Bitcoin trading performance evaluation: A comparative study of momentum and mean reversion strategies from 2020 to 2025

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Abstract

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This thesis studies the performance of two systematic Bitcoin trading strategies: momentum and mean reversion. The focus is on two widely used technical analysis tools — the moving average crossover strategy (momentum based) and the Bollinger Bands strategy (mean reversion based). Using high frequency Bitcoin price data, this thesis evaluates each approach relative to one another and to a buy-and-hold benchmark. This study also includes transaction fee modelling to estimate actual profitability of active strategies.

Annual returns, Sharpe ratio, volatility, profit factor, and maximum drawdown are used to assess the performance of different strategies, and to make the comparison of profitability and risks. The findings show that Bitcoin has mean-reverting behaviour on hourly data analysis, and the Bollinger-based strategy outperforms both the momentum strategy and passive HODLing both in terms of return and risk-weighted performance. The momentum strategy shows moderate return potential, while buy-and-hold remains effective over long term but is not optimal in high-frequency environments.

These results suggest that the effectiveness of a trading strategy strongly depends on time resolution, whether hourly or daily data is used to analyse the performance. This helps researchers to better understand how cryptocurrency markets behave and it gives useful guidance for traders and investors to choose suitable trading strategies.

Keywords
Bitcoin, Cryptocurrency, Momentum, Mean-reversion, Buy-and-hold

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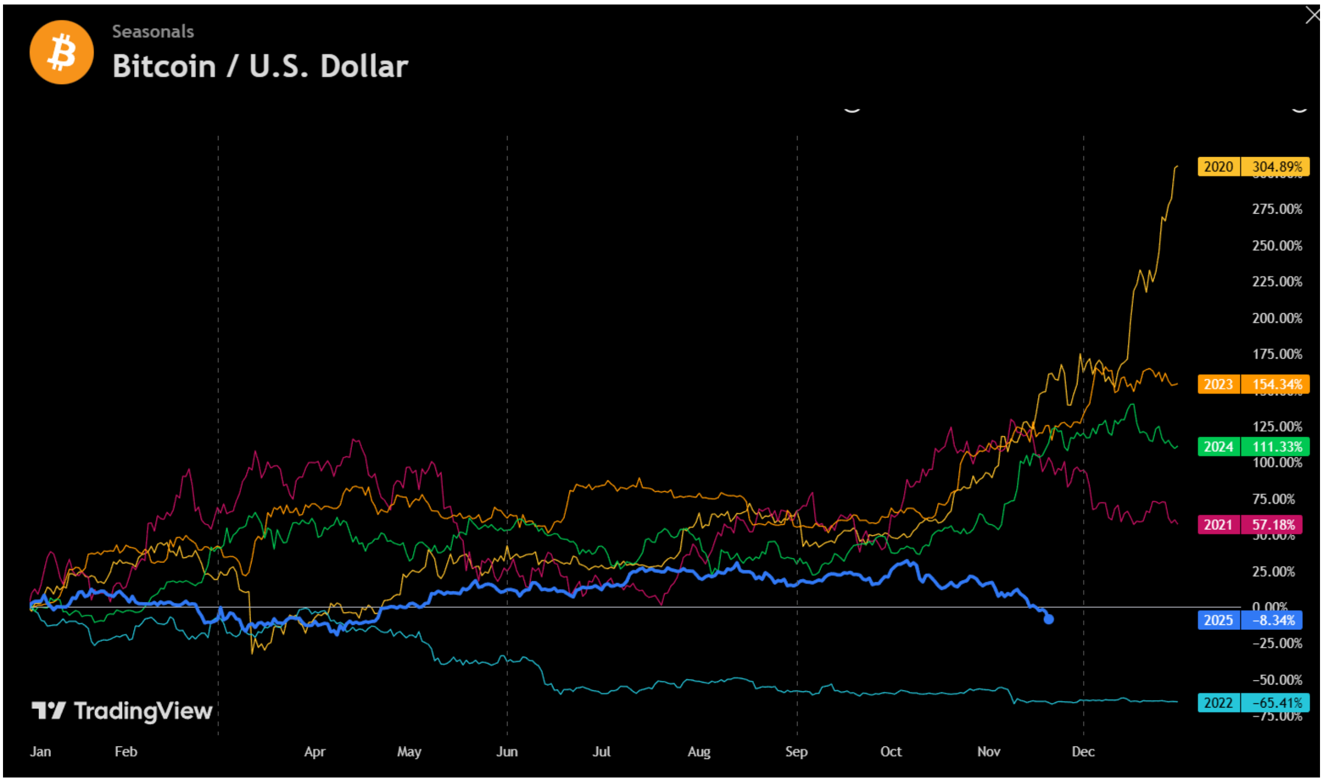
1 Introduction

Among all asset classes, Bitcoin has shown one of the most volatile price patterns. Bitcoin was created by a pseudonymous person or group called Satoshi Nakamoto in 2008. Its original goal was to create a digital monetary system that would operate without a centralized authority. In 2009, the first version of Bitcoin was released and the first block, called the "Genesis Block", was mined. (Nordnet s.a.) The cryptocurrency's first major surge occurred in October 2010, when its long-standing value of under $0.10 began to rise noticeably. Since becoming tradable on popular cryptocurrency exchanges, Bitcoin has experienced several dramatic rallies followed by steep declines. Its price movements often reflect shifts in investor confidence as well as basic market forces of supply and demand. Although Bitcoin's mysterious creator originally designed it to serve as a digital payment system for everyday transactions, it quickly evolved into something much broader. (Edwards 2025.) Despite the fact that Bitcoin offers interesting profit opportunities, world's number one investor, Warren Buffett, has instructed not to invest to nonproductive assets like cryptocurrencies or gold (CNBC 2025).

Bitcoin started to attract traders who speculated on its price swings, and investors started to see it as a potential source of wealth creation, and even a hedge against inflation. Over time, financial institutions have also developed investment products that are linked to Bitcoin, and this has further accelerated market activity. Typical to Bitcoin are frequent and often extreme price movements which are mainly due to active traders and investors who seek to profit from short-term changes. (Edwards 2025.)

Bitcoin's high volatility and the resulting profit opportunities have motivated traders and researchers to explore systematic trading strategies that try to exploit repetitive market behaviours. Two of the most widely studied patterns in financial markets are momentum, where price trends are expected to continue, and mean reversion, where prices are assumed to move back toward their long-term average after significant deviations. Momentum and mean reversion represent two fundamentally different ways of interpreting market behaviour. Momentum thrives in strong, directional markets; mean reversion performs best when prices oscillate around an equilibrium. Both strategies can be profitable, but they rely on entirely different market conditions, assumptions, and risk-management techniques. In picture 1 is shown Bitcoin's percentual yearly movements 2020 – 2025.



Picture 1. Bitcoin's percentual yearly movements 2020 - 2025. Source: TradingView.

Technical indicators are commonly used to operationalize these theories. Momentum-based strategies often rely on moving average crossovers to identify trend direction and potential entry points. In contrast, mean-reversion strategies frequently utilize tools such as Bollinger Bands to detect periods when prices may be statistically overbought and likely to reverse. In addition, a passive buy-and-hold strategy is included as a benchmark. Bitcoin's high volatility makes it an ideal environment to test how these opposing strategies behave under real-world market conditions.

The thesis is structured as follows: Chapter 2 provides the theoretical background for the study, it introduces the concepts of momentum and mean reversion, as well as the basics of technical analysis. Chapter 3 describes the key performance indicators used in the evaluation of trading strategies. In this study annual return, Sharpe ratio, volatility, profit factor, and maximum drawdown were used. Chapter 4 explains the data sources and methodology, it outlines data preprocessing, strategy implementation, and the assumptions used to the simulation, including fee modelling. Chapter 5 presents the empirical results, compares the performance of the strategies, and discusses the effects of different time resolutions and trading costs. Finally, chapter 6 summarizes the conclusions of the study, highlights practical implications, and discusses limitations and potential directions for future research.

1.1 Research objectives

The aim of this thesis is to assess momentum, mean-reversion, and passive HODLing strategies profitability and risk profile, using key financial indicators such as volatility, drawdown, and the

Sharpe ratio. It also assesses how each strategy behaves under varying market conditions, including bull and bear phases, to understand their resilience during periods of market stress.

1.2 Main research questions

By empirically analysing the performance of momentum, mean-reversion and passive HODLing strategies in the Bitcoin market, this thesis seeks to answer several key questions:

1. Which strategy offers the best risk-return trade-off?
2. How does the performance of a momentum-based trading model differ from that of a mean-reversion strategy?
3. When comparing annual returns, the Sharpe ratio, and maximum drawdown, does a buy-and-hold approach outperform the two active trading strategies?
4. How does sampling frequency (daily vs hourly) affect performance?
5. What role do fees and transaction costs play?

