MASTERARBEIT

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Algorithmischer Handel auf Kryptowährungsmärkten: Entwicklung und Optimierung von Algorithmen und Strategien für den automatischen Handel mit Kryptowährungen unter Verwendung quantitativer Ansätze und maschinellem Lernen.

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Algorithmic trading in cryptocurrency markets: development and optimization of algorithms and strategies for automatic trading of cryptocurrencies using quantitative approach and machine learning

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Abstract:
This thesis conducts an analysis and comparison of trading strategies, specifically short-term momentum, mean reversion, and pair arbitrage, in the context of Bitcoin, Ethereum, and BNB markets. A comparative assessment is made with the buy and hold strategy. The trading strategies under scrutiny include Ehlers moving average crossover pairs, a standard deviation-based mean reversion approach, and pair trading. Various algorithmic trading frameworks are examined, and the development and enhancement processes are detailed.

In order to replicate real-world trading conditions as accurately as possible, transaction fees and slippage are factored into the calculations. The findings highlight the challenge of outperforming a buy and hold strategy, but they also demonstrate the feasibility of achieving this with momentum strategies, even when accounting for transaction costs.

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Table of Abbreviations

ADX - Average Directional Index

BBWidth - Bollinger Bands Width

BNB - Binance Coin

BTC - Bitcoin

EMA - Exponential Moving Average

EMH – Efficient Market Hypothesis

ETH - Ethereum

FAMA - Fractal Adaptive Moving Average

MAE - Maximum Adverse Excursion

MAMA - MESA Adaptive Moving Average

RSI - Relative Strength Index

SMA - Simple Moving Average

STDev - Standard Deviation

TF - Trend Following

MR - Mean Reversion

1 Introduction

1.1 Background

Economic theory teaches that markets should be efficient: all new information should be available to all market participants, and this information should be immediately reflected in asset prices[1]. However, this is often not the case, and markets have been shown to temporarily deviate from efficiency[2]. These market inefficiencies are referred to as anomalies and provide traders with opportunities to generate profits in asset markets. When anomalies exist, and the market efficiency hypothesis is accepted as the baseline scenario, traders can make bets in asset markets towards market efficiency. If an anomaly exists in an asset, it can be assumed that the asset will eventually return to market efficiency as rational investors realize the anomaly's existence.

Anomalies can be found on many stock markets[3] and even in the cryptocurrency market[4] Volatile market conditions provide a great

1. [11] Fama, E., 1965. The Behavior of Stock-Market Prices The Journal of BusinessVol. 38, No. 1 (Jan., 1965), pp. 34-105 (72 pages) Published By: The University of Chicago Press

2. [2] De Bondt. W & Thaler. R. Does the Stock Market Overreact? (1985). The Journal of finance. Volume 40, Issue 3. July 1985. Pages 793-805

3. [3] Chan L. K. C, JegadeeshN, Lakonishok, J. The Profitability of Momentum Strategies. 1999. Financial Analysts Journal. Volume 55, 1999 - Issue 6

4. [4] Yang. H., Behavioral Anomalies in Cryptocurrency Markets. 2019. Department of Banking and Finance, University of Zurich, Switzerland

opportunity for traders to profit from market inefficiencies. Phenomena like mispricing anomalies can become profitable events in volatile market conditions. Imagine a scenario where market participants overreact to a news event, causing the underlying asset's price to increase by hundreds of percentages within a few hours, even if the news turns out to be false or misinformation.

The first cryptocurrency was introduced to the market in 2008 in an article written by the pseudonym Satoshi Nakamoto. Bitcoin was the first decentralized digital currency created specifically for peer-to-peer transactions encrypted on the blockchain. Blockchain represents a public ledger containing all cryptographic transactions ever recorded, publicly available for anyone to view. Since then, this asset class has steadily gained market share and public interest. Cryptocurrencies are known as a highly speculative asset class in an unregulated market environment. They are difficult to value properly due to the lack of financial information, such as cash flows. Short-term trading opportunities found in the Bitcoin market might be of interest due to the potentially volatile market conditions. There have been relatively few studies conducted on this asset class because of the young trading history of cryptocurrencies. Therefore, further research is required [5][6]

The main idea behind this thesis is to study the performance of momentum mean reversion, and Arbitrage strategies in short time-frame Cryptocurrency trading. The goal is to create workflow for Algorithmic Trading and describe Strategy development and enhancement process. Subsequently, this study

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[5] Yang. H., Behav ora Anoma es n Cryptocurrency Markets. 2019. Department of Bank ng and F nance, Un vers ty of Zur ch, Sw tzer and

[6] Nakamoto, S. (2008) B tco n: A Peer-to-Peer E ectron c Cash System. https://b tco n.org/b tco n.pdf

compares these strategies and their performance against each other and a buy-and-hold strategy.

1.2 Motivation

The significance of this study lies in many key elements. First, the rise in popularity of cryptocurrencies such as Bitcoin and Ethereum has attracted a growing number of investors, leading to an increase in their market capitalization. Consequently, liquidity and volatility in cryptocurrency markets have increased dramatically, making them attractive hubs for both trading and investment activities.

Secondly, the trading environment in cryptocurrency markets is characterized by intense competition and rapid fluctuations. These dynamics require the development of increasingly sophisticated and adaptive strategies that reinforce the role of algorithmic trading as a key determinant of successful participation in these markets. It is in this context that we begin to explore the intricacies associated with the development and training of trading algorithms in the field of cryptocurrencies.

1.3 . Research Questions

This research delves into and contrasts three distinct trading approaches within the Cryptocurrency market, focusing on momentum, mean reversion, and arbitrage anomalies. The assessed trading strategies encompass John Ehlers's MAMA crossover technique, representing a momentum-based strategy, Bollinger's akin to mean reversal, categorized under the mean reversion trading archetype, and Markowitz's Statistic Pair Arbitrage. The primary aim is to identify the most favorable parameters for these strategies and assess their comparative performance in relation to the buy-and-hold strategy. Evaluating the trading models involves gauging their annual returns and the associated risk incurred in pursuit of these profits. The research inquiries can be summarized as follows:

1. Which framework offers the most advantageous approach to crafting and executing algorithmic trading strategies in the cryptocurrency market?
2. How can one systematically develop and enhance an algorithmic trading strategy?
3. What variations exist in the outcomes achieved by the Momentum, Mean Reversion, and Statistic Pair Arbitrage strategies when applied to the cryptocurrency market?
4. Does the buy and hold strategy outperform the above strategies in terms of Annual Return, Recovery Factor and Maximum Drawdown?

1.4 Limitations

This research does come with its set of constraints. To begin with, the strategies under scrutiny will exclusively undergo testing using BTC, ETH, and BNB. While the realm of cryptocurrencies features a multitude of options, this study's trading analysis centers solely on the trio mentioned. Notably, Bitcoin commenced its trading journey in 2009, yet the dataset spans from 2018 to 2023, thus failing to encompass the comprehensive history of Bitcoin trading.

Furthermore, it's worth noting that the dataset utilized for this research was exclusively derived from the Binance cryptocurrency exchange. Despite the exchange's status as one of the most liquid platforms and its dominance in trading volumes, accounting for approximately 50% of all trading activities according to Coinmarketcap.com, a comprehensive analysis would ideally involve data aggregation from all exchanges. This is particularly significant as major players might discreetly engage in buying on some exchanges and selling on others, a dynamic that may not be reflected in the trading volume data from a single exchange.

Moreover, this study won't undertake a comprehensive assessment of all possible strategy variations across all currencies. Owing to resource and time limitations, development will focus primarily on Bitcoin, with subsequent testing of the most promising strategy options on Ethereum and Binance Coin. Consequently, it's important to recognize that the most lucrative strategies identified in this study may not necessarily yield the same results in the context of a complete portfolio if all potential strategy permutations were assessed.

1.5 Structure of the thesis

The dissertation is structured as follows. The theoretical foundations of market efficiency and anomalies are presented in Chapter 2. This theory also encompasses the trading strategies used in this research. Chapter 3 outlines the methodology of the study, the development, and evaluation of strategies. Chapter 4 encompasses the development process, involving the selection and configuration of the framework for research, as well as the process of strategy development and improvement. Chapter 5 presents and discusses the results. In the final section, conclusions are drawn, and potential future research on the subject is explored.

2 Theoretical Fundamentals

This chapter provides an in-depth exploration of the efficient market hypothesis, mean reversion, pairwise statistical arbitrage, and momentum anomalies. Additionally, it introduces the technical analysis and trading indicators utilized in the empirical segment of this study. The primary objective is to equip the reader with a more profound comprehension of the principal themes, theories, and overall framework applied in this research.

Contrarian, statistic pair arbitrage and momentum trading have been subjects of extensive research, with various notable studies[7,8,9] contributing to the understanding of these trading strategies. However, when it comes to cryptocurrencies, as a relatively new asset class, there remains a scarcity of research. Limited attention has been given to exploring the impulse for research in this domain or the development of trading strategies exclusively tailored for cryptocurrency markets[10].

A study conducted by Resta, Pagnottoni, and Giulia (2020) did compare mean reversion and trend trading with the buy-and-hold strategy. Their research was based on time series data spanning from January 1, 2012, to August 20, 2019, and their findings favored the buy-and-hold strategy in day

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[7] Jegadeesh. N., and T tman. S., Returns to Buy ng W nners and Se ng Losers: Imp cat ons for Stock Market Eff c ency. 1993. The journa of f nance. Vo ume 48, Issue 1. March 1993. Pages 65-91

[8] Ba vers R. and Wu Y., Momentum and mean revers on across nat ona equ ty markets. (2006). Journa of emp r ca f nance. Journa of Emp r ca F nance. Vo ume 13, Issue 1, January 2006, Pages 24-48 11. Ba vers R. and Wu Y., Momentum and mean revers on across nat ona equ ty markets. (2006). Journa of emp r ca f nance. Journa of Emp r ca F nance. Vo ume 13, Issue 1, January 2006, Pages 24-48

[9] Patro and Wu, 2004, Pred ctab ty of short-hor zon returns n nternat ona equ ty markets

[10] Gerr tsen, D. Bour , E., Ramezan far, E & Roubaud, D. The prof tab ty of techn ca trad ng ru es n the B tco n market. 2020. F nance Research Letters

trading when compared to mean reversion and trend trading strategies. Resta et al. incorporated moving averages in conjunction with price levels for their trend strategy and employed Bollinger Bands in combination with the relative strength indicator (RSI) for the mean reversion strategy.

The majority of studies on cryptocurrency markets have primarily concentrated on the period from 2010 to 2019. This period coincided with Bitcoin's remarkable surge in market value, establishing it as a household name within the asset class. During this timeframe, Bitcoin's price soared from less than $1 to temporarily exceeding $20,000. Subsequently, Bitcoin's market capitalization, liquidity, and overall market efficiency have steadily escalated[11] . The influx of institutional participants into the market has been particularly noteworthy, with the Greyscale Bitcoin Trust emerging as the largest holder, managing approximately $30 billion worth of Bitcoin. A market report by Glassnode in 2021 revealed a surge in transaction volumes exceeding $10 million within the Bitcoin network, indicating heightened institutional interest and market evolution. Coingecko's data from 2021 identified 27 companies holding Bitcoin on their balance sheets, with MicroStrategy being the largest, with holdings worth $7 billion. During the period of 2022 and the first half of 2023, against the backdrop of the crypto winter, the adoption of cryptocurrencies into the traditional market slowed down, however, in the second half of 2023, the SEC approved 8 out of 10 applications for crypto ETFs. The evolving maturity of the market itself constitutes a compelling rationale for investigating the efficacy of diverse trading strategies within this dynamic landscape.

[11] Sensoy, 2019, The neff c ency of B tco n rev s ted: A h gh-frequency ana ys s w th a ternat ve currenc es

2.1 Efficient Market Hypothesis

At the heart of modern financial theory lies the concept of the Efficient Market Hypothesis (EMH), formulated in 1965 by the renowned economist and Nobel laureate Eugene Fama. The EMH posits a fundamental financial principle, asserting that the market rapidly and accurately incorporates all available information, and assets always trade at their fair value. This concept swiftly became central in the realm of investments and finance.

The EMH implies three forms of market efficiency (weak, semi-strong, strong):

1) In the weak form, the market is considered efficient if current prices already reflect all available historical information, rendering the use of technical analysis meaningless.
2) semi-strong form suggests that the market is efficient concerning all publicly available information but does not incorporate firms' internal information.
3) the strong form of EMH assumes absolute market efficiency, suggesting that not even a company's internal information can provide investors with any advantage.

Despite the EMH's widespread use and influence, it has also received criticism. Some researchers and practitioners argue that markets can periodically deviate from efficiency due to various anomalies.

2.2 Anomalies

There are several anomalies in the market that challenge the efficient market hypothesis, which assumes that asset prices always reflect all available information and always trade at fair value. We will look at three of them.

2.2.1 Momentum Anomaly

The momentum anomaly, also known as the "momentum effect," is a phenomenon in financial markets where assets that have exhibited strong price growth in the past tend to continue rising in the future, while assets with poor past performance continue to underperform. This anomaly questions the hypothesis of market efficiency and the notion that historical data is irrelevant for predicting future asset prices.

Key characteristics of the momentum anomaly include:

1. Strong Past Performance: Assets that have experienced significant price increases over a defined period, such as several months, are considered momentum assets. This surge can be triggered by various factors, including news, fundamental changes, or investor psychology.
2. Trend Continuation: The momentum anomaly suggests that this price increase is not random and is likely to persist in the same direction in the future. In other words, assets that have risen in the past tend to continue rising, while those that have fallen tend to keep declining.
3. Enhanced Returns: Research indicates that portfolios based on momentum strategies can provide investors with above-average returns compared to passive strategies like "buy and hold."
4. The momentum anomaly piques the interest of researchers and investors because it challenges the efficient market hypothesis, which posits that asset prices instantaneously reflect all available information, and gaining an advantage by analyzing historical data is implausible. Investors employ momentum strategies to identify assets showing strong growth, with the expectation that this upward trajectory will persist, allowing them to profit from price differentials.

2.2.2 Mean Reversion Anomaly

The second anomaly is known as the "mean reversion anomaly." This anomaly, quite contrary to the popular belief in market efficiency, challenges the notion that asset prices adhere to a random walk pattern and that future price movements cannot be predicted solely based on historical data.

At its core, the mean reversion anomaly embodies the following key elements:

- Return to the Mean: The anomaly's essence lies in the concept that assets that have strayed significantly from their historical average prices tend to gravitate back toward that mean or average level. It's like a pendulum swinging back after a significant deviation. In simple terms, if an asset has been overvalued or undervalued compared to its historical average, it carries the tendency to realign its price closer to that historical average over time.
- The Contrarian Approach: Those who harness this anomaly often don the mantle of contrarian traders. They actively seek out assets that have recently experienced substantial price declines, anticipating that these assets will stage a comeback as their prices regress to historical means. Conversely, they steer clear of assets that have enjoyed remarkable price hikes, expecting a course correction in the opposite direction.

The Role of Historical Data: The mean reversion strategy heavily relies on delving into historical data. By sifting through the channels of an asset's price history, investors aim to spot those with notable deviations from their historical averages. Their aim is to capitalize on the expectation that these assets will converge back to their historical means, much like a long-lost friend finding their way back.

Balancing Risk and Reward: While the mean reversion anomaly opens the door to potential profits, it does not come without its share of risks. The challenge lies in pinpointing the when and how of the reversion. The timing is crucial, as reversion may not be immediate, and its magnitude can vary.

The mean reversion anomaly's enigmatic presence in financial markets defies the conventional wisdom of market efficiency. It introduces a realm of opportunities for traders and investors to exploit the innate tendency of asset prices to gravitate toward their historical means. By identifying assets that have taken a significant detour from their historical averages, investors endeavor to capitalize on forthcoming price adjustments, grounded in the belief that historical patterns are destined to echo in the future.

2.2.3 Statistic Pair Arbitrage Anomaly

The market pair arbitrage anomaly is a captivating facet of financial markets that challenges the notion of market efficiency. Within this anomaly lies the potential for profit by skillfully exploiting disparities between asset prices.

Key aspects of the market pair arbitrage anomaly include:

1. Pairing and Arbitrage: The anomaly involves disparities in the prices of two or more assets that are typically considered homogeneous. A pair arbitrageur aims to capitalize on these disparities by buying undervalued assets while simultaneously selling overvalued assets.
2. Matching and Correction: Pair arbitrage is based on the assumption that prices of paired assets, over the long term, tend to converge toward a certain equilibrium. In other words, if a pair of assets has temporarily diverged, it is expected to reestablish balance.
3. Statistical Analysis: To identify suitable pairs of assets and pinpoint the precise timing for entering and exiting trades, a pair arbitrageur applies statistical methods and time series analysis.

4. Risk and Reward: Pair arbitrage, like any trading strategy, is not without risks. A high degree of confidence in price correction is accompanied by the potential for profit, but errors can lead to losses.

The market pair arbitrage anomaly motivates traders and investors to seek out pairs of assets where prices have diverged and anticipate their return to equilibrium. This strategy is rooted in the belief that prices of paired assets will eventually converge towards their mean, allowing traders to profit from the difference.

2.3 Strategies

Technical analysis involves predicting future price movements of assets by analyzing historical data. The application of technical analysis challenges the weak form of the efficient market hypothesis, first introduced by Eugene Fama in 1970. According to the weak form of market efficiency, no trading strategy should enable investors to consistently generate profits, as stock prices are believed to reflect all past price data.[12]

In his 1965 publication, Fama explored the impact of historical asset prices on future prices. He proposed the hypothesis that stock prices follow a random walk, contending that interpreting charts and patterns offers little real value to market participants. Fama's research indicated that a buy-and-hold strategy outperformed any technical analysis method.

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[12] Fama, E., 1970. Eff c ent Cap ta Markets: A Rev ew of Theory and Emp r ca Work. The Journa of F nance Vo . 25, No. 2, Papers and Proceed ngs of the Twenty-E ghth Annua Meet ng of the Amer can F nance Assoc at on New York, N.Y. December, 28-30, 1969 (May, 1970), pp. 383-417 (35 pages) Pub shed By: W ey

This highlights the ongoing debate between proponents of technical analysis and the efficient market hypothesis, with Fama's work emphasizing the challenges of achieving consistent profits through historical data analysis. The weak form of the efficient market hypothesis and the random walk theory inherently suggest that the utilization of any technical analysis methods should not yield profits.

However, numerous studies have delved into this topic and have indicated that technical analysis does offer value, primarily due to the existence of anomalies in financial markets. Technical analysis is geared towards identifying these anomalies, which encompass non-efficient price movements of assets. Discovering these anomalies in financial markets can potentially lead to profits exceeding those of a simple buy-and-hold strategy. Traders employ various techniques within the realm of technical analysis. This study primarily focuses on mean reversion and momentum anomalies, as there is substantial evidence supporting the ability of trading strategies based on these anomalies to generate profits across diverse markets and timeframes. The chosen strategies for this study are introduced below, selected for their prominence in existing research. This selection facilitates a comparative analysis of the study's results with similar research, enhancing the depth of analysis.

2.3.1 MAMA & FAMA Momentum Strategy

The trading strategy based on the intersection of MAMA (MESA Adaptive Moving Average) and FAMA (Following Adaptive Moving Average) by Ehlers is a method that utilizes two adaptive moving averages to generate trading signals. This strategy is designed to identify points of trend reversal in the market and provide precise entry and exit points for positions.[13]

[13] https://www.mesasoftware.com/papers/MAMA.pdf

Here are the key principles of Ehlers' trading strategy using the intersection of MAMA and FAMA:

MAMA and FAMA: MAMA is an adaptive moving average that adjusts to the current market volatility, providing a more accurate representation of the current trend. FAMA, on the other hand, is a following adaptive moving average that tracks MAMA and represents the average of MAMA over a specified period.

1. Intersection Signals: The core idea of the strategy is that a buy signal is generated when MAMA crosses below FAMA, indicating a potential start of a downtrend. A sell signal is generated when MAMA crosses above FAMA, suggesting a potential start of an uptrend.
2. Signal Filtering: To reduce false signals, additional filters can be applied, such as volume indicators or other technical tools.
3. Risk Management: It's essential to manage risks by setting stop-loss and take-profit levels to protect your capital.

2.3.1.1MAMA Calculation

Ehlers' trading strategy based on the intersection of MAMA and FAMA provides traders with a tool to identify trend reversals and make decisions regarding entry and exit points for positions. However, like any method, it requires careful testing and customization to fit specific market conditions and individual trader needs.

The MESA Adaptive Moving Average (MAMA) indicator is a complex algorithm that adapts the moving average to the current market volatility. Its formula is intricate and involves several steps, including the calculation of the central line, dominant cycle, and quadratic phase.

The general formula of the MAMA indicator can be expressed as follows:

MAMA = CER * (Price + (α * DominantCycle + (1 - α) * DominantCycle[-1]))

Where:

- MAMA - The value of the MESA Adaptive Moving Average indicator.
- CER - The central line coefficient.
- Price - The current asset price.
- α - The adaptation coefficient.
- DominantCycle - The value of the dominant cycle at the current bar.
- DominantCycle[-1] - The value of the dominant cycle at the previous bar.

This is a general formula, and the specific values of coefficients and parameters may vary depending on the indicator's settings and the analysis software used.

Calculating the Dominant Cycle in the MESA Adaptive Moving Average (MAMA) indicator typically involves the following steps:

1. Calculation of the Center of Gravity (COG): First, the Center of Gravity (COG) is computed, which is a weighted sum of price data. This can be done using the formula:
2. COG = (Price + 2Price[1] + 3Price[2] + ... + (n-1)*Price[n-1]) / (1 + 2 + 3 + ... + (n-1))
3. Where Price represents price data, and n is the number of periods for COG.
4. Centering Price Data: Next, the price data is centered relative to COG by subtracting COG from each price.
5. Centered Price = Price - COG
6. Calculation of Cycles: Fourier transformation is applied to the centered price data to identify the primary cycles in the market. Fourier

transformation can be performed using specialized functions or libraries in software environments designed for time series analysis.

