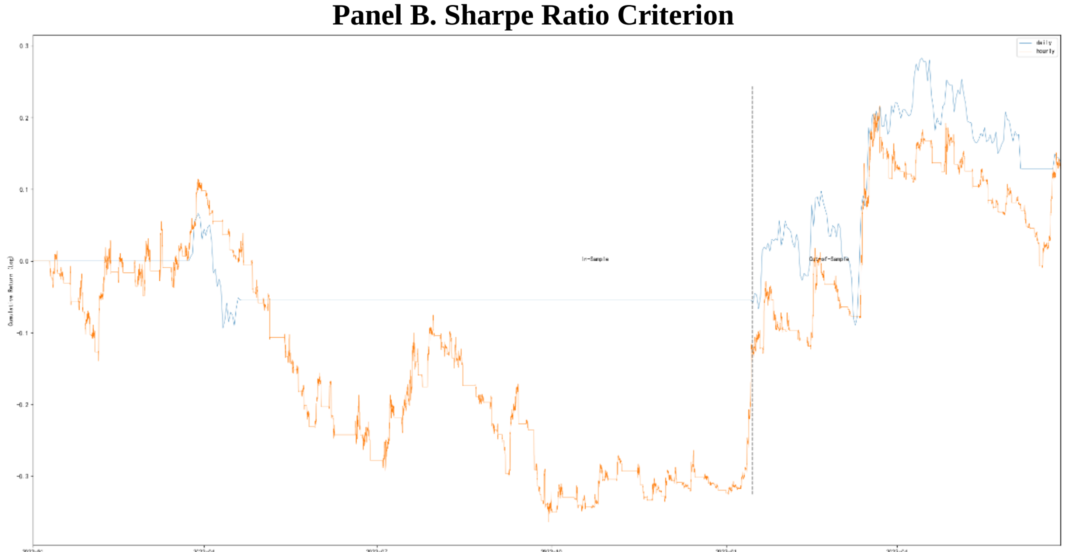
This table presents the profitability of technical trading strategies in the in-sample periods and subsequent out-of-sample periods. The left and right panels are based on the annualized return criterion and Sharpe ratio criterion, respectively. Within each panel, we have 2 columns for different groups of technical trading strategies based on daily, and hourly trading data we considered. In the panel titled "Best Strategy (In-Sample)", we list the description, annualized return, Sharpe ratio, maximum drawdown, nominal p-value, reality check p-value, and stepwise test p-value of the best-performing strategy in-sample. In the panel titled "Best Strategy (Out-of-Sample)", we list the annualized return, Sharpe ratio, nominal p-value, reality check p-value, and stepwise test p-value of the best-performing strategy out-of-sample. In the panel titled "All Profitable Strategies (In-Sample)", we list the average number of profitable technical trading strategies from 500 stepwise tests in-sample and the ratio of the average number of profitable technical trading strategies to the total number of technical trading strategies considered. In the panel titled "All Profitable Strategies (Out-of-Sample)", we list the average number of profitable technical trading strategies from 500 stepwise tests out-of-sample and the ratio of the average number of profitable technical trading strategies to the total number of technical trading strategies in-sample. We use 5% significance level in our tests.

Furthermore, we provide an example of the optimal strategy, which is the EMAC approach with parameters of a rapid interval of 28 and a sluggish interval of 59. The annualized profit is -5.126%, the Sharpe ratio is -0.476, and the maximum drawdown is 14.794%. However, this approach lacks exceptional effectiveness in both the in-sample and out-of-sample intervals, as its average annualized profit is insignificant and fails to reject the null hypothesis. Therefore, there is a need for a more dependable and enduring methodology in generating consistent returns, highlighting the deficiency in profitability of the approach. Figure 4 illustrates the cumulative natural logarithm profits of the most superior technical trading approaches based on daily and hourly trading data.

FIGURE 4
PERFORMANCE OF THE BEST TECHNICAL TRADE EMAC STRATEGY - BTC/USDT

Panel A. Annualized Return Criterion

Panel B. Sharpe Ratio Criterion



This figure plots the performances of the best technical trade strategies of daily, and hourly trading data from Jan 01 2022 to Jun 26 2023. Panel A and B plot the results based on the annualized return criterion and Sharpe ratio criterion, and we use Jan 14 2023 as the cutoff of the in-/out-of-sample period.

Table 4 presents the test outcomes for the RSI approach in the context of financial performance evaluation. It discusses the performance criteria, both in-sample and out-of-sample, as well as the evaluation of different approaches. An example is provided in column (1), which demonstrates the parameters for the most successful RSI approach. These parameters include an RSI period of 14, an RSI upper limit of 70, and an RSI lower limit of 20. The approach yielded an average annualized return of 21.039%, a Sharpe ratio of 0.883, and a maximum downturn of 12.974%. However, both the in-sample and out-of-sample periods showed inadequate performance as indicated by the p-values. The out-of-sample annualized return of 111.07% was deemed insignificant, and the p-values were unable to reject the null hypothesis. Therefore, we can conclude that the RSI approach failed to generate profits in both the in-sample and out-of-sample periods, suggesting its lack of effectiveness. Additionally, Figure 5 provides a visualization of the cumulative log returns of the most successful technical trading approaches based on daily and hourly trading data.

TABLE 4
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH RSI STRATEGIES - BTC/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	100	100	100	100
Best Strategy (In-Sample)				
Description	rsi(14, 70, 20)	rsi(14, 74, 20)	rsi(14, 70, 20)	rsi(14, 74, 20)
Annualized Return	21.039%	-27.541%	21.039%	-27.541%
Sharpe Ratio	0.883	-0.774	0.883	-0.774
Max Drawdown	12.974%	40.613%	12.974%	40.613%
P-Value (Nominal)	0.185	0.215	0.000	0.000
P-Value (Reality Check)	0.572	0.932		1.000
P-Value (Stepwise Check)	0.289	0.781		0.982
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	111.07%	212.982%	111.07%	212.982%
Sharpe Ratio	2.192	3.580	2.192	3.580
Max Drawdown	15.21%	15.683%	15.21%	15.683%
P-Value (Nominal)		0.408		0.000
P-Value (Reality Check)		0.861		1.000
P-Value (Stepwise Check)		0.847		0.982
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000		60.944
Average Number / Number of Strategies		0.0%		60.944%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number		0.000		60.944
Average Number / Number of Strategies (In-Sample)		0.0%		60.944%

FIGURE 5
PERFORMANCE OF THE BEST TECHNICAL TRADE RSI STRATEGY - BTC/USDT

Panel A. Annualized Return Criterion

Panel B. Sharpe Ratio Criterion

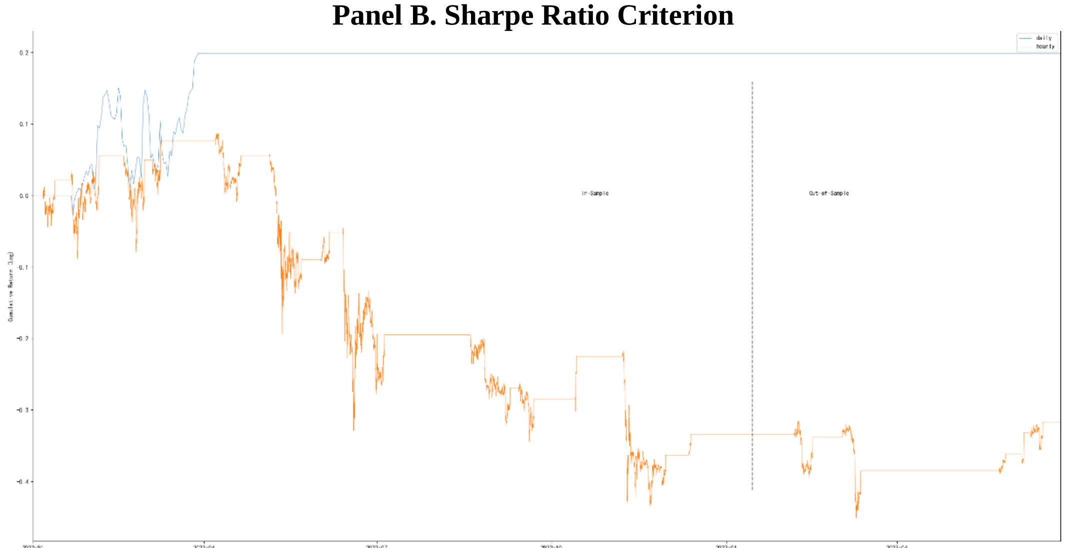


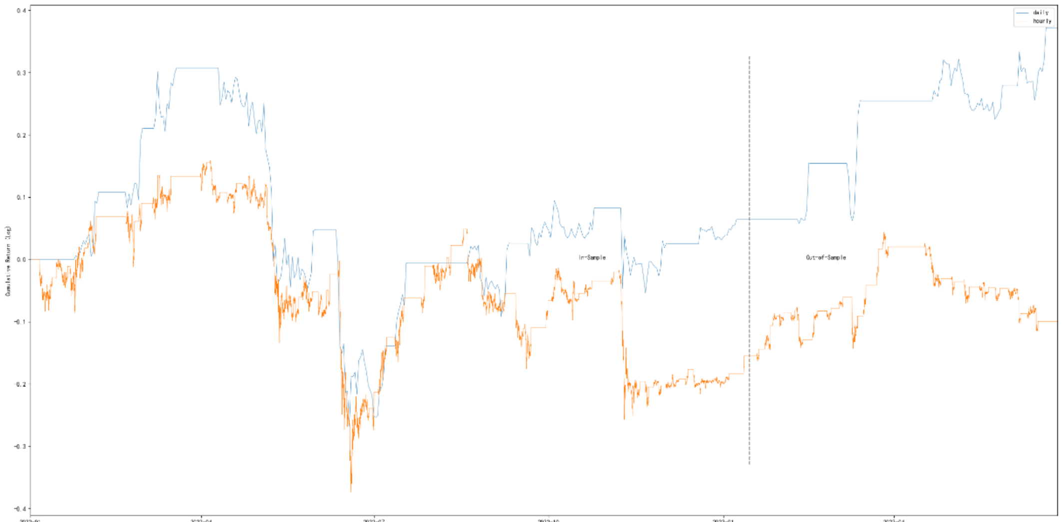
Table 5 presents the findings and analysis of the Bollinger Bands strategy in both the in-sample and out-of-sample periods. The results of the test for this strategy are reported in a table, with the left and right panels representing the evaluation based on annualized return and Sharpe ratio as performance criteria. As shown in column (1), for example, the best strategy is Bollinger Bands strategy with parameters of period of 24, devfactor of 1. For the optimal strategy, the annualized return is 6.371%, the Sharpe ratio is 0.139, and the maximum drawdown is 43.792%. However, this strategy did not demonstrate exceptional performance in both the in-sample and out-of-sample periods, as its average annualized return was insignificant and it failed to reject the null hypothesis. Moreover, it did not generate profits during the out-of-sample period. The lack of profitability of the strategy in both periods highlights the necessity for a more reliable and sustainable approach to consistently generate returns. To illustrate the findings, the cumulative log returns of the best-performing technical trading strategies are plotted. We plot the cumulative log returns of the best-performing technical trading strategies based on daily, and hourly trading data in Figure 6.

TABLE 5
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH BOLLINGER BANDS STRATEGIES - BTC/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	15	15	15	15
Best Strategy (In-Sample)				
Description	bbands(24, 1)	bbands(18, 3)	bbands(24, 1)	bbands(18, 3)
Annualized Return	6.371%	-13.881%	6.371%	-13.881%
Sharpe Ratio	0.139	-0.365	0.139	-0.365
Max Drawdown	43.792%	41.29%	43.792%	41.29%
P-Value (Nominal)	0.444	0.355	0.000	0.000
P-Value (Reality Check)	0.748	0.869	0.000	0.003
P-Value (Stepwise Check)	0.754	0.777	0.000	0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	126.31%	59.914%	126.31%	59.914%
Sharpe Ratio	2.689	1.997	2.689	1.997
Max Drawdown	8.462%	10.117%	8.462%	10.117%
P-Value (Nominal)	0.056	0.333	0.000	0.000
P-Value (Reality Check)	0.106	0.658	0.000	0.003
P-Value (Stepwise Check)	0.098	0.660	0.000	0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	10.000	12.834
Average Number / Number of Strategies	0.0%	0.0%	66.667%	85.56%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	0.994	0.000	10.000	12.834
Average Number / Number of Strategies (In-Sample)	6.627%	0.0%	66.667%	85.56%

FIGURE 6
PERFORMANCE OF THE BEST TECHNICAL TRADE BOLLINGER BANDS STRATEGY - BTC/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion

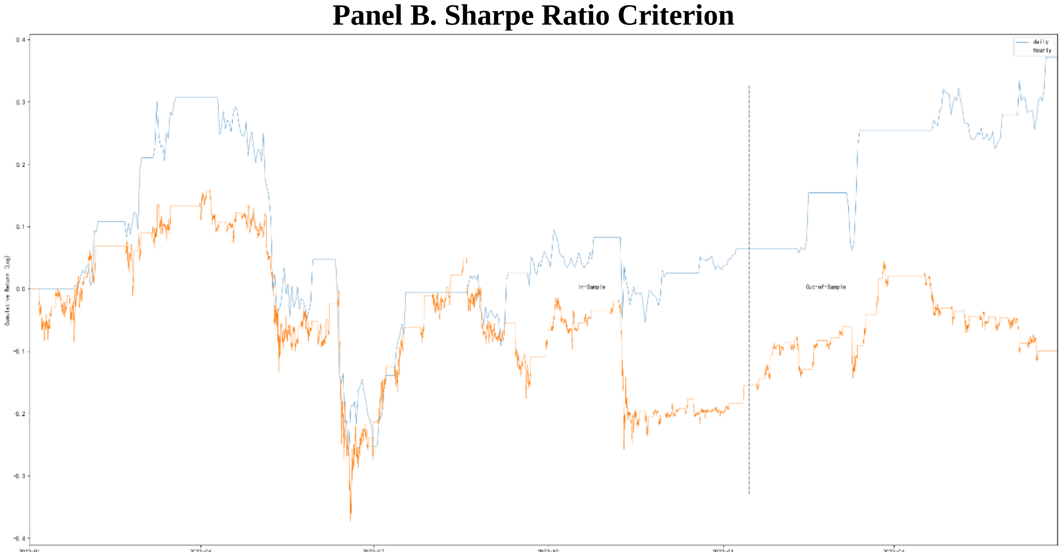


Table 6 shows the performance of the MACD strategy, analyzing its results in both the in-sample and out-of-sample periods. It specifically focuses on metrics such as the annualized return, Sharpe ratio, and maximum drawdown. As displayed in column (1), for instance, the best-performing MACD strategy with fast period of 10, slow period of 20, signal period of 6, sma period of 30, dir period of 10 as its parameters. This optimal strategy yields an annualized return of -8.445%, a Sharpe ratio of -0.233, and a maximum drawdown of 48.699%. It features a specific MACD strategy with its parameters and performance metrics, showcasing its lack of profitability in both the in-sample and out-of-sample periods. It emphasizes the necessity for a more reliable and sustainable approach to consistently generate returns. Lastly, the paragraph mentions the inclusion of a figure that displays the cumulative log returns of the best-performing technical trading strategies based on different trading data frequencies. Figure 7 shows the cumulative log returns of the best-performing technical trading strategies based on daily, and hourly trading data.