2 Theoretical background

The concepts of momentum and mean-reversion represent two opposing hypotheses in financial markets. Momentum suggests that assets which have performed well (or poorly) recently will continue to do so in the near future — essentially, “winners continue to win, and losers continue to lose”. (Jegadeesh & Titman 1993.)

Mean-reversion strategies on the other hand assume that prices will eventually return to their long-term average or equilibrium level after significant deviations, suggesting that very high or low returns are followed by corrections (Chang, Lizardi & Shah 2022). Many empirical studies emphasize that the relative success of each strategy depends on market regime — trend vs. range-bound — and other asset-specific characteristics, e.g., time-series persistence, volatility, and liquidity. A central theme across the literature is that the parameterization of technical indicators (e.g., moving-average lengths, standard-deviation multiples for Bollinger Bands) has a significant impact on returns. Chang et al. (2022) highlight that range detection (via Hurst exponent) and switching between momentum and mean-reversion strategies can improve returns. It reflects that assets may shift between trending and mean-reverting behaviour. This means that in addition to raw returns, the incorporation of risk-adjusted metrics (Sharpe ratio, maximum drawdown) and robustness testing is crucial.

The emergence of cryptocurrencies has sparked research into whether classic anomalies like momentum and mean-reversion are being carried over to this new asset class. For example, Jia, Goodell and Shen (2022) reported evidence of a momentum effect in cryptocurrencies, identifying momentum as a significant factor for crypto returns. Grobys et al. (2025) focused on momentum strategies for major cryptocurrencies and emphasized that while momentum can exist, it is prone to severe crashes and tail-risk, making risk management critical.

Together, these studies show that while technical strategies can produce excess returns under certain circumstances, they are highly dependent on parameter choices, market regime, and underlying asset class.

2.1 Gaps in literature and the relevance to this study

While there is substantial literature on both momentum and mean-reversion strategies in equity markets, and a growing body of work in cryptocurrencies, several gaps remain:

- Many studies focus on daily or longer timeframes; few explore short-timeframe (hourly) strategies in cryptocurrencies as this research intends to do.

- The comparative performance of momentum vs mean-reversion in cryptocurrencies remains unclear, especially when considering optimized parameters and risk-weighted performance.
- Parameter optimization is often done heuristically; systematic cross-validation (especially in crypto) is more limited.
- Tail-risk and drawdown behaviour in crypto momentum/mean-reversion strategies have not been sufficiently studied in the context of real-world feasibility (liquidity, slippage, frequent trading).

This thesis tries to address these shortcomings by investigating optimized parameter sets for moving average crossovers and Bollinger Bands in short-timeframe Bitcoin trading and directly comparing them to a buy-and-hold benchmark, with emphasis on both returns and risk.

In summary, momentum and mean-reversion are well-established theoretical paradigms for designing trading strategies. Previous empirical studies in equities show varying success for technical strategies depending on parameter settings, market regime and asset class. In cryptocurrency markets, momentum effects appear present, but they are less robust and mean-reversion evidence is more unclear. Parameter optimisation and risk management (especially tail-risk) are therefore critical. This thesis builds on and extends the existing literature by focusing on short-timeframe Bitcoin trading, optimised indicator parameters, and direct comparative analysis of momentum vs mean-reversion alongside a passive buy-and-hold strategy.

2.2 Day Trading explained

Investing in cryptocurrencies can be thrilling, but it also requires making key strategic decisions. One of the most important choices investors make is whether to pursue day trading or HODLing (holding assets for the long term). Both methods offer clear advantages and drawbacks and understanding them can help determine which strategy suits best with own goals and risk tolerance. (Binance 2025.)

Day trading is a short-term investment strategy focused on buying and selling cryptocurrencies within the same day to profit from price fluctuations. Traders rely heavily on technical analysis, market indicators, and trading tools to identify short-term opportunities and minimize risk. (Kuepper 2025; Osakevälittäjät 2025.)

Key characteristics of day trading:

- Market analysis: Traders study charts, patterns, and price trends to forecast short-term movements.
- Rapid trades: Positions are opened and closed quickly—often within hours or even minutes.

- Leverage and margin trading: Some traders use borrowed funds to amplify returns, though this also increases potential losses.
- Constant monitoring: Success requires staying alert to market changes throughout the day. (Binance 2025; Kuepper 2025.)

Advantages of day trading:

- Quick profit potential: Well-timed trades can generate returns in a short period.
- Volatility opportunities: Frequent price swings in crypto markets provide numerous opportunities to make profit.
- Skill development: Active trading helps to build technical and analytical expertise. (Binance 2025; Kuepper 2025.)

Disadvantages of day trading:

- High risk: Unpredictable price movements can lead to sudden and substantial losses.
- Time and discipline: Continuous focus and emotional control are essential to avoid impulsive decisions.
- Emotional stress: Market volatility can cause anxiety and lead to mistakes.
- Transaction fees: Frequent trades accumulate trading costs that can significantly reduce profits. (Binance 2025; Kuepper 2025.)

2.3 HODLing explained

HODLing is a long-term investment approach where investors purchase cryptocurrencies and hold them for months or years, regardless of short-term volatility. The term originated from a misspelled online post (“HODL”) and later became an acronym for “Hold On for Dear Life.” Unlike day traders, HODLers focus on long-term growth and typically make very few transactions. This approach requires patience and confidence in the cryptocurrency’s long-term potential. (Binance 2025; Black 2025, 239.)

Advantages of HODLing:

- Reduced stress: There’s no need to track the market movements daily.
- Simplicity: No advanced trading skills or tools are required.
- Potential for long-term gains: Many established cryptocurrencies have historically increased in value over time.
- Lower costs: Minimal trading means fewer transaction fees. (Binance 2025.)

Disadvantages of HODLing:

- Market downturn exposure: Portfolio value can drop significantly during crashes.
- Delayed returns: Profits may take years to realize.
- Missed opportunities: Long-term holders may lose short-term trading profits.
- Project risk: Not all cryptocurrencies will remain valuable in the future. (Binance 2025.)

In essence, day trading suits investors seeking fast-paced action and short-term profits but willing to accept higher risk and stress. HODLing, on the other hand, appeals to those with patience, long-term vision, and a preference for a simpler, lower-stress investment style. (Binance 2025.) Figure 1 shows the comparison between day trading and HODLing.

Figure 1: Comparison of Day Trading vs. HODling strategies. Source: Binance 2025.

	Day Trading	**HODLing**
Time commitment	High	Low
Risk level	Very high	Medium
Profit potential	Short-term gains	Long-term appreciation
Market knowledge	Advanced	Basic to intermediate
Emotional involvement	High	Low
Fees and costs	High (frequent transactions)	Low (fewer trades)

2.4 Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis (EMH) is an investment hypothesis that states that the prices of financial assets reflect all available information (Black 2025, 238). This is based on the belief that the market cannot be consistently “beat” based on risk adjustment alone, because asset prices only react to new information (Ava Trade 2025).According to Black (2025, 237), if EMH is true, meaning that the market is difficult to beat, then the traders should choose to buy and hold low-cost index funds to minimize trading costs and asset management fees.

EMH dates back to the 20th century, but it was not until the 1970s that the American economist Eugene Francis Fama developed the idea in depth. Fama defined an efficient market as one in which participants pursue profits rationally. All relevant basic information is freely available to all who participate to the market, and they compete intelligently using this information. In an efficient market, the prices of various financial assets ultimately reflect their true absolute value. (Ava Trade 2025.)

Efficient Market Hypothesis can be classified in different levels. Fama classified the three levels of the EMH as follows:

- Strong EMH: In a strong EMH, all information (public or private) is discounted to the current price of financial assets. In such scenario, according to the EMH, there is a perfect market in which investors have no advantage over the market. Therefore, it is almost impossible to earn a higher return than the market.
- Medium-strong EMH: The most likely scenario is considered to be a semi-strong EMH, according to which all relevant public information is rapidly reflected in the

prices of financial assets. Market participants absorb and process new information quickly. This leads to a new equilibrium as a result of new demand or supply forces. In this form, investors can only gain an advantage if they possess unique information that is not readily available to the public.

- Weak EMH: In this form, EMH suggests that asset prices have discounted all relevant past information. Once historical information is taken into account, technical analysis strategies cannot give traders an advantage in the market. However, incoming new information (fundamental analysis) can help to identify overvalued or undervalued assets in the market. All in all, proponents of EMH debate that financial markets are difficult to beat by nature. While this may be true, the difficulty is not due to market discounts, but largely due to the collective sentiment of investors which tends to move faster than price developments. (Ava Trade 2025.)