7. Determination of the Dominant Cycle: The dominant cycle is identified as the cycle with the highest amplitude in the frequency spectrum found in the previous step.

Calculating the Dominant Cycle in the MAMA indicator involves the use of mathematical and statistical methods for processing price data. This process is often automated in trading platforms or software tools designed for market analysis.

2.3.1.2FAMA calculation

FAMA = (Price + α*SignalPeriodPrice + (1 - α)*SignalPeriodPrice[-1]) / 2

Where:

- FAMA - The value of the MESA Adaptive Moving Average (MAMA) indicator.
- Price - The current price of the asset.
- α - The smoothing factor.
- SignalPeriodPrice - The price at the signal period.
- SignalPeriodPrice[-1] - The price at the previous signal period.

The formula represents a calculation of the FAMA component of the MAMA indicator, which is part of the MESA (Maximum Entropy Spectrum Analysis) adaptive moving average system. The α parameter controls the degree of smoothing applied to the indicator.

2.3.2 Mean Reversion Strategy

The Mean Reversion strategy is a trading strategy that is based on the assumption that assets whose prices have deviated significantly from their mean will eventually revert to that mean. This strategy assumes that prices of assets that are too high or low tend to correct and return to a level close to the average price in a certain period.

Our strategy is based on the Simple Moving Average (SMA) and its standard deviations. When the price deviates downward from the SMA by more than r percent but remains within the range of k standard deviations, with the short-term Exponential Moving Average (EMA) reversing and moving towards the SMA for n consecutive bars, we initiate a long position and contra versa.

Simple Moving Average (SMA) is calculated by taking the sum of a set of values (usually closing prices) over a specified number of periods (n) and then dividing that sum by the number of periods. The formula for SMA is:
SMA = (Sum of values for the past n periods) / n
In mathematical terms:

SMA = (P1 + P2 + P3 + ... + Pn) / n

Where:

- SMA is the Simple Moving Average.
- P1, P2, P3, ..., Pn are the prices or values for each of the n periods you're using for the average.
- n is the number of periods you choose for the calculation.

The Exponential Moving Average (EMA) is calculated using a slightly more complex formula than the Simple Moving Average (SMA). The EMA gives more weight to recent prices, making it more responsive to price changes.

The formula for EMA is as follows:
EMA = (Closing Price - EMA[previous day]) * (2 / (n + 1)) + EMA[previous day]

Where:

- EMA is the Exponential Moving Average.
- Closing Price is the closing price of the current period.
- EMA[previous day] is the EMA value from the previous day (or the initial EMA value on the first day).
- n is the number of periods you choose for the EMA, and it determines the smoothing factor.

The formula involves two main components:

1) (Closing Price - EMA[previous day]): This calculates the difference between the current closing price and the previous day's EMA.
2) (2 / (n + 1)): This is the smoothing factor, which gives more weight to recent prices. The higher the value of n, the more weight recent prices will have.

To calculate the initial EMA on the first day, you typically use the SMA for the first n periods as the starting point.

The formula for calculating the standard deviation is as follows:

Standard Deviation (σ) = $\sqrt{\Sigma}$ [(X - μ)^2 / N]

Where:

- σ (sigma) represents the standard deviation.
- X represents each individual data point.
- μ (mu) represents the mean (average) of the data set.
- N represents the total number of data points in the data set.
- Σ signifies the summation, meaning you'll perform this calculation for each data point and then sum up the results.

Here's a step-by-step breakdown of the formula:

- Calculate the mean (average) of the data set by adding up all the data points (X) and dividing by the total number of data points (N).
- For each data point, subtract the mean (μ).
- Square the result for each data point.
- Sum up all these squared differences.
- Divide the sum by the total number of data points (N).
- Take the square root (√) of the result to obtain the standard deviation (σ).

The standard deviation measures how spread out the data points are from the mean. It provides a way to quantify the amount of variation or dispersion in a data set.

2.3.3 Pair Arbitrage Strategy

Pair Trading, also known as Pairs Trading, is a trading strategy based on the concept of statistical arbitrage. It involves the idea that the prices of two correlated assets or instruments may temporarily diverge but ultimately converge again.

The logic of the strategy is as follows:

- Calculate the proportion of assets relative to each other.
- Build an SMA on the data of this asset proportion.
- Create an order grid when there is a deviation from the mean, with sell orders for the asset that has diverged upward and buy orders for the asset that has diverged downward.

The strategy can be further improved with the use of filters and stop-loss orders.

3 Methodology

To address the research questions, a comprehensive range of sources has been utilized, including both classical literature on trading and algorithmic trading, as well as online resources from Google, and an analysis of various online platforms such as ResearchGate, Medium, Investopedia, tradingview.com, and others.

Regarding the timeframe of the data, it was imperative to incorporate both historical and contemporary research. Classical literature on capital market theories has been employed to establish fundamental concepts, the process of strategy development, and the evaluation of strategy outcomes. In contrast, online research was conducted to identify a suitable framework for research and development, categorize modern trading strategies, and gather investment hypotheses for testing.

The online research was executed using keywords and phrases such as "algorithmic trading," "algorithmic cryptocurrency trading strategies," "algorithmic trading strategy development process," and "frameworks for cryptocurrency algorithmic trading."

The research can be divided into the following sequential stages:

1) Framework Development: This phase involves the search for or creation of a framework that enables the development, testing, optimization, and execution of trading strategies.
2) Data Collection and Preparation: Historical market data is collected and prepared for analysis.

3) Metric Selection: Key metrics are chosen for evaluating the trading strategy.
4) Strategy Development and Enhancement: The process of creating and improving a profitable trading strategy takes place.
5) Results Analysis and Recommendations: The final stage involves analyzing the outcomes in relation to the research objectives and formulating recommendations for the development of algorithmic trading strategies.

3.1 Frameworks for algorithmic trading of Cryptocurrencies

The framework for algorithmic trading is a fundamental and crucial aspect, and a good framework can provide a trader with a significant advantage in developing trading algorithms. In general, a framework serves two primary functions: strategy development and execution. Many traders and funds divide the trading framework into two separate software components, written in different programming languages, to ensure the fulfillment of necessary tasks.

For research and strategy development, simplicity and broad functionality are essential. Python has gained significant popularity for this reason. Libraries like Pandas, NumPy, and Matplotlib are developed in Python. Python allows for the rapid creation of trading strategies with a straightforward syntax. It also enables the application of machine learning for further improvements, providing an advantage in developing advanced market description models.

For executing trading transactions on exchanges, speed is of paramount importance. C# and C++ are highly recommended for this purpose.

Both components of trading infrastructure constitute a complex system that requires substantial resources for development. This complexity has traditionally been a significant barrier to entry for new competitors in the market. However, in recent years, services that allow individual traders and startups to access ready-made infrastructure solutions through subscription models have gained popularity. This trend has been eliminating the aforementioned barrier.

As our work aims to create a research and development process for algorithmic trading strategies, we will analyze the available ready-made infrastructure solutions in the market. In one of these solutions, we will examine the process of creating and enhancing a profitable algorithmic trading system. The main criteria for selection will include functionality, comprehensiveness, speed, and cost-effectiveness.

Frameworks can come in the form of online platforms or desktop versions. Low latency is required for intraday trading and high-frequency trading, which entails placing infrastructure near the exchange's servers. This can only be achieved with a desktop version, which we will deploy near the exchange servers that we rent. As of the time of writing this thesis, the primary cryptocurrency exchange in terms of liquidity is Binance.com, whose servers are hosted on AWS Tokyo. Therefore, in addition to the criterion of a desktop version, we consider criteria such as the ability for back testing, the capability for no-code development, enabling traders to use an object-oriented programming interface to create strategies without coding, additional functionality through an API, the availability of guides and free educational materials for rapid learning and utilization of the framework without prior knowledge or skills. Since this research work has budget constraints, we will also explore cost-effective solutions, as some options may cost tens or hundreds of thousands of euros. After evaluating the above-mentioned criteria, we will proceed to the collection and preparation of historical market data.

3.2 Data

As previously mentioned, one of the advantages of the trading system could be the utilization of alternative data. Often, this includes extensive datasets, such as unstructured sentiment data, on-chain data, and others that may exhibit a regression dependency on price dynamics. Creating models based on such data requires advanced knowledge in Data Science, which is not within our specialization. Therefore, our focus will be on gaining an advantage from a model based on historical market data.

3.2.1 Market Data

Market data exhibits a fractal structure, which is why algorithmic traders strive to obtain the most detailed tick data, accounting for the smallest price changes. Tick data refers to data that records each individual trade or price movement, providing a more granular view of market activity.

From this data, we can aggregate the required data format—discrete in terms of time or price/volume changes. Our task is to acquire the most detailed data available and build derived functions (indicators) for our strategies based on this data.

Market data is divided into offline datasets and online data providers that update with minimal time delay through API connections to exchanges, capturing the latest transaction and price change data.

We will be using data from the Binance.com exchange, which has a daily trading volume of $8.45 billion, making it the world's largest cryptocurrency exchange by liquidity in 2023.

We will use an online dataset through API connections to the exchange to avoid the partial data loss associated with offline datasets collected by market participants.

The main drawback of our data is that Bitcoin was introduced in 2009, and Ethereum in 2015, but the data available to us only begins at the end of 2017, coinciding with the launch of trading on the exchange. Therefore, our sample will be divided into an In Sample period for training from January 1, 2018, to January 1, 2023, and an Out of Sample period from January 1, 2023, to October 1, 2023.

3.2.2 OHLCV Data Structure

When it comes to data structure, tick data is typically transformed into OHLCV data, which includes candlestick timestamps along with their Open, High, Low, Close, and Volume values.

	High	Low	Open	Close	Volume	Adj Close
Date						
2019-01-02	1553.359985	1460.930054	1465.199951	1539.130005	7983100	1539.130005
2019-01-03	1538.000000	1497.109985	1520.010010	1500.280029	6975600	1500.280029
2019-01-04	1594.000000	1518.310059	1530.000000	1575.390015	9182600	1575.390015
2019-01-07	1634.560059	1589.189941	1602.310059	1629.510010	7993200	1629.510010
2019-01-08	1676.609985	1616.609985	1664.689941	1656.579956	8881400	1656.579956

Figure 1 OHLCV Data Structure[14]

These data are used to create derivative functions that will take into account volatility, average price values, deviations, and other values necessary for the researcher to develop a trading algorithm.

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[14] Web resource: https://techflare.blog/mastering-dataframe-how-to-aggregate-ohlcv-data-in-a-different-time-period/

3.3 Key Performance Indicators

Key Performance Indicators (KPIs) or trading metrics are an integral part of developing a successful trading strategy. These performance metrics are typically presented in a strategy performance report, which is a data compilation based on various mathematical aspects of the trading system's operation. A deep understanding of the contents of the strategy performance report is crucial for traders in analyzing the strengths and weaknesses of their system.

The strategy performance report provides an objective assessment of the trading system's effectiveness. This document allows traders to analyze the actual results of their trades. Additionally, historical data can be used to apply a set of trading rules to determine how the system would have performed in the past. This process is known as backtesting. Most market analysis platforms provide traders with the ability to generate strategy performance reports during testing on historical data. This is a valuable tool for traders who want to evaluate the performance of their trading system before applying it to real markets.

Max. trade drawdown	-233368.57	-233368.57	0.00	-431235.79
Max. trade % drawdown	-28.32	-28.32	0.00	-55.19
Max. system drawdown	-274963.61	-274963.61	0.00	-431235.79
Max. system % drawdown	-44.10%	-44.10%	0.00%	-55.19%
Recovery Factor	2.96	2.96	nan	3.02
CAR/MaxDD	0.19	0.19	nan	0.18
RAR/MaxDD	0.98	0.98	nan	0.18
Profit Factor	1.54	1.54	nan	inf
Payoff Ratio	0.93	0.93	nan	nan
Standard Error	66316.07	66316.07	0.00	136819.59
Risk-Reward Ratio	0.32	0.32	-nan(ind)	0.23
Ulcer Index	11.75	11.75	0.00	15.43
Ulcer Performance Index	0.24	0.24	-inf	0.29
Sharpe Ratio of trades	0.39	0.39	0.00	inf
K-Ratio	0.03	0.03	-nan(ind)	0.02

Figure 2. Key Performance Strategies Identifier[15]

Among the primary metrics tracked by quantitative researchers are Net Profit, Maximum Drawdown, Win-Loss Ratio, Reward-to-Risk Ratio, Average Win, Average Loss, Holding Time, Average MAE, Profit Factor, and Recovery Factor.

The issue with most metrics is that they only show one side of the story. For example, Net Profit doesn't provide a complete picture without considering Maximum Drawdown, Win rate offers insight into a strategy's success without factoring in the risk-reward ratio, and so on.

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[15] Web resource: https://www.quantifiedstrategies.com/trading-strategy-and-system-performance-metrics/

Therefore, traders often rely on metrics that demonstrate profitability weighted against risk, such as Recovery Factor and Profit Factor. A good strategy, according to various sources, should have a Profit Factor of no more than 2 and a Recovery Factor of more than 3. It's important to note that the average profit per trade and the maximum profit per trade shouldn't have significant disparities; otherwise, the strategy might have outliers—situations where the strategy made a large profit once but was ineffective the rest of the time, resulting in good metrics but failing in forward tests.

Furthermore, having a large sample size is crucial, which should be statistically significant—ideally, 10,000 or more trading transactions.

As a result of studying various approaches, we will use the Recovery Factor as our primary metric in our development. We will then filter the optimal values from the top 20 results using other metrics from this selection.

3.4 Strategies Enhancement

Enhancing a trend-following strategy with filters is an important aspect of optimizing a trading strategy. Filters allow you to focus on more reliable trends and filter out signals that may lead to false trades. Here are several ways to improve a trend-following strategy using filters:

1) Volatility Filter: Addition of a volatility filter to determine how volatile the market is at any given moment. If volatility is too high, it may indicate unstable conditions, and the trading strategy should be temporarily disabled or position sizes reduced.
2) Average Volume Filter: Check the average trading volume in the market. If the volume is too low, it can reduce the reliability of trend signals. An average volume filter can help exclude trades during periods of low liquidity.

3) Time of Day Filter: Some trends may be more reliable during specific trading hours. For example, morning hours might be a more suitable time for trading in certain markets. A time of day filter can help limit activity during riskier periods.
4) Filter Signals from Various Indicators: Use multiple technical indicators to confirm trend signals. For example, you can combine indicators such as moving averages and the RSI to confirm the strength of the trend before entering a trade.
5) Stop-Loss and Take-Profit Systems: implement stop-loss and take-profit systems to protect positions and lock in profits. These systems can complement your trend-following strategy.

Filters can be customized based on the specific strategy and market type you plan to trade. They will help reduce the number of false signals and increase the reliability of your trend-following strategy. It's important to remember the need for testing and optimizing filters on historical data before using them in real-time trading.

3.5 Portfolio

Portfolio trading is an essential part of creating an effective trading system since each instrument exhibits high and low volatility seasonality. By combining assets with low correlation, a smoother yield curve can be achieved.

The level of correlation is measured as beta relative to the market. Portfolios with low beta are called market neutral. In our case, since the goal of a trader is not to assemble and hold a portfolio, but to actively manage capital and engage in high-frequency trading, we will analyze how a combination of a portfolio of BTC, ETH and BNB will have better results than bitcoin alone.

Therefore, if adding a new asset to the portfolio increases the recovery factor and profit factor, we decrease our correlation to the market and increase risk-adjusted returns. Conversely, if the values of the above-mentioned metrics decrease, it suggests that the instrument should be excluded from the portfolio.

In addition to the strategy metrics, we gather an initial list of instruments from among all cryptocurrencies traded on the exchange. Next, we analyze the average trading volumes of the target timeframe over the last three months and the order book depth, retaining only the instruments where our trade volume will not exceed 1% of the total volume. This is crucial because trading large volumes on an illiquid instrument can lead to market impact beyond acceptable limits, making the strategy profitable in paper trading but unprofitable in reality.

4 Algorithmic Trading R&D Workflow

4.1 Frameworks for algorithmic trading of Cryptocurrencies

Within this study, 53 algorithmic trading platforms were analyzed (Attachment 1). The first step of the funnel was to filter out only desktop versions since web platforms are not suitable for our requirements in terms of functionality, flexibility, and data processing speed.

The second step, from the initial 53 platforms, resulted in 12 desktop versions. Among these, we selected platforms that would serve as a universal solution for trading different types of strategies. We also eliminated platforms that didn't allow for simultaneous development, optimization, and live trading. At this stage, we removed 2 more platforms, leaving us with 10 framework options suitable for algorithmic cryptocurrency trading:

- Multicharts
- Quantower
- Wealth Lab
- Superalgos
- Python with libraries NumPy, Ta-Lib, Pandas
- cTrader
- Ichibot
- Freqtrade
- TSLab
- Quantconnect

From the remaining list, all frameworks were analyzed for the presence of educational materials, guides, video tutorials, the ability to use object-oriented programming, and the existence of a community for discussing ideas and problem-solving related to the use of the software solution. As a result, the decision was made to use TSLab for the research.

Figure 3. TSLab Interface

TSLab platform is specifically designed for traders and encompasses a wide array of tools tailored for strategy development, optimization, and execution. It also offers the capability to configure personalized trading terminals. A notable feature of TSLab is its "no code development" accessibility, which allows traders with limited programming experience to create their trading strategies using a visual interface and pre-built blocks.

Key features of TSLab include:

- Intuitive Visual Interface: The platform offers an intuitively designed visual interface, making the process of creating and configuring trading strategies accessible to a broad spectrum of traders.

- Strategy Development Blocks: TSLab provides pre-built blocks and components that can be combined to create complex trading strategies, simplifying the development process.
- No Programming Required: TSLab does not necessitate deep programming knowledge from users. Traders can create, optimize, and launch strategies on the platform without writing any code (Fig. 4).
- Strategy Optimization: The platform enables traders to optimize their strategies, enhancing their performance and efficiency.

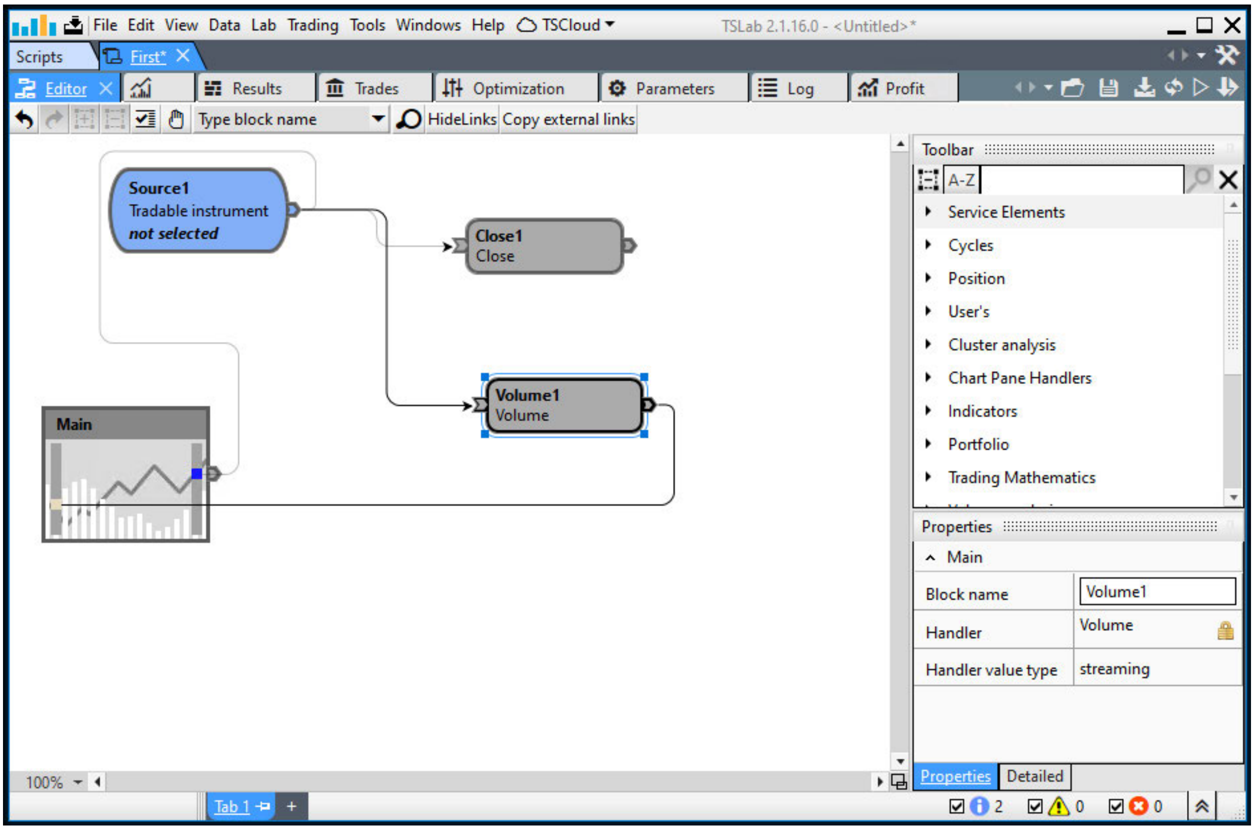

Figure 4. TSLab “no code” development

In this section, we looked at which framework provides the optimal solution for developing and executing strategies on the cryptocurrency market

4.2 Data Feeding

TSLab allows for the use of both types of market data – offline and online. For the sake of convenience and speed in development, we will utilize an online data provider, which requires us to generate an API key from our exchange profile.

For the purpose of strategy development and further testing, we will employ the Binance.com exchange. As of the writing of this thesis, Binance.com is the largest exchange by trading volumes. To proceed, we create a new account on the exchange, which can be done by anyone, except for citizens of unsupported countries, such as the United States (US citizens have a separate registered and licensed exchange, Binance.us). After creating the account, we go through the user verification process to activate the account and enable the creation of API keys for remote access to the exchange quotes.