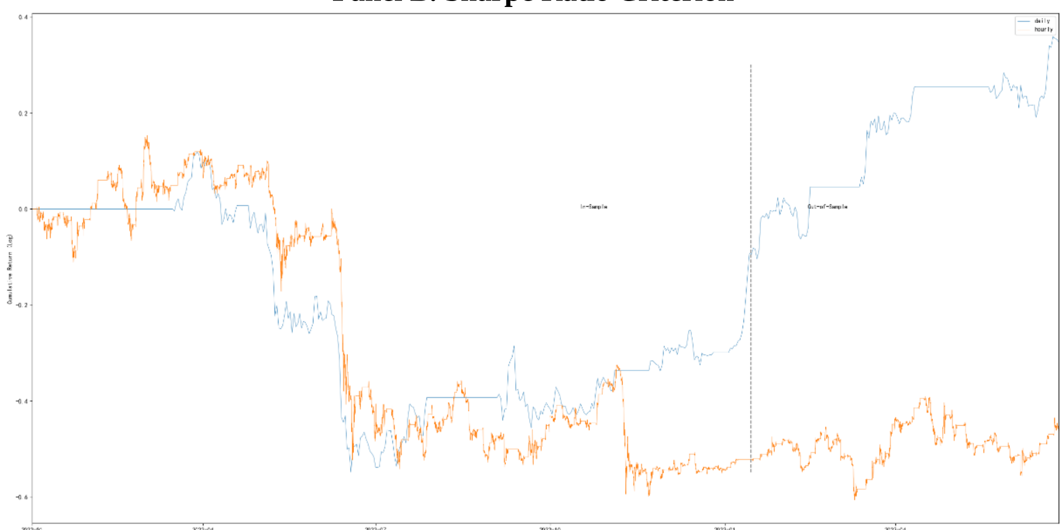
TABLE 6
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH MACD STRATEGIES - BTC/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	12	12	12	12
Best Strategy (In-Sample)				
Description	macd(10, 20, 6, 30, 10)	macd(10, 25, 6, 30, 10)	macd(10, 20, 6, 30, 10)	macd(10, 25, 6, 30, 10)
Annualized Return	-8.445%	-39.533%	-8.445%	-39.533%
Sharpe Ratio	-0.233	-1.148	-0.233	-1.148
Max Drawdown	48.699%	52.842%	48.699%	52.842%
P-Value (Nominal)	0.407	0.121	0.000	0.000
P-Value (Reality Check)	0.731	0.926	0.000	0.004
P-Value (Stepwise Check)	0.647	0.641	0.000	0.004
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	102.083%	45.594%	102.083%	45.594%
Sharpe Ratio	2.467	1.157	2.467	1.157
Max Drawdown	9.169%	15.884%	9.169%	15.884%
P-Value (Nominal)	0.051	0.431	0.000	0.000
P-Value (Reality Check)	0.040	0.560	0.000	0.004
P-Value (Stepwise Check)	0.041	0.558	0.000	0.004
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	12.000	11.000
Average Number / Number of Strategies	0.0%	0.0%	100.0%	91.667%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	8.008	0.000	12.000	11.000
Average Number / Number of Strategies (In-Sample)	66.733%	0.0%	100.0%	91.667%

FIGURE 7
PERFORMANCE OF THE BEST TECHNICAL TRADE MACD STRATEGY - BTC/USDT

Panel A. Annualized Return Criterion

Panel B. Sharpe Ratio Criterion



ETH/USDT

Profitability Over the Whole Sample

Table 7 presents the test results considering the whole sample period. The left and right panels are based on annualized return and Sharpe ratio as performance criteria, respectively. Within each panel, we have 2 columns for different groups of technical trading strategies based on daily, and hourly trading data we considered. We focus on two sets of indicators generated from the data snooping test: 1) performance metrics and associated p-values of the best strategy, and 2) the number of profitable strategies that produce significantly positive performance metrics. We use 5% as the nominal significance level of our tests. The "Description" row displays the best strategy based on daily, and hourly trading data. To make our results comparable to prior studies, we provide the nominal p-value generate from the simple individual test in the next row. In the next two rows, we report the p-values based on the reality check test and the stepwise test. For example, as shown in column (1), emac(28, 47) is the best-performing strategy. The parameters for the

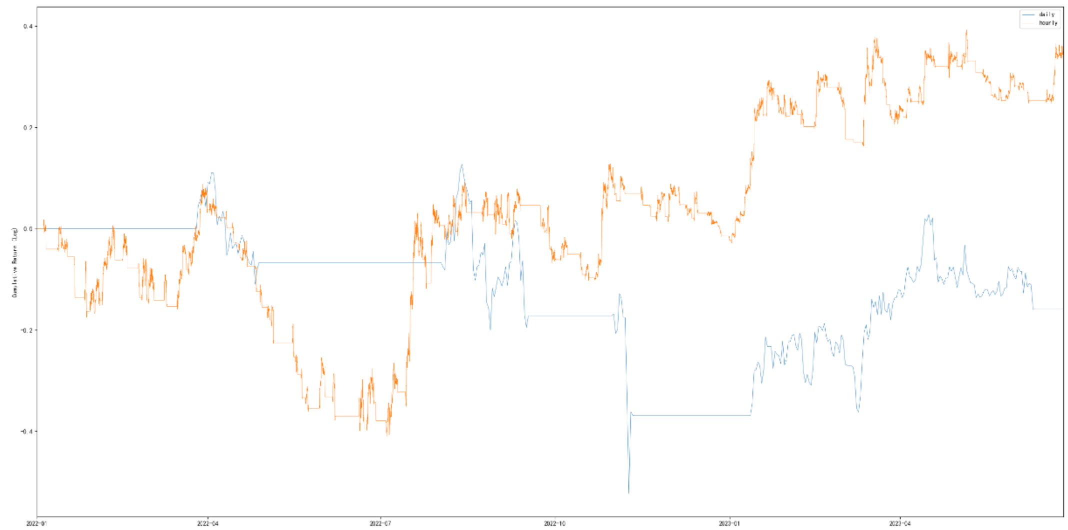
EMAC strategy are fast period of 28, slow period of 47, which generates an average annualized return of -10.184%, a Sharpe ratio of -0.228, and a maximum drawdown of 47.811%. A negative annualized return indicates that the strategy lacks profitability and may need revision. Figure 8 shows the cumulative log returns of the best-performing technical trading strategies based on daily, and hourly trading data.

TABLE 7
THE PERFORMANCE OF TECHNICAL TRADE STRATEGIES IN THE WHOLE SAMPLE - ETH/USDT

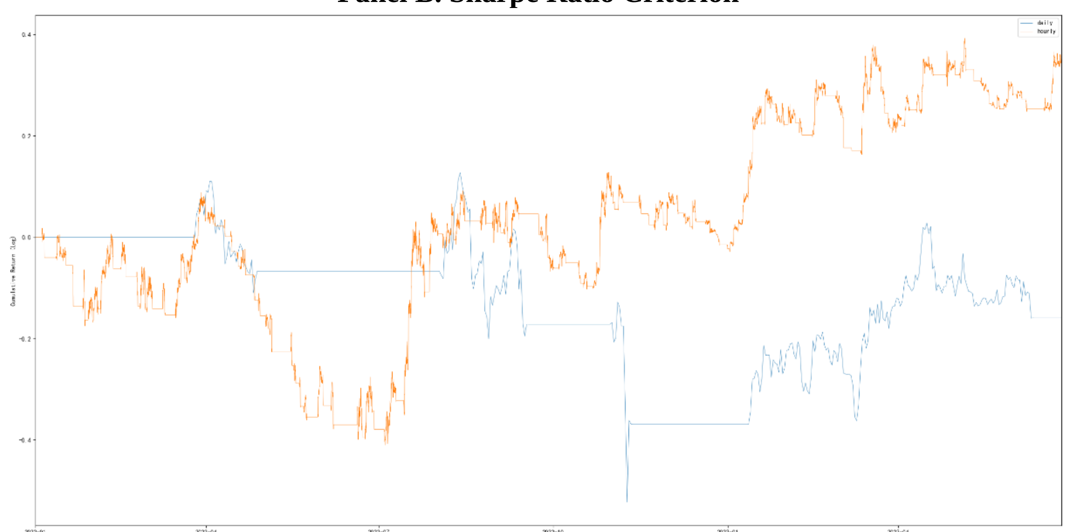
Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	217	217	217	217
Best Strategy				
Description	emac(28, 47)	emac(18, 56)	emac(28, 47)	emac(18, 56)
Annualized Return	-10.184%	26.135%	-10.184%	26.135%
Sharpe Ratio	-0.228	0.503	-0.228	0.503
Max Drawdown	47.811%	39.254%	47.811%	39.254%
P-Value (Nominal)	0.391	0.270	0.000	0.000
P-Value (Reality Check)	0.986	0.820	1.000	1.000
P-Value (Stepwise Check)	0.951	0.791	0.987	0.864
All Profitable Strategies (500 Tests)				
Minimum Number	0	0	7	2
Maximum Number	0	0	7	3
Average Number	0.000	0.000	7.000	2.964
Average Number / Number of Strategies	0.0%	0.0%	3.226%	1.366%

FIGURE 8
PERFORMANCE OF THE BEST TECHNICAL TRADE STRATEGY IN THE WHOLE SAMPLE - ETH/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion



Profitability in In-Sample and Out-of-Sample Periods

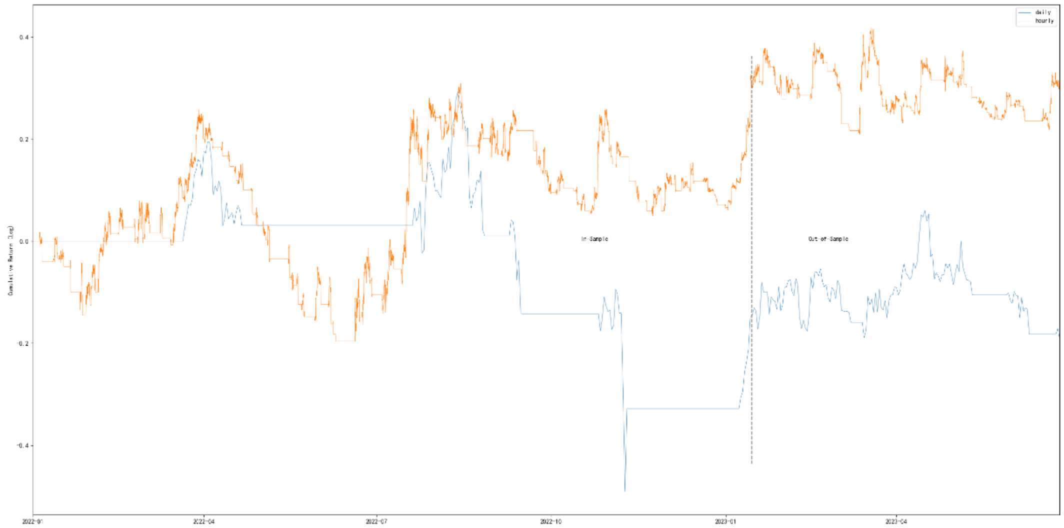
Table 8 presents the test results and performance evaluation of the EMAC strategy for trading the ETH-USDT pair. It provides a detailed description of the panel presentations and the results obtained from different performance criteria and tests. We highlight the details of the best strategy, specifically the EMAC strategy with parameters of a fast period of 10 and a slow period of 41. This strategy has an annualized return of -13.264%, a Sharpe ratio of -0.295, and a maximum drawdown of 54.335%. The strategy does not exhibit outstanding performance in either the in-sample or out-of-sample period. In the in-sample period, its average annualized return is not statistically significant and fails to reject the null hypothesis. Similarly, in the out-of-sample period, the strategy fails to generate significant profits, with an annualized return of 3.782% that also fails to reject the null hypothesis. Figure 9 shows the cumulative log returns of the best-performing technical trading strategies based on daily and hourly trading data. This visual representation provides additional insights into the performance of the strategies.

TABLE 8
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH EMAC STRATEGIES - ETH/USDT

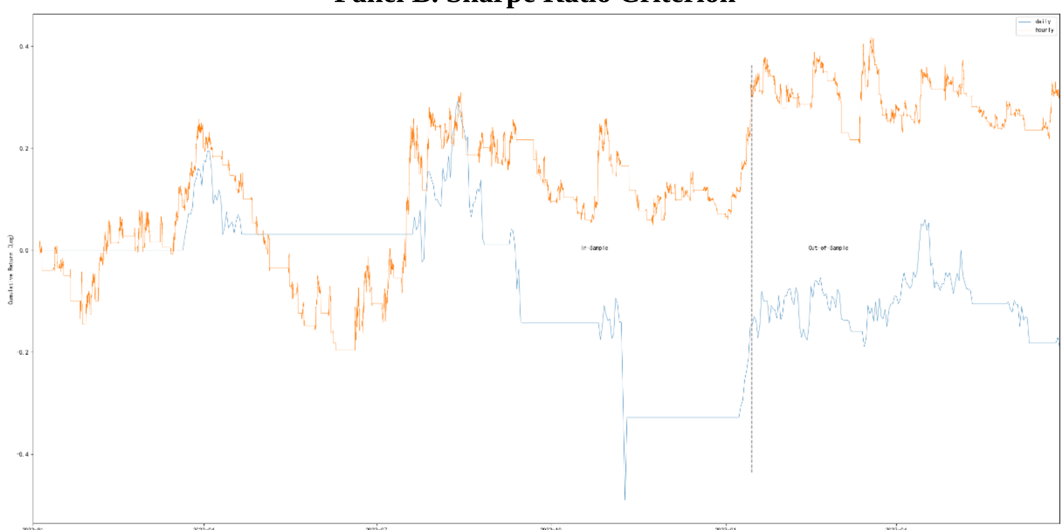
Performance Metric	Annualized Return		Sharpe Ratio	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	90	90	90	90
Best Strategy (In-Sample)				
Description	emac(10, 41)	emac(10, 59)	emac(10, 41)	emac(10, 59)
Annualized Return	-13.264%	34.096%	-13.264%	34.096%
Sharpe Ratio	-0.295	0.592	-0.295	0.592
Max Drawdown	54.335%	36.478%	54.335%	36.478%
P-Value (Nominal)	0.382	0.273	0.001	0.000
P-Value (Reality Check)	0.830	0.481	0.004	0.774
P-Value (Stepwise Check)	0.708	0.464	0.012	0.666
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	3.782%	49.318%	3.782%	49.318%
Sharpe Ratio	0.112	1.092	0.112	1.092
Max Drawdown	19.45%	14.013%	19.45%	14.013%
P-Value (Nominal)	0.493	0.475	0.000	0.010
P-Value (Reality Check)	0.642	0.695	0.004	0.774
P-Value (Stepwise Check)	0.630	0.672	0.012	0.666
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	57.996	36.114
Average Number / Number of Strategies	0.0%	0.0%	64.44%	40.127%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	0.000	0.000	57.996	36.114
Average Number / Number of Strategies (In-Sample)	0.0%	0.0%	64.44%	40.127%

FIGURE 9
PERFORMANCE OF THE BEST TECHNICAL TRADE EMAC STRATEGY - ETH/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion



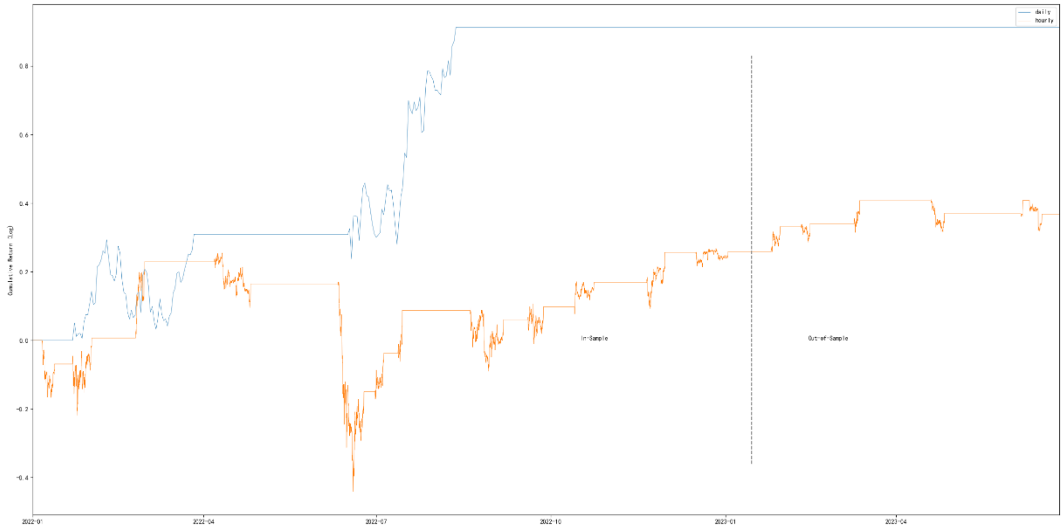
The assessment results for the Relative Strength Index (RSI) strategy within and outside the organization are displayed in Table 9. For instance, in column (1), the top-rated RSI strategy with an RSI duration of 14, RSI superior of 70, and RSI inferior of 20 as its parameters yields a standardized gain of 140.785%, a Sharpe measure of 1.757, and a maximum intensity index reduction of 23.022%. However, this strategy does not demonstrate exceptional performance within the organization as its average standardized gain is insignificant and does not reject the null hypothesis. Moreover, it fails to generate profits in the subsequent out-of-office period, with an insignificant standardized gain of 202.397% that does not reject the null hypothesis. Ultimately, the strategy proves ineffective in generating profits within the organization and outside the office, suggesting a lack of effectiveness. Figure 10 illustrates the cumulative logarithmic returns of the top-rated technical trading strategies based on daily and hourly trading data.