2.4.1 Criticism towards EMH

The most significant criticism of the efficient market hypothesis has always come from behavioural economists, who have argued that market inefficiency arises from psychological and cognitive tendencies that affect investor’s decision making, such as information processing errors, behavioural biases, emotional reactions and subjective misinterpretations, for example poor analysis. Cyclical market bubbles and busts also serve as empirical evidence of financial market inefficiency. It may be possible to determine when markets are in a bubble or bust, but it is not easy to determine how far they can rise or fall. The main argument against the EMH is that it is indeed possible to beat the market year after year in the long run. Legendary investors, such as Warren Buffett, have consistently outperformed the market for many years. (Ava Trade 2025.)

However, there is also some evidence that supports the EMH. One of the strongest pieces of evidence for efficient markets is that large mutual funds, hedge funds, and other professional asset managers fail to consistently outperform the market in the long run. Even large financial institutions, which are equipped with extensive research budgets, vast data sources, and advanced quantitative trading systems, can rarely achieve sustained excess returns. This shows that market is moving towards efficiency. (Ava Trade 2025.)

Another evidence of efficient markets is mean reversion. Assets that have significantly underperformed for an extended period of time tend to eventually perform better over the same period. Moreover, repetitive market cycles reflect consistent pattern of investor behaviour and contribute to long-term market efficiency. (Ava Trade 2025.)

2.5 Random Walk theory

Another hypothesis similar to the EMH is the Random Walk theory. According to the Random Walk theory (Malkiel 2020, 26 – 27), stock prices cannot be reliably predicted. According to the EMH, prices reflect all relevant information about the financial asset, while in the Random Walk theory, prices literally walk randomly and can be affected by even “irrelevant” information. For traders, the theory suggests that it is possible to beat the market only by taking on additional risk. The theory was first published in 1973 by Burton Malkiel in his book “A Random Walk Down Wall Street,” in which he compared stock prices to the “steps of a drunken man” that cannot be reliably predicted. Supporters of the Random Walk theory advise investors to invest in passive funds, such as mutual funds, to have the opportunity to make a profit rather than increasing their risk by trading individual stocks. (Ava Trade 2025.)

However, Verma, Sharma and Sam (2022) studied Random Walk theory in five cryptocurrency markets, and the results of this study provide strong evidence against the random walk hypothesis. The findings are in an alignment with the conclusions of previous studies conducted by Vidal-Tomás, Ibáñez and Farinós (2019). The findings suggest that the cryptocurrency market, as an emerging market, does not operate efficiently. Since price movements do not follow a random walk, cryptocurrency appears to exhibit a degree of predictability. This predictability can create opportunities for arbitrage and allow traders to earn extraordinary returns, which is very appealing for investors and active day traders. Because an asset that is capable to generate above-average returns naturally attracts interest.

2.6 Mean Reversion

The concept of mean reversion is commonly applied in financial analysis across various data sets, such as asset prices. It is based on the idea that when an asset’s current price falls below its historical average, it may offer an opportunity to buy, and if prices rise significantly above the average, they are expected to decline over time. Traders and investors use this principle to determine optimal entry and exit points in their investment and trading decisions. (Chen 2025.)

Mean reversion proposes that asset prices tend to move back toward their long-term average in the long run. The larger the deviation from this mean, the more likely it becomes that the price will revert toward it. This assumption supports many investment strategies that try to profit from temporary mispricings—buying assets that have fallen below their historical norm and selling those that have risen above it. (Chen 2025.)

However, deviations from the mean are not always temporary. A permanent change in earnings or company fundamentals may indicate a structural change rather than a short-term deviation, in which case the asset may not return to its previous mean. (Chen 2025.)

In addition to asset prices and returns, mean reversion can be applied also to other financial metrics, such as interest rates or valuation ratios like the price-to-earnings (P/E) ratio, which also tend to fluctuate around long-term historical levels. Traders and investors use mean reversion techniques to identify and profit from market inefficiencies when asset prices deviate significantly from their historical average. The underlying assumption is that prices will eventually correct and revert to their average level. (Chen 2025.) Common ways for investors to use mean reversion are:

- Statistical Analysis: Tools such as Z-scores are used to measure how far a price has diverged from its mean. A Z-score greater than 1.5 or less than -1.5 can signal a potential trading opportunity.
- Pairs Trading: Traders identify two historically correlated assets. When their price relationship diverges, they buy the undervalued asset and sell the overvalued asset, expecting the spread to revert to its mean.
- Volatility-Based Strategies: Some traders apply volatility mean reversion by buying options when volatility is unusually high and waiting for it to return to its long-term average.
- Risk Management: Stop-loss and take-profit levels are often set near the mean to manage downside risk and lock in profits when prices recover.
- Algorithmic Trading: Traders who use quantitative strategies incorporate mean reversion principles into automated models to detect and exploit short-term pricing inefficiencies. (Chen 2025.)

The success of mean reversion strategies depends largely on the time horizon and market conditions. Short-term traders may analyse hourly or daily data, while long-term investors may focus on multi-year trends. Mean reversion generally performs better in range-bound markets—where prices oscillate around an equilibrium—than in trending markets, where prices move persistently in one direction. (Chen 2025.)

The process of calculating mean reversion begins with collecting historical price data for the asset under analysis. The chosen time frame depends on the trader's strategy. Once the data is gathered, the average (mean) price over the selected period is calculated. The degree of deviation from this mean can then be measured using statistical indicators such as standard deviation or Z-scores. This quantitative assessment helps investors determine how far the current price has strayed from its typical range and evaluate the likelihood of a return toward equilibrium. (Chen 2025.)

Z-score is usually used in trading to calculate mean reversion. It measures how far the price is from its moving average in standard-deviation units and it is effectively the statistical basis behind Bollinger Bands.:

$$Z = \frac{P_t - MA_t}{\sigma_t}$$

Where P_t is current price, MA_t is moving average price, and σ_t is standard deviation of price over the same period.

Interpretation of Z-score:

- $Z > +2$ = price is unusually high → likely mean-reversion downward.
- $Z < -2$ = price is unusually low → likely mean-reversion upward.

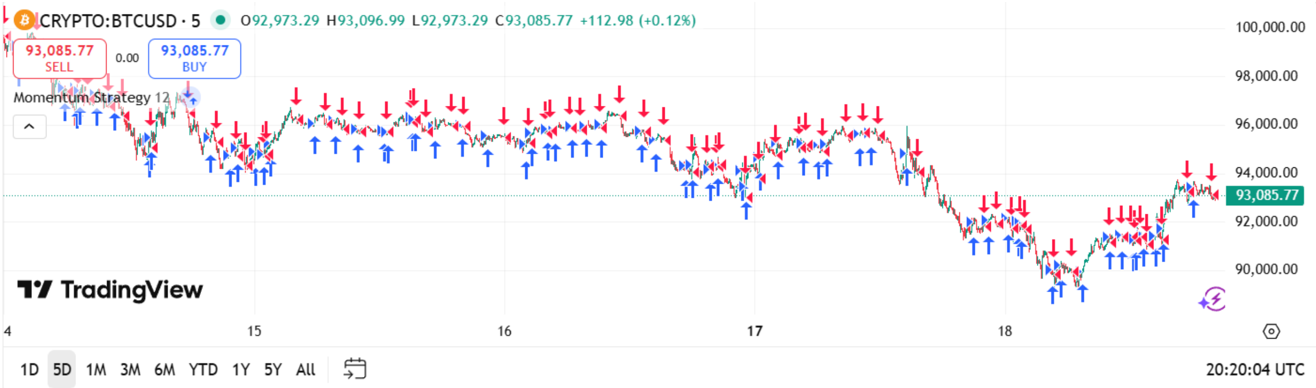
2.7 Momentum

Momentum refers to the phenomenon where a rising stock price is likely to rise more than it falls. Similarly, a falling stock price is likely to continue to fall rather than turn up. Momentum is more useful during bull markets than bear markets, as there are more ups than downs. This is because bull markets tend to last longer than bear markets. (Havia 2022.)

Momentum is a trading approach built on the principle of purchasing assets that have already shown strong performance and selling those that are underperforming—in other words, “buy high and sell higher.” The strategy seeks to capitalize on continuing price trends rather than betting on reversals. Investor Richard Driehaus popularized the concept of momentum. He believed that better returns could be achieved by focusing on fast-growing assets rather than undervalued ones. His philosophy was in stark contrast to the approaches of traditional value investors such as Benjamin Graham and Warren Buffett. Driehaus argued that it was more profitable to invest in stocks already growing and sell them at an even higher price than to wait for the market to recognize undervalued securities. (Gratton 2025.)