So, we generate an API key, consisting of a Public Key and Secret Key, by navigating to the API Management section after the verification process.

Then we click on "Create Key" and give it a custom name. As shown in Figure 6, we named the key "HSMW_Master_thesis_Pinchuk." In the created key, we select "Enable reading" to have the capability of retrieving data from the exchange into our software.

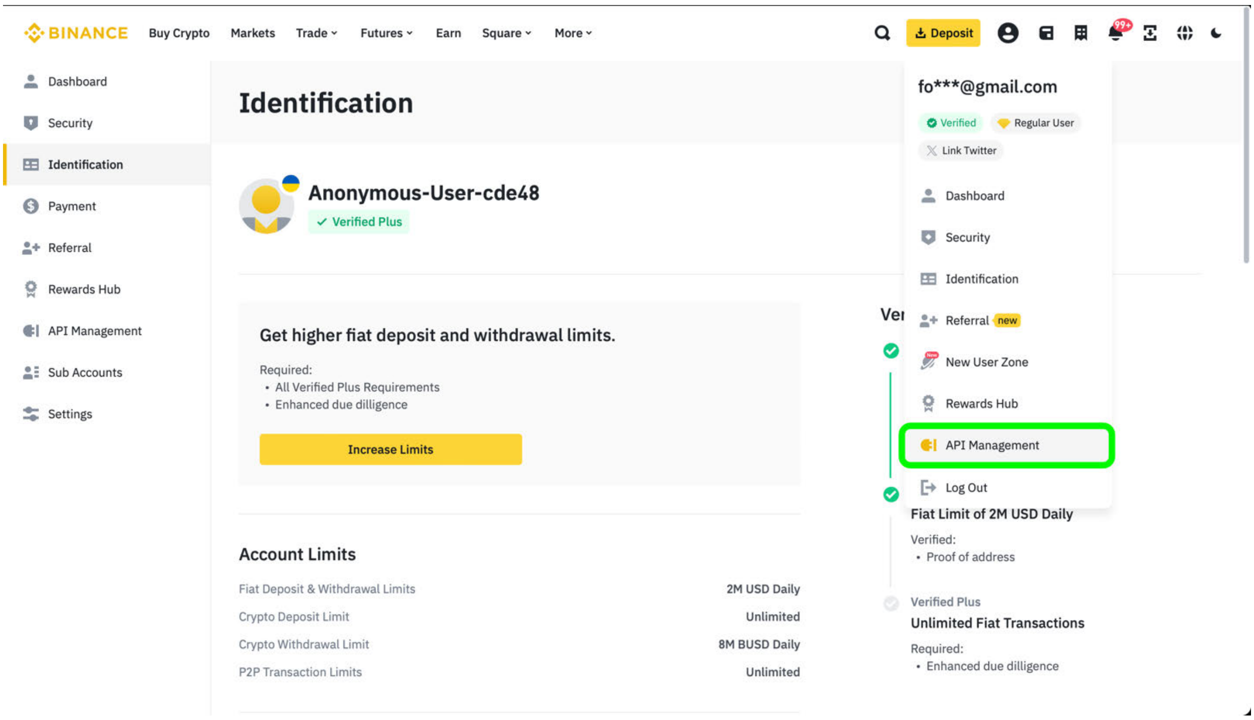

Figure 5. Creation of API Key

As we can see in Figure 6, at the time of creation, we have two keys – the Secret Key and the API Key, also known as the Public Key.

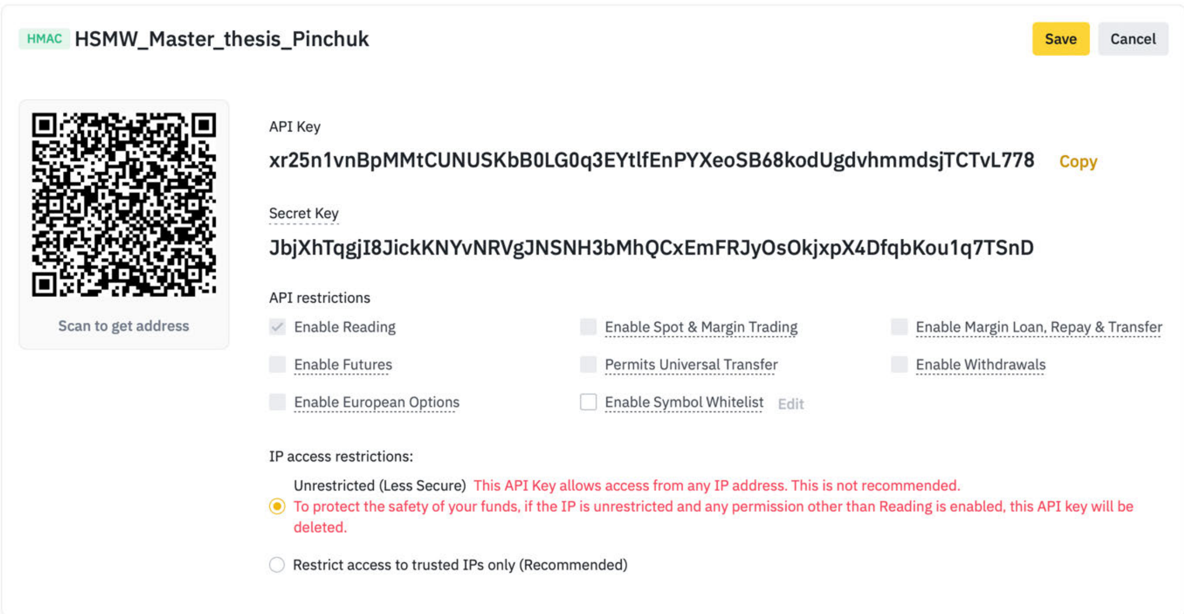

Figure 6. API Key Setup

After copying both keys to a secure location, we click on "Save." It's crucial to save the "Secret Key" as there won't be an option to retrieve it later, and creating a new key will be necessary.

Next, we navigate to the main page of the TSLab company website in the "Personal Account" section. We select to create a new connector and, from the list of "TS LAB Data Providers," choose the Binance.com exchange. For new accounts, there's an offer for a free subscription for the first 3 months, which we opt for. After the 3-month period, the subscription will cost 60 euros per month. This is a reasonable option if the researcher creates and tests their trading system during that time and wishes to trade it using TSlab. For students, there's a chance to learn how to create trading algorithms during the trial period completely free of charge.

When creating the key, we enter the previously saved "Public API Key" and choose the maximum usage period of 3 months (Figure 7).

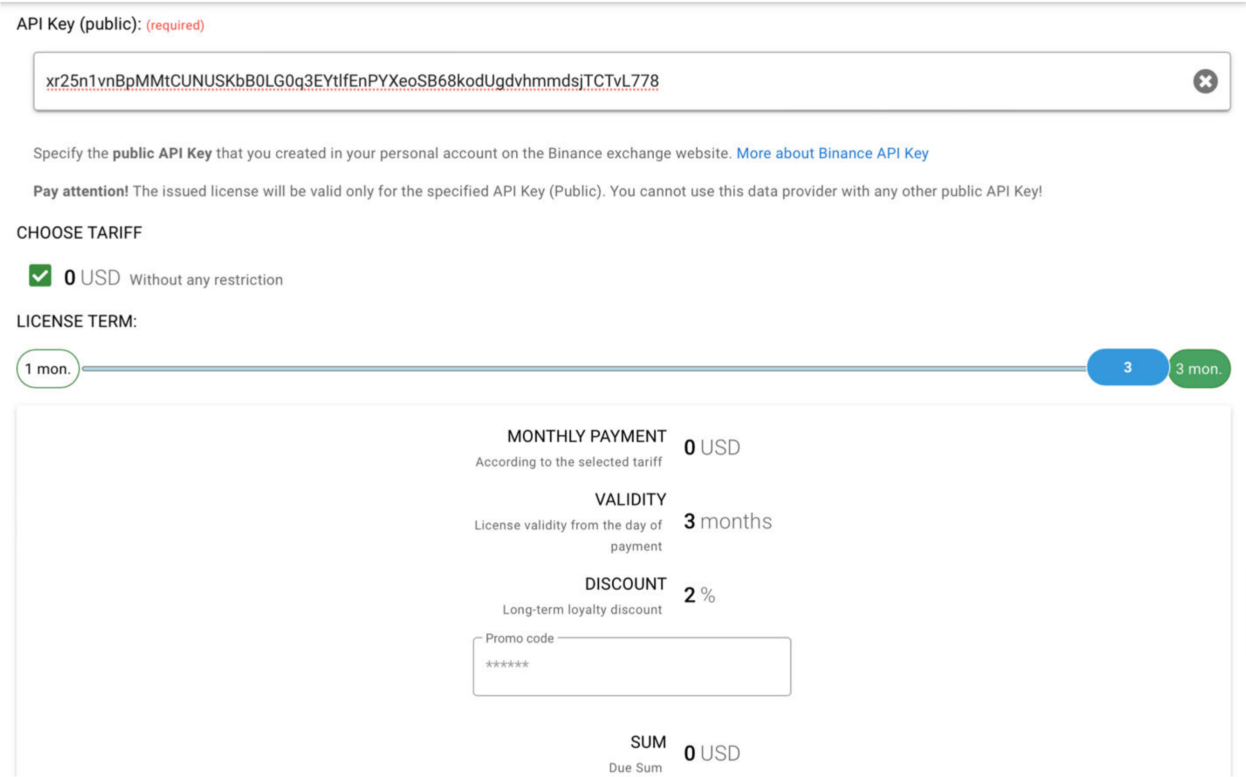

Figure 7. Creation of TSLab data online connector

We click "Done," and our connector is successfully created. We then proceed to the connector's page, where we can find a section titled "Key" with the code we will need later for creating an online data provider in TSLAB (Figure 8).

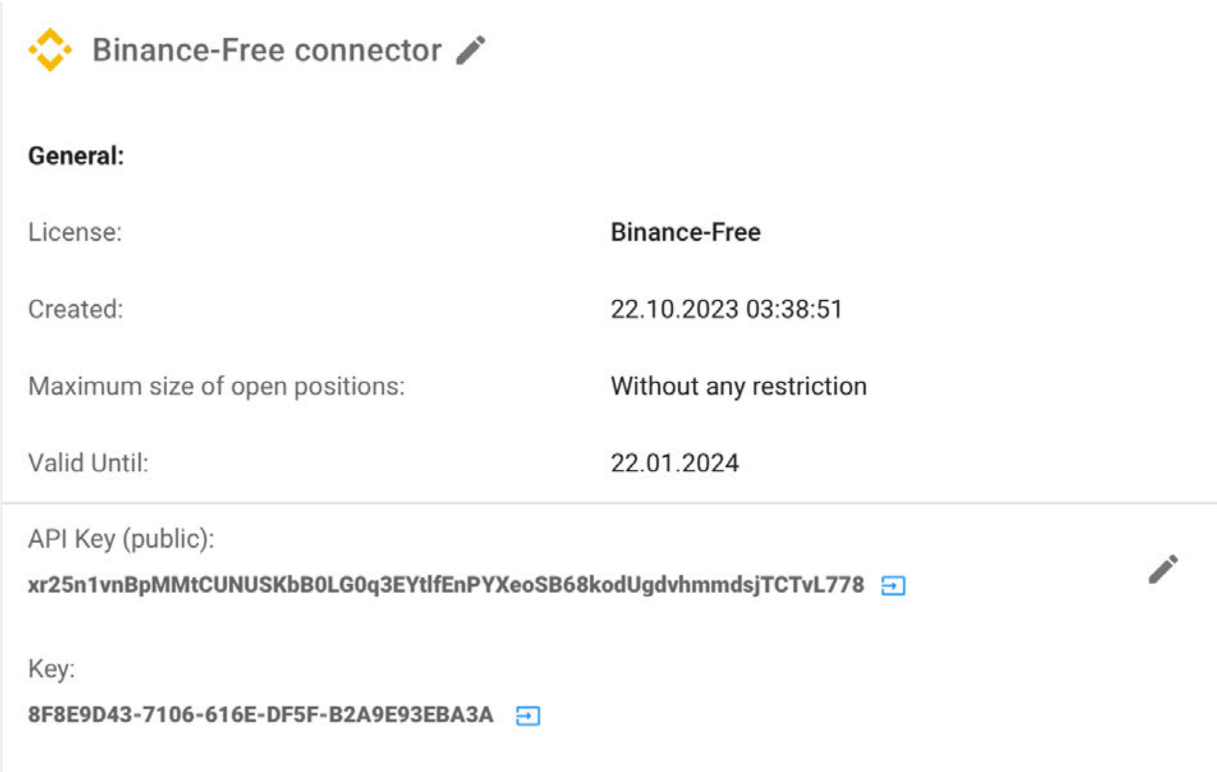

Figure 8. License key for TSLab connector

Next, we proceed to create a connector in TSLab to receive real-time market quotes. To do this, we download the software from the website https://www.tslab.pro/download and install it on our personal computer or Windows server.

In the TSLab menu, go to the "Data" section and select "Add Online Data Provider."

To create the provider, we will need to enter the API Public and API Secret Keys saved earlier. We leave the other parameters unchanged and click "Next."

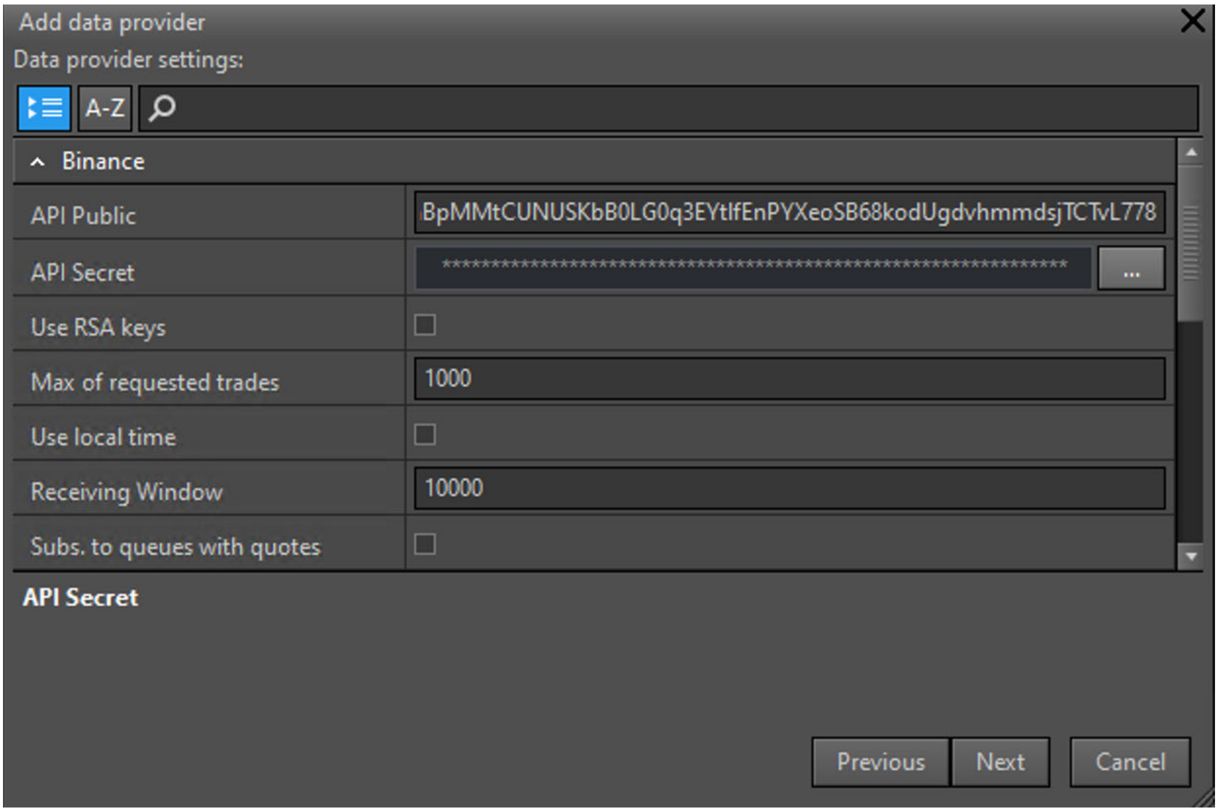

Figure 9. Data connector configuration

Then select the created Data Provider from the list and click the "Key" button, where we enter the key saved earlier from the TSLab website (Figure 10).

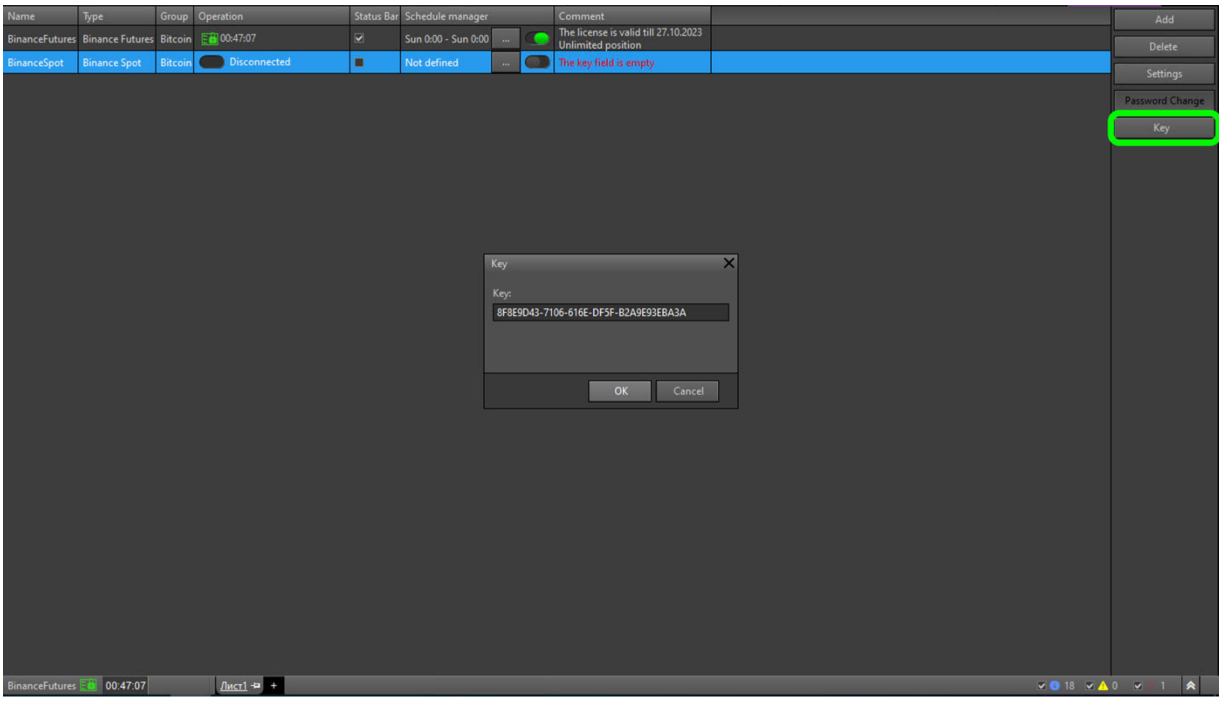

Figure 10. TSLab license key entry

The last step is to edit the connection schedule so that the data provider always automatically reconnects if the connection is lost. (Figure 11)

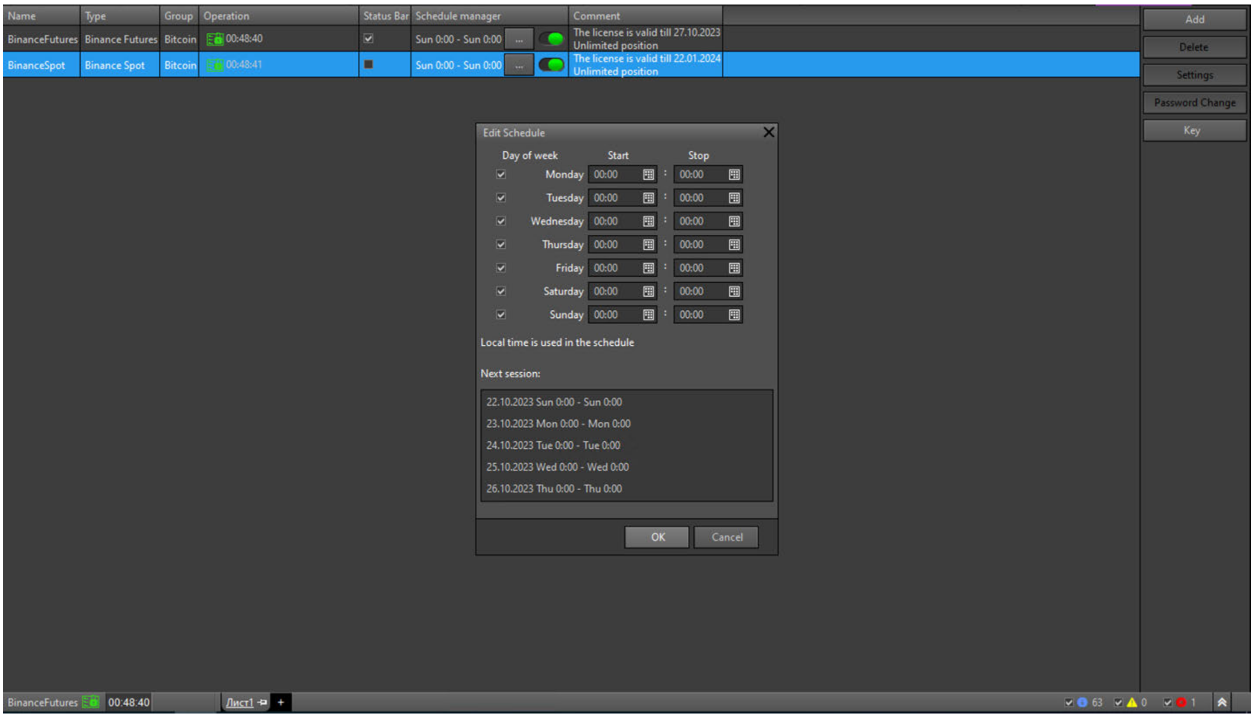

Figure 11. Creation of API Key

So we have gained access to real-time data from the Binance exchange, and now we have access to trading historical data for all cryptocurrency trading pairs since they were listed on the exchange.