TABLE 9
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH RSI STRATEGIES - ETH/USDT

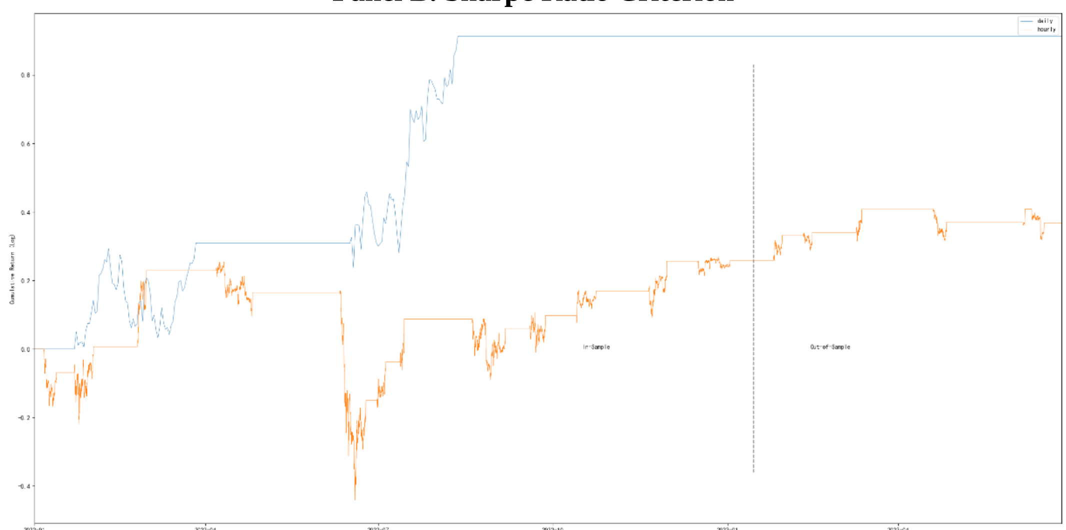
Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	100	100	100	100
Best Strategy (In-Sample)				
Description	rsi(14, 70, 20)	rsi(14, 74, 20)	rsi(14, 70, 20)	rsi(14, 74, 20)
Annualized Return	140.785%	28.181%	140.785%	28.181%
Sharpe Ratio	1.757	0.474	1.757	0.474
Max Drawdown	23.022%	50.152%	23.022%	50.152%
P-Value (Nominal)	0.037	0.314	0.000	0.000
P-Value (Reality Check)	0.261	0.719		0.000
P-Value (Stepwise Check)	0.088	0.682		0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	202.397%	290.384%	202.397%	290.384%
Sharpe Ratio	3.855	3.436	3.855	3.436
Max Drawdown	5.4%	13.39%	5.4%	13.39%
P-Value (Nominal)		0.226		0.000
P-Value (Reality Check)		0.730		0.000
P-Value (Stepwise Check)		0.607		0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.010	0.000		98.000
Average Number / Number of Strategies		0.0%		98.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number		0.000		98.000
Average Number / Number of Strategies (In-Sample)		0.0%		98.0%

FIGURE 10
PERFORMANCE OF THE BEST TECHNICAL TRADE RSI STRATEGY - ETH/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion



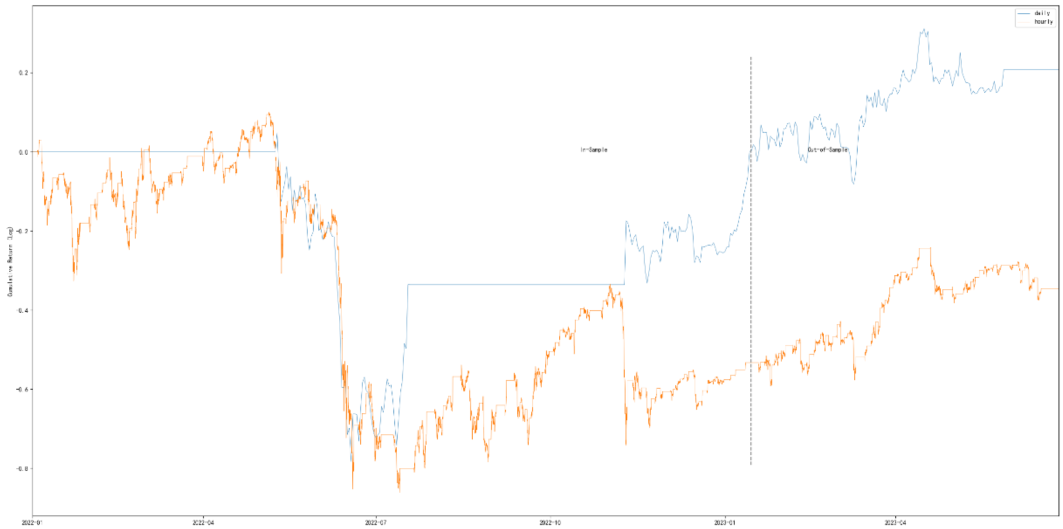
The results of examining the performance of the Bollinger Bands tactic are discussed in Table 10. The evaluation of performance is conducted in both in-sample and out-of-sample timeframes to assess the effectiveness of the tactic. Two critical factors, namely the annualized return and the Sharpe ratio, are used to measure success. These performance indicators provide a comprehensive understanding of the profitability and risk-adjusted performance of the tactic. We highlight the performance metrics of the Bollinger Bands plan with parameters set at a period of 18 and a devfactor of 3. This specific configuration of the tactic outperforms all other tactics considered in our study. It achieves an annualized gain of 0.055%, a Sharpe ratio of 0.001, and a maximum decline of 56.461%. However, despite these promising performance metrics, further analysis reveals that this tactic fails to generate substantial profits both in the in-sample and out-of-sample timeframes. The mean annualized gain of the Bollinger Bands plan is negligible in the in-sample timeframe, providing insufficient statistically significant evidence to reject the null hypothesis. Similarly, in the subsequent out-of-sample timeframe, the annualized gain of the tactic is 103.933%, which is not significant enough to refute the null hypothesis. These findings indicate a lack of effectiveness in the approach and suggest the need for alternative trading tactics. We plot the cumulative log returns of the best-performing technical trading strategies based on daily, and hourly trading data in Figure 11.

TABLE 10
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH BOLLINGER BANDS STRATEGIES - ETH/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	15	15	15	15
Best Strategy (In-Sample)				
Description	bbands(18, 3)	bbands(27, 2)	bbands(18, 3)	bbands(27, 2)
Annualized Return	0.055%	-40.161%	0.055%	-40.161%
Sharpe Ratio	0.001	-0.766	0.001	-0.766
Max Drawdown	56.461%	61.756%	56.461%	61.756%
P-Value (Nominal)	0.500	0.218	0.000	0.000
P-Value (Reality Check)	0.749	0.949		0.012
P-Value (Stepwise Check)	0.749	0.753		0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	103.933%	70.129%	103.933%	70.129%
Sharpe Ratio	2.406	1.553	2.406	1.553
Max Drawdown	9.855%	14.144%	9.855%	14.144%
P-Value (Nominal)		0.208		0.000
P-Value (Reality Check)		0.444		0.012
P-Value (Stepwise Check)		0.481		0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000		9.000
Average Number / Number of Strategies		0.0%		60.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number		0.000		9.000
Average Number / Number of Strategies (In-Sample)		0.0%		60.0%

FIGURE 11
PERFORMANCE OF THE BEST TECHNICAL TRADE BOLLINGER BANDS STRATEGY - ETH/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion

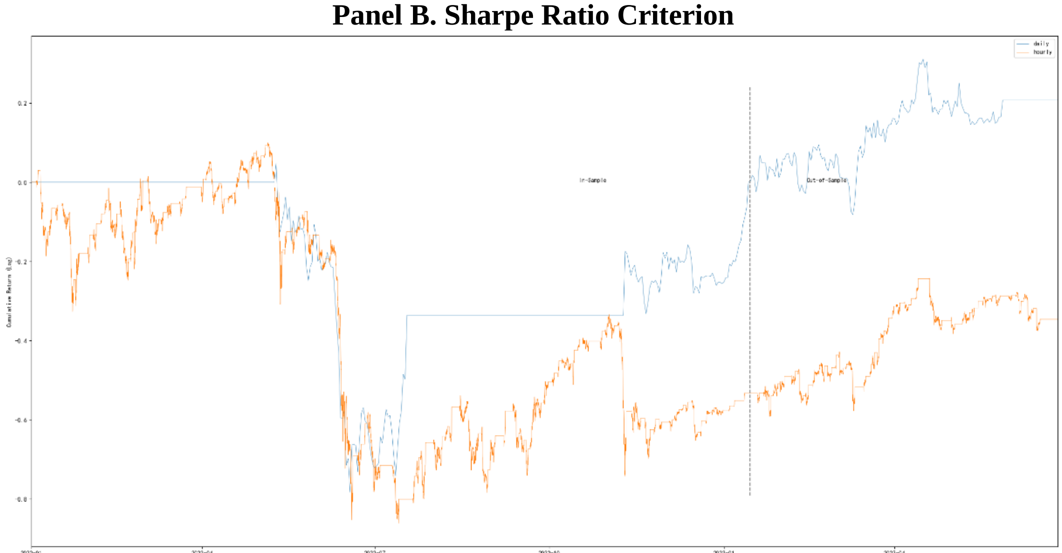


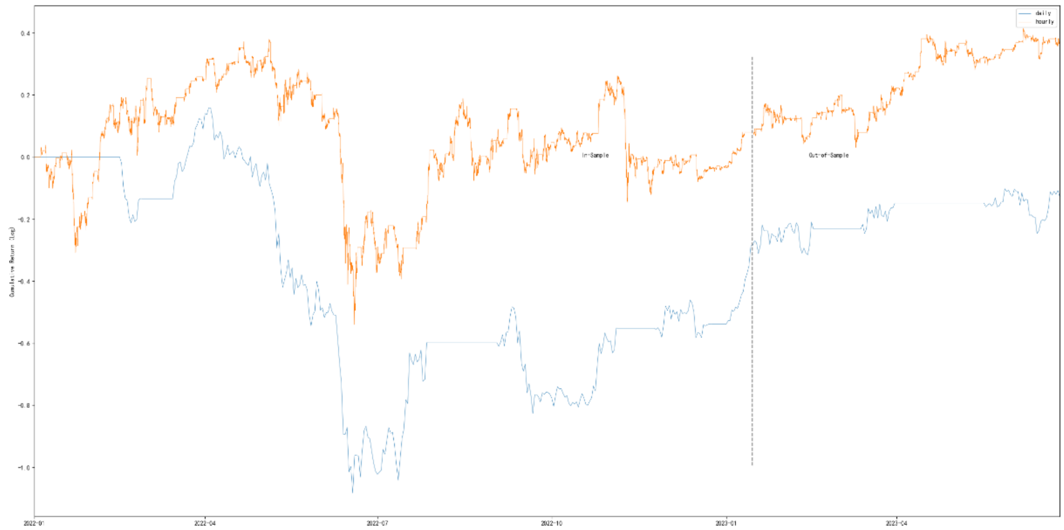
Table 11 presents the test results for the MACD strategy, analyzed both in-sample and out-of-sample. The left and right panels are based on annualized return and Sharpe ratio as performance criteria, respectively. As displayed in column (1), for instance, the best-performing MACD strategy with fast period of 10, slow period of 20, signal period of 6, sma period of 30, dir period of 10 as its parameters. This optimal strategy yields an annualized return of -24.076%, a Sharpe ratio of -0.413, and a maximum drawdown of 71.128%. The strategy does not have outstanding performance in the in-sample period as its average annualized return is insignificant and can not reject the null hypothesis. Moreover, it also fails to generate profits in the next out-of-sample period, with an insignificant annualized return of 40.642% that fails to reject the null hypothesis. The strategy fails to generate profits in both the in-sample and out-of-sample periods, indicating a lack of effectiveness in the approach. The result of the cumulative log returns of the best-performing technical trading strategies based on daily, and hourly trading data is given in Figure 12.