Driehaus founded Driehaus Capital Management, where he honed and implemented his momentum-based strategies. His approach was both simple and illogical: to identify assets that show accelerating growth, increasing trading volumes, and strong upward price trends, and then ride those trends for as long as they last. (Gratton 2025.)

Momentum investing is heavily dependent on market volatility and precise timing. The investor is constantly reallocating capital—entering positions as the uptrend strengthens and quickly exiting as the momentum weakens. This dynamic process is often compared to riding waves in the ocean: the investor rides through one uptrend before moving on to the next, avoiding the inevitable crash that follows. (Gratton 2025.) Picture 2 shows Bitcoin’s signals created with momentum strategy.



Picture 2. Bitcoin's Momentum strategy buy/sell signals during a five-day period. Source: TradingView

Success in momentum trading depends on strict risk management and discipline, as it is done in fast-moving and often unpredictable markets. The fear of missing out can easily lead traders to abandon their strategies or enter trades too late. Several key principles guide momentum traders in overcoming these challenges:

- Choose liquid assets that are easy to enter or exit.
- Manage risk carefully during both entry and exit stages.
- Take trades early in the momentum cycle to capitalize on the most profitable phase.
- Set hold times strategically to avoid being overly influenced by short-term trends.
- Exit at the right moment, before momentum fades and prices reverse. (Gratton 2025.)

Timing is crucial in momentum trading. The best opportunities often arise when unexpected news or market shocks trigger sharp price movements. Skilled traders recognize these early signals and act quickly, taking profits before most market participants react. As momentum builds, new traders enter the market, increasing volatility and sometimes fuelling short-term corrections or reversals. (Gratton 2025.)

Early investments tend to offer the highest possible returns with relatively lower risk, while late investments often coincide with overheated markets and declining profitability. However, many traders fail to recognize opportunities early enough in the cycle and instead join trends after they mature—precisely when the risk of reversal is greatest. (Gratton 2025.)

In order to exit at the right time, Stop-loss orders are an essential part of momentum trading because they safeguard traders from unexpected price reversals that can rapidly wipe out profits. By setting a predetermined exit point, a stop-loss automatically closes the position if the market starts moving in the opposite direction. This mechanism helps traders control risk and prevent small losses from turning into significant defeats. (Gratton 2025.)

2.7.1 Momentum anomaly

Momentum anomaly is one of the most studied and successful anomaly phenomena. An anomaly refers to a long-term deviation in market efficiency. By exploiting an anomaly, it may be possible to obtain abnormal returns in relation to risk. Market efficiency, on the other hand, is financial theoretical concept that states that the price of a stock should contain all available information, in which case “predicting” price changes based on historical price data should be useless. (Sijoittaja 2025.)

Hundreds of different anomalies have been discovered throughout history. It has been commonly observed in investment research that anomalies found in historical data tend to decrease or disappear completely after they are discovered. One explanation for this is that the market compensates for the inefficiency found through its pricing. Some anomaly studies also contain bias that affects the results. (Sijoittaja 2025.)

However, the momentum anomaly has persisted as a flaw in the efficient market hypothesis and among more sophisticated valuation models. The phenomenon has also been found to be true in more recent studies, in markets across countries, and across many asset classes. A phenomenon can be considered an anomaly when valuation models in financial theory fail to fully explain the returns generated by a security/portfolio, and adding a factor describing the anomaly to the model improves the model's explanatory power. (Sijoittaja 2025.)

The factors that explain stock returns found in investment research can be roughly divided into risk factors and anomaly factors. Investing naturally involves risks, the effect of which on returns the risk factors seek to explain. Anomaly factors, in turn, arise mainly from the behavioural psychology of investors. In theory, efficient markets should “remove inefficiency” by utilizing the arbitrage found. However, the division into risk and anomaly factors has raised many arguments for and against. Momentum is a good example of the limitations of the division. (Sijoittaja 2025.)

2.8 Technical Analysis

The examination of price patterns and market behaviour is commonly known as technical analysis. More precisely, it involves analyzing past price data to identify trends and signals that may help forecast the future price movements of a financial asset. The foundations of technical analysis date back several centuries. One of its earliest documented practitioners was Joseph de la Vega, who in 1683 applied analytical techniques to anticipate price behaviour in the Dutch financial markets. (Vantage Editorial Team s.a.)

Technical analysis can be used to support a short- or medium-term investment strategy. With the help of technical analysis, an investor can try to exploit short-term market deviations to generate a return. Technical analysis involves tools and calculation formulas, and one of the most common tools is the moving average. The most common way of interpreting it, is to compare the moving average to the price of a security. A moving average gives a buy signal when the price of a security rises through its average. A sell signal is generated when the price of a security slides below its average. (Heikinheimo 2023; Lepikkö 2020 63 – 64.)

Technical analysis aims to find attractive risk/reward ratio buying or selling positions (Heikinheimo 2023). Technical analysis works because shares change owners in the market all the time as a result of the interaction between buyers and sellers. Due to the imbalance between demand and supply, share prices fluctuate constantly, and the market values of even large companies – worth tens, hundreds or even thousands of billions – fluctuate by up to several percent within a day, depending on market conditions. The share price, which changes from one second to the next, is affected by the actions of millions of buyers and sellers – the fundamental value, (its assets, earnings capacity, intellectual property, etc.), of the company does not change at all in such a short period of time, even if the share price fluctuates strongly. (Lepikkö 2020, 63 – 64.) In the case of Bitcoin, this mechanism differs fundamentally from traditional equity markets, because Bitcoin has no underlying corporate fundamentals to anchor its value. Its price is entirely determined by supply and demand, sentiment, liquidity, and speculative behaviour. This makes Bitcoin far more susceptible to rapid intraday price swings caused by liquidity shocks, herd behaviour, and other microstructural effects.

Every transaction and price change can be read from price charts, which provide traders with valuable information about whether there is more buying or selling pressure in the market and in which direction the market is trending. And identifying trends is one of the most important benefits of technical analysis. Shares can only move in three different ways. Sometimes prices are in an uptrend, sometimes they are down, and sometimes they are sideways. Traders thus try to identify the direction of the trend using technical analysis. And when they take trades in the direction of the trend, they are more often right than wrong. This is because trends are more likely to continue than to reverse. This is also agreed upon in the academic world and is called the momentum phenomenon. Technical analysis also works because history tends to repeat itself. The repetitive behaviour of price movements is due to market psychology and that is why it is possible to predict future price changes. (Lepikkö 2020, 63 – 64.)

Greed, fear, uncertainty and the desire to take risks have defined human action for millennia - human components such as emotions and instincts are barely distinguishable from each other. When we learn to read the psychological patterns of buyers and sellers, we can interpret and process any price chart. (Lepikkö 2020, 63 – 64.)

As a final factor in the functionality of technical analysis, it has become a self-fulfilling prophecy. As millions of people around the world make decisions based on technical analysis concepts, they are also confirming the reliability and repeatability of indicators and technical patterns. Even mainstream financial media is talking about technical analysis concepts such as moving averages, important psychological support and resistance levels, and candlestick patterns. A growing number of traders are also using technical analysis in their investment decisions. (Lepikkö 2020, 63 – 64.)

Technical analysis does not aim for a 100% success rate. A large part of the signals from technical analysis are wrong. If, in principle, the price can go either down or up, technical analysis gives the trader a small competitive advantage, which, if implemented systematically and disciplinedly, combined with good cash and risk management, has the potential to make good returns in the long run. It is important to know how to apply technical analysis correctly in different market environments and examine price graphs simultaneously in several different time frames (multi-timeframe analysis). Only then it is possible to maximize the competitive advantage potential offered by technical analysis. The market can surprise with its movements both up and down. Sometimes market prices seem to be moving in completely irrational directions. Sometimes trends last much longer than you might think. The answer to staying on the "right" side of the market is to follow price – not all the opinions and other noise that we are exposed to every day as traders. (Lepikkö 2020, 63 – 64.)

2.9 Moving Averages

In technical analysis, traders rely on various indicators to guide their buying and selling decisions. One of the most common is the moving average (MA) — a tool that smooths out daily price fluctuations by calculating a continuously updated average price.

The moving average helps reduce the influence of short-term, random price changes over a chosen period. There are two main types:

- Simple Moving Average (SMA) — the basic form, which is calculated by taking the arithmetic mean of prices over a set number of days.
- Exponential Moving Average (EMA) — a more responsive version that gives greater importance to recent price data than to older prices.

Moving averages are primarily used to identify the direction of a trend or to highlight potential support and resistance levels for a stock. Because they rely on historical data, they are considered lagging indicators or trend-following tools. (Fernando 2025.)