The final step is to ensure that everything is working correctly. We go to the "Lab" page, then to "Scripts," and create a new script. Open the new script and go to the "Editor" tab, where you will see the visual constructor for your future strategy. Open the cube of the "Tradable instrument" class and select the desired trading instrument (Figure 12).

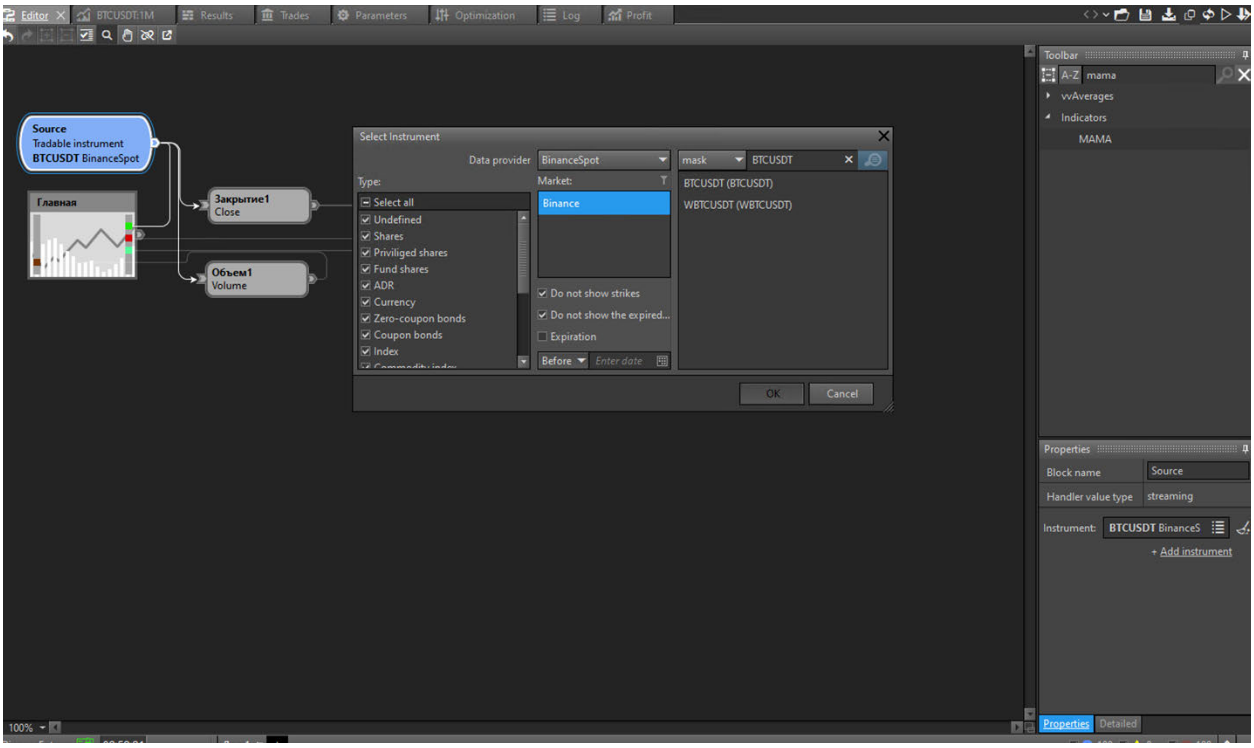

Figure 12. Tradable source selection

When you navigate to the trading instrument's page in the script with the selected data source, you should see real-time updated market data for the trading pair (Figure 13).

Figure 13. Online data feeding

4.3 Performance evaluation

To create a successful trading strategy, we need an effective evaluation algorithm, which should be defined before the development process begins. Quantitative researchers in hedge funds seek strategies with a stable and smooth profit curve without so-called "outliers" when the lion's share of profit comes from individual trades.

Another factor to consider during development is the viability and robustness of the strategy when dealing with changes in liquidity. During periods of low liquidity, the order book's density decreases, resulting in slippage, where the price of the exchange order signal differs from the actual execution price in a negative direction. Slippage is considered a transaction cost. The research has shown that for Bitcoin, with a small average profit per trade (less than 0.5%) for a capital of more than 1 million euros, and even for some low-liquidity trading pairs, a strategy's performance curve deteriorates significantly. Therefore, one of the first metrics is to have an average profit per trade of more than 0.5%.

Since our research is based on statistics, having a sample with maximum statistical significance is important to us. In other words, it is important for us to have a minimum of 50-100 trades on In-Sample backtests. Ideally, the number of trades per instrument/portfolio should exceed 10,000. However, due to the short history of cryptocurrencies, we don't have enough data to adhere to this rule. Nevertheless, we will discard backtests with a small number of trades to avoid "outliers." So, the second metric is not less than 50-100 trades on the backtest per instrument.

The next metric will be the top 20 results based on the Recovery Factor because the Recovery Factor will be our primary metric showing profitability weighted against risk. It should be greater than 3 in a year to be considered a good strategy by many traders.

From the top 20 results based on the Recovery Factor, we will select the best result based on the Profit Factor.

This evaluation algorithm was developed after studying numerous online and offline sources with works by quantitative researchers and traders regarding the process of developing trading strategies and evaluating their effectiveness.

Overall, creating a strategy evaluation system during the development of trading algorithms is a separate area for research that can significantly improve traders' trading results and provide a trading advantage.

At this stage, we have everything we need to start the actual development of the trading strategy.

4.4 Strategies

The first step in creating a strategy is to take into account exchange commissions and potential slippage. At the time of writing this work, the standard commissions on Binance.com were 0.04% for market orders and 0.02% for limit orders. For backtesting purposes, we consider the maximum possible commission of 0.04% and add a buffer for slippage of 0.06%, resulting in total order costs of 0.1%. It is crucial to account for these costs because strategies created and optimized without considering expenses will likely be unprofitable in the real market.

The initial capital for trading will amount to $100,000 USDT for each backtest.

At this stage, we will conduct backtests only on the BTCUSDT trading pair. The hypothesis is that if a strategy works with Bitcoin, it is highly likely to be suitable for other cryptocurrencies, and vice versa.

4.4.1 Trend Following Strategy

In this master's thesis, we will dive deeper than simple moving averages and develop a trend-following strategy using more complex models by John Ehlers. John Ehlers is a renowned engineer and author in the field of technical analysis and market indicators. His evaluation methods include various filtering and forecasting techniques aimed at improving trading strategy signals.

In his article "MAMA – the mother of adaptive moving averages," he describes the high efficiency of his MAMA indicator, which stands for MESA Adaptive Moving Average. The nonlinear behavior of this filter is achieved by reversing the phase every half period. When combined with FAMA (another moving average developed by Ehlers), intersections, according to the author, generate excellent entry and exit signals, relatively free from reversals. We will use Ehlers' work to create a trading strategy and test its effectiveness in the cryptocurrency market.

To create this strategy, we will need to write the aforementioned indicators in the C# language for the TSLab platform. In our case, my extended library in TSLab already includes MAMA and FAMA, but the code with the formulas for these indicators is also provided at the end of this research.

Having the indicators and market data, we can create the first version of the trading strategy. The main goal of algorithmic trading is to achieve market neutrality, which can be done by trading both long positions and short sales. Therefore, our strategies will have long and short logic.

For trend-following strategies, 1-hour data was chosen through trial and error since the average volatility on smaller timeframes (1 minute, 5 minutes, 15 minutes, 30 minutes) is insufficient to cover transaction costs, which significantly affect strategy stability.

So, we create the first simple version of the strategy, which we will further refine.

Trend Following v0.01

```
Longs

If MAMA cross under FAMA
        open long
        If MAMA < FAMA
                close long

Shorts

If MAMA cross over FAMA
        open short
        If MAMA > FAMA
                close short
```

In the indicators, we will keep the default parameters: fast limit - 0.5, slow limit - 0.05. At this stage, we don't have risk management in our trades, and we always trade with our entire capital.

Figure 14 shows a flowchart of the strategy in the TSLab framework.

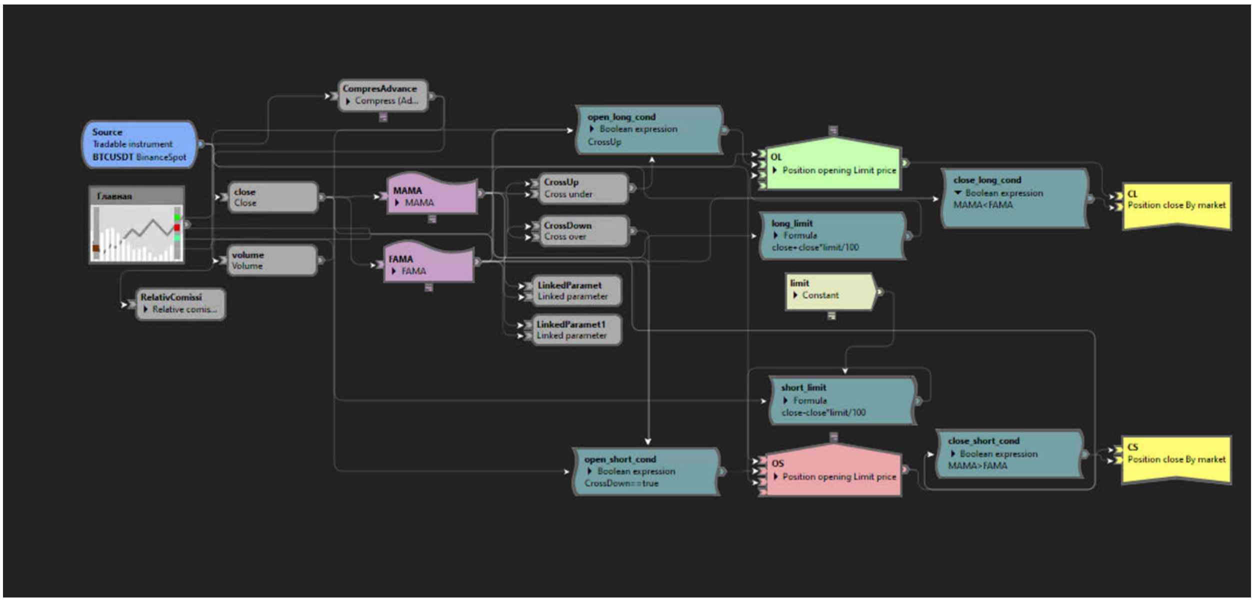

Figure 14. “No code” strategy script

Position opening occurs with limit orders and a fixed slippage of 0.06%. Accordingly, in cases of insufficient liquidity in real trading, we may not fill the position completely, but we won't have a worse execution price than in testing. When developing the strategy using market orders, we don't control slippage, which creates liquidity risk when entering a position. When exiting trades, we have no other option to close the position quickly other than with market orders, so the risk of losses due to low liquidity remains.

As seen in Table and 1 Figure 15, even without any filters, the strategy shows positive results. In the next iterations, we will attempt to improve the strategy.

Table 1. Trend following V0.01 performance

	All	Buy	Sell	Market
Net profit/loss	+286388.93	+231398.22	+54990.71	+29236.90
Commission	+171690.06	+74205.88	+97484.18	+99.99
Net profit/loss %	286.39%	231.40%	54.99%	29.24%
Gross MFE	+818189.66	+400562.63	+417627.03	+56219.68
CAGR Year	30.43%	26.55%	8.99%	5.17%
CAGR Month	2.21%	1.95%	0.71%	0.42%
Profit per Bar	+6.53	+5.28	+1.25	+0.67
Number of trades	739	370	369	1
Average profit/loss	+387.56	+625.41	+149.03	+29236.90
Average profit/loss %	0.38%	0.625%	0.15%	29.24%
Bars Held (Average)	+58.31	+61.05	+55.56	+43118.00
Winning trades	218	114	104	1
Winning %	29.50%	30.81%	28.18%	100.00%
Gross profit	+1432923.64	+789936.74	+642986.89	+29236.90
Average profit	+6573.04	+6929.27	+6182.56	+29236.90
Average profit %	6.57%	6.93%	6.18%	29.24%
Bars Held (Average)	+121.39	+127.90	+114.25	+43118.00
Maximum consecutive	5	4	5	1
Loss trades	521	256	265	0
Loss %	70.50%	69.19%	71.82%	0.00%
Gross loss	1146534.70	558538.52	587996.18	0.00
Average loss	2200.64	2181.79	2218.85	0.00
Average loss %	2.20%	2.18%	2.22%	0.00%
Bars Held (Average)	+31.92	+31.28	+32.54	0.00
Maximum consecutive	14	14	14	0
Maximum drawdown	55256.31	77154.57	101023.582	75403.74
Maximum drawdown day	08.06.2022	31.12.2022	11.11.2021	15.12.2018
Maximum drawdown %	33.16%	39.16%	46.29172640%	75.40%
Maximum drawdown day%	29.01.2018	08.02.2018	11.11.2021	15.12.2018
Fixed Maximum drawdown	53539.86	76794.82	99948.07050970	0.00
Fixed Maximum drawdown day	20.06.2022	01.01.2023	14.11.2021	N\A
Profit factor	+1.24	+1.41	+1.10	0.00
Recovery Factor	+5.18	+2.99	+0.54	+0.39
Fixed Recovery Factor	+5.35	+3.01	+0.55	(?)
Payoff ratio	+2.99	+3.18	+2.79	?
Sharpe ratio	+0.32	+0.26	+0.13	+0.13
Sortino ratio	+0.93	+0.62	+0.26	+0.22

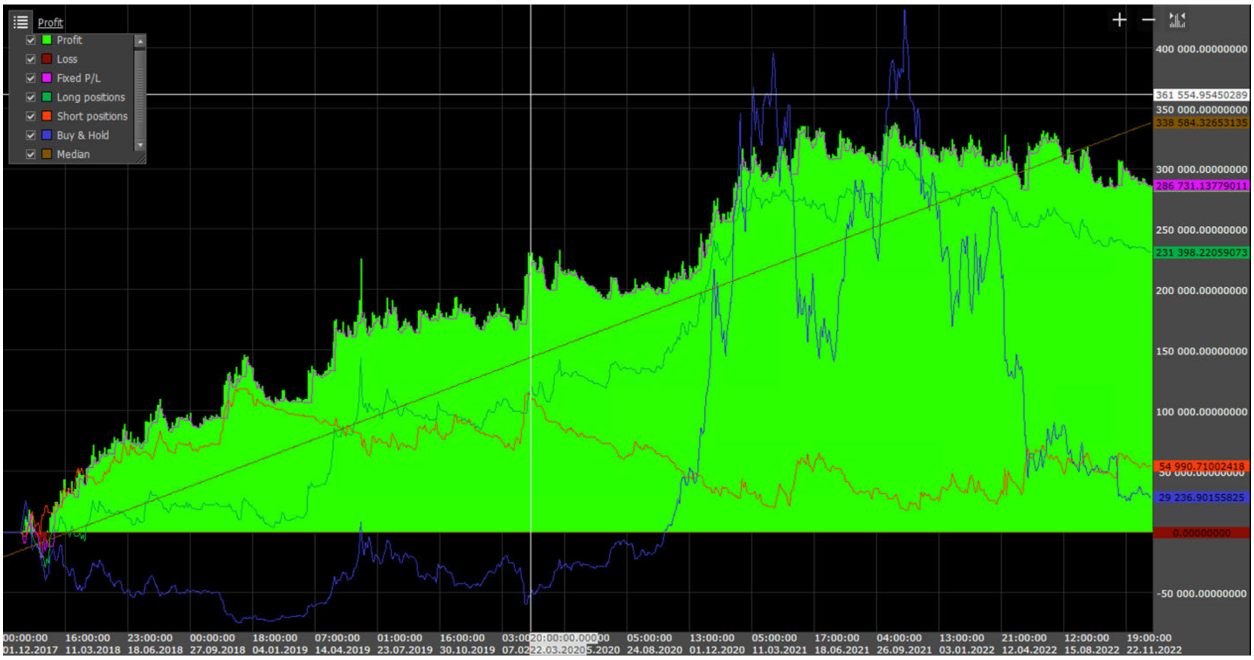

Figure 15. Trend following V0.01 equity curve

Next, we add a trend filter. The ADX (Average Directional Index) indicator is well-suited for this purpose as it measures the strength of the trend. Let's use the indicator with the standard period of 14. The logic is that if the indicator value is above the threshold of 35, then the market is more likely to be trending, and we should open a trade based on a trend following strategy. Conversely, if the value is less than 35, it's likely that the market is in a ranging state, and such trades should be avoided.

Trend Following v0.02

```
Longs

If MAMA cross under FAMA and ADX(14)> 35
        open long
        If MAMA < FAMA
                close long

Shorts

If MAMA cross over FAMA and ADX(14) > 35
        open short
        IF MAMA > FAMA
                Close short
```

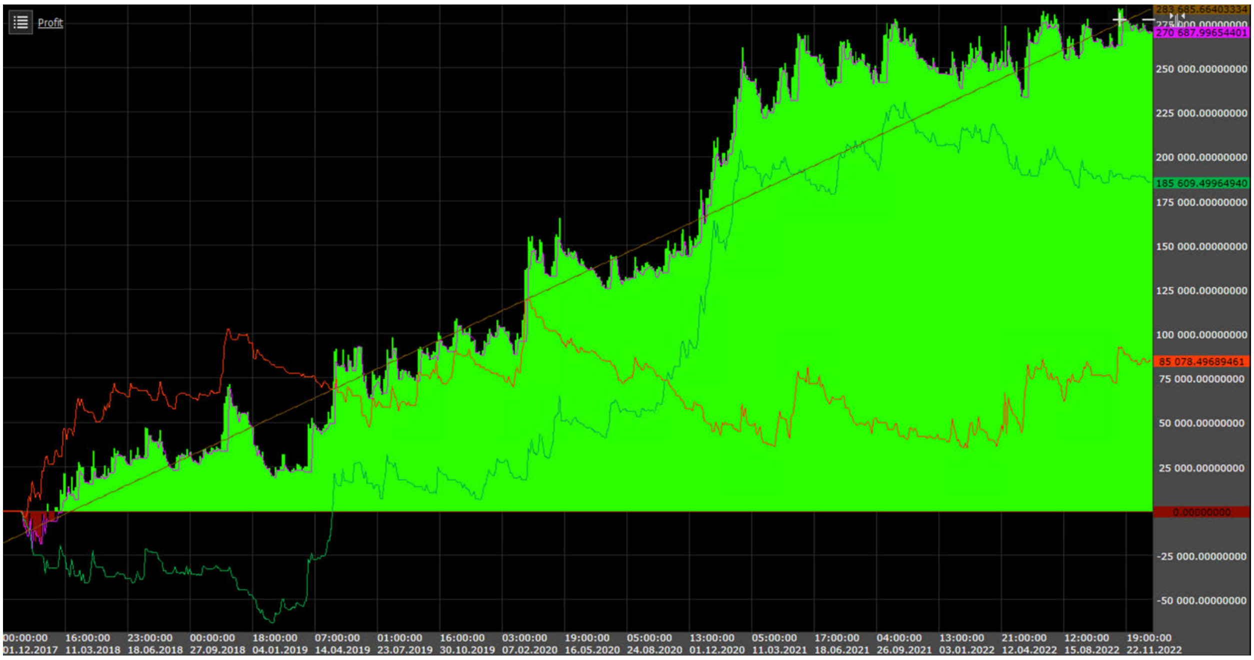

Figure 16. Trend following V0.02 equity curve

After adding the trend filter, the metrics improved slightly, with the Recovery Factor increasing from 1.25 to 1.30, the Profit Factor from 5.18 to 5.33, and the Maximum Drawdown decreasing from -33.16% to 29.96%. In the third version of the trend-following strategy, we add another trend filter using the RSI (Relative Strength Index) indicator with the standard period of 14. The logic here is that if RSI > 50, the trend is considered upward, and if RSI < 50, the trend is considered downward.