TABLE 11
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH MACD STRATEGIES - ETH/USDT

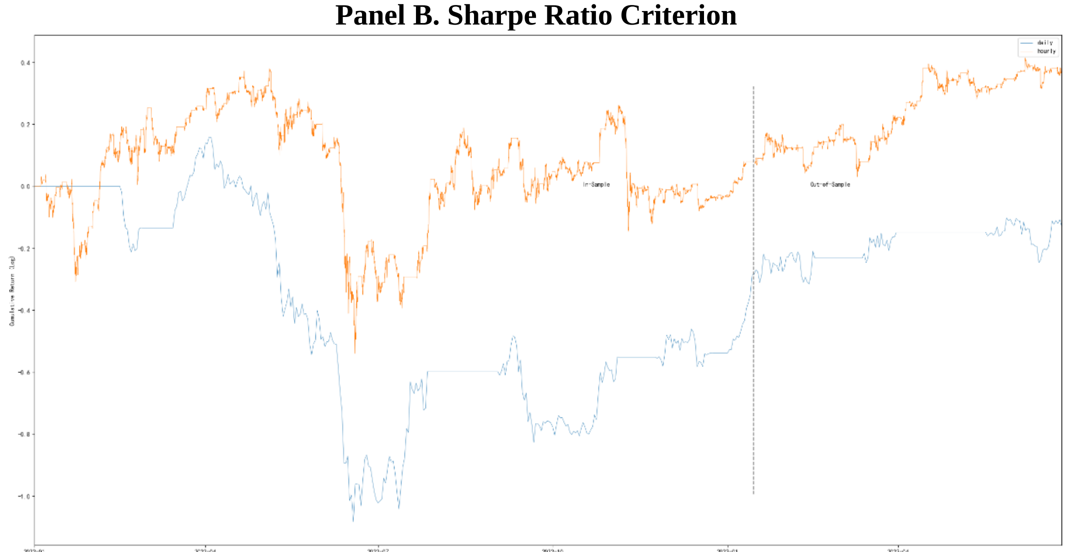
Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	12	12	12	12
Best Strategy (In-Sample)				
Description	macd(10, 20, 6, 30, 10)	macd(10, 25, 10, 30, 10)	macd(10, 20, 6, 30, 10)	macd(10, 25, 10, 30, 10)
Annualized Return	-24.076%	8.052%	-24.076%	8.052%
Sharpe Ratio	-0.413	0.110	-0.413	0.110
Max Drawdown	71.128%	60.117%	71.128%	60.117%
P-Value (Nominal)	0.337	0.455	0.000	0.000
P-Value (Reality Check)	0.728	0.580	0.001	0.000
P-Value (Stepwise Check)	0.607	0.579	0.000	0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	40.642%	86.392%	40.642%	86.392%
Sharpe Ratio	1.175	1.540	1.175	1.540
Max Drawdown	13.366%	15.679%	13.366%	15.679%
P-Value (Nominal)	0.293	0.152	0.000	0.000
P-Value (Reality Check)	0.335	0.203	0.001	0.000
P-Value (Stepwise Check)	0.280	0.232	0.000	0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	12.000	7.000
Average Number / Number of Strategies	0.0%	0.0%	100.0%	58.333%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	0.000	0.000	12.000	7.000
Average Number / Number of Strategies (In-Sample)	0.0%	0.0%	100.0%	58.333%

FIGURE 12
PERFORMANCE OF THE BEST TECHNICAL TRADE MACD STRATEGY - ETH/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion



ROBUSTNESS CHECKS

In this section, we present the results of a series of robustness checks aimed at reinforcing the analysis conducted on the effectiveness of the cryptocurrency market. One aspect that has come under scrutiny is the selection of Jan 14, 2023, as the dividing point for our analysis. Questions have been raised suggesting that the obtained findings might be coincidental rather than genuine indications of market effectiveness. To address this concern and ensure the durability of our research, we meticulously performed additional checks using Nov 21, 2022, and Mar 09, 2023, as the dividing points for our in-sample and out-of-sample periods, respectively. The outcomes of these supplementary examinations are presented in the Appendix.

The findings derived from these robustness checks consistently align with the initial results obtained using Jan 14, 2023, as the dividing point. This alignment confirms and strengthens our previous conclusion regarding the effectiveness of the digital currency market. The supplementary evidence provided through this subsequent analysis significantly enhances the validity, reliability, and overall credibility of our research findings. The inclusion of these additional results reinforces our confidence in the accuracy and durability of our conclusions. By addressing doubts about chance and confirming the consistency of our findings across different dividing points, we establish a solid foundation for our research and emphasize the importance of our study in understanding the efficacy of the digital currency market.

CONCLUSION

In this paper, we utilize comprehensive data on the cryptocurrency pair BTC/USDT and ETH/USDT, spanning from January 2022 to June 2023, to investigate the profitability of various technical trading strategies. We employ different indicator selections and time resolutions to develop a range of technical trading methodologies. By analyzing the examined and unexamined time periods, we establish statistically significant conclusions regarding the lack of profitability observed in these methodologies. To mitigate the data-snooping bias, we employ a cutoff date of January 2023. Notably, our findings remain robust when considering different performance measures and using November 21, 2022, and March 09, 2023 as the boundaries for the in-sample and out-of-sample periods.

In the field of finance, a significant challenge for traders is the careful selection of a technical trading approach that can generate profits using historical data. This task becomes more complex when traders seek strategies that can consistently produce positive outcomes in future periods not encompassed in the available data sample. The issue lies in the fact that while certain technically-driven trading strategies may exhibit profitability across the entire dataset under examination, it is highly likely that these favorable results are primarily attributed to the deliberate choice of parameters rather than the identification of market inefficiencies.

Consequently, the primary contribution of this research is its support for the efficient market hypothesis within the cryptocurrency market. This implies that the information contained within historical data is generally priced efficiently into the market, leaving limited opportunities for traders to consistently exploit market inefficiencies and generate superior returns. In other words, traders may retrospectively discover profitable technical trading strategies through backtesting, but accurately predicting and implementing these strategies in advance, when they are still unknown, proves to be a challenging endeavor.

In summary, this analysis illuminates the difficulties faced by traders in the selection of effective trading approaches and reaffirms the notion that the cryptocurrency market operates efficiently. The findings of this research suggest that traders should exercise caution when making trading decisions solely based on historical data and technical indicators.

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APPENDIX

FIGURE A1
PERFORMANCE OF THE BEST TECHNICAL TRADE EMAC STRATEGY AND NOV 2022 AS THE CUTOFF - BTC/USDT

Panel A. Annualized Return Criterion

Panel B. Sharpe Ratio Criterion

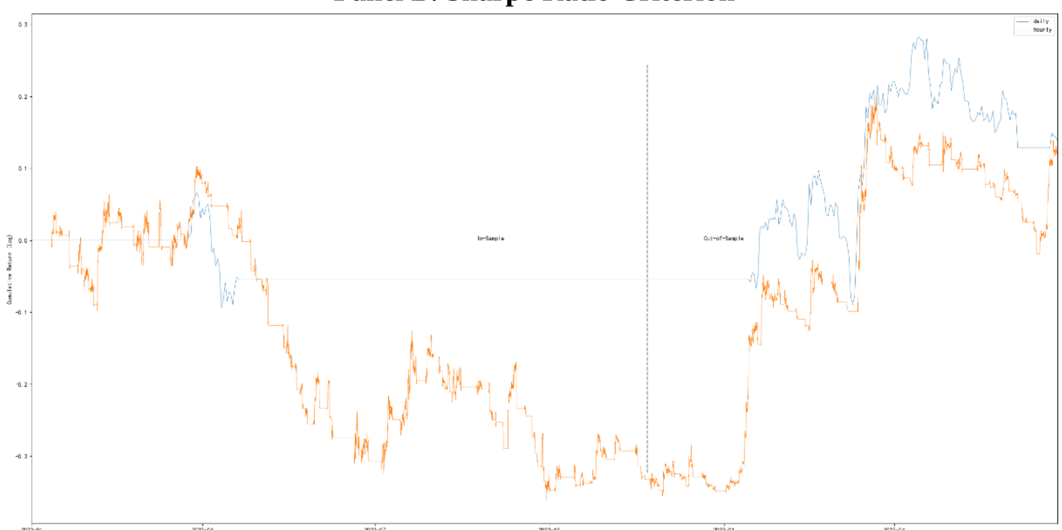


FIGURE A2
PERFORMANCE OF THE BEST TECHNICAL TRADE RSI STRATEGY AND NOV 2022 AS THE CUTOFF - BTC/USDT

Panel A. Annualized Return Criterion

Panel B. Sharpe Ratio Criterion

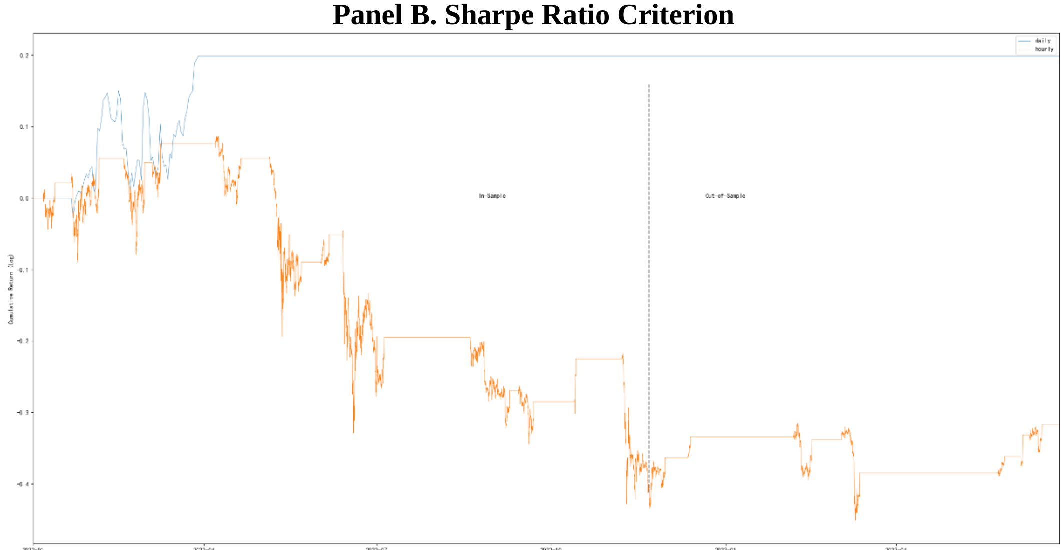
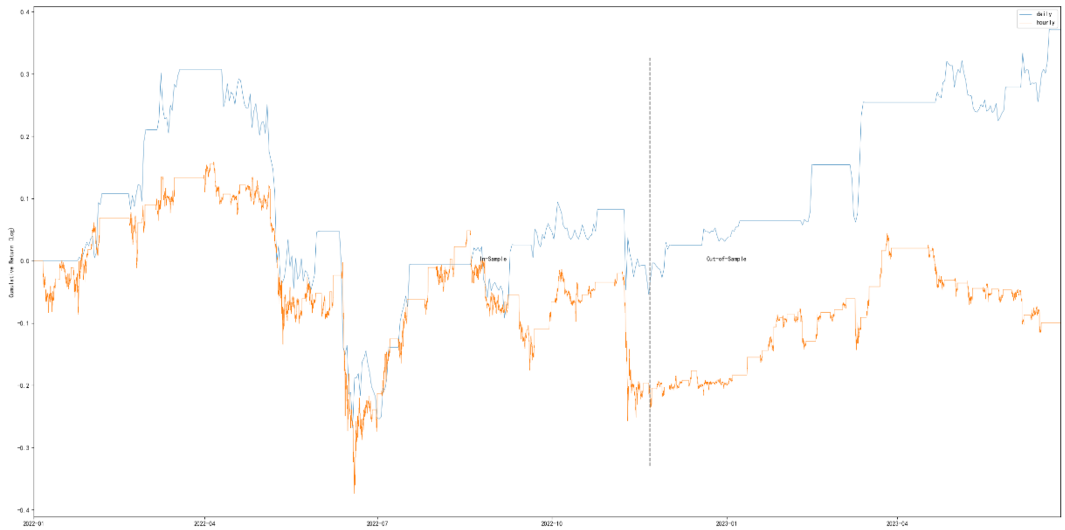


FIGURE A3
PERFORMANCE OF THE BEST TECHNICAL TRADE BOLLINGER BANDS STRATEGY AND NOV 2022 AS THE CUTOFF - BTC/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion

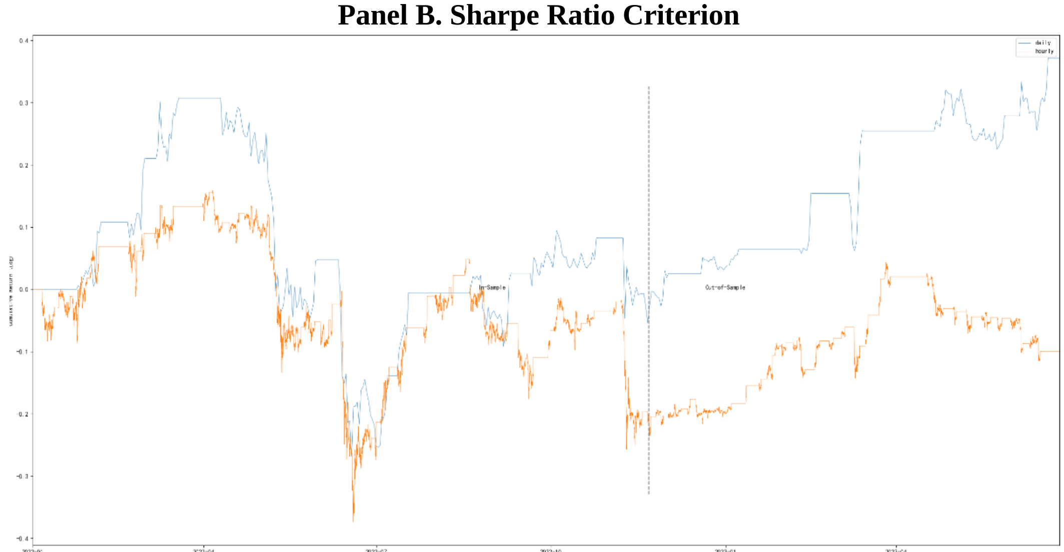
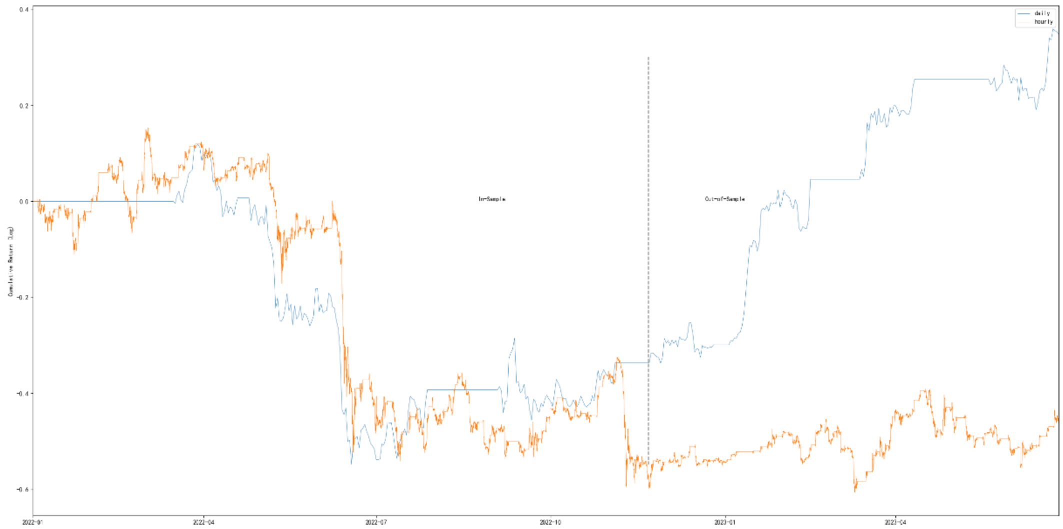


FIGURE A4
PERFORMANCE OF THE BEST TECHNICAL TRADE MACD STRATEGY AND NOV 2022 AS THE CUTOFF - BTC/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion

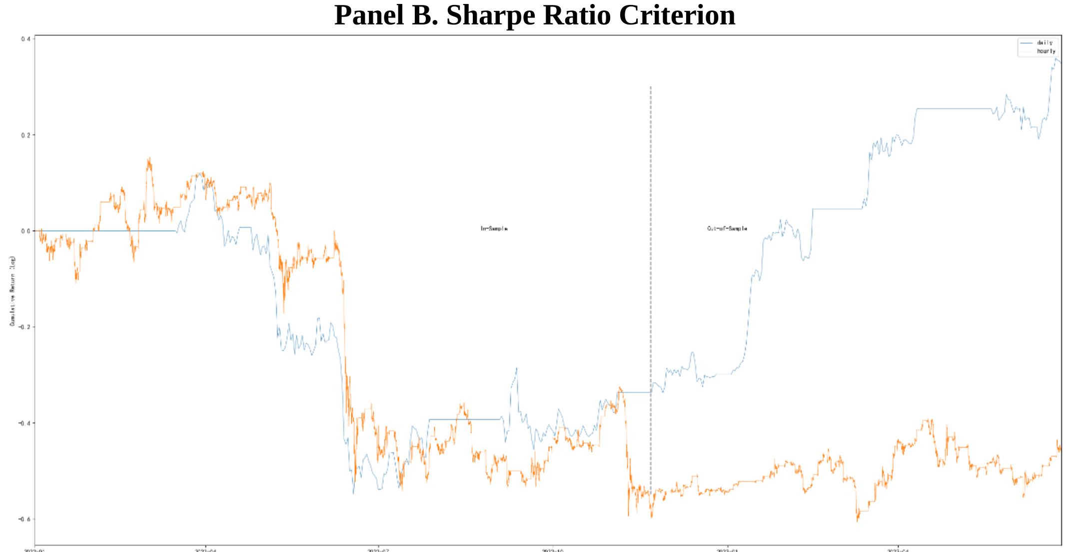


FIGURE A5
PERFORMANCE OF THE BEST TECHNICAL TRADE EMAC STRATEGY AND MAR 2023 AS THE CUTOFF - BTC/USDT

Panel A. Annualized Return Criterion

Panel B. Sharpe Ratio Criterion

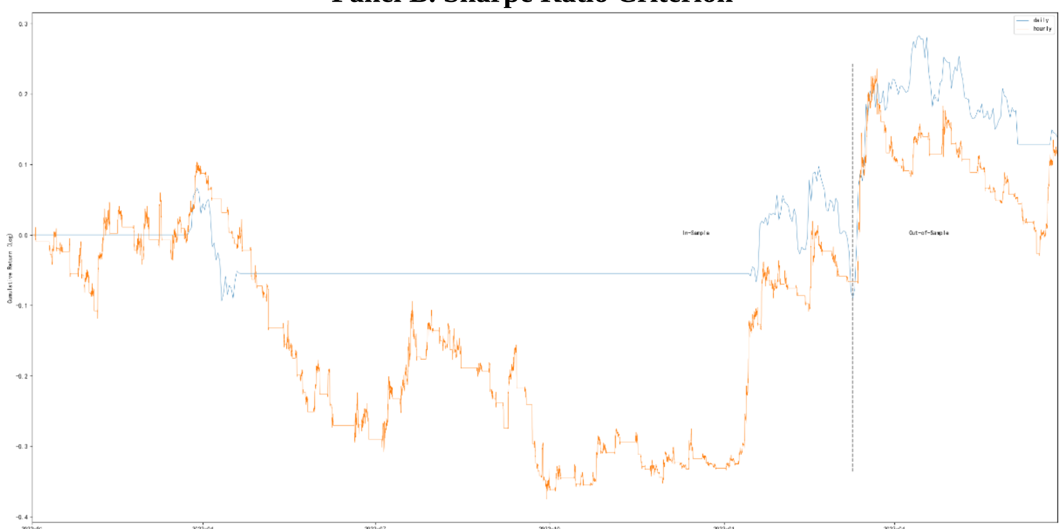


FIGURE A6
PERFORMANCE OF THE BEST TECHNICAL TRADE RSI STRATEGY AND MAR 2023 AS THE CUTOFF - BTC/USDT

Panel A. Annualized Return Criterion

Panel B. Sharpe Ratio Criterion

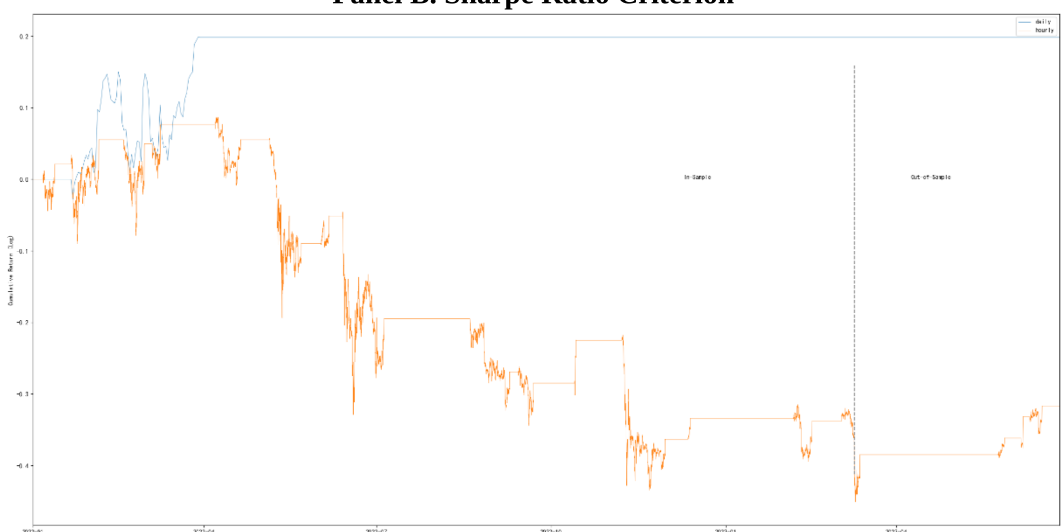
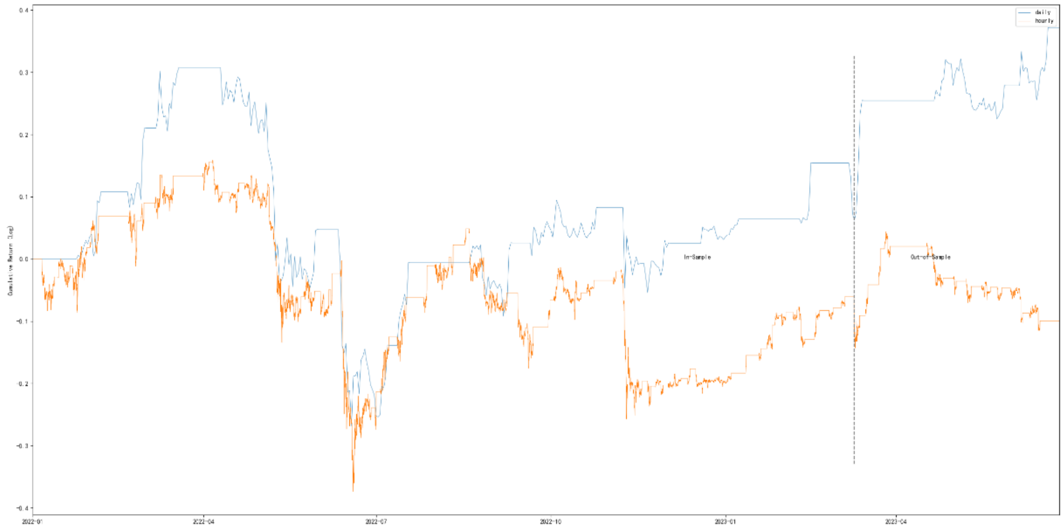


FIGURE A7
PERFORMANCE OF THE BEST TECHNICAL TRADE BOLLINGER BANDS STRATEGY AND MAR 2023 AS THE CUTOFF - BTC/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion

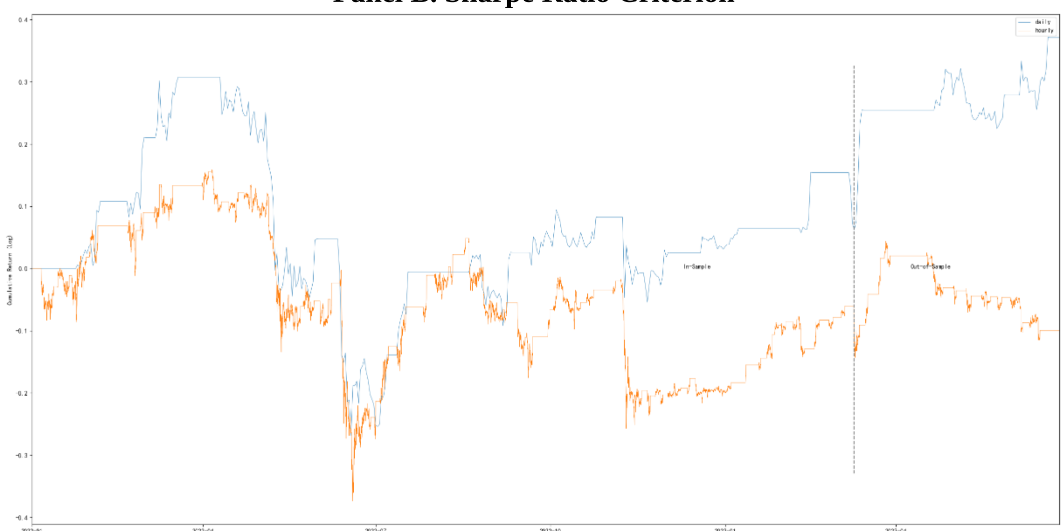
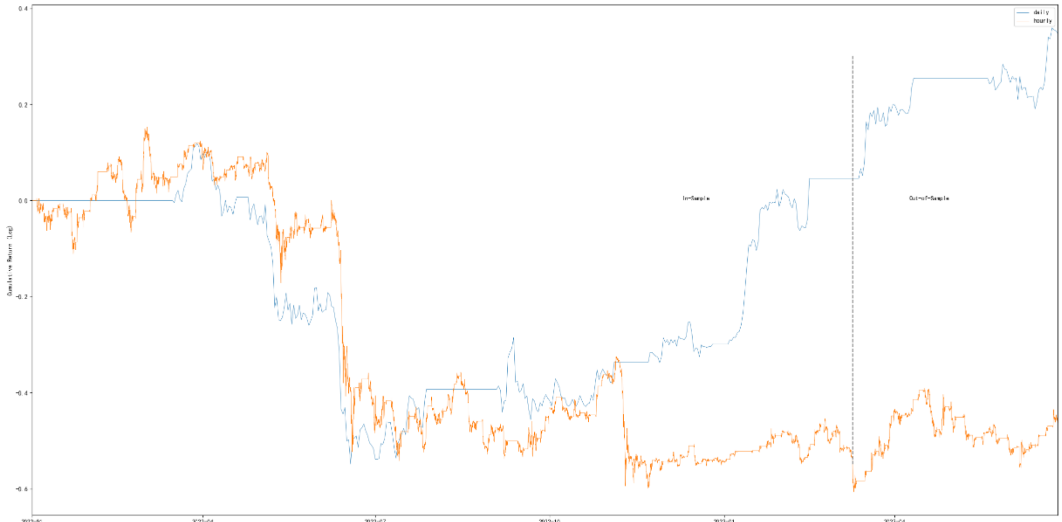


FIGURE A8
PERFORMANCE OF THE BEST TECHNICAL TRADE MACD STRATEGY AND MAR 2023 AS THE CUTOFF - BTC/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion

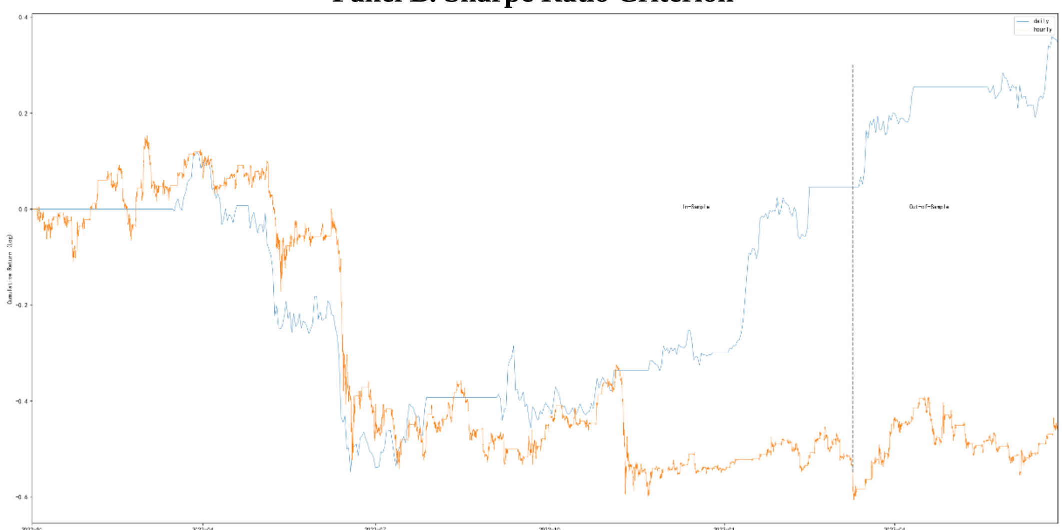
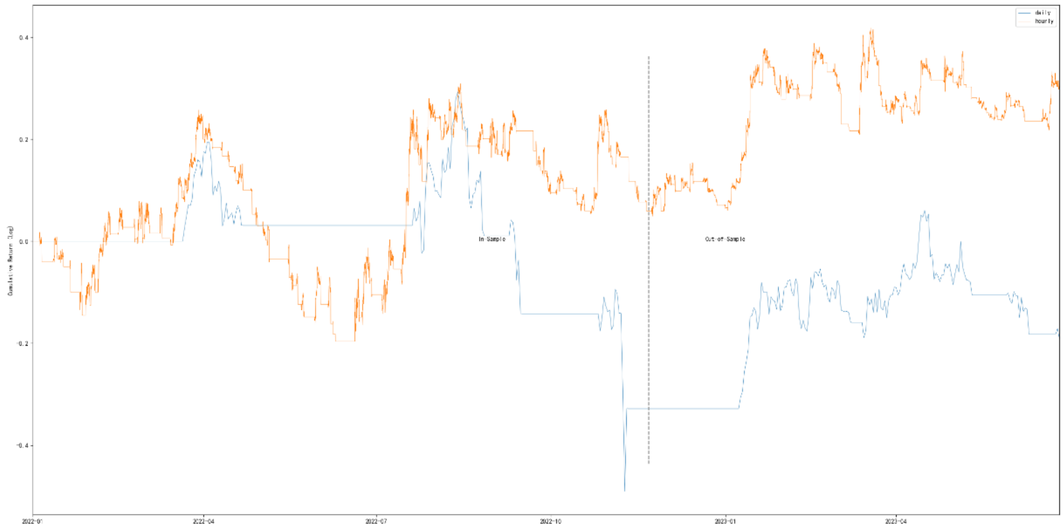


FIGURE A9
PERFORMANCE OF THE BEST TECHNICAL TRADE EMAC STRATEGY AND NOV 2022 AS THE CUTOFF - ETH/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion

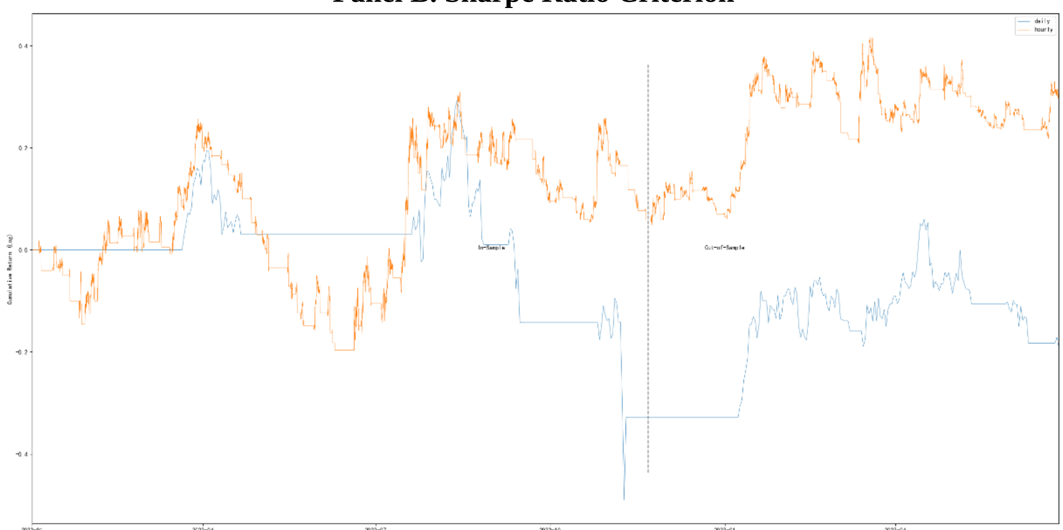
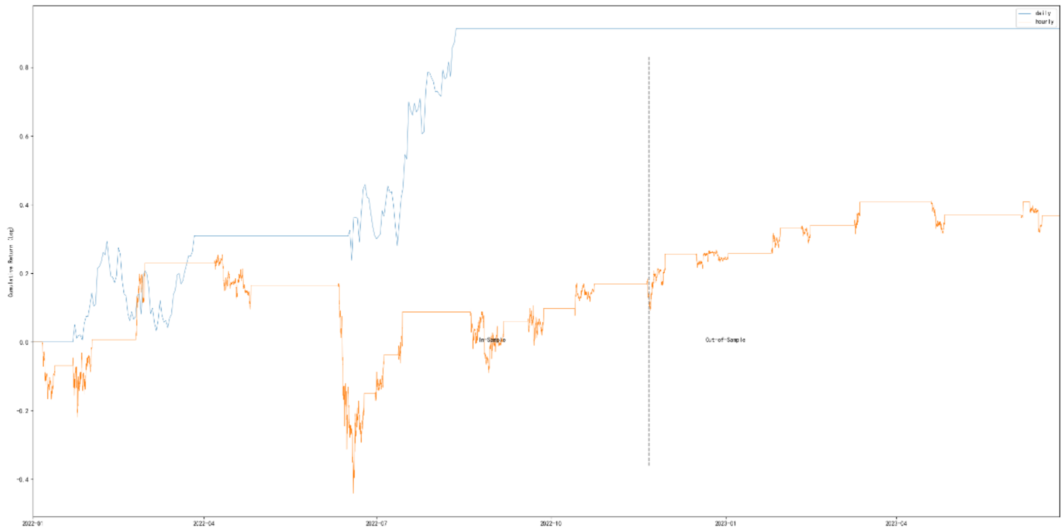


FIGURE A10
PERFORMANCE OF THE BEST TECHNICAL TRADE RSI STRATEGY AND NOV 2022 AS THE CUTOFF - ETH/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion

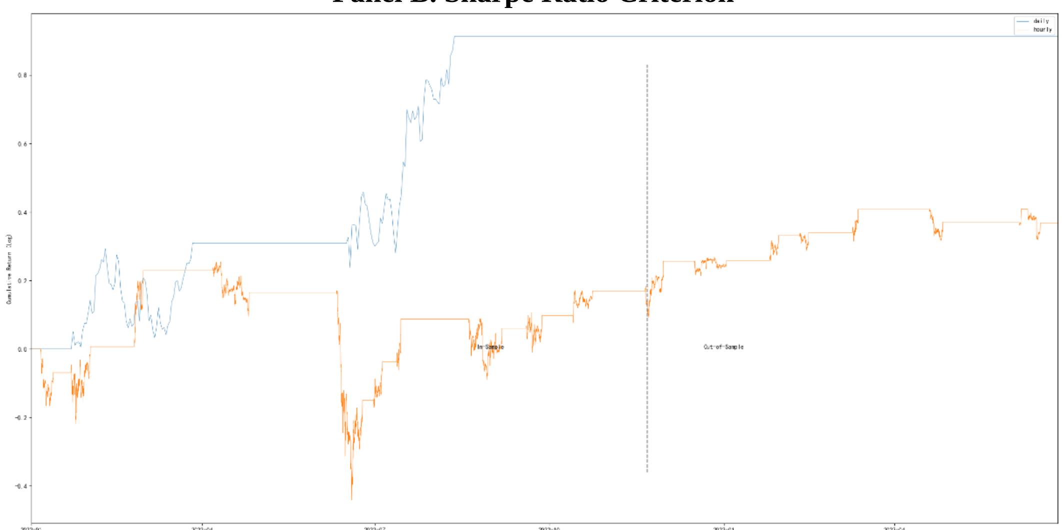
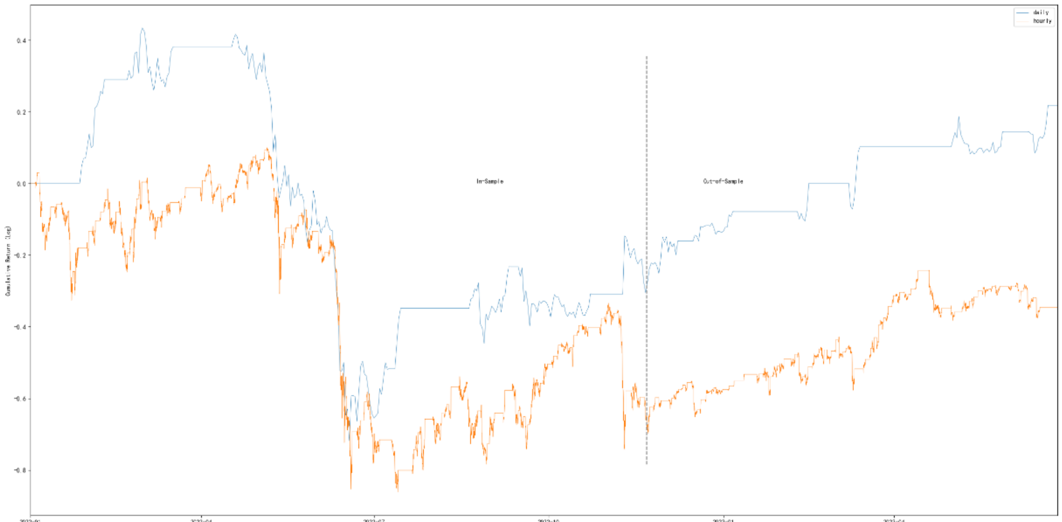


FIGURE A11
PERFORMANCE OF THE BEST TECHNICAL TRADE BOLLINGER BANDS STRATEGY AND NOV 2022 AS THE CUTOFF - ETH/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion

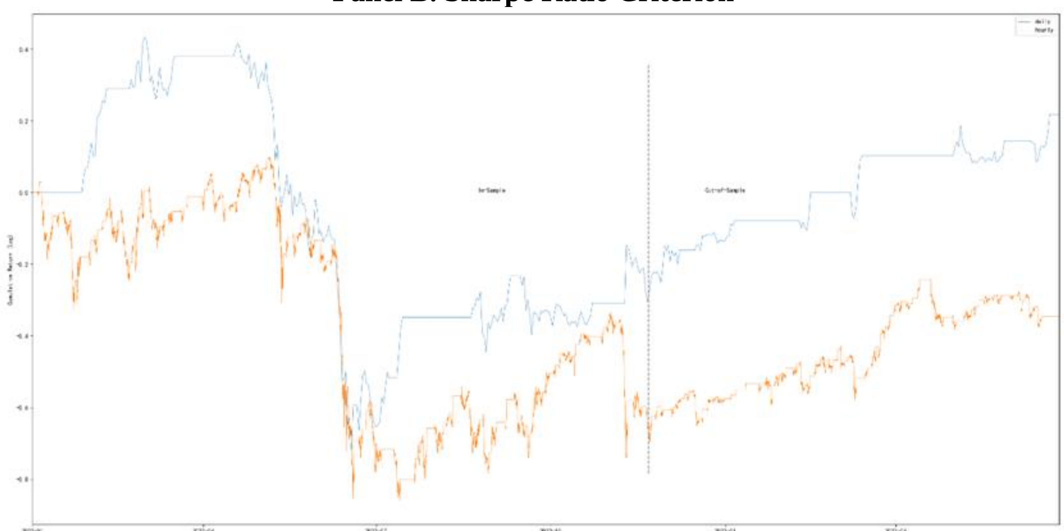
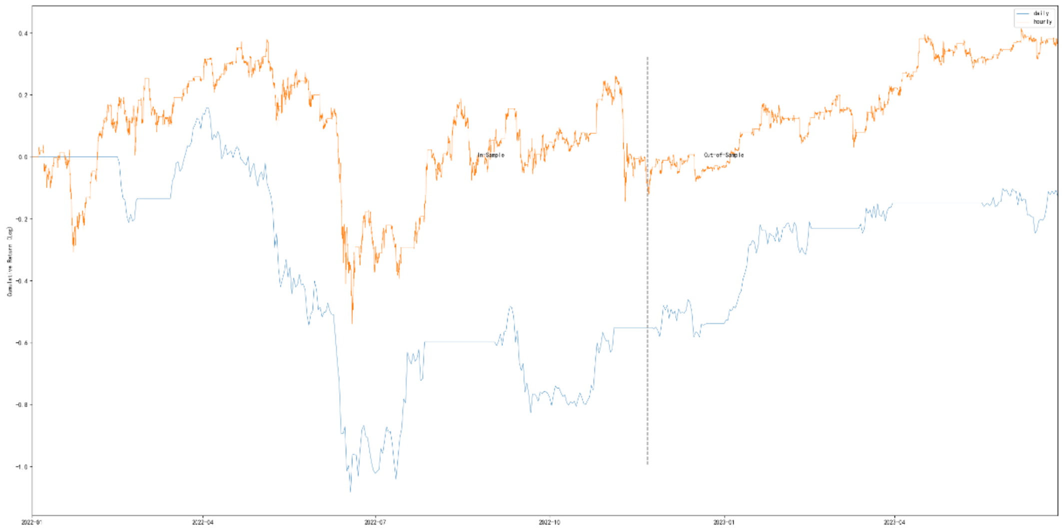


FIGURE A12
PERFORMANCE OF THE BEST TECHNICAL TRADE MACD STRATEGY AND NOV 2022 AS THE CUTOFF - ETH/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion

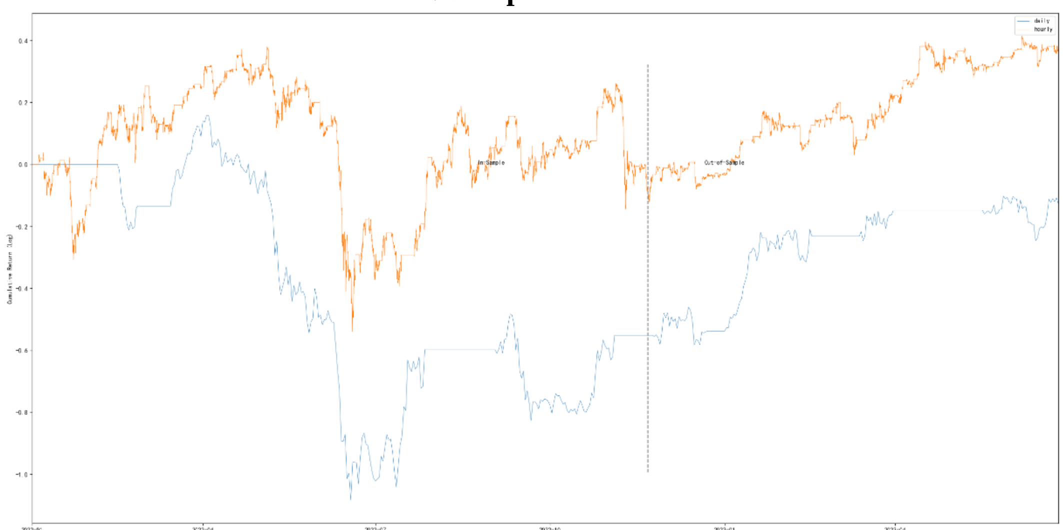
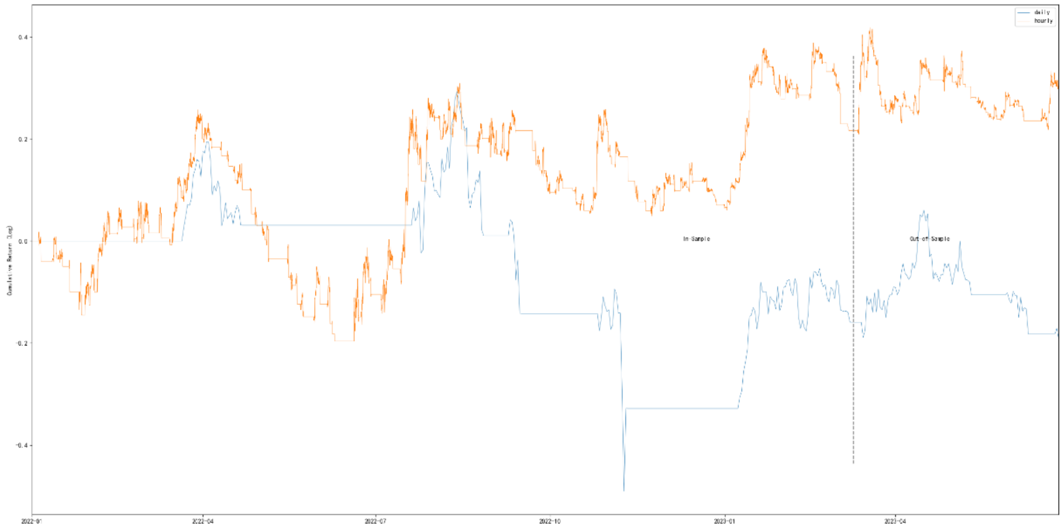


FIGURE A13
PERFORMANCE OF THE BEST TECHNICAL TRADE EMAC STRATEGY AND MAR 2023 AS THE CUTOFF - ETH/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion

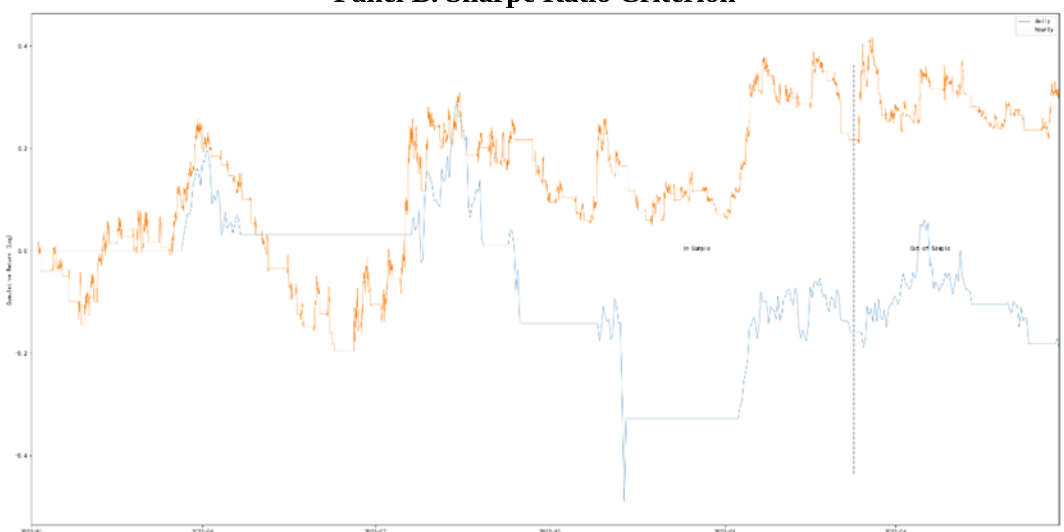
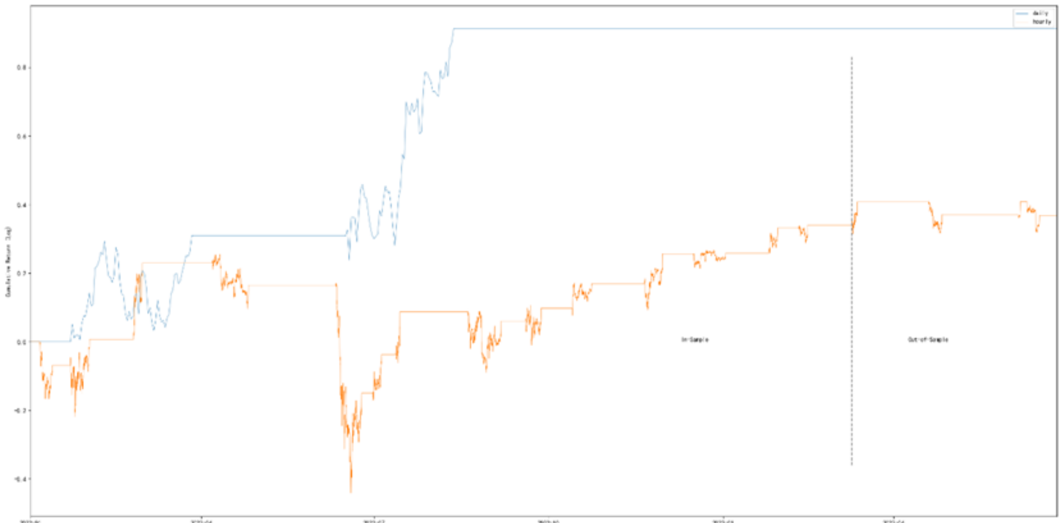