The longer the time frame, the slower the Moving average will react to price changes. For example, a 200-day MA will react more slowly than a 20-day MA because it averages over a larger set of data. The 50-day and 200-day MAs are particularly popular with traders and often serve as key reference points for major trend signals. (Fernando 2025.)

Traders adjust the length of a moving average to suit their strategy: short-term traders tend to prefer shorter MAs, while long-term investors use longer ones to identify broader trends.

While no indicator can predict future prices perfectly, moving averages — when combined with other forms of technical analysis — can help traders make more informed decisions. A rising MA generally signals an uptrend, while a falling MA suggests a downtrend. (Fernando 2025.)

Crossovers between moving averages can also confirm changes in momentum:

- A bullish crossover occurs when a short-term MA rises above a long-term MA, indicating upward momentum.
- A bearish crossover happens when a short-term MA falls below a long-term MA, signaling downward momentum. (Fernando 2025.)

2.9.1 Simple Moving Average (SMA)

A simple moving average is calculated by finding the arithmetic mean of a series of prices over a chosen time frame. To compute it, all prices in the series are added together and then divided by the number of observations. (Fernando 2025.) Picture 3 shows the Simple Moving Average on Bitcoin chart with blue colour. The formula to calculate the SMA is:

$$SMA = \frac{A1 + A2 + \ldots + An}{n}$$

Where:

A = Average in period n

n = Number in time periods

Picture 3. Simple Moving Average on the Bitcoin chart with blue colour. Source: TradingView.

2.9.2 Exponential Moving Average (EMA)

The exponential moving average (EMA) is a type of moving average that places greater emphasis on the most recent price data, making it more sensitive to new market developments compared to the simple moving average (SMA). (Fernando 2025.)

To calculate an EMA, you first determine the SMA for the selected time period as a starting point. Next, you compute the smoothing factor (also called the multiplier), which controls how much weight is given to the latest prices. The formula for the smoothing factor is:

$$[2 / (\text{Selected time period} + 1)]$$

The multiplier for the 20-day MA would be: [2 / (20 + 1)] = 0.0952. This multiplier is then applied to the most recent price and combined with the previous EMA value to produce the current EMA. In this way, newer data points have a stronger impact on the EMA, while the influence of older prices gradually diminishes.

$$EMA_t=[V_t\times(s/1+d)]+EMA_y\times[1-(s/1+d)]$$

Where:
EMAt = EMA today
Vt = Value today
EMAy = EMA yesterday
s = Smoothing factor
d = Number of days (Fernando 2025.)

2.9.3 Using SMA and EMA together

Traders often use both the Simple Moving Average (SMA) and Exponential Moving Average (EMA) to gain a more complete picture of market trends. Each type of moving average offers unique insights — the SMA provides a smoother, longer-term view of the overall direction, while the EMA responds faster to recent price changes. (Fernando 2025.)

By combining them, traders can identify momentum changes and confirm trend reversals more reliably. One of the most common ways of using both indicators is through the use of crossover strategies.

- Bullish Crossover (Golden Cross): This occurs when a short-term moving average (such as the 15-day MA) crosses above a long-term moving average (such as the 50-day MA). Golden Cross is usually interpreted as a signal that bullish momentum is building and high trading volumes confirm that.

- Bearish Crossover (Death Cross): This occurs when a short-term moving average crosses below a long-term MA. It indicates that a downtrend is gaining momentum and that prices may continue to decline. (Fernando 2025.)

Crossovers are especially useful because they provide visual and data-driven confirmation of changing market conditions. However, like all indicators, traders should use them in conjunction with other forms of technical analysis, because they can produce false signals if used alone. (Chen 2025; Fernando 2025.) The Picture 4 shows 50-day MA and 200-day MA on Bitcoin chart.

Picture 4: 50-day Moving Average (orange line) and 200-day Moving Average (green line) on Bitcoin chart. Source: TradingView.

2.9.4 Advantages and Limitations of Moving Averages

Moving averages are one of the most widely used technical analysis tools because of their simplicity, adaptability, and ability to clarify market direction. However, to be able to use them efficiently, traders need to understand their strengths and limitations — and ideally combine them with other indicators and market analysis techniques to make well-informed decisions. (Fernando 2025.)

Advantages:

- Trend Identification: Moving averages help traders and investors quickly identify the general direction of a market — whether it's an uptrend, downtrend, or is the asset moving sideways. This makes them essential tool for recognizing long- and short-term market trends.

- Noise reduction: Moving averages make it easier to see the underlying pattern in price movements by smoothing out random price swings. This helps traders avoid reacting to temporary volatility.

- Versatility: MAs can be applied to any time frame — from minutes to months — making them useful for both day traders and long-term investors.
- Support and Resistance Levels: Moving averages often act as dynamic support or resistance levels. Traders monitor price actions around these levels to anticipate potential reversals or breakouts.
- Basis for Other Indicators: Many advanced technical indicators, such as the Moving Average Convergence Divergence (MACD) or Bollinger Bands, are based on moving averages, demonstrating their fundamental role in technical analysis. (Fernando 2025.)

Limitations:

- Lagging Nature: Because moving averages are based on historical data, they inherently lag behind current market activity. This delay can cause signals to appear after a trend has already begun or ended.
- False signals: In sideways or volatile markets, moving averages can produce misleading crossover signals that lead to unprofitable trades.
- Parameter Sensitivity: Results depend greatly on the chosen timeframe. Shorter MAs react quickly but can be too sensitive, while longer MAs offer stability but can be too slow to react to trend changes.
- No Predictive Power: While MAs are great for identifying trends, they do not predict future prices. They are tools for confirmation, not for prediction. (Fernando 2025.)

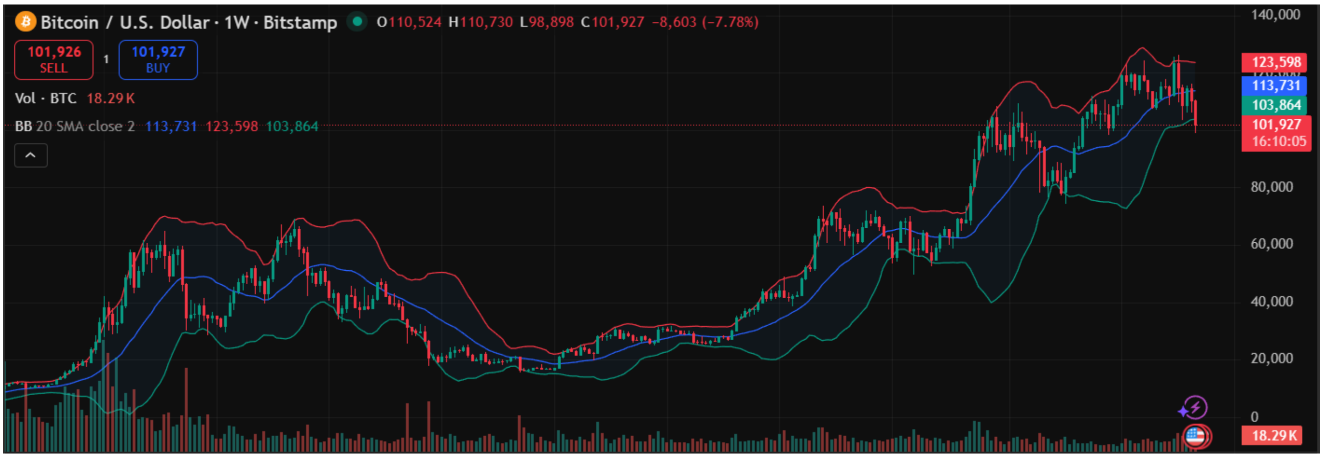
In summary, moving averages are important tools in technical analysis because they filter out short-term volatility and reveal the direction of the underlying trend in asset prices. Their ability to smooth data, highlight market momentum, and generate crossover signals make them valuable for both short-term traders and long-term investors. However, because moving averages are lagging indicators, they are most effective when used together with other analytical techniques. (Fernando 2025.)

Both momentum and mean-reversion strategies are based on basic principles of moving averages but apply them in different ways: momentum strategies seek to capitalize on the continuation of price trends, while mean-reversion strategies assume that prices will eventually return to their historical mean. Understanding how these models interact with indicators such as the SMA and EMA provides a deeper understanding of how traders design, evaluate, and optimize systematic trading strategies. (Fernando 2025.)