Table 2. Trend following V0.02 performance

	All	Buy	Sell	Market
Net profit/loss	+270687.99	+185609.50	+85078.50	+29236.90
Commission	+134608.88	+57843.40	+76765.48	+99.99
Net profit/loss %	270.69%	185.61%	85.079%	29.24%
Gross MFE	+673123.60	+329650.14	+343473.46	+56219.68
CAGR Year	29.37%	22.91%	12.86%	5.17%
CAGR Month	2.14%	1.71%	0.99%	0.42%
Profit per Bar	+6.18	+4.24	+1.94	+0.67
Number of trades	575	288	287	1
Average profit/loss	+470.76	+644.48	+296.44	+29236.90
Average profit/loss %	0.47%	0.65%	0.30%	29.24%
Bars Held (Average)	+61.11	+63.87	+58.33	+43118.00
Winning trades	176	93	83	1
Winning %	30.61%	32.29%	28.92%	100.00%
Gross profit	+1179159.01	+628218.99	+550940.02	+29236.90
Average profit	+6699.77	+6755.04	+6637.83	+29236.91
Average profit %	6.70%	6.76%	6.63%	29.24%
Bars Held (Average)	+123.73	+129.86021505	+116.85	+43118.00
Maximum consecutive	4	5	4	1
Loss trades	399	195	204	0
Loss %	69.39%	67.71%	71.08%	0.00%
Gross loss	908471.01	442609.49	465861.52	0.00
Average loss	2276.87	2269.80	2283.64	0.00
Average loss %	2.28%	2.27%	2.28%	0.00%
Bars Held (Average)	+33.49	+32.40	+34.53	0.00
Maximum consecutive	13	15	15	0
Maximum drawdown	50807.26	63106.25	84387.12	75403.75
Maximum drawdown day	08.02.2019	04.02.2019	11.02.2022	15.12.2018
Maximum drawdown %	29.96%	63.11%	38.49%	75.40%
Maximum drawdown day%	08.02.2019	04.02.2019	11.02.2022	15.12.2018
Fixed Maximum drawdown	50651.28	62939.83	83540.51	0.00
Fixed Maximum drawdown day	08.02.2019	04.02.2019	15.02.2022	N\A
Profit factor	+1.30	+1.42	+1.18	0.00
Recovery Factor	+5.33	+2.94	+1.01	+0.39
Fixed Recovery Factor	+5.34	+2.95	+1.02	(?)
Payoff ratio	+2.94	+2.98	+2.91	?
Sharpe ratio	+0.29	+0.184	+0.17	+0.13
Sortino ratio	+0.64	+0.40	+0.37	+0.22

Trend Following v0.03.

```
Longs

If MAMA cross under FAMA and ADX(14)> 35 and RSI (14) > 50
        open long
        If MAMA < FAMA
                close long

Shorts

If MAMA cross over FAMA and ADX(14) > 35 and RSI (14) < 50
        open short
        IF MAMA > FAMA
                Close short
```

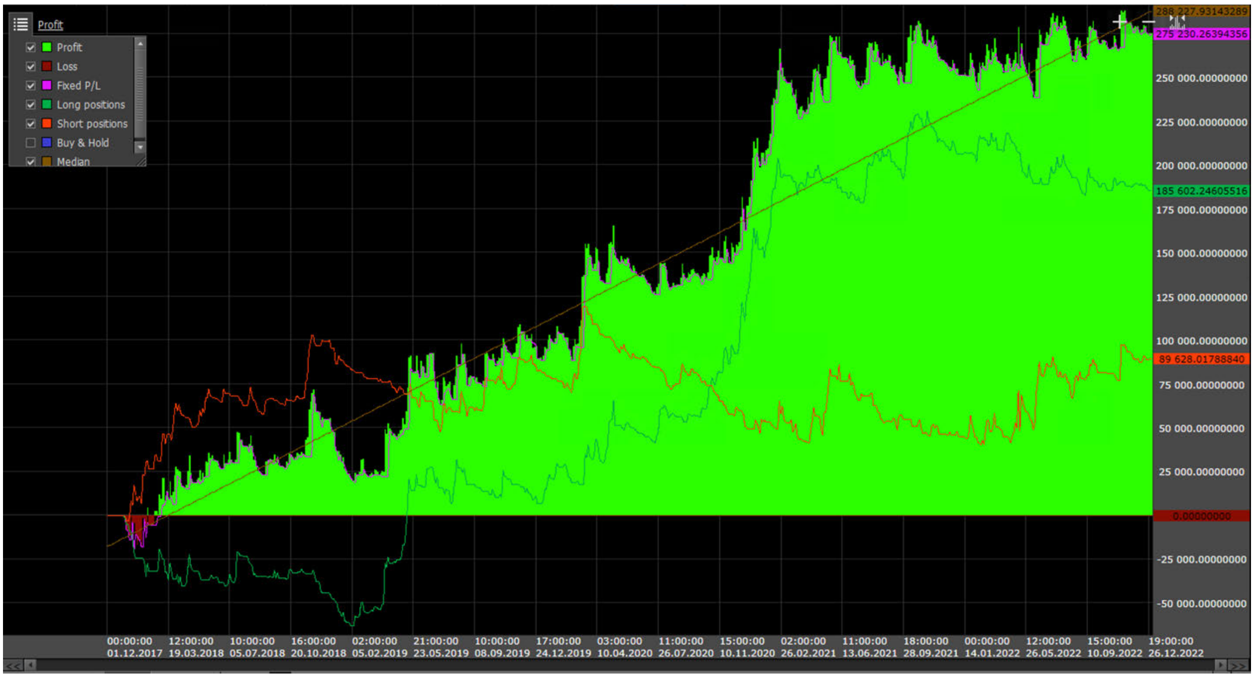

Figure 17. Trend following V0.03 equity curve

The backtest results show that after adding RSI to the strategy, we were able to increase the Net Profit/Loss from 270.69% to 275.23%, with almost no change in the maximum drawdown. As a result of this change, the Profit Factor increased from 5.33 to 5.42.

Table 3. Trend following V0.03 performance

	All	Buy	Sell	Market
Net profit/loss	+275230.26	+185602.25	+89628.02	+29236.90
Commission	+133982.46	+57442.99	+76539.46	+99.99
Net profit/loss %	275.23%	185.60%	89.63%	29.24%
Gross MFE	+670532.02	+329148.31	+341383.71	+56219.68
CAGR Year	29.68%	22.91%	13.40%	5.17%
CAGR Month	2.16%	1.71%	1.04%	0.42%
Profit per Bar	+6.28	+4.23	+2.05	+0.666
Number of trades	572	286	286	1
Average profit/loss	+481.17	+648.96	+313.39	+29236.90
Average profit/loss %	0.48%	0.65%	0.31%	29.24%
Bars Held (Average)	+61.17	+63.86	+58.47	+43118.00
Winning trades	175	92	83	1
Winning %	30.59%	32.17%	29.02%	100.00%
Gross profit	+1178824.59	+627884.57	+550940.02	+29236.90
Average profit	+6736.14	+6824.83	+6637.83	+29236.90
Average profit %	6.74%	6.82%	6.64%	29.24%
Bars Held (Average)	+123.73	+129.93	+116.86	+43118.00
Maximum consecutive	4	5	4	1
Loss trades	397	194	203	0
Loss %	69.41%	67.83%	70.98%	0.00%
Gross loss	903594.32	442282.32	461312.00	0.00
Average loss	2276.06	2279.81	2272.47	0.00
Average loss %	2.28%	2.28%	2.27%	0.00%
Bars Held (Average)	+33.59	+32.53	+34.60	0.00
Maximum consecutive	13	15	15	0
Maximum drawdown	50807.26	63440.68	79837.60	75403.75
Maximum drawdown day	08.02.2019	04.02.2019	11.02.2022	15.12.2018
Maximum drawdown %	30.02%	63.44%	36.42%	75.40%
Maximum drawdown day%	08.02.2019	04.02.2019	11.02.2022	15.12.2018
Fixed Maximum drawdown	50651.28	63274.28	78990.99	0.00
Fixed Maximum drawdown day	08.02.2019	04.02.2019	23.02.2022	N\A
Profit factor	+1.30	+1.42	+1.19	0.00
Recovery Factor	+5.42	+2.93	+1.12	+0.39
Fixed Recovery Factor	+5.44	+2.93	+1.14	(?)
Payoff ratio	+2.96	+2.99	+2.92	?
Sharpe ratio	+0.29	+0.19	+0.17	+0.13
Sortino ratio	+0.64	+0.40	+0.39	+0.22

In the fourth version of the script, we added the DI+ (Directional Indicator Plus) and DI- (Directional Indicator Minus) indicators, which are two components of the ADX (Average Directional Index) indicator. They are used to assess the direction of the trend in the market:

- DI+ (Directional Indicator Plus): This component measures the strength of the bullish movement (price increases) in the market. DI+ is calculated based on upward price changes.
- DI- (Directional Indicator Minus): This component measures the strength of the bearish movement (price decreases) in the market. DI- is calculated based on downward price changes.

If DI+ predominates, it may indicate a bullish trend, and conversely, if DI- predominates, it may indicate a bearish trend. We use the indicators with the standard period of 14.

Trend Following v0.04

```
Longs

If MAMA cross under FAMA and ADX(14) > 35 and RSI (14) >50 and DI+(14) >
DI-(14)
        open long
        If MAMA < FAMA
                close long

Shorts

If MAMA cross over FAMA and ADX(14) > 35 and RSI (14) <50 and DI+(14) > DI-
(14)
        open short
        If MAMA > FAMA
                Close short
```

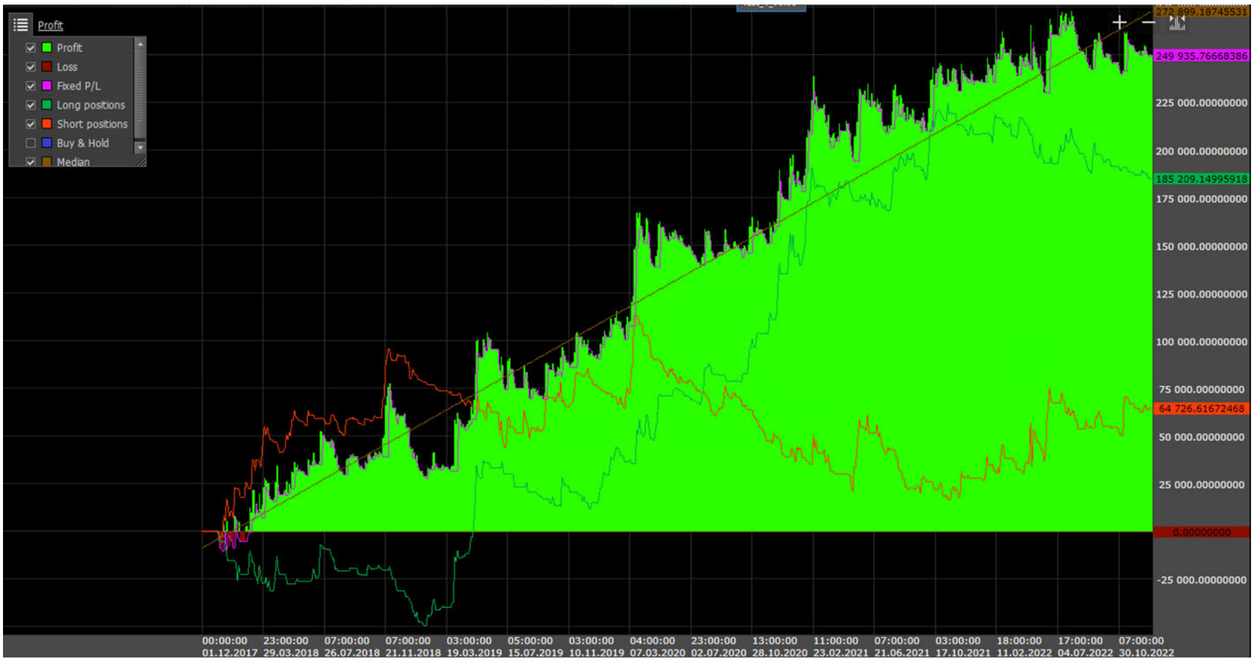

Figure 18. Trend following V0.04 equity curve

As shown in the Figure 18 and Table 4, this filter worsened the overall results of Net Profit/Loss and Recovery Factor, so we are discarding it and will not use it in future versions of the strategy.

It is known that when abnormally high or low volatility occurs, which is not considered in the In Sample dataset used for training, the strategy ceases to be profitable and can result in unpredictable losses. For this reason, we will introduce a volatility trading range using the Bollinger Bands Width indicator. BBWidth (Bollinger Bands Width) is a technical indicator that measures the width of the Bollinger Bands. Bollinger Bands are an important tool in technical analysis, consisting of a simple moving average, upper bands (upper boundaries), and lower bands (lower boundaries). The BBWidth indicator assesses the difference between the upper and lower bands. Essentially, it represents the distance of two standard deviations upwards and downwards from the Simple Moving Average with a standard calculation period of 20.

Table 4. Trend following V0.04 performance

	All	Buy	Sell	Market
Net profit/loss	+249935.77	+185209.15	+64726.62	+29236.90
Commission	+114997.77	+44829.99	+70167.78	+99.99
Net profit/loss %	249.94%	185.21%	64.73%	29.24%
Gross MFE	+584871.75	+272847.03	+312024.72	+56219.68
CAGR Year	27.92%	22.88%	10.31%	5.17%
CAGR Month	2.04%	1.71%	0.81%	0.42%
Profit per Bar	+5.70	+4.23	+1.48	+0.67
Number of trades	484	223	261	1
Average profit/loss	+516.40	+830.53	+247.99	+29236.90
Average profit/loss %	0.52%	0.83%	0.25%	29.24%
Bars Held (Average)	+63.28	+67.84	+59.39	+43118.00
Winning trades	148	74	74	1
Winning %	30.58%	33.18%	28.35%	100.00%
Gross profit	+1033119.62	+524861.02	+508258.60	+29236.90
Average profit	+6980.54	+7092.72	+6868.36	+29236.90
Average profit %	6.98%	7.09%	6.86%	29.24%
Bars Held (Average)	+125.65	+133.59	+117.70	+43118.00
Maximum consecutive	3	8	4	1
Loss trades	336	149	187	0
Loss %	69.42%	66.82%	71.65%	0.00%
Gross loss	783183.86	339651.87	443531.99	0.00
Average loss	2330.90	2279.54	2371.83	0.00
Average loss %	2.33%	2.28%	2.37%	0.00%
Bars Held (Average)	+35.81	+35.18	+36.31	0.00
Maximum consecutive	11	14	13	0
Maximum drawdown	47586.01	49680.46	97657.18	75403.75
Maximum drawdown day	08.02.2019	04.02.2019	11.11.2021	15.12.2018
Maximum drawdown %	27.18%	49.68%	45.76%	75.40%
Maximum drawdown day%	08.02.2019	04.02.2019	11.11.2021	15.12.2018
Fixed Maximum drawdown	47430.03	49514.03	96581.67	0.00
Fixed Maximum drawdown day	08.02.2019	04.02.2019	14.11.2021	N\A
Profit factor	+1.32	+1.55	+1.15	0.00
Recovery Factor	+5.25	+3.73	+0.66	+0.39
Fixed Recovery Factor	+5.27	+3.74	+0.67	(?)
Payoff ratio	+2.99	+3.11	+2.90	?
Sharpe ratio	+0.29	+0.19	+0.14	+0.13
Sortino ratio	+0.66	+0.47	+0.30	+0.22

We restrict trading within the range of BBWidth values from 1% to 20%. Furthermore, the values of this range will be optimized for the specific instrument or portfolio, making them constants named vlt_min and vlt_max.

Trend Following v0.05

Longs

If MAMA **cross under** FAMA **and** ADX(14) > 35 **and** RSI(14) > 50 **and** BBWidth(20) > vlt min **and** BBWidth(20) < vlt max

    open long

    If MAMA < FAMA

        close long

Shorts

If MAMA **cross over** FAMA **and** ADX(14) > 35 **and** RSI(14) < 50 **and** BBWidth(20) > vlt min **and** BBWidth(20) < vlt max

    open short

    If MAMA > FAMA

        close short

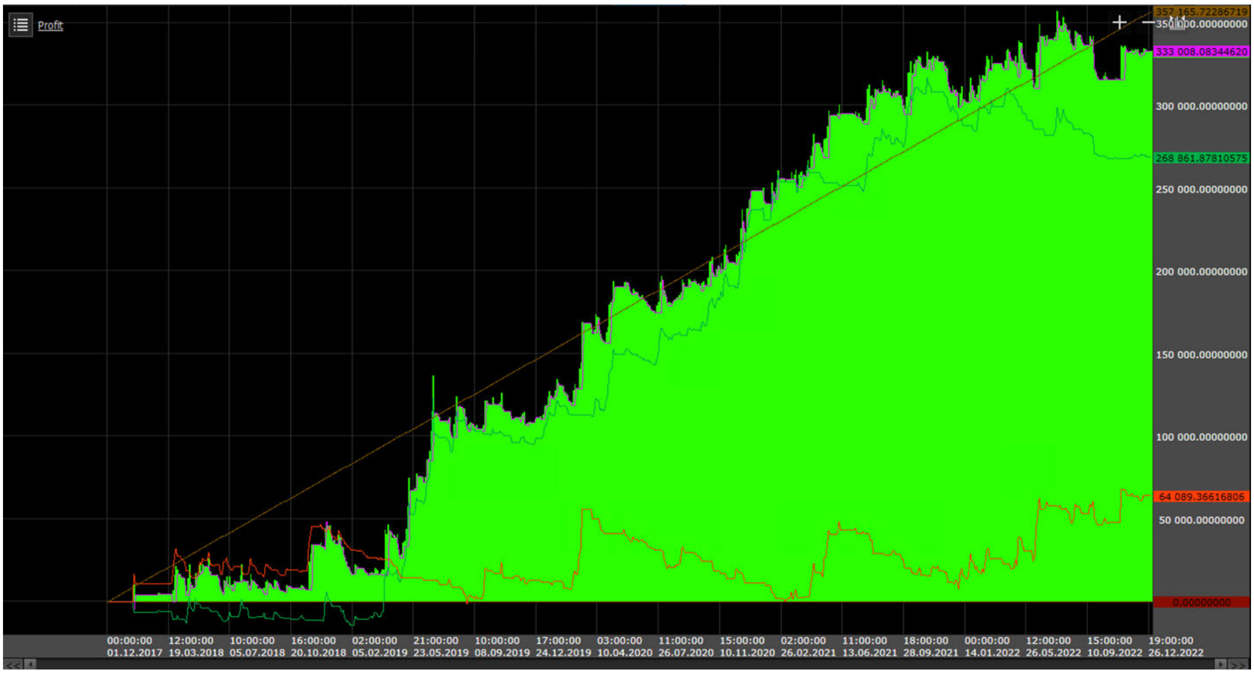

Figure 19. Trend following V0.05 equity curve

Table 5. Trend following V0.05 performance

	All	Buy	Sell	Market
Net profit/loss	+332951.24	+268861.88	+64089.37	+29236.90
Commission	+104832.94	+46715.53	+58117.41	+99.99
Net profit/loss %	332.95%	268.86%	64.09%	29.24%
Gross MFE	+483105.96	+236682.52	+246423.44	+56219.68
CAGR Year	33.38%	29.25%	10.22%	5.17%
CAGR Month	2.40%	2.13%	0.80%	0.42%
Profit per Bar	+7.60	+6.13	+1.46	+0.67
Number of trades	455	232	223	1
Average profit/loss	+731.76	+1158.89	+287.40	+29236.90
Average profit/loss %	0.73%	1.16%	0.29%	29.24%
Bars Held (Average)	+55.88	+60.09	+51.50	+43118.00
Winning trades	133	74	59	1
Winning %	29.23%	31.90%	26.46%	100.00%
Gross profit	+963336.99	+572572.01	+390764.99	+29236.90
Average profit	+7243.14	+7737.46	+6623.14	+29236.90
Average profit %	7.24%	7.74%	6.62%	29.24%
Bars Held (Average)	+121.33	+129.26	+111.39	+43118.00
Maximum consecutive	4	4	4	1
Loss trades	322	158	164	0
Loss %	70.77%	68.10%	73.54%	0.00%
Gross loss	630385.75	303710.13	326675.62	0.00
Average loss	1957.72	1922.22	1991.92	0.00
Average loss %	1.96%	1.92%	1.99%	0.00%
Bars Held (Average)	+28.84	+27.69	+29.95	0.00
Maximum consecutive	17	12	25	0
Maximum drawdown	39054.33	45857.47	55779.53	75403.75
Maximum drawdown day	29.09.2022	29.11.2022	05.03.2021	15.12.2018
Maximum drawdown %	22.56%	19.41%	35.83%	75.40%
Maximum drawdown day%	09.03.2019	08.02.2019	05.03.2021	15.12.2018
Fixed Maximum drawdown	37102.18	44731.95	54089.79	0.00
Fixed Maximum drawdown day	18.10.2022	03.12.2022	18.03.2021	N\A
Profit factor	+1.53	+1.89	+1.20	0.00
Recovery Factor	+8.53	+5.86	+1.15	+0.39
Fixed Recovery Factor	+8.97	+6.01	+1.18	(?)
Payoff ratio	+3.70	+4.03	+3.33	?
Sharpe ratio	+0.34	+0.30	+0.13	+0.13
Sortino ratio	+0.93	+0.95	+0.31	+0.22

The results of the backtest clearly show that the volatility trading range significantly improved all key metrics, including Net Profit/Loss, Average Profit, Recovery Factor, Profit Factor, and so on. For instance, the Recovery Factor has increased to 8.53.

Next, we will attempt to improve the strategy by introducing additional conditions for the BBWidth indicator. Reversals or trend continuations are often preceded by a slowing market and reduced volatility. To filter out false signals, we will add a condition to check if the BBWidth value at the time of the entry signal is lower than it was in the previous hour and less than it was 2 hours ago.

Trend Following v0.06.