FIGURE A14
PERFORMANCE OF THE BEST TECHNICAL TRADE RSI STRATEGY AND MAR 2023 AS THE CUTOFF - ETH/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion

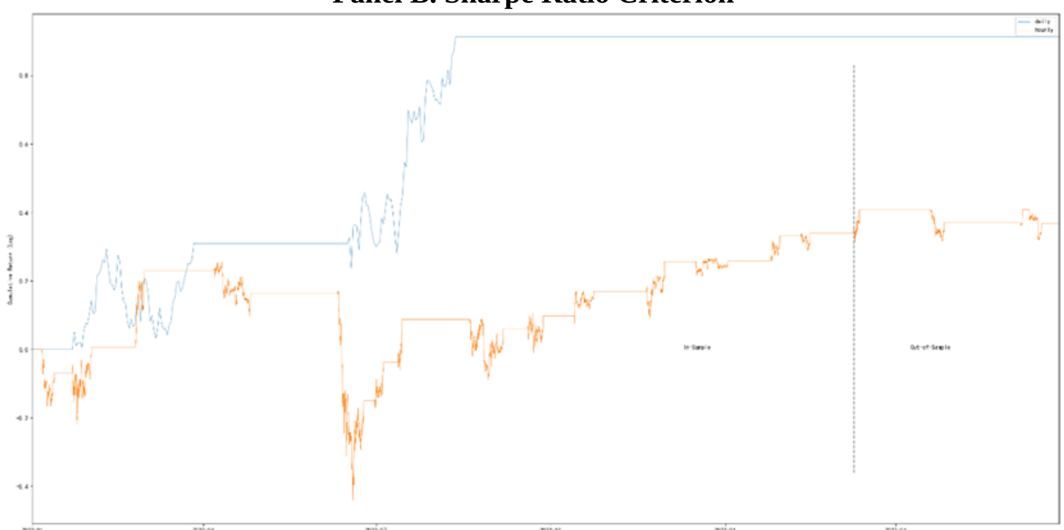


FIGURE A15
PERFORMANCE OF THE BEST TECHNICAL TRADE BOLLINGER BANDS STRATEGY AND MAR 2023 AS THE CUTOFF - ETH/USDT

Panel A. Annualized Return Criterion

Panel B. Sharpe Ratio Criterion

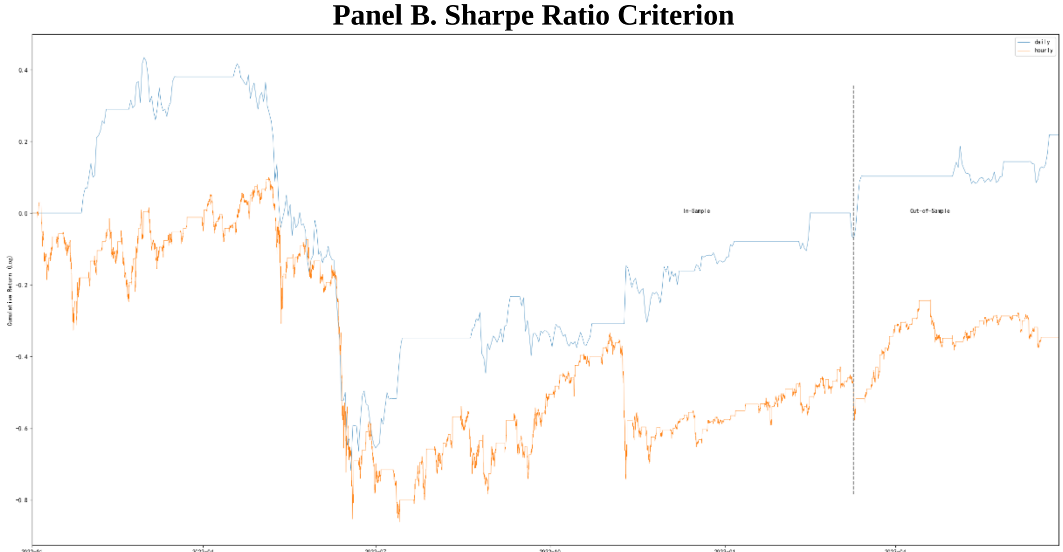
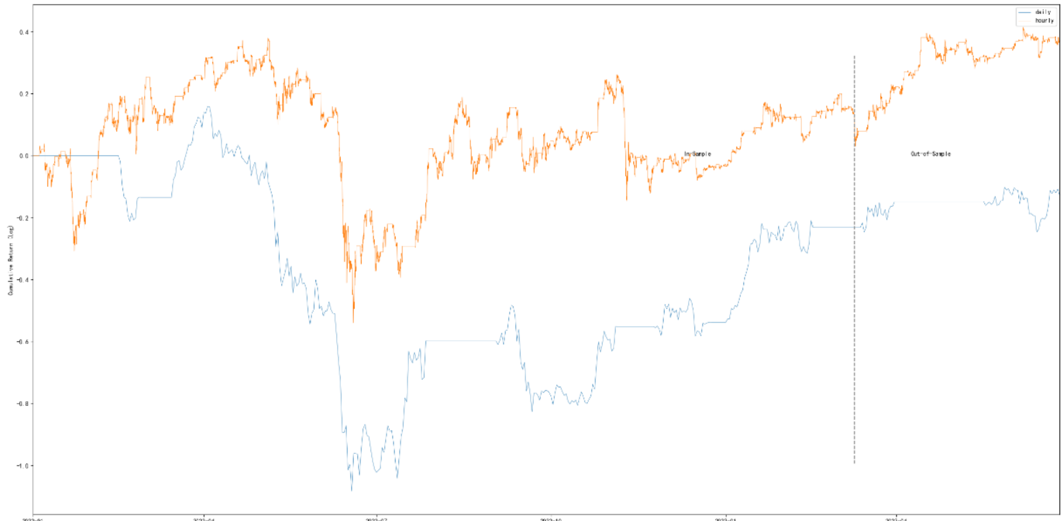


FIGURE A16
PERFORMANCE OF THE BEST TECHNICAL TRADE MACD STRATEGY AND MAR 2023 AS THE CUTOFF - ETH/USDT

Panel A. Annualized Return Criterion



Panel B. Sharpe Ratio Criterion

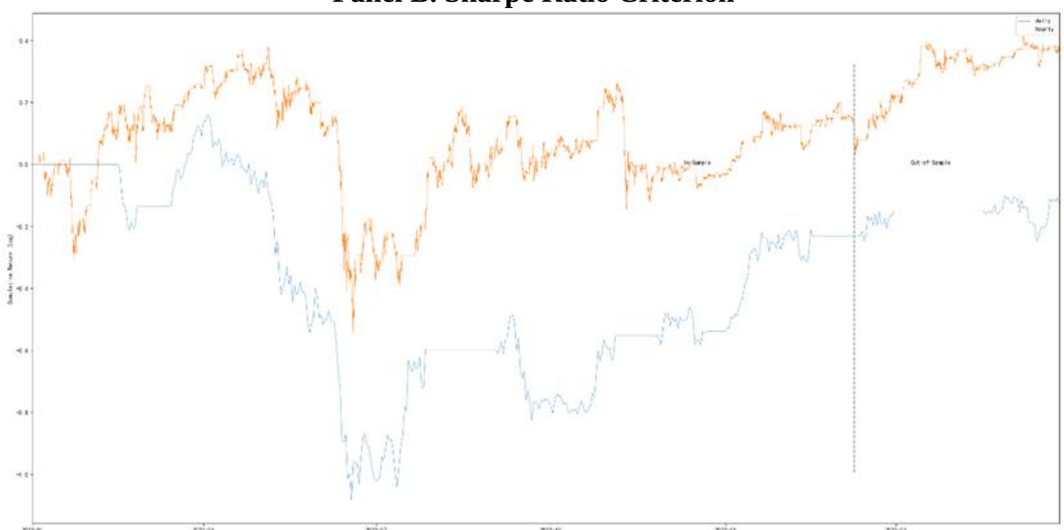


TABLE A1
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH EMAC STRATEGIES AND NOV 2022 AS THE CUTOFF - BTC/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	90	90	90	90
Best Strategy (In-Sample)				
Description	emac(28, 59)	emac(28, 41)	emac(28, 59)	emac(28, 41)
Annualized Return	-5.952%	-31.173%	-5.952%	-31.173%
Sharpe Ratio	-0.514	-1.156	-0.514	-1.156
Max Drawdown	14.794%	37.138%	14.794%	37.138%
P-Value (Nominal)	0.314	0.138	0.000	0.000
P-Value (Reality Check)	0.933	0.939	0.903	0.000
P-Value (Stepwise Check)	0.833	0.691	0.459	0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	101.408%	132.086%	101.408%	132.086%
Sharpe Ratio	1.933	2.567	1.933	2.567
Max Drawdown	17.125%	21.282%	17.125%	21.282%
P-Value (Nominal)	0.327	0.063	0.027	0.000
P-Value (Reality Check)	0.885	0.169	0.903	0.000
P-Value (Stepwise Check)	0.721	0.150	0.459	0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	61.000	90.000
Average Number / Number of Strategies	0.0%	0.0%	67.778%	100.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	0.000	0.000	61.000	90.000
Average Number / Number of Strategies (In-Sample)	0.0%	0.0%	67.778%	100.0%

TABLE A2
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH RSI STRATEGIES AND NOV 2022 AS THE CUTOFF - BTC/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	100	100	100	100
Best Strategy (In-Sample)				
Description	rsi(14, 70, 20)	rsi(14, 74, 20)	rsi(14, 70, 20)	rsi(14, 74, 20)
Annualized Return	24.941%	-36.448%	24.941%	-36.448%
Sharpe Ratio	0.954	-1.021	0.954	-1.021
Max Drawdown	12.974%	40.236%	12.974%	40.236%
P-Value (Nominal)	0.185	0.168	0.000	0.000
P-Value (Reality Check)	0.573	0.950		0.000
P-Value (Stepwise Check)	0.265	0.737		0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	75.265%	199.079%	75.265%	199.079%
Sharpe Ratio	1.896	3.272	1.896	3.272
Max Drawdown	15.21%	17.438%	15.21%	17.438%
P-Value (Nominal)		0.166		0.000
P-Value (Reality Check)		0.759		0.000
P-Value (Stepwise Check)		0.626		0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000		100.000
Average Number / Number of Strategies		0.0%		100.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number		0.000		100.000
Average Number / Number of Strategies (In-Sample)		0.0%		100.0%

TABLE A3
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH BOLLINGER BANDS STRATEGIES AND NOV 2022 AS THE CUTOFF - BTC/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	15	15	15	15
Best Strategy (In-Sample)				
Description	bbands(24, 1)	bbands(18, 3)	bbands(24, 1)	bbands(18, 3)
Annualized Return	-5.914%	-20.56%	-5.914%	-20.56%
Sharpe Ratio	-0.129	-0.527	-0.129	-0.527
Max Drawdown	43.792%	41.29%	43.792%	41.29%
P-Value (Nominal)	0.452	0.310	0.000	0.000
P-Value (Reality Check)	0.834	0.883	0.000	0.000
P-Value (Stepwise Check)	0.797	0.748	0.000	0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	84.397%	54.599%	84.397%	54.599%
Sharpe Ratio	2.234	2.010	2.234	2.010
Max Drawdown	10.153%	11.326%	10.153%	11.326%
P-Value (Nominal)	0.048	0.227	0.000	0.000
P-Value (Reality Check)	0.094	0.566	0.000	0.000
P-Value (Stepwise Check)	0.072	0.562	0.000	0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	10.000	12.000
Average Number / Number of Strategies	0.0%	0.0%	66.667%	80.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	1.006	0.000	10.000	12.000
Average Number / Number of Strategies (In-Sample)	6.707%	0.0%	66.667%	80.0%

TABLE A4
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH MACD STRATEGIES AND NOV 2022 AS THE CUTOFF - BTC/U

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	12	12	12	12
Best Strategy (In-Sample)				
Description	macd(10, 20, 6, 30, 10)	macd(10, 25, 6, 30, 10)	macd(10, 20, 6, 30, 10)	macd(10, 25, 6, 30, 10)
Annualized Return	-31.482%	-47.376%	-31.482%	-47.376%
Sharpe Ratio	-0.975	-1.374	-0.975	-1.374
Max Drawdown	48.699%	52.63%	48.699%	52.63%
P-Value (Nominal)	0.180	0.098	0.000	0.000
P-Value (Reality Check)	0.884	0.938	0.000	0.001
P-Value (Stepwise Check)	0.668	0.589	0.000	0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	187.155%	58.623%	187.155%	58.623%
Sharpe Ratio	3.265	1.547	3.265	1.547
Max Drawdown	10.125%	16.462%	10.125%	16.462%
P-Value (Nominal)	0.006	0.380	0.000	0.000
P-Value (Reality Check)	0.011	0.537	0.000	0.001
P-Value (Stepwise Check)	0.011	0.522	0.000	0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	12.000	12.000
Average Number / Number of Strategies	0.0%	0.0%	100.0%	100.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	12.000	0.000	12.000	12.000
Average Number / Number of Strategies (In-Sample)	100.0%	0.0%	100.0%	100.0%

TABLE A5
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH EMAC STRATEGIES AND MAR 2023 AS THE CUTOFF - BTC/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	90	90	90	90
Best Strategy (In-Sample)				
Description	emac(28, 59)	emac(28, 35)	emac(28, 59)	emac(28, 35)
Annualized Return	-6.543%	-5.446%	-6.543%	-5.446%
Sharpe Ratio	-0.361	-0.176	-0.361	-0.176
Max Drawdown	16.26%	38.043%	16.26%	38.043%
P-Value (Nominal)	0.347	0.424	0.000	0.000
P-Value (Reality Check)	0.875	0.730	1.000	1.000
P-Value (Stepwise Check)	0.786	0.667	0.760	0.522
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	3.808%	32.903%	3.808%	32.903%
Sharpe Ratio	0.825	0.901	0.825	0.901
Max Drawdown	1.232%	18.93%	1.232%	18.93%
P-Value (Nominal)	0.054	0.325	0.044	0.000
P-Value (Reality Check)	0.987	0.847	1.000	1.000
P-Value (Stepwise Check)	0.633	0.716	0.760	0.522
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	0.000	81.676
Average Number / Number of Strategies	0.0%	0.0%	0.0%	90.751%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	0.000	0.000	0.000	81.676
Average Number / Number of Strategies (In-Sample)	0.0%	0.0%	0.0%	90.751%