2.10 Bollinger Bands

Bollinger Bands are a widely used technical analysis tool designed to measure market volatility through Standard Deviations (SD) and identify trends through Moving Average and help to understand whether a security may be overvalued or undervalued via the principle of mean reversion, which implies that, over time, an asset's price naturally tends to move back toward its historical average or long-term mean. Bollinger Bands were created in the 1980s by financial analyst John Bollinger and the indicator consists of three dynamic lines that move in relation to the price of a security. Bolling Bands can be used to analyse stocks, futures, commodities and currency, and in addition to measuring the volatility or trend strength, they are also a valuable tool to assess potential entry or exit points. (Binance 2018; Lund, s.a.)

The middle line represents the 20-day Simple Moving Average (SMA) of the asset's closing prices (blue line in picture 5) and it reflects the intermediate-term trend. The upper and lower bands (red and green lines in picture 5) are typically placed two standard deviations above and below this SMA. These outer bands expand and contract automatically in response to price volatility — widening during periods of high volatility and narrowing when the market is more stable. (Binance 2018; Thompson 2025.) The standard deviation represents how much individual prices deviate from their average value. In other words, it measures the degree of price dispersion and serves as a key indicator of market volatility. When prices fluctuate widely, the standard deviation is higher; when prices remain stable, it is lower. In the context of Bollinger Bands, the standard deviation is typically calculated over the same time period as the Simple Moving Average (SMA) used in the indicator. (Lund s.a.) In the Picture 5 are shown Bollinger Bands in the Bitcoin chart.



Picture 5. Bollinger Bands seen on Bitcoin chart. Source: TradingView 2025.

Because the bands are based on standard deviations, they show when prices are statistically high or low relative to their recent average. When prices approach the upper band, which is usually viewed as a potential resistant level, traders often interpret the asset as overbought, suggesting that a price decline could follow. Conversely, when prices near the lower band, which is considered as a support level, the asset may be considered oversold, indicating that a rebound could be likely. (Thompson 2025.)

Bollinger Bands visually highlight when prices have strayed too far from their mean, signalling that a price correction or reversal could be approaching. However, during periods of a strong price trend, these signals can become less reliable. When momentum is high, the price may continue to move along the upper or lower Bollinger Band for an extended period rather than reversing immediately. This is because persistent market sentiment or strong buying and selling pressure can maintain the trend and keep prices near the extreme ends of the bands. (Lund s.a.) While Bollinger Bands are valuable for visualizing volatility, they are considered as a secondary indicator, meaning they work best when they are used to reinforce signals with other analytical tools rather than using alone. (Binance 2018; Thompson 2025.)

Bollinger Bands are calculated by choosing the number of periods for the Simple Moving Average (usually 20 days) and the number of standard deviations that determine the distance between the upper and lower bands (usually two). Upper and lower bands formulas are as follows:

UPPER BAND = 20-day SMA + (20-day standard deviation x 2)

LOWER BAND = 20-day SMA – (20-day standard Deviation x 2) (Binance 2018).

3 Key Performance Metrics

Five key performance indicators are used to assess the effectiveness of the Bitcoin trading strategies examined in this study. These indicators were chosen because they provide a balanced picture of profitability, risk, and overall strategy quality, while still being simple enough to calculate and interpret. Together, they provide a clear and comparable assessment of how each trading model performs relative to both market conditions and alternative strategies.

3.1 Annual Return

Annual return measures the total percentage gain or loss produced by a strategy over a one-year period. It is the most direct indicator of profitability and allows different trading strategies to be compared on a common scale. While annual return is essential for understanding performance, it does not explain the level of risk taken to achieve those results. For this reason, it is interpreted together with the other metrics presented below. (Chen 2025.) The formula to calculate annual return is:

$$\text{Annual Return} = \frac{V_{\text{end}} - V_{\text{begin}}}{V_{\text{begin}}}$$

Where V_{begin} is the initial portfolio value, and V_{end} is the ending portfolio value.

3.2 Sharpe Ratio

Sharpe Ratio was developed by economist William F. Sharpe in 1966. It evaluates a strategy's return relative to the amount of volatility it experiences. It is calculated by dividing the excess return (return above the risk-free rate) by the standard deviation of returns. A higher Sharpe ratio indicates that the strategy delivers better risk-adjusted performance and compensates the investor more efficiently for the risk taken. (Fernando 2025; Nordnet Koulu s.a.) This metric is particularly important in the of Bitcoin, where price swings are substantial and unmanaged volatility can distort the true quality of a strategy's returns. The Sharpe Ratio measures excess return compared to volatility and is calculated:

$$\text{Sharpe Ratio} = \frac{R_p - R_f}{\sigma_p}$$

Where R_p is average return of the strategy, R_f is risk-free rate, and σ_p is standard deviation of returns. If hourly or daily data is used, then Sharpe Ratio should be annualized:

$$\text{Sharpe}_{\text{annual}} = \text{Sharpe}_{\text{period}} \times \sqrt{K}$$

Where K = 365 for daily returns, and K = 8760 for hourly returns.

In Picture 6 are shown the Volatility of the portfolio in one month, one year and three years, and Sharpe Ratio for one year and three years. The higher the Sharpe Ratio, the better the investment has performed in relation to its risk.

Riski	18.11.2025
Salkun volatiliteetti, 1 kk	12,99%
Salkun volatiliteetti, 1 v	15,01%
Salkun volatiliteetti, 3 v	14,37%
Sharpen luku, 1 v	1,96
Sharpen luku (3 v)	1,43

Picture 6. Volatility and Sharpe Ratio of the portfolio. Source: Nordnet

3.3 Volatility

Volatility is a measure of how much an investment's value fluctuates around its average return. The larger the portfolio's change relative to the average change, the greater the volatility. And the greater the portfolio's volatility, the greater the uncertainty surrounding its return. Volatility is usually calculated as the standard deviation of daily returns and is expressed as a percentage over a given period of time. (Nordnet Koulu s.a.)

Low volatility can indicate lower risk, but it can also mean that, for example, the turnover of a stock is so small that it may be difficult to get rid of it. Low volatility can also be a harbinger of a coming crash. A high percentage of volatility means that the price of an investment fluctuates – it can rise sharply, but it can also fall sharply, even collapse. If you want less risk, you can choose investments with low volatility, but if you want returns, you can choose an investment with high volatility. Volatility therefore describes price fluctuations and is also a measure of overall risk. (Nordnet Koulu s.a.) Since Bitcoin is known for its high variability, analyzing the volatility of each trading strategy helps determine whether a model smooths out price movements or amplifies them. Volatility is also a key component of the Sharpe ratio, making it central to understanding risk-adjusted performance. Volatility is the standard deviation of returns and is calculated:

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(R_i - \bar{R})^2}$$

Where R_i are individual returns, $\bar{R}$ is average return, and N is number of return observations. If volatility is annualized, then the formula is:

$$\sigma_{\text{annual}} = \sigma_{\text{period}} \times \sqrt{K}$$

Where K is the number of periods per year (e.g., 365 for daily).

3.4 Profit Factor

Profit Factor is calculated by dividing the total win by the total loss. It shows how many units of profit the strategy generates for every unit of loss. A profit factor above 1.0 suggests that the strategy is profitable overall, while values above 1.5 or 2.0 reflect stronger performance and more efficient trading. This metric is especially useful when comparing short-term trading strategies that generate frequent trades, as it reveals the balance between wins and losses. (Groette 2025.)

While profit factor is a useful indicator, it should not be considered as a standalone measure of a strategy's success, just as no other indicator should be used alone. It does not take into account the number of trades taken, the size of individual wins and losses, the level of risk involved, or the consistency of returns over time. For this reason, profit factor is typically evaluated together with other performance metrics to provide a more complete and accurate picture of the overall effectiveness of a trading strategy. (Groette 2025.) The formula to calculate profit factor:

$$\text{Profit Factor} = \frac{\text{Gross Profit}}{\text{Gross Loss}}$$

Where Gross Profit = sum of all winning trades, and Gross Loss = sum of all losing trades (expressed as positive values). If Profit Factor is > 1, it means that the strategy is profitable. Profit Factor of > 1.5–2.0 indicates strong trade efficiency.

3.5 Maximum Drawdown

Maximum drawdown (MDD) measures the largest drop in the value of an investment from a previous peak to the next trough before reaching a new peak. It is a valuable indicator for assessing the downside risk of an investment, but it does not tell how often losses occur or how long it takes to recover after a decline. In general, a lower MDD indicates that an investment has experienced less severe losses, while a drawdown of 100% indicates a complete loss of capital. MDD is especially useful for comparing the risk levels of different trading strategies, as it highlights their ability to preserve capital—an essential consideration for investors. (Hayes 2025.) Because cryptocurrency markets can experience sudden and deep declines, maximum drawdown is essential for understanding downside risk. Maximum drawdown is calculated as follows:

$$\mathrm{MDD} = \max_t \left(\frac{P_{\text{peak}} - P_{\text{trough}}}{P_{\text{peak}}} \right)$$

Maximum drawdown tracks cumulative equity curve, identifies all peaks, measures drop from each peak to the next trough, and selects the largest drop.