Longs

If MAMA **cross under** FAMA **and** ADX(14) > 35 **and** RSI(14) > 50 **and** BBWidth(20) > vlt min **and** BBWidth(20) < vlt max **and** BBWidth(20) < BBWidth(20)[i-1] **and** BBWidth(20) < BBWidth [i-2]

    open long
    If MAMA < FAMA
        close long

Shorts

If MAMA **cross over** FAMA **and** ADX(14) > 35 **and** RSI(14) < 50 **and** BBWidth(20) > vlt min **and** BBWidth(20) < vlt max **and** BBWidth(20) < BBWidth(20)[i-1] **and** BBWidth(20) < BBWidth [i-2]

    open short
    If MAMA > FAMA
        close short

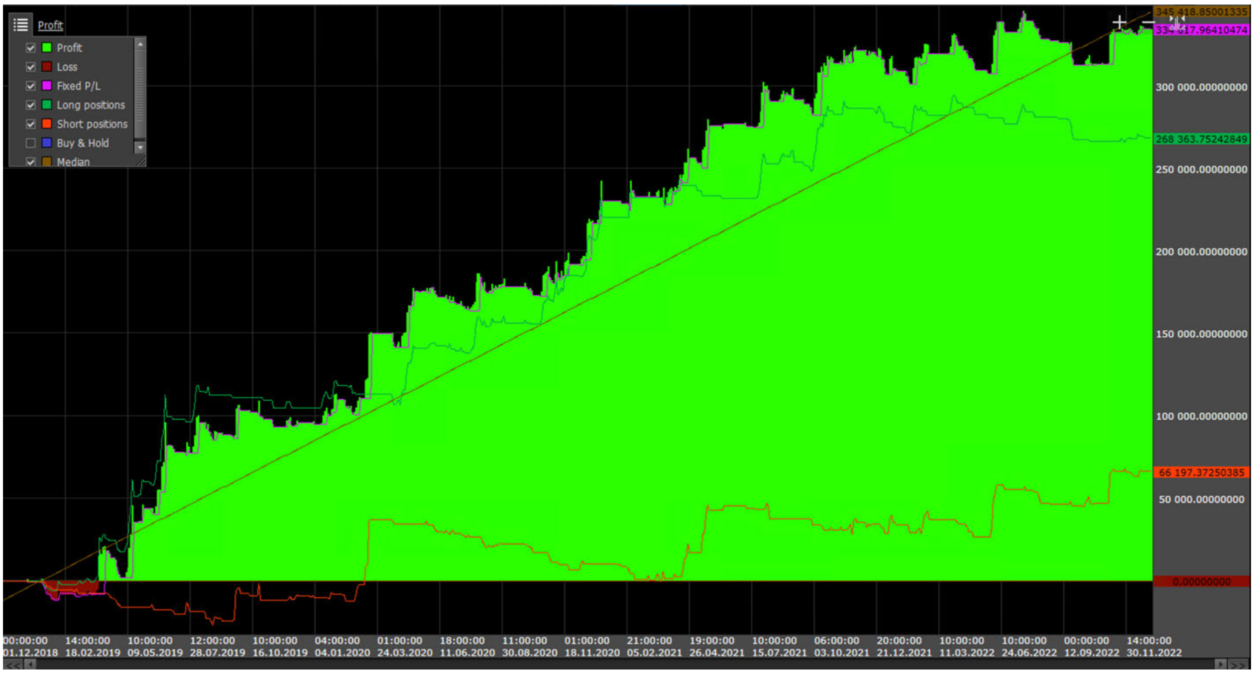

Figure 20. Trend following V0.06 equity curve

The results of the 6th version of the strategy improved compared to the previous one, indicating that the filter is effective. Net Profit remained nearly unchanged, while the Maximum Drawdown decreased from 22.56% to 14.27%.

This is very promising, as it shows that we were able to filter out false signals without affecting profitable trades. In the latest version of the strategy, we achieved an increase in the Recovery Factor from 8.53 to 10.02.

Table 6. Trend following V0.06 performance

	All	Buy	Sell	Market
Net profit/loss	+334561.13	+268363.75	+66197.37	+336739.84
Commission	+58715.22	+27495.83	+31219.39	+99.99
Net profit/loss %	334.56%	268.36%	66.20%	336.734%
Gross MFE	+337928.13	+171635.70	+166292.43	+65216.08
CAGR Year	43.25%	37.57%	13.23%	43.42%
CAGR Month	2.99%	2.66%	1.03%	3.01%
Profit per Bar	+9.52	+7.64	+1.88	+9.58
Number of trades	257	136	121	1
Average profit/loss	+1301.79	+1973.26	+547.09	+336739.84
Average profit/loss %	1.30%	1.97%	0.55%	336.74%
Bars Held (Average)	+58.27	+64.21	+51.59	+34419.00
Winning trades	77	44	33	1
Winning %	29.96%	32.35%	27.27%	100.00%
Gross profit	+658044.06	+435800.30	+222243.75	+336739.84
Average profit	+8546.03	+9904.55	+6734.66	+336739.84
Average profit %	8.55%	9.90%	6.74%	336.74%
Bars Held (Average)	+132.75	+146.86	+113.94	+34419.00
Maximum consecutive	4	4	5	1
Loss trades	180	92	88	0
Loss %	70.04%	67.64%	72.73%	0.00%
Gross loss	323482.93	167436.55	156046.38	0.00
Average loss	1797.13	1819.96	1773.25	0.00
Average loss %	1.80%	1.82%	1.77%	0.00%
Bars Held (Average)	+26.41	+24.68	+28.21	0.00
Maximum consecutive	15	10	18	0
Maximum drawdown	33378.70	28407.28	38468.46	11569.59
Maximum drawdown day	07.10.2022	29.11.2022	05.03.2021	29.01.2019
Maximum drawdown %	14.27%	7.23%	28.88%	11.57%
Maximum drawdown day%	30.04.2019	29.11.2022	26.08.2019	29.01.2019
Fixed Maximum drawdown	32483.24	27281.76	36778.73	0.00
Fixed Maximum drawdown day	23.09.2022	03.12.2022	18.03.2021	N\A
Profit factor	+2.03	+2.60	+1.42	0.00
Recovery Factor	+10.02	+9.45	+1.72	+29.11
Fixed Recovery Factor	+10.30	+9.84	+1.80	(?)
Payoff ratio	+4.75	+5.44	+3.80	?
Sharpe ratio	+0.41	+0.40	+0.15	+0.24
Sortino ratio	+1.55	+2.12	+0.45	+0.47

The 7th version of the strategy was our final attempt to filter out false signals. Upon analyzing the backtest trades, it was observed that in flat markets, FAMA and MAMA are often close to each other and frequently cross, leading to a series of losing trades (Figure 21).

Figure 21. Flat market phase

The solution was to create a filter that, at the moment of the moving averages crossing, checks whether there have been crossings in the last N hours. N is a constant that was optimized in the range from 1 to 30 after creating the filter. The filter was named MA_diff.

MA_diff = MAMA - FAMA

For entering long positions, MA_diff should have a negative value for the past N hours, and for short positions, it should have a positive value for the past N hours. After adding the filter, we conducted a backtest of the strategy with N=1. Then, we performed a brute force optimization from 1 to 30, as the typical duration of a trade in our strategy is around 30 hours.

Trend Following v0.07

MA_diff = MAMA-FAMA

Longs

If MAMA **cross under** FAMA **and** ADX(14) > 35 **and** RSI(14) > 50 **and** BBWidth(20) > vlt_min **and** BBWidth(20) < vlt_max **and** BBWidth(20) < BBWidth(20)[i-1] **and** BBWidth(20) < BBWidth [i-2] **and** MA_diff>MA_diff[i-N]

    open long
    If MAMA < FAMA
        close long

Shorts

If MAMA **cross over** FAMA **and** ADX(14) > 35 **and** RSI(14) < 50 **and** BBWidth(20) > vlt_min **and** BBWidth(20) < vlt_max **and** BBWidth(20) < BBWidth(20)[i-1] **and** BBWidth(20) < BBWidth(20)[i-2] **and** MA_diff>MA_diff[i-N]

    open short
    If MAMA > FAMA
        close short

During optimization, it's important to avoid outliers and ensure that neighboring values to the optimal one are similar in performance (Figure 22). In our case, the values 24 and 10 are both ideal. After analyzing the trades, we decided to choose the value of 10 because selecting N=24 would filter out many profitable trades, reducing Net Profit/Loss by 56%, which is not desirable.

Net profit/loss %	Maximum drawdown %	Number of trades	Average profit/loss %	Winning trades %	Winning trades	Profit factor	Recovery Factor	Fixed Recovery Factor	Payoff ratio	n.Value
303.36	-8.46	166	1.83	37.35	62	2.49	12.02	12.47	4.18	25
292.27	-12.44	175	1.67	36.00	63	2.35	10.86	11.24	4.18	24
291.83	-8.46	162	1.80	37.04	60	2.43	10.65	11.01	4.13	26
350.02	-12.08	221	1.58	31.22	69	2.19	10.49	10.78	4.83	11
348.04	-12.08	224	1.55	31.25	70	2.17	10.43	10.71	4.78	10
347.31	-12.54	225	1.54	31.11	70	2.17	10.41	10.69	4.80	9
344.86	-12.44	239	1.44	31.38	75	2.12	10.33	10.62	4.63	5
343.89	-12.39	244	1.41	31.15	76	2.10	10.30	10.59	4.63	3
343.79	-12.39	243	1.41	31.28	76	2.10	10.30	10.58	4.62	4
340.68	-12.62	231	1.47	30.74	71	2.12	10.21	10.49	4.78	8
323.61	-12.12	199	1.63	33.67	67	2.23	10.13	10.42	4.40	17
330.47	-12.29	195	1.69	33.85	66	2.29	10.11	10.40	4.47	18
335.14	-14.24	255	1.31	30.20	77	2.04	10.04	10.32	4.71	2
334.56	-14.27	257	1.30	29.96	77	2.03	10.02	10.30	4.76	1
284.21	-12.71	177	1.61	35.03	62	2.28	10.02	10.35	4.23	23
330.12	-13.14	237	1.39	30.38	72	2.07	9.89	10.16	4.75	6
328.48	-12.04	213	1.54	31.46	67	2.15	9.84	10.11	4.69	12

Figure 22. Optimization of N for MA_diff

Based on the backtest results after optimization, it's clear that our hypothesis worked, and we were able to increase the win rate from 29.96% to 31.25%. All other metrics, including Net Profit/Loss, also improved.

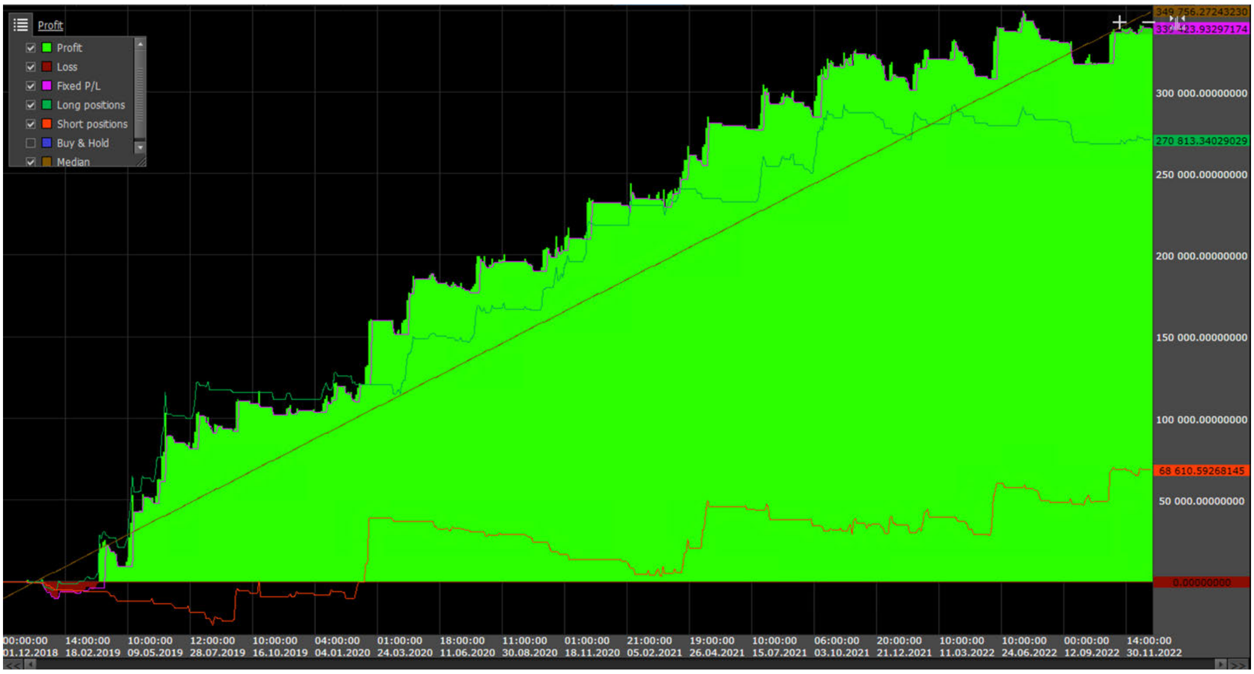

Figure 23. Trend following V0.07 equity curve

On versions 0.01 through 0.07 of the Trend Following strategy, there is only one exit point from a trade - reversing indicator signals. Since these signals are not predetermined, we cannot control the risk on a trade with this approach. Risk control and expected value are the main tasks of a trader and quantitative researcher creating strategies. To make a complete strategy, we need to understand the maximum risk at the time of entering a trade. To do this, we need to add a Stop Loss.

Table 7. Trend following V0.07 performance

	All	Buy	Sell	Market
Net profit/loss	+339423.93	+270813.34	+68610.59	+336739.84
Commission	+49746.93	+23294.08	+26452.85	+99.99
Net profit/loss %	339.42%	270.81%	68.61%	336.74%
Gross MFE	+312682.77	+156076.47	+156606.30	+65216.08
CAGR Year	43.64%	37.79%	13.63%	43.42%
CAGR Month	3.02%	2.67%	1.06%	3.01%
Profit per Bar	+9.66	+7.71	+1.95	+9.58
Number of trades	215	115	100	1
Average profit/loss	+1578.71	+2354.90	+686.11	+336739.84
Average profit/loss %	1.58%	2.35%	0.69%	336.74%
Bars Held (Average)	+64.62	+71.64	+56.54	+34419.00
Winning trades	68	40	28	1
Winning %	31.68%	34.78%	28.00%	100.00%
Gross profit	+629741.06	+418559.44	+211181.61	+336739.84
Average profit	+9260.90	+10463.98	+7542.20	+336739.84
Average profit %	9.26%	10.46%	7.54%	336.74%
Bars Held (Average)	+140.97	+154.20	+122.07	+34419.00
Maximum consecutive	4	4	4	1
Loss trades	147	75	72	0
Loss %	68.37%	65.22%	72.00%	0.00%
Gross loss	290317.12	147746.11	142571.02	0.00
Average loss	1974.95	1969.95	1980.15	0.00
Average loss %	1.97%	1.97%	1.98%	0.00%
Bars Held (Average)	+29.29	+27.61	+31.06	0.00
Maximum consecutive	15	10	15	0
Maximum drawdown	33378.70	24543.82	36940.84	11569.59
Maximum drawdown day	07.10.2022	29.11.2022	05.03.2021	29.01.2019
Maximum drawdown %	11.49%	6.33%	28.60%	11.57%
Maximum drawdown day%	26.04.2019	13.04.2020	26.08.2019	29.01.2019
Fixed Maximum drawdown	32483.24	23465.46	35251.11	0.00
Fixed Maximum drawdown day	23.09.2022	15.10.2022	24.03.2021	N\A
Profit factor	+2.17	+2.83	+1.48	0.00
Recovery Factor	+10.17	+11.03	+1.86	+29.11
Fixed Recovery Factor	+10.45	+11.54	+1.95	(?)
Payoff ratio	+4.69	+5.31	+3.81	?
Sharpe ratio	+0.42	+0.41	+0.16	+0.24
Sortino ratio	+1.73	+2.31	+0.49	+0.47

Stop Losses can be fixed (in points or percentages) or more advanced, taking into account volatility. The latter are often based on standard deviations or highs and lows over a period (for example, the minimum of the trading session for intraday longs or the maximum of the week for swing shorts). We will use the minimum over a period of K, which will be 30 by default and then optimized.

Trend Following v0.08

```
Constant =N
N=30

Longs

If MAMA cross under FAMA and ADX(14) > 35 and RSI(14) > 50 and
BBWidth(20) > vlt  min and BBWidth(20) < vlt  max and BBWidth(20) <
BBWidth(20)[i-1] and BBWidth(20) < BBWidth(20)[i-2] and MA_diff > MA_diff[i-
1-10]
        open long
        Stoploss at Lowest Low for N
        If MAMA < FAMA
                close long

Shorts

If MAMA cross over FAMA and ADX(14) > 35 and RSI(14) < 50 and BBWidth(20)
> vlt  min and BBWidth(20) < vlt  max and BBWidth(20) < BBWidth(20)[i-1] and
BBWidth(20) < BBWidth(20)[i-2] and MA_diff > MA_diff[i-1-10]

        open short
        Stoploss at Highest High for N
        If MAMA > FAMA
```

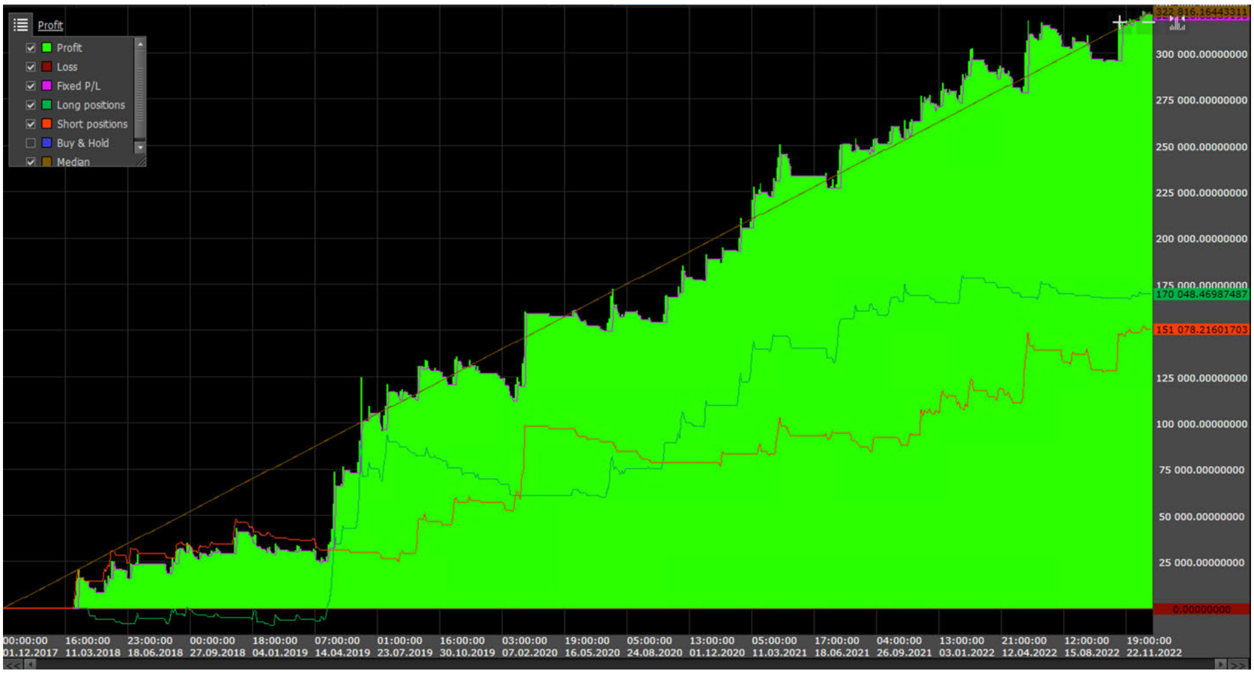

Figure 24. Trend following V0.08 equity curve

After adding the Stop Loss, the values for the periods of Lowest For, Highest For, RSI, ADX, and BBWidth were combined into a single parameter, which was optimized from 10 to 200 with a step of 5. The optimal parameter selected was 120, which corresponds to 5 days. In the event that we reached the minimum over 5 days in a long position or the maximum over 5 days in a short position, the trade was forcibly closed.

Table 8. Trend following V0.08 performance

	All	Buy	Sell	Market
Net profit/loss	+321126.69	+170048.47	+151078.22	+29236.90
Commission	+56954.30	+23793.82	+33160.48	+99.99
Net profit/loss %	321.13%	170.05%	151.08%	29.24%
Gross MFE	+294173.74	+128584.39	+165589.35	+56219.68
CAGR Year	32.66%	21.56%	19.84%	5.17%
CAGR Month	2.35%	1.62%	1.50%	0.42%
Profit per Bar	+7.33	+3.88	+3.45	+0.67
Number of trades	243	118	125	1
Average profit/loss	+1321.51	+1441.09	+1208.63	+29236.90
Average profit/loss %	1.32%	1.44%	1.21%	29.24%
Bars Held (Average)	+58.87	+59.94	+57.86	+43118.00
Winning trades	80	39	41	1
Winning %	32.92%	33.05%	32.80%	100.00%
Gross profit	+601637.63	+298457.70	+303179.93	+29236.90
Average profit	+7520.47	+7652.76	+7394.63	+29236.90
Average profit %	7.52%	7.65%	7.40%	29.24%
Bars Held (Average)	+123.30	+128.87	+118.00	+43118.00
Maximum consecutive	5	5	4	1
Loss trades	163	79	84	0
Loss %	67.08%	66.95%	67.20%	0.00%
Gross loss	280510.94	128409.23	152101.71	0.00
Average loss	1720.93	1625.43	1810.74	0.00
Average loss %	1.72%	1.63%	1.81%	0.00%
Bars Held (Average)	+27.25	+25.91	+28.50	0.00
Maximum consecutive	9	7	12	0
Maximum drawdown	25166.15	30570.72	22759.15	75403.75
Maximum drawdown day	24.02.2020	20.07.2020	28.08.2019	15.12.2018
Maximum drawdown %	12.31%	16.10%	15.52%	75.40%
Maximum drawdown day%	22.04.2019	20.07.2020	28.08.2019	15.12.2018
Fixed Maximum drawdown	23867.39	29874.58	21287.65	0.00
Fixed Maximum drawdown day	02.03.2020	15.07.2020	23.08.2019	N\A
Profit factor	+2.15	+2.32	+1.99	0.00
Recovery Factor	+12.76	+5.56	+6.64	+0.38
Fixed Recovery Factor	+13.45	+5.69	+7.10	(?)
Payoff ratio	+4.37	+4.71	+4.08	?
Sharpe ratio	+0.37	+0.24	+0.31	+0.13
Sortino ratio	+1.40	+1.17	+1.13	+0.22

As a result of adding the Stop Loss and optimizing the combined parameter, we were able to increase the percentage of winning trades from 31.25% to 32.92%. This increase in the win rate led to the Recovery Factor growing from 10.43 to 12.76. In the 9th version of the strategy, we add another exit point when the Take Profit level is reached. The average profit in the trades of the last version of the strategy was 7.52%, and the goal of Take Profit is to increase this metric. Instead of specifying a fixed Take Profit value, we set a constant S. By default, we set this value to 50%, and then we optimize it from 10 to 100 with a step of 5.