TABLE A6
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH RSI STRATEGIES AND MAR 2023 AS THE CUTOFF - BTC/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	100	100	100	100
Best Strategy (In-Sample)				
Description	rsi(14, 70, 20)	rsi(14, 74, 20)	rsi(14, 70, 20)	rsi(14, 74, 20)
Annualized Return	18.191%	-28.299%	18.191%	-28.299%
Sharpe Ratio	0.826	-0.843	0.826	-0.843
Max Drawdown	12.974%	40.613%	12.974%	40.613%
P-Value (Nominal)	0.185	0.179	0.000	0.000
P-Value (Reality Check)	0.603	0.943		0.275
P-Value (Stepwise Check)	0.303	0.740		0.007
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	58.893%	433.89%	58.893%	433.89%
Sharpe Ratio	2.719	3.716	2.719	3.716
Max Drawdown	6.034%	15.043%	6.034%	15.043%
P-Value (Nominal)		0.125		0.000
P-Value (Reality Check)		0.794		0.275
P-Value (Stepwise Check)		0.461		0.007
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000		99.944
Average Number / Number of Strategies		0.0%		99.944%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number		0.000		99.944
Average Number / Number of Strategies (In-Sample)		0.0%		99.944%

TABLE A7
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH BOLLINGER BANDS STRATEGIES AND MAR 2023 AS THE CUTOFF - BTC/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	15	15	15	15
Best Strategy (In-Sample)				
Description	bbands(24, 1)	bbands(18, 3)	bbands(24, 1)	bbands(18, 3)
Annualized Return	6.258%	-7.137%	6.258%	-7.137%
Sharpe Ratio	0.143	-0.190	0.143	-0.190
Max Drawdown	43.792%	41.29%	43.792%	41.29%
P-Value (Nominal)	0.438	0.418	0.000	0.000
P-Value (Reality Check)	0.767	0.831	0.063	0.001
P-Value (Stepwise Check)	0.774	0.770	0.053	0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	74.409%	88.478%	74.409%	88.478%
Sharpe Ratio	2.406	2.544	2.406	2.544
Max Drawdown	7.387%	8.038%	7.387%	8.038%
P-Value (Nominal)	0.211	0.468	0.000	0.000
P-Value (Reality Check)	0.284	0.823	0.063	0.001
P-Value (Stepwise Check)	0.342	0.821	0.053	0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	3.240	15.000
Average Number / Number of Strategies	0.0%	0.0%	21.6%	100.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	0.000	0.000	3.240	15.000
Average Number / Number of Strategies (In-Sample)	0.0%	0.0%	21.6%	100.0%

TABLE A8
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH MACD STRATEGIES AND MAR 2023 AS THE CUTOFF - BTC/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	12	12	12	12
Best Strategy (In-Sample)				
Description	macd(10, 20, 6, 30, 10)	macd(10, 25, 6, 30, 10)	macd(10, 20, 6, 30, 10)	macd(10, 25, 6, 30, 10)
Annualized Return	3.942%	-37.755%	3.942%	-37.755%
Sharpe Ratio	0.102	-1.129	0.102	-1.129
Max Drawdown	48.699%	52.842%	48.699%	52.842%
P-Value (Nominal)	0.456	0.109	0.000	0.000
P-Value (Reality Check)	0.634	0.917	0.886	0.000
P-Value (Stepwise Check)	0.638	0.606	0.768	0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	38.571%	129.238%	38.571%	129.238%
Sharpe Ratio	1.506	2.497	1.506	2.497
Max Drawdown	8.501%	13.564%	8.501%	13.564%
P-Value (Nominal)	0.227	0.204	0.192	0.000
P-Value (Reality Check)	0.238	0.327	0.886	0.000
P-Value (Stepwise Check)	0.237	0.275	0.768	0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	0.000	12.000
Average Number / Number of Strategies	0.0%	0.0%	0.0%	100.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	0.000	0.000	0.000	12.000
Average Number / Number of Strategies (In-Sample)	0.0%	0.0%	0.0%	100.0%

TABLE A9
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH EMAC STRATEGIES AND NOV 2022 AS THE CUTOFF - ETH/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	90	90	90	90
Best Strategy (In-Sample)				
Description	emac(10, 41)	emac(10, 59)	emac(10, 41)	emac(10, 59)
Annualized Return	-30.853%	6.83%	-30.853%	6.83%
Sharpe Ratio	-0.721	0.129	-0.721	0.129
Max Drawdown	54.335%	36.478%	54.335%	36.478%
P-Value (Nominal)	0.249	0.452	0.000	0.000
P-Value (Reality Check)	0.928	0.627	0.000	0.000
P-Value (Stepwise Check)	0.716	0.625	0.000	0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	66.799%	86.923%	66.799%	86.923%
Sharpe Ratio	1.167	1.692	1.167	1.692
Max Drawdown	17.262%	14.02%	17.262%	14.02%
P-Value (Nominal)	0.313	0.201	0.000	0.000
P-Value (Reality Check)	0.464	0.325	0.000	0.000
P-Value (Stepwise Check)	0.623	0.334	0.000	0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	62.958	90.000
Average Number / Number of Strategies	0.0%	0.0%	69.953%	100.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	0.000	0.000	62.958	90.000
Average Number / Number of Strategies (In-Sample)	0.0%	0.0%	69.953%	100.0%

TABLE A10
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH RSI STRATEGIES AND NOV 2022 AS THE CUTOFF - ETH/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	100	100	100	100
Best Strategy (In-Sample)				
Description	rsi(14, 70, 20)	rsi(14, 74, 20)	rsi(14, 70, 20)	rsi(14, 74, 20)
Annualized Return	178.637%	17.017%	178.637%	17.017%
Sharpe Ratio	1.898	0.285	1.898	0.285
Max Drawdown	23.022%	50.152%	23.022%	50.152%
P-Value (Nominal)	0.037	0.394	0.000	0.000
P-Value (Reality Check)	0.258	0.742		0.000
P-Value (Stepwise Check)	0.059	0.719		0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	132.971%	297.597%	132.971%	297.597%
Sharpe Ratio	3.375	3.651	3.375	3.651
Max Drawdown	5.429%	13.511%	5.429%	13.511%
P-Value (Nominal)		0.119		0.000
P-Value (Reality Check)		0.679		0.000
P-Value (Stepwise Check)		0.468		0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.126	0.000		100.000
Average Number / Number of Strategies		0.0%		100.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number		1.002		100.000
Average Number / Number of Strategies (In-Sample)		1.002%		100.0%

TABLE A11
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH BOLLINGER BANDS STRATEGIES AND NOV 2022 AS THE CUTOFF - ETH/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	15	15	15	15
Best Strategy (In-Sample)				
Description	bbands(27, 1)	bbands(27, 2)	bbands(27, 1)	bbands(27, 2)
Annualized Return	-28.983%	-51.833%	-28.983%	-51.833%
Sharpe Ratio	-0.511	-1.022	-0.511	-1.022
Max Drawdown	68.393%	61.756%	68.393%	61.756%
P-Value (Nominal)	0.315	0.168	0.000	0.000
P-Value (Reality Check)	0.853	0.959	0.000	0.000
P-Value (Stepwise Check)	0.741	0.743	0.000	0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	85.187%	60.392%	85.187%	60.392%
Sharpe Ratio	2.270	1.462	2.270	1.462
Max Drawdown	9.962%	13.885%	9.962%	13.885%
P-Value (Nominal)	0.041	0.130	0.000	0.000
P-Value (Reality Check)	0.066	0.349	0.000	0.000
P-Value (Stepwise Check)	0.043	0.375	0.000	0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	10.000	13.484
Average Number / Number of Strategies	0.0%	0.0%	66.667%	89.893%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	4.784	0.000	10.000	13.484
Average Number / Number of Strategies (In-Sample)	31.893%	0.0%	66.667%	89.893%

TABLE A12
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH MACD STRATEGIES AND NOV 2022 AS THE CUTOFF - ETH/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	12	12	12	12
Best Strategy (In-Sample)				
Description	macd(10, 20, 6, 30, 10)	macd(10, 25, 10, 30, 10)	macd(10, 20, 6, 30, 10)	macd(10, 25, 10, 30, 10)
Annualized Return	-46.165%	-8.06%	-46.165%	-8.06%
Sharpe Ratio	-0.893	-0.112	-0.893	-0.112
Max Drawdown	71.128%	60.117%	71.128%	60.117%
P-Value (Nominal)	0.200	0.458	0.000	0.000
P-Value (Reality Check)	0.829	0.644	0.000	0.000
P-Value (Stepwise Check)	0.633	0.612	0.000	0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	118.104%	96.161%	118.104%	96.161%
Sharpe Ratio	2.170	1.774	2.170	1.774
Max Drawdown	13.421%	15.709%	13.421%	15.709%
P-Value (Nominal)	0.072	0.086	0.000	0.000
P-Value (Reality Check)	0.088	0.148	0.000	0.000
P-Value (Stepwise Check)	0.076	0.157	0.000	0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	12.000	12.000
Average Number / Number of Strategies	0.0%	0.0%	100.0%	100.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	0.878	0.000	12.000	12.000
Average Number / Number of Strategies (In-Sample)	7.317%	0.0%	100.0%	100.0%

TABLE A13
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH EMAC STRATEGIES AND MAR 2023 AS THE CUTOFF - ETH/USDT

Performance Metric	Annualized Return		Sharpe Ratio	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	90	90	90	90
Best Strategy (In-Sample)				
Description	emac(10, 41)	emac(10, 59)	emac(10, 41)	emac(10, 59)
Annualized Return	-12.565%	19.995%	-12.565%	19.995%
Sharpe Ratio	-0.277	0.377	-0.277	0.377
Max Drawdown	54.335%	36.478%	54.335%	36.478%
P-Value (Nominal)	0.382	0.341	0.009	0.090
P-Value (Reality Check)	0.825	0.515	0.981	0.989
P-Value (Stepwise Check)	0.708	0.503	0.543	0.620
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	0.0%	55.991%	0.0%	55.991%
Sharpe Ratio	0.000	1.300	0.000	1.300
Max Drawdown	0.0%	15.363%	0.0%	15.363%
P-Value (Nominal)	0.149	0.446	0.000	0.000
P-Value (Reality Check)	0.942	0.744	0.981	0.989
P-Value (Stepwise Check)	0.630	0.693	0.543	0.620
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	1.040	6.898
Average Number / Number of Strategies	0.0%	0.0%	1.156%	7.664%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	0.000	0.000	1.040	6.898
Average Number / Number of Strategies (In-Sample)	0.0%	0.0%	1.156%	7.664%

TABLE A14
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH RSI STRATEGIES AND MAR 2023 AS THE CUTOFF - ETH/USDT

Performance Metric	Annualized Return		Sharpe Ratio	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	100	100	100	100
Best Strategy (In-Sample)				
Description	rsi(14, 70, 20)	rsi(14, 74, 20)	rsi(14, 70, 20)	rsi(14, 74, 20)
Annualized Return	115.792%	33.193%	115.792%	33.193%
Sharpe Ratio	1.642	0.579	1.642	0.579
Max Drawdown	23.022%	50.152%	23.022%	50.152%
P-Value (Nominal)	0.037	0.264	0.000	0.000
P-Value (Reality Check)	0.284	0.644		1.000
P-Value (Stepwise Check)	0.074	0.588		0.866
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	48.137%	372.142%	48.137%	372.142%
Sharpe Ratio	2.880	3.541	2.880	3.541
Max Drawdown	2.081%	14.279%	2.081%	14.279%
P-Value (Nominal)		0.341		0.000
P-Value (Reality Check)		0.938		1.000
P-Value (Stepwise Check)		0.893		0.866
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000		100.000
Average Number / Number of Strategies		0.0%		100.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number		0.000		100.000
Average Number / Number of Strategies (In-Sample)		0.0%		100.0%

TABLE A15
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH BOLLINGER BANDS STRATEGIES AND MAR 2023 AS THE CUTOFF - ETH/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	15	15	15	15
Best Strategy (In-Sample)				
Description	bbands(27, 1)	bbands(27, 2)	bbands(27, 1)	bbands(27, 2)
Annualized Return	-5.248%	-34.55%	-5.248%	-34.55%
Sharpe Ratio	-0.090	-0.661	-0.090	-0.661
Max Drawdown	68.393%	61.756%	68.393%	61.756%
P-Value (Nominal)	0.461	0.236	0.000	0.000
P-Value (Reality Check)	0.763	0.931	0.203	0.000
P-Value (Stepwise Check)	0.737	0.774	0.039	0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	50.643%	95.085%	50.643%	95.085%
Sharpe Ratio	1.572	1.999	1.572	1.999
Max Drawdown	12.225%	9.141%	12.225%	9.141%
P-Value (Nominal)	0.204	0.152	0.000	0.000
P-Value (Reality Check)	0.228	0.372	0.203	0.000
P-Value (Stepwise Check)	0.252	0.411	0.039	0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	5.990	14.000
Average Number / Number of Strategies	0.0%	0.0%	39.933%	93.333%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	0.000	0.000	5.990	14.000
Average Number / Number of Strategies (In-Sample)	0.0%	0.0%	39.933%	93.333%

TABLE A16
THE IN-/OUT-OF-SAMPLE PERIOD PERFORMANCE OF TECHNICAL TRADE STRATEGIES WITH MACD STRATEGIES AND MAR 2023 AS THE CUTOFF - ETH/USDT

Performance Metric	**Annualized Return**		**Sharpe Ratio**	
	(1)	(2)	(3)	(4)
Time Resolution	1d	1h	1d	1h
Number of Strategies	12	12	12	12
Best Strategy (In-Sample)				
Description	macd(10, 20, 6, 30, 10)	macd(10, 25, 10, 30, 10)	macd(10, 20, 6, 30, 10)	macd(10, 25, 10, 30, 10)
Annualized Return	-17.738%	9.346%	-17.738%	9.346%
Sharpe Ratio	-0.303	0.132	-0.303	0.132
Max Drawdown	71.128%	60.117%	71.128%	60.117%
P-Value (Nominal)	0.371	0.443	0.000	0.000
P-Value (Reality Check)	0.691	0.561	0.753	0.000
P-Value (Stepwise Check)	0.604	0.561	0.713	0.000
Performance of the Best Strategy (Out-of-Sample)				
Annualized Return	7.857%	163.844%	7.857%	163.844%
Sharpe Ratio	0.300	2.537	0.300	2.537
Max Drawdown	13.265%	10.859%	13.265%	10.859%
P-Value (Nominal)	0.445	0.084	0.432	0.000
P-Value (Reality Check)	0.442	0.095	0.753	0.000
P-Value (Stepwise Check)	0.442	0.134	0.713	0.000
All Profitable Strategies (In-Sample, 500 Tests)				
Average Number	0.000	0.000	0.000	12.000
Average Number / Number of Strategies	0.0%	0.0%	0.0%	100.0%
Performance of Profitable Strategies (Out-of-Sample, 500 Tests)				
Average Number	0.000	0.000	0.000	12.000
Average Number / Number of Strategies (In-Sample)	0.0%	0.0%	0.0%	100.0%