4 Methodology

Historical Bitcoin price data (in EUR) was obtained from Cryptodownload.com. Python (pandas and matplotlib libraries) were used for preprocessing, calculating returns, and generating descriptive statistics and moving average indicators. The dataset was cleaned, chronologically ordered, and inspected for missing or irregular values to ensure the accuracy of the backtesting results.

Unlike previous studies that performed extensive parameter optimization using grid searches and heatmap visualization, this thesis applied a fixed, commonly used parameter configuration for the Bollinger Bands and Moving Average strategies. This design choice reduces the risk of data-snooping bias and overfitting to historical data and reflects a more realistic trading scenario where parameters are chosen based on prior knowledge rather than retroactive optimization.

4.1 Data Source and processing of daily data

Historical Bitcoin price data in euros (BTCEUR) was obtained from CryptoDataDownload.com, which provides OHLCV (open, high, low, close, volume) data collected from major cryptocurrency exchanges. The downloaded dataset consisted of hourly observations. To be consistent with the frequency of observations of long-term strategy performance commonly used in academic research, the data was also re-divided into daily time intervals and the results of both hourly and daily data were analysed.

Daily open, high, low, and close (OHLC) prices were constructed using standard financial rules: the first hourly price of each day represents the daily open, the highest and lowest hourly prices represent the daily high and low, and the final hourly close represents the daily close. Daily trading volume was compiled as the sum of hourly volumes. The final dataset spans the period from 31.10.2020 to 3.11.2025 and contains 1829 daily, and 43916 hourly observations. Figure 2 shows the data used in this thesis study.

Figure 2. Description of data used in the study.

Variable	**Description**
Price	Close price of BTC/EUR
Period	Oct 2020 – Nov 2025
Frequency	1-hour
Market	Spot
Exchange	Gemini

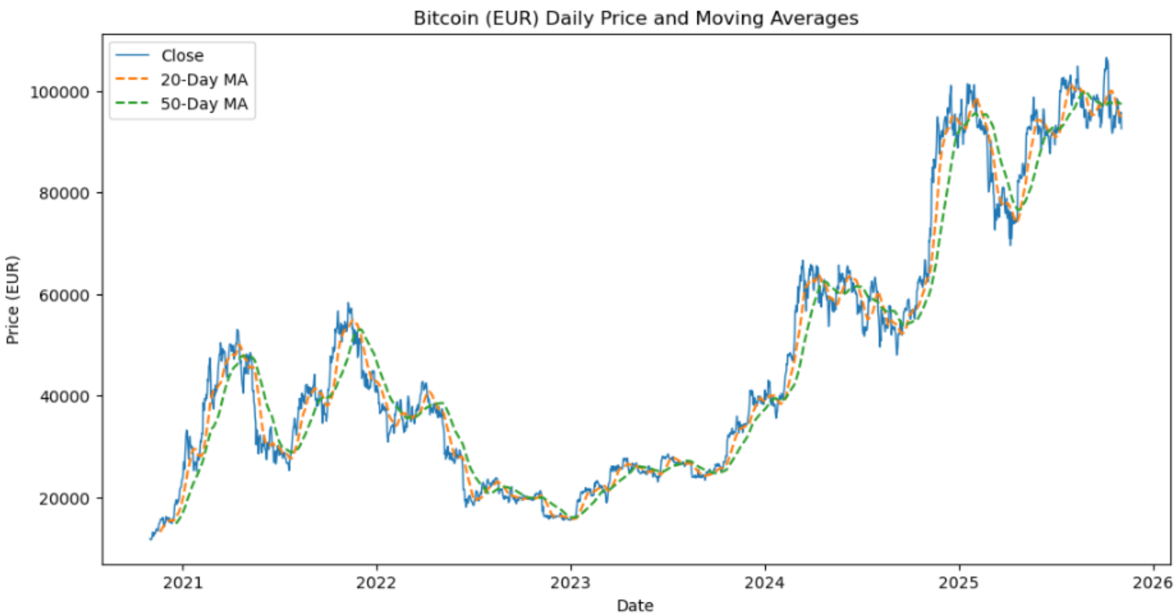
Daily simple returns were calculated as:

$$\mathbf{Rt} = \frac{\boldsymbol{Pt - Pt - 1}}{\boldsymbol{Pt - 1}}$$

where P_t is the closing price on day t. Log returns were also calculated for robustness checks.

To test the performance of different trading anomalies, three portfolios were constructed: a passive buy-and-hold (HODL) benchmark, a momentum strategy, and a mean reversion strategy. Each strategy was initialized with a hypothetical investment of €10,000.

Picture 7 shows Bitcoin's daily price fluctuations and 20-day and 50-day Moving Averages. This visualization highlights how a moving-average-based momentum strategy attempts to capture long-term trends in Bitcoin's price. However, it also illustrates the limitations of daily data: many intraday fluctuations and short-term reversions are smoothed out and invisible at this time resolution, which partially explains why the momentum strategy performed better on daily data while mean-reversion strategies excelled on intraday (hourly) data.



Picture 7. Bitcoin's daily price fluctuations and 20-day and 50-day Moving Averages.

Comparison of the HODLing strategy to Momentum and Mean Reversion strategies. The buy-and-hold (HODL) strategy serves as the benchmark. The entire 10 000 € is allocated to Bitcoin at the beginning of the sample, and the position is held till the end of the sample period. The HODLing strategy's stock curve evolves exclusively based on daily Bitcoin returns. This approach reflects the passive investment philosophy that is commonly followed in retail cryptocurrency markets.

The momentum strategy is based on the assumption that assets showing an upward price trend will continue to rise in the short term. A moving average crossover rule is applied using the 20-day (short-term) and 50-day (medium-term) simple moving averages (MA20 and MA50). Trading rules for moving average are as follows:

- Enter (long): when MA20 crosses above MA50 (bullish trend signal).
- Exit (move to cash): when MA20 falls below MA50 (bearish trend signal).
- Only long positions are taken; no leverage or short selling is used.

This model captures continuous uptrends while it avoids prolonged downtrends. To avoid prediction bias, signals are lagged by one day.

The mean reversion strategy assumes that extreme price movements will revert to their mean. Bollinger Bands, built around a 20-day moving average and two standard deviations wide, are used to identify overbought and oversold conditions.

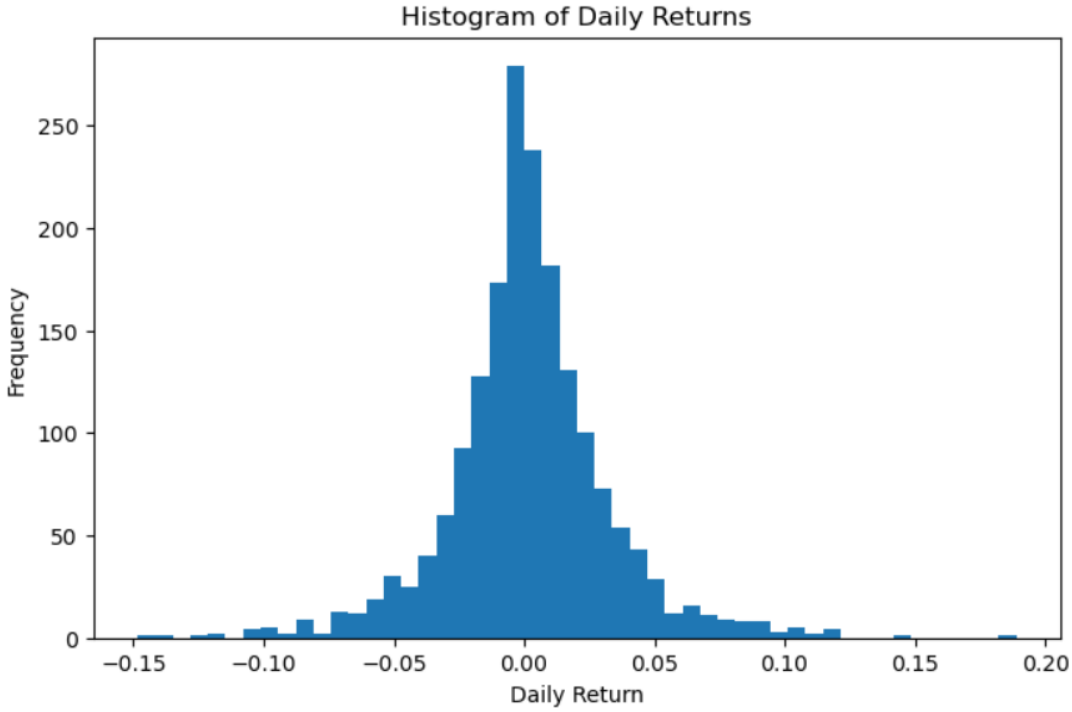
$$\textit{Upper Band} = MA20 + 2 \times \sigma 20$$

$$\textit{Lower Band} = MA20 - 2 \times \sigma 20$$

Trading rules for Bollinger Bands:

- Enter (long): when the closing price falls below the lower Bollinger Band (oversold).
- Exit: when the price crosses back above the middle band (20-day moving average).