Trend Following v0.09

```
Constant =S
N=50

Longs

If MAMA cross under FAMA and ADX(120) > 5 and RSI(120) > 50 and
BBWidth(120) > vlt  min and BBWidth(120) < vlt  max and BBWidth(20) <
BBWidth(120)[i-1] and BBWidth(120) < BBWidth(120)[i-2] and MA_diff > MA_diff[i-
1-10]
        open long
        Stoploss at Lowest Low for(120)
        If trade profit over S%
                Close long
        else MAMA < FAMA
                close long

Shorts

If MAMA cross over FAMA and ADX(120) > 5 and RSI(120) < 50 and BBWidth(120)
> vlt  min and BBWidth(120) < vlt  max and BBWidth(120) < BBWidth(120)[i-1] and
BBWidth(120) < BBWidth(120)[i-2] and MA_diff > MA_diff[i-1-10]

        open short
        Stoploss at Highest High(120)
        If trade profit over S%
                Close long
        else MAMA > FAMA
```

After the backtest and optimizing the Take Profit length parameter, the optimal value was found to be 45. As a result of the final iteration of strategy improvement, the average profit was increased to 7.93%, which had a significant impact on the overall results: the Recovery Factor increased to 14.07, the Profit Factor increased to 2.26, and Net Profit/Loss reached 353.97%.

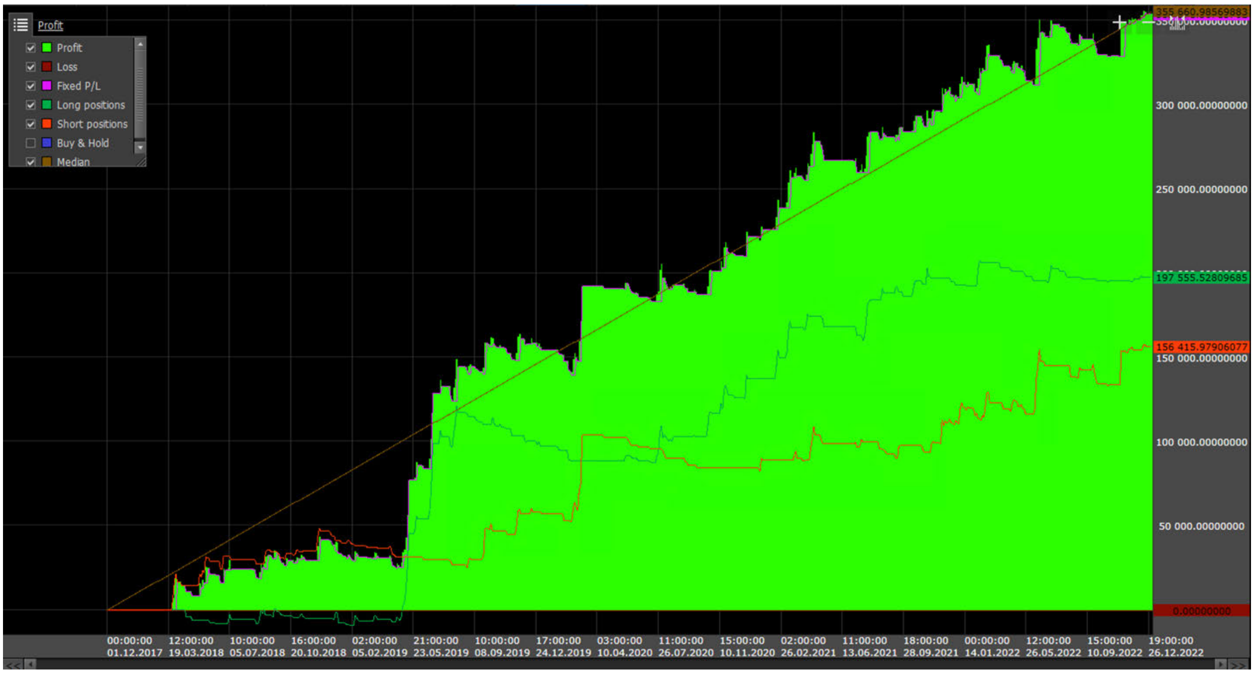

Figure 25. Trend following V0.09 equity curve

Despite all the improvements, we still don't control the maximum risk per trade in the strategy because there is no risk management, and we open each position with the entire capital. With the introduction of a stop loss, we can address this issue.

Table 9. Trend following V0.09 performance

	All	Buy	Sell	Market
Net profit/loss	+353971.51	+197555.53	+156415.98	+29236.90
Commission	+56856.75	+23821.35	+33035.40	+99.99
Net profit/loss %	353.97%	197.56%	156.42%	29.24%
Gross MFE	+292437.30	+127948.27	+164489.03	+56219.68
CAGR Year	34.63%	23.90%	20.33%	5.17%
CAGR Month	2.47%	1.77%	1.53%	0.42%
Profit per Bar	+8.07	+4.51	+3.57	+0.67
Number of trades	243	118	125	1
Average profit/loss	+1456.67	+1674.19	+1251.33	+29236.90
Average profit/loss %	1.46%	1.67%	1.25%	29.24%
Bars Held (Average)	+58.13	+59.31	+57.02	+43118.00
Winning trades	80	39	41	1
Winning %	32.92%	33.05%	32.80%	100.00%
Gross profit	+634482.44	+325964.76	+308517.68	+29236.90
Average profit	+7931.03	+8358.07	+7524.82	+29236.90
Average profit %	7.93%	8.36%	7.52%	29.27%
Bars Held (Average)	+121.05	+126.95	+115.44	+43118.00
Maximum consecutive	5	5	4	1
Loss trades	163	79	84	0
Loss %	67.08%	66.95%	67.20%	0.00%
Gross loss	280510.94	128409.23	152101.71	0.00
Average loss	1720.93	1625.43	1810.74	0.00
Average loss %	1.72%	1.63%	1.81%	0.00%
Bars Held (Average)	+27.25	+25.91	+28.50	0.00
Maximum consecutive	9	7	12	0
Maximum drawdown	25166.15	30570.72	22759.15	75403.75
Maximum drawdown day	24.02.2020	20.07.2020	28.08.2019	15.12.2018
Maximum drawdown %	12.31%	14.06%	15.52%	75.40%
Maximum drawdown day%	22.04.2019	20.07.2020	28.08.2019	15.12.2018
Fixed Maximum drawdown	23867.39	29874.58	21287.65	0.00
Fixed Maximum drawdown day	02.03.2020	02.08.2020	23.08.2019	N\A
Profit factor	+2.26	+2.54	+2.03	0.00
Recovery Factor	+14.07	+6.46	+6.87	+0.39
Fixed Recovery Factor	+14.83	+6.61	+7.35	(?)
Payoff ratio	+4.61	+5.14	+4.16	?
Sharpe ratio	+0.34	+0.23	+0.30	+0.13
Sortino ratio	+1.55	+1.44	+1.18	+0.22

In the 10th version of the strategy, we will introduce risk management to risk 1% of the capital for each trade. To achieve this, we need to calculate the percentage distance between the entry price and the stop loss. Then, we divide 1% by the stop loss size percentage. This will give us the portion of capital we can allocate to the trade. Also, after checking all the filters, it was decided to remove the ADX filter, since it does not provide any benefit and is an unnecessary parameter for optimization.

Trend Following v0.10

```
Constant =S
N=50

Longs

If MAMA cross under FAMA and RSI(120) > 50 and BBWidth(120) > vlt  min and
BBWidth(120) < vlt  max and BBWidth(20) < BBWidth(120)[i-1] and BBWidth(120) <
BBWidth(120)[i-2] and MA_diff > MA_diff[i-1-10]
        open long
        Stoploss at Lowest Low for(120)
        If trade profit over S%
                Close long
        else MAMA < FAMA
                close long

Shorts

If MAMA cross over FAMA and RSI(120) < 50 and BBWidth(120) > vlt  min and
BBWidth(120) < vlt  max and BBWidth(120) < BBWidth(120)[i-1] and BBWidth(120)
< BBWidth(120)[i-2] and MA_diff > MA_diff[i-1-10]

        open short
        Stoploss at Highest High(120)
        If trade profit over S%
                Close long
        else MAMA > FAMA
                close long
```

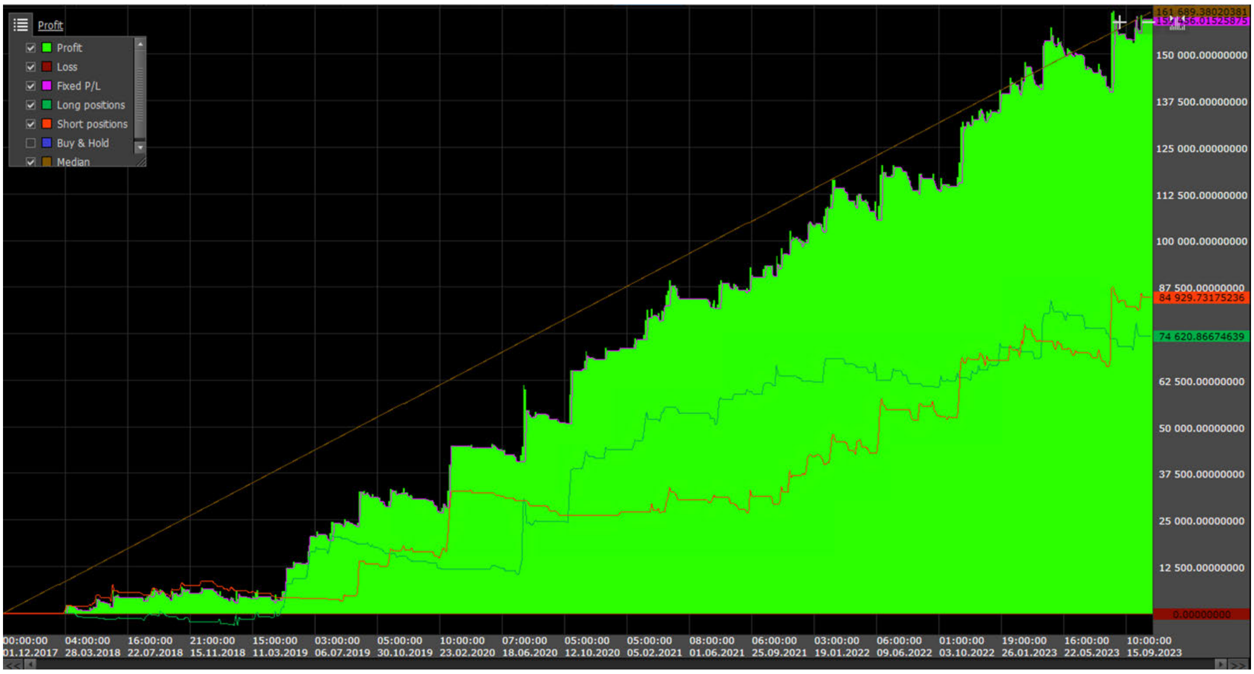

Figure 26. Trend following V0.10 equity curve

After integrating money management into the strategy, our Recovery Factor experienced a significant decline, dropping from 14.06 to 9.25. However, despite this outcome, it remains the only correct decision to employ a fixed risk per trade. This is because, sooner or later, a streak of losing trades will occur, and employing a variable risk per trade significantly heightens the risk of capital loss. When applying this approach to a cryptocurrency portfolio, the Recovery Factor should improve through diversification among less-correlated assets. In this section, we've explored how to systematically develop and enhance trading strategies. For the forthcoming strategy types, we won't delve into each iteration but rather acquaint ourselves with the final strategy versions.

Table 10. Trend following V0.10 performance

	All	Buy	Sell	Market
Net profit/loss	+159550.60	+74620.87	+84929.73	+167955.96
Commission	+35702.77	+13867.33	+21835.44	+99.99
Net profit/loss %	159.55%	74.62%	84.93%	167.95%
Gross MFE	+337021.80	+148822.24	+188199.56	+56219.68
CAGR Year	17.49%	9.88%	10.95%	18.12%
CAGR Month	1.33%	0.78%	0.86%	1.38%
Profit per Bar	+3.12	+1.46	+1.66	+3.29
Number of trades	307	147	160	1
Average profit/loss	+519.71	+507.62	+530.81	+167955.96
Average profit/loss %	1.17%	1.36%	1.01%	167.96%
Bars Held (Average)	+56.17	+57.46	+54.99	+50391.00
Winning trades	103	50	53	1
Winning %	33.55%	34.01%	33.13%	100.00%
Gross profit	+302076.51	+139073.78	+163002.73	+167955.96
Average profit	+2932.78	+2781.47	+3075.52	+167955.96
Average profit %	6.79%	7.12%	6.47%	167.96%
Bars Held (Average)	+115.45	+120.24	+110.94	+50391.00
Maximum consecutive	5	5	4	1
Loss trades	204	97	107	0
Loss %	66.45%	65.99%	66.88%	0.00%
Gross loss	142525.91	64452.91	78072.99	0.00
Average loss	698.66	664.46	729.65	0.00
Average loss %	1.65%	1.60%	1.69%	0.00%
Bars Held (Average)	+26.25	+25.10	+27.28	0.00
Maximum consecutive	9	7	12	0
Maximum drawdown	17256.99	13561.78	11024.12	75403.75
Maximum drawdown day	15.08.2023	27.09.2023	15.08.2023	15.12.2018
Maximum drawdown %	6.73%	8.89%	6.25%	75.40%
Maximum drawdown day%	15.08.2023	20.07.2020	15.08.2023	15.12.2018
Fixed Maximum drawdown	16219.79	11555.60	9986.91	0.00
Fixed Maximum drawdown day	15.08.2023	28.08.2023	23.08.2023	N\A
Profit factor	+2.12	+2.16	+2.09	0.00
Recovery Factor	+9.25	+5.50	+7.70	+2.28
Fixed Recovery Factor	+9.84	+6.46	+8.50	(?)
Payoff ratio	+4.20	+4.19	+4.22	?
Sharpe ratio	+0.41	+0.25	+0.32	+0.17
Sortino ratio	+1.38	+0.81	+1.35	+0.30

4.4.2 Mean Reversion

Mean Reversion V0.05

```
close  diff  long = (Close-SMA  long)/SMA  long
close  diff  long = (Close-SMA  short)/SMA  short
StDev  perc  = close  StDev/Close
StDev  min = 0.03
long  diff  perc = 0.03
short  diff  perc = 0.03
EMA  filters  bars  short = EMA(5) < EMA[i-1] < EMA[i-2] < EMA[i-3]
EMA  filters  bars  long = EMA(5) > EMA[i-1] > EMA[i-2] > EMA[i-3]


Longs
If close  diff  long <= (-1*long  diff  perc) && EMA  filters  bars  long==true &&
min>sd1  lower && StDev  perc>StDev  min
        open long
        Stoploss 10%
                Close long
        else close  diff  long>=0
                close long

Shorts

If close  diff  short >= short  diff  perc && EMA  filters  bars  short==true &&
max<sd1  upper  && StDev  perc>StDev  min
        open short
        Stoploss 10%
                Close long
        else close  diff  short<=0
                close long
```

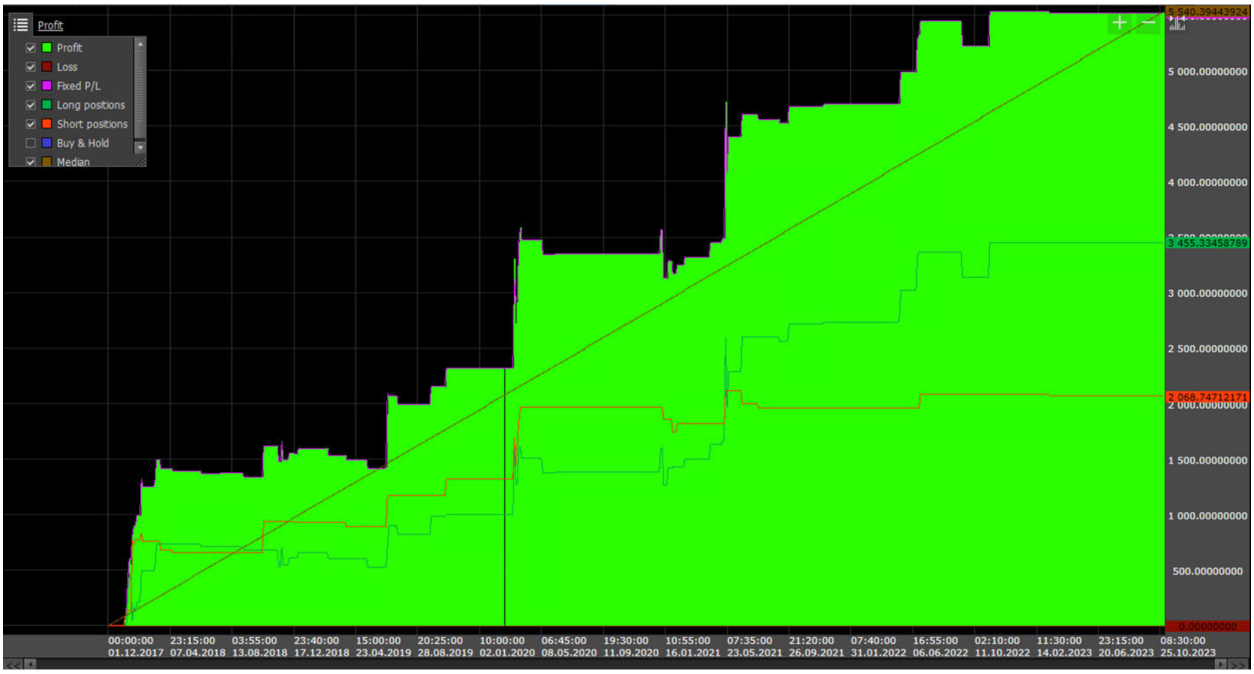

Figure 26. Mean Reversion V0.05 equity curve

Table 11. Mean Reversion V0.05 performance

	All	Buy	Sell	Market
Net profit/loss	+5524.08	+3455.33	+2068.75	+16566.86
Commission	+1420.94	+898.76	+522.19	+9.99
Net profit/loss %	55.24%	34.55%	20.69%	165.66%
Gross MFE	+51426.81	+39467.95	+11958.86	+56061.93
CAGR Year	7.71%	5.14%	3.22%	17.95%
CAGR Month	0.61%	0.41%	0.26%	1.37%
Profit per Bar	+0.01	+0.01	+0.003	+0.03
Number of trades	113	71	42	1
Average profit/loss	+48.89	+48.67	+49.25	+16566.86
Average profit/loss %	0.82%	0.80%	0.85%	165.66%
Bars Held (Average)	+34.77	+38.60	+28.31	+611926.00
Winning trades	71	47	24	1
Winning %	62.83%	66.20%	57.14%	100.00%
Gross profit	+12658.49	+9270.39	+3388.09	+16566.86
Average profit	+178.29	+197.24	+141.17	+16566.86
Average profit %	2.92%	3.19%	2.38%	165.67%
Bars Held (Average)	+26.40	+29.68	+20.00	+611926.00
Maximum consecutive	8	8	6	1
Loss trades	42	24	18	0
Loss %	37.17%	33.80%	42.86%	0.00%
Gross loss	7134.40	5815.06	1319.35	0.00
Average loss	169.86	242.29	73.30	0.00
Average loss %	2.73%	3.87%	1.19%	0.00%
Bars Held (Average)	+48.93	+56.08	+39.38	0.00
Maximum consecutive	3	3	4	0
Maximum drawdown	1037.71	1037.71	565.46	7570.46
Maximum drawdown day	13.03.2020	13.03.2020	06.02.2018	15.12.2018
Maximum drawdown %	8.39%	9.39%	5.13%	75.70%
Maximum drawdown day%	13.03.2020	13.03.2020	06.02.2018	15.12.2018
Fixed Maximum drawdown	992.23	992.23	444.83	0.00
Fixed Maximum drawdown day	13.03.2020	13.03.2020	06.02.2018	N\A
Profit factor	+1.77	+1.59	+2.57	0.00
Recovery Factor	+5.32	+3.33	+3.66	+2.19
Fixed Recovery Factor	+5.56	+3.48	+4.65	(?)
Payoff ratio	+1.05	+0.81	+1.93	?
Sharpe ratio	+0.31	+0.34	+0.21	+0.16
Sortino ratio	+1.96	+1.35	+0.99	+0.30

4.4.3 Pair Arbitrage

Pair Arbitrage V0.04

Dev_K=2

Longs

If ``close < (SMA-(StDev*(Dev K+(0.1-1.0))))
    open long
    Stoploss at SMA-Dev*2
    If close>SMA
        Close long

Shorts

If close > (SMA+(StDev*(Dev K+(0.1-1.0))))

    open short
    Stoploss at SMA+Dev*2
    If close<SMA
        Close long

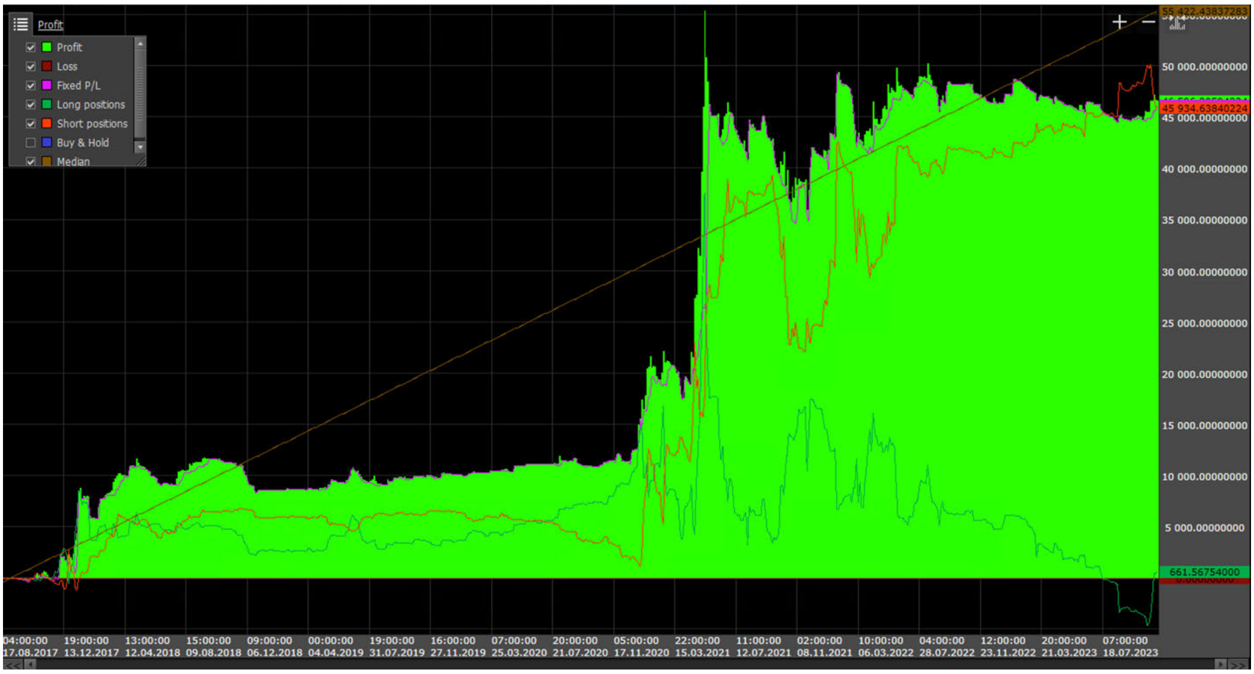

Figure 27. Statistic Arbitrage V0.04 equity curve

Table 12. Statistic Arbitrage V0.04 performance

	All	Buy	Sell	Market
Net profit/loss	+46596.20	+661.56	+45934.64	+1388158.26
Commission	+22229.46	+9214.76	+13014.70	+100.00
Net profit/loss %	46.60%	0.66%	45.93%	1388.15%
Gross MFE	+2849497.45	+1360597.07	+1488900.38	+69756.53
CAGR Year	6.35%	0.11%	6.27%	54.46%
CAGR Month	0.51%	0.01%	0.51%	3.64%
Profit per Bar	+0.86	+0.01232865	+0.86	+25.87
Number of trades	8416	4208	4208	2
Average profit/loss	+5.54	+0.16	+10.92	+694079.13
Average profit/loss %	0.17%	0.22%	0.124%	694.08%
Bars Held (Average)	+36.03	+36.04	+36.04	+52941.00
Winning trades	3681	1847	1834	2
Winning %	43.74%	43.89%	43.58%	100.00%
Gross profit	+316594.62	+151677.12	+164917.51	+1388158.26
Average profit	+86.00	+82.12	+89.92	+694079.13
Average profit %	3.76%	4.01%	3.51%	694.07%
Bars Held (Average)	+47.43	+46.77	+48.08	+52941.00
Maximum consecutive	21	27	20	2
Loss trades	4735	2361	2374	0
Loss %	56.26%	56.11%	56.42%	0.00%
Gross loss	269998.42	151015.55	118982.87	0.00
Average loss	57.02	63.96	50.12	0.00
Average loss %	2.6%	2.74%	2.49%	0.00%
Bars Held (Average)	+27.18	+27.64	+26.73	0.00
Maximum consecutive	34	60	34	0
Maximum drawdown	12252.40248419	25401.89	16934.55	69016.03
Maximum drawdown day	28.10.2021	11.10.2023	29.10.2021	15.12.2018
Maximum drawdown %	8.25%	20.83%	12.20%	18.03%
Maximum drawdown day%	28.10.2021	11.10.2023	29.10.2021	15.12.2018
Fixed Maximum drawdown	12179.95	25302.64	16813.75	0.00
Fixed Maximum drawdown day	08.11.2021	22.09.2023	08.11.2021	N\A
Profit factor	+1.17	+1.01	+1.38	0.00
Recovery Factor	+3.80	+0.03	+2.71	+20.11
Fixed Recovery Factor	+3.82	+0.03	+2.73	(?)
Payoff ratio	+1.51	+1.28	+1.79	?
Sharpe ratio	+0.22	+0.02	+0.20	+0.26
Sortino ratio	+0.64	+0.02	+0.40	+0.55

5 Results

The developed strategies of three types were optimized to compare their performance on out-of-sample data and determine which of the strategies would be more effective on the cryptocurrencies BTC, ETH, and BNB. Due to the limited data available, we had to deviate from the plan of optimizing strategies for the period from 2018 to 2023 and instead test them from January 1, 2023, to October 1, 2023. This short period lacks statistical significance due to the limited number of trades. Instead, we decided to conduct a walk-forward test with one year of optimization data and a three-month out-of-sample period. By optimizing with a rolling approach, we achieved an almost 5-year span of out-of-sample trading.

It's important to note that competing with a buy-and-hold strategy can be quite challenging, as there is a survivorship bias at play. The market has grown significantly, and fixed-risk strategies often underperform during strong bull markets. However, it's worth highlighting that in an uncertain future, algorithmic trading strategies allow for a systematic approach with limited risks, unlike buy-and-hold, where an investor's risk is 100%. Taking data from the beginning of 2022, trend-following strategies and mean-reversion strategies yielded positive results, while buy-and-hold incurred losses exceeding 80%.

Among the trend-following, mean-reversion, and pair arbitrage strategies, the best results were achieved by the Ehlert's trend-following strategy, which even outperformed the market for BTC and ETH (Tables 13-15).

So we can conclude that there are strategies that allow you to win compared to buy and hold.

Table 13. BTC strategies performance comparison to buy and hold

	Trend Following	Mean Reversion	Arbitrage	Buy & Hold
Net profit/loss	+305300.09	+5524.08	+46596.20	+169658.34
Commission	+72448.02	+1420.942	+22229.46	+99.99
Net profit/loss %	305.30%	55.24%	46.57%	169.65%
Gross MFE	+337021.80	+51426.81	+2849497.45	+56219.68
CAGR Year	26.67%	7.71%	6.35%	18.24%
CAGR Month	1.96%	0.61%	0.50%	1.39%
Profit per Bar	+5.97	+0.01	+0.86	+3.32
Number of trades	307	113	8416	1
Average profit/loss	+994.46	+48.89	+5.54	+169658.34
Average profit/loss %	1.18%	0.82%	0.17%	169.66%
Bars Held (Average)	+56.19	+34.78	+36.04	+50409.00
Winning trades	102	71	3681	1
Winning %	33.23%	62.83%	43.73811787%	100.00%
Gross profit	+592165.53	+12658.49	+316594.62295994	+169658.34
Average profit	+5805.54	+178.29	+86.00777587	+169658.34
Average profit %	6.85%	2.92%	3.76%	169.66%
Bars Held (Average)	+115.98	+26.4	+47.43	+50409.00
Maximum consecutive	5	8	21	1
Loss trades	205	42	4735	0
Loss %	66.77%	37.17%	56.26%	0.00%
Gross loss	286865.44	7134.40	269998.42	0.00
Average loss	1399.34	169.86	57.02	0.00
Average loss %	1.65%	2.73%	2.61%	0.00%
Bars Held (Average)	+26.44	+48.93	+27.18	0.00
Maximum consecutive	9	3	34	0
Maximum drawdown	39698.23	1037.71	12252.40	75403.75
Maximum drawdown day	15.08.2023	13.03.2020	28.10.2021	15.12.2018
Maximum drawdown %	9.94%	8.39%	8.25%	75.40%
Maximum drawdown day%	15.08.2023	13.03.2020	28.10.2021	15.12.2018
Fixed Maximum drawdown	37353.20	992.23	12179.95	0.00
Fixed Maximum drawdown day	23.08.2023	13.03.2020	08.11.2021	N\A
Profit factor	+2.06	+1.77	+1.17	0.00
Recovery Factor	+7.69	+5.32	+3.80	+2.25
Fixed Recovery Factor	+8.17	+5.58	+3.82	(?)
Payoff ratio	+4.15	+1.04	+1.51	?
Sharpe ratio	+0.41	+0.32	+0.22	+0.16
Sortino ratio	+1.42	+1.96	+0.64	+0.30

Table 14. ETH strategies performance comparison to buy and hold

	Trend Following	Mean Reversion	Arbitrage	Buy & Hold
Net profit/loss	+506492.11	+6061.16	+46596.21	+15583.33
Commission	+124231.08	+407.77	+22229.46	+9.99
Net profit/loss %	506.49%	60.61%	46.60%	155.83%
Gross MFE	+29513.24	+1610.33	+2849497.45	+4163.97
CAGR Year	35.59%	8.33%	6.35%	17.20%
CAGR Month	2.53%	0.66%	0.51%	1.31%
Profit per Bar	+9.90	+0.01	+0.86	+0.025
Number of trades	399	32	8416	1
Average profit/loss	+1269.40	+189.41	+5.54	+15583.33
Average profit/loss %	1.37%	3.02%	0.17%	155.84%
Bars Held (Average)	+55.53	+27.63	+36.04	+611979.00
Winning trades	135	26	3681	1
Winning %	33.83%	81.25%	43.74%	100.00%
Gross profit	+1181591.31	+6858.14	+316594.62	+15583.33
Average profit	+8752.53	+263.77	+86.01	+15583.36
Average profit %	8.41%	4.21%	3.76%	155.83%
Bars Held (Average)	+110.39	+22.54	+47.42	+611979.00
Maximum consecutive	5	9	21	1
Loss trades	264	6	4735	0
Loss %	66.17%	18.75%	56.26188213%	0.00%
Gross loss	675099.20	796.98	269998.41701770	0.00
Average loss	2557.19	132.83	57.02184098	0.00
Average loss %	2.23%	2.13%	2.61489711%	0.00%
Bars Held (Average)	+27.47	+49.67	+27.18183738	0.00
Maximum consecutive	14	2	34	0
Maximum drawdown	130371.69	783.98	12252.40	8848.24
Maximum drawdown day	14.08.2023	06.02.2018	28.10.2021	15.12.2018
Maximum drawdown %	20.03%	6.46%	8.25430176%	88.48%
Maximum drawdown day%	14.08.2023	06.02.2018	28.10.2021	15.12.2018
Fixed Maximum drawdown	125786.47	284.72	12179.95	0.00
Fixed Maximum drawdown day	12.08.2023	15.10.2018	08.11.2021	N\A
Profit factor	+1.750	+8.60	+1.17	0.00
Recovery Factor	+3.89	+7.73	+3.80	+1.76
Fixed Recovery Factor	+4.03	+21.29	+3.83	(?)
Payoff ratio	+3.42	+1.99	+1.51	?
Sharpe ratio	+0.37	+0.22	+0.23	+0.18
Sortino ratio	+1.47	+2.26	+0.64	+0.34

Table 15. BNB strategies performance comparison to buy and hold

	Trend Following	Mean Reversion	Arbitrage	Buy & Hold
Net profit/loss	+143189.10	+13409.52	+251153.48	+2822861.52
Commission	+34735.60	+836.32	+136790.57	+99.48
Net profit/loss %	143.18%	134.095%	251.15%	2822.86%
Gross MFE	+3218.10	+348.94	+1530496.41	+684.07
CAGR Year	16.19%	15.45%	22.42%	76.84%
CAGR Month	1.24%	1.18%	1.68%	4.80%
Profit per Bar	+2.80	+0.021	+4.68	+55.21
Number of trades	277	52	10850	1
Average profit/loss	+516.92	+257.87	+23.15	+2822861.52
Average profit/loss %	1.42%	3.43%	0.066%	2837.56%
Bars Held (Average)	+89.76	+28.29	+9.55354839	+50410.00
Winning trades	85	43	4333	1
Winning %	30.68%	82.69%	39.94%	100.00%
Gross profit	+360933.92	+20272.505	+1511374.45	+2822861.52
Average profit	+4246.28	+471.45	+348.81	+2822861.52
Average profit %	11.00%	6.03%	2.37%	2837.56%
Bars Held (Average)	+187.40	+28.21	+12.63	+50410.00
Maximum consecutive	5	10	26	1
Loss trades	192	9	6517	0
Loss %	69.31%	17.31%	60.07%	0.00%
Gross loss	217744.81	6862.99	1260220.96	0.00
Average loss	1134.08	762.55	193.37	0.00
Average loss %	2.81%	9.00%	1.47%	0.00%
Bars Held (Average)	+46.53	+28.67	+7.51	0.00
Maximum consecutive	10	1	38	0
Maximum drawdown	21053.49	1907.59	221203.77	46352.12
Maximum drawdown day	15.09.2023	12.05.2022	06.06.2023	07.12.2018
Maximum drawdown %	11.74%	10.767%	39.36%	46.35%
Maximum drawdown day%	06.12.2020	22.12.2017	06.06.2023	07.12.2018
Fixed Maximum drawdown	20276.33	1751.68	219973.70	0.00000000
Fixed Maximum drawdown day	08.09.2023	13.03.2020	29.08.2023	N\A
Profit factor	+1.65	+2.95	+1.20	0.00000000
Recovery Factor	+6.80	+7.023	+1.14	+60.90
Fixed Recovery Factor	+7.06	+7.65	+1.14	(?)
Payoff ratio	+3.74	+0.618	+1.80	?
Sharpe ratio	+0.30	+0.216	+0.16	+0.21
Sortino ratio	+0.87	+4.45	+0.83	+0.84

Conclusion

The objective of this dissertation was to explore the effectiveness of mean-reversion, momentum, and pair arbitrage trading strategies on short timeframes in the Bitcoin, Ethereum, and BNB markets. The aim was to determine if there were any notable performance differences among these strategies. This research identifies the most optimal algorithmic trading software, describes the strategy development and enhancement process, tests three types of strategies on the mentioned cryptocurrencies, and then compares them with a simple "buy and hold" strategy. The goal is to investigate whether a trader, by holding Bitcoin, can outperform mean-reversion, pair statistical arbitrage, and momentum strategies based on annual returns, the Recovery Factor, and maximum drawdown.

The main finding of this research suggests that it is challenging to beat a "buy and hold" strategy using momentum, pair arbitrage, or mean-reversion strategies on a highly bullish market during 2019-2021. However, it is relatively easy on a bearish market. Although it is challenging, achieving significant annual returns with short-term trading is entirely possible. Some momentum strategies managed to yield higher annual returns than the "buy and hold" strategy, but the results were inconsistent across different subsets of data. On the other hand, none of the mean-reversion strategies could outperform the "buy and hold" strategy in short-term trading based on annual returns. Recovery Factor and maximum drawdown values were better when using momentum and mean-reversion strategies compared to the "buy and hold" strategy on the training dataset, but these results couldn't be consistently replicated with a different subset of data, except for momentum strategies on Bitcoin and Ethereum. Strategies based on mean-reversion theory yielded relatively lower annual returns compared to the "buy and hold" strategy. Ehlers' moving average crossover strategy actually outperformed the "buy and hold" strategy across all parameters for Bitcoin and Ethereum, but underperformed for BNB.

The main difference with momentum and mean-reversion strategies in short-term Bitcoin trading is the number of trading strategies based on these theories. The pair arbitrage strategy showed promising results for BNB but performed weakly for Bitcoin and Ethereum. This study focused on short-term trading, which raises the possibility that momentum strategies work better on short timeframes. Still, it is entirely possible that mean-reversion strategies yield better results on longer timeframes. This can be a subject for further research, comparing mean-reversion and momentum strategies on different timeframes in the Bitcoin market.

In conclusion, for trading cryptocurrencies on short timeframes, it is advisable to use momentum trading strategies instead of mean-reversion and statistical arbitrage strategies or attempt to combine them to enhance overall results. It's essential to understand that the results obtained from momentum trading are not always better and sometimes even worse when compared to pure "buy and hold," especially in a strongly bullish market. However, it's crucial to recognize that momentum trading strategies can generate profits in both rising and falling markets, while the cryptocurrency holdings of holders significantly depreciate.

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Attachments

Attachment 1

Mesa Adaptive Moving Average code on C#

```
using System.Collections.Generic;

namespace MAMA_Ehlers
{
    class Program
    {
        static void Main(string[] args)
        {
            // Replace this list with your time series data
            List<double> prices = new List<double>
            {
                100.0, 101.5, 103.0, 104.5, 106.0, 107.5, 109.0
                // Add the rest of your data here
            };

            // MAMA Ehlers Parameters
            double fastLimit = 0.5; // Default value
            double slowLimit = 0.05; // Default value
            double signalLimit = 0.15; // Default value       // Calculate MAMA
            List<double> mama = CalculateMAMA(prices, fastLimit, slowLimit, signalLimit);

            // Display the results
            Console.WriteLine("Prices: " + string.Join(", ", prices));
            Console.WriteLine("MAMA: " + string.Join(", ", mama));
        }
```

```
    static List<double> CalculateMAMA(List<double> prices, double fastLimit, double slowLimit, double signalLimit)
    {
        List<double> mama = new List<double>();
        List<double> mamaSignal = new List<double>();

        double mamaPrev = 0;
        double mamaSignalPrev = 0;

        for (int i = 0; i < prices.Count; i++)
        {
            double mamaCurr = 0;
            double mamaSignalCurr = 0;

            if (i == 0)
            {
                mama.Add(prices[i]);
                mamaSignal.Add(prices[i]);
                mamaPrev = prices[i];
                mamaSignalPrev = prices[i];
            }
            else
            {
                double hilbertPrev = CalculateHilbertTransform(prices[i], prices[i - 1], mamaPrev, mamaSignalPrev);
                double detrenderPrev = CalculateDetrender(hilbertPrev);
                double prevCycle = CalculateCycle(detrenderPrev);

                double hilbertCurr = CalculateHilbertTransform(prices[i], prices[i - 1], mamaPrev, mamaSignalPrev);
                double detrenderCurr = CalculateDetrender(hilbertCurr);
                double currCycle = CalculateCycle(detrenderCurr);
```

```
            double smoothedPeriod = CalculateSmoothingPeriod(currCycle, prevCycle, fastLimit, slowLimit);
            double alpha = CalculateAlpha(smoothedPeriod);

            mamaCurr = alpha * prices[i] + (1 - alpha) * mamaPrev;

            if (i < 2)
            {
                mamaSignalCurr = mamaCurr;
            }
            else
            {
                mamaSignalCurr = alpha * mamaCurr + (1 - alpha) * mamaPrev;
            }

            double im = CalculateIm(prices[i], mamaPrev, mamaSignalPrev);
            double mamaNormalized = mamaCurr + signalLimit * im;
            mama.Add(mamaNormalized);
            mamaSignal.Add(mamaSignalCurr);

            mamaPrev = mamaCurr;
            mamaSignalPrev = mamaSignalCurr;
        }
    }

    return mama;
}

static double CalculateHilbertTransform(double price, double prevPrice, double prevMama, double prevMamaSignal)
{
    // Implement the Hilbert Transform calculation
    // This method depends on your specific implementation and library
    return 0; // Placeholder, replace with your implementation
```

```
    }

    static double CalculateDetrender(double hilbertValue)
    {
        // Implement the Detrender calculation
        // This method also depends on your specific implementation
        return 0; // Placeholder, replace with your implementation
    }

    static double CalculateCycle(double detrenderValue)
    {
        // Implement the Cycle calculation
        // This method also depends on your specific implementation
        return 0; // Placeholder, replace with your implementation
    }

    static double CalculateSmoothingPeriod(double currentCycle, double previousCycle,
double fastLimit, double slowLimit)
    {
        // Implement the Smoothing Period calculation
        // This method also depends on your specific implementation
        return 0; // Placeholder, replace with your implementation
    }

    static double CalculateAlpha(double smoothingPeriod)
    {
        return 2.0 / (smoothingPeriod + 1);
    }

    static double CalculateIm(double price, double prevMama, double prevMamaSignal)
    {
        // Implement the Im calculation
        // This method also depends on your specific implementation
```

```
            return 0; // Placeholder, replace with your implementation
        }
    }
}
```

Attachment 2

Fractal Adaptive Moving Average code on C#

```
using System;
using System.Collections.Generic;

namespace FAMA_Ehlers
{
    class Program
    {
        static void Main(string[] args)
        {
            // Replace this list with your time series data
            List<double> prices = new List<double>
            {
                100.0, 101.5, 103.0, 104.5, 106.0, 107.5, 109.0
                // Add the rest of your data here
            };

            // FAMA Ehlers Parameters
            int period = 14; // Period for calculating the FAMA

            // Calculate FAMA
            List<double> fama = CalculateFAMA(prices, period);

            // Display the results
            Console.WriteLine("Prices: " + string.Join(", ", prices));
            Console.WriteLine("FAMA: " + string.Join(", ", fama));
        }

        static List<double> CalculateFAMA(List<double> prices, int period)
        {
            List<double> fama = new List<double>();

            for (int i = 0; i < prices.Count; i++)
            {
                double famaValue = 0;
```

```
            if (i >= period - 1)
            {
                double sum = 0;

                for (int j = i; j > i - period; j--)
                {
                    sum += Math.Log(prices[j] / prices[j - 1]);
                }

                famaValue = sum / (Math.Log(prices[i] / prices[i - period]) * period);
            }

            fama.Add(famaValue);
        }

        return fama;
    }
  }
}
```

Selbstständigkeitserklärung

Hiermit erkläre ich, dass ich die vorliegende Arbeit selbstständig und nur unter Verwendung der angegebenen Literatur und Hilfsmittel angefertigt habe. Stellen, die wörtlich oder sinngemäß aus Quellen entnommen wurden, sind als solche kenntlich gemacht.

Diese Arbeit wurde in gleicher oder ähnlicher Form noch keiner anderen Prüfungsbehörde vorgelegt.

Mittweida, den 30. October 2023

Bohdan Pinchuk [redacted]