This approach is designed to take advantage on temporary price fluctuations during sideways or mean-reverting market patterns.



Picture 8. Histogram of Bitcoin's daily returns.

The histogram in picture 8 illustrates the distribution of Bitcoin’s daily returns over the period under review. The distribution is centred close to zero, indicating that most daily price changes are relatively small and fall within a narrow range. The left tail shows occasional sharp declines (e.g., returns below -10%), while the right tail exhibits occasional upward jumps. This strong tail is a well-known feature of cryptocurrency returns and reflects Bitcoin’s vulnerability to sudden liquidity shocks, sentiment-driven volatility, and rapid speculative flows. This distributional property is especially relevant for risk management and helps explain why metrics such as maximum drawdown and Sharpe ratio are important when evaluating Bitcoin trading strategies.

Figure 3. Distribution of Bitcoin's daily returns.

Count	1829
mean	0.16 %
std	3.1 %
min	-14.84 %
25 %	-1.30 %
50 %	0.03 %
75 %	1.58 %
max	18.9 %

Figure 3 shows the distribution of Bitcoin's daily returns, suggesting a highly volatile asset. The average return of 0.16% suggests a small increase over time, but the standard deviation of 3.1% reveals significant short-term fluctuations. The minimum and maximum values (–14.84% and +18.90%) indicate Bitcoin's exposure to large price shocks in both directions. The median return is close to zero, which means that most hourly movements are small, while the quartile values indicate that both moderate losses and gains occur frequently. All in all, the results reflect a return distribution with frequent small changes and occasional extreme movements, consistent with Bitcoin's reputation as a high-risk, high-volatility asset.

4.2 Bitcoin hourly data

The analysed data consists of 43,916 hourly observations of Bitcoin prices and related market variables between 2020 and 2025. A continuous time index was created using hourly frequency and compared to the observed timestamps, confirming that there were no missing or irregular intervals in the time series. This guarantees that the price data is complete and uninterrupted throughout the sample period, providing stable input for analysing the hourly trading strategy. The absence of missing hourly data removes the need for padding or interpolation, preventing biases that could otherwise affect signal generation and trading returns. This strengthens the validity of the empirical results and ensures that strategy performance is based on genuine price changes and not because of artificial data changes.

4.3 Adding transaction fees

To guarantee that the back-tested results reflect realistic trading conditions, transaction fees were included into the simulation. Each time a position was opened or closed, a fee of 0.1% was charged on the trade value. This models the cost of executing trades on typical cryptocurrency exchanges, where fees generally range between 0.05% and 0.2% depending on trading volume and user level.

The fee is deducted directly from the portfolio with each trading transaction, meaning strategies with higher trading frequencies are affected by relatively higher transaction costs. In this study, the mean reversion strategy executed 423 trades, while the momentum strategy executed 138 trades, and the buy-and-hold strategy executed only one trade at entry. As a result, the impact of transaction costs was significantly higher for the mean reversion model, moderately significant for momentum, and almost insignificant for HODLing strategy.

Mathematically, the fee was applied per transaction as:

$$\mathit{Cost} = \mathit{Fee\ rate} \times \mathit{Portfolio\ value}$$

The fee was deducted from the returns of the given period. The net equity curve was then calculated based on returns after fees.

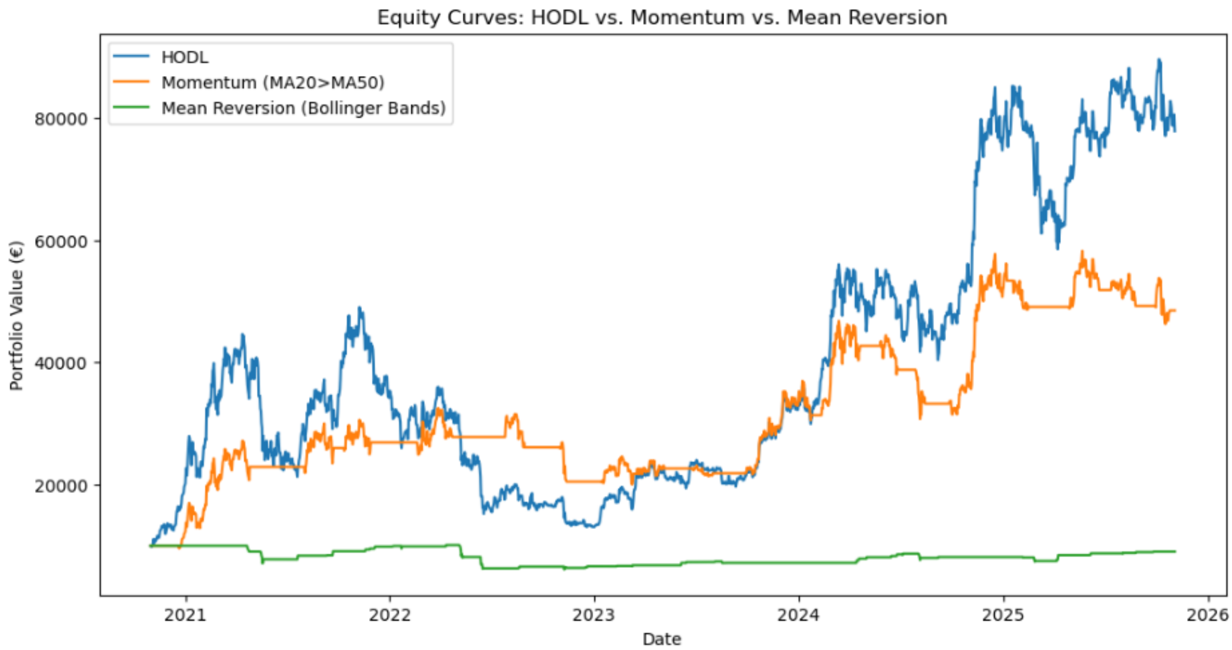
This modelling approach ensures that the reported performance metrics reflect realistic trades and helps to spot strategies that are only theoretically profitable from those that remain viable under real market conditions. However, the simulation assumes idealized execution with no slippage and equal fee rates across all trades, which simplifies real-world dynamics. A more detailed model could incorporate variable fees depending on order type or liquidity conditions.

5 Results

Picture 6 illustrates the evolution of the portfolio value for each strategy over the sample period collected from the daily data. The HODL portfolio shows the highest long-term growth during prolonged bull markets, but it also experiences the deepest declines, especially during major Bitcoin price corrections.

The momentum strategy shows a smoother equity curve, and it avoids some of the biggest downturns by moving into cash during bearish periods. However, it can be weaker during strong but short-lived rallies where trend signals lag behind price changes.

The mean reversion strategy shows a more defensive profile. Its equity curve represents lower volatility, and the strategy is not profitable.



Picture 9. Comparison of Momentum and Mean Reversion strategies with passive HODLing strategy with initial capital of 10 000 €. Daily data was used.

5.1 Interpretation of Results

The results highlight important behavioural features of Bitcoin's price dynamics. The HODL strategy benefits from Bitcoin's long-term bullish trend and produces the highest cumulative return over multi-year periods. However, its volatility and maximum drawdown are significantly higher than those of the active strategies. This confirms that Bitcoin's price behaviour is characterized by significant long-term appreciation accompanied by extreme short-term fluctuations.

The momentum strategy managed to avoid some of Bitcoin's deepest declines, demonstrating that a moving-average crossover approach provides protection against declines during prolonged bear markets. However, the strategy's timing lag was the cause to miss significant gains during strong recoveries. This is especially important in Bitcoin markets, where price increases often occur quickly and strongly. As a result, the strategy exhibited lower volatility than HODLing, smaller maximum drawdowns, but also a lower Sharpe Ratio. This result suggests that, during the sample period, the reduction in risk did not lead to better risk-adjusted performance.

The mean reversion strategy typically offers the smoothest return profile, with lower volatility and smaller drawdowns. Its trades focus in short-lived price reversals, allowing it to benefit when Bitcoin experiences temporary oversold conditions. However, this strategy can underperform significantly during extended bull markets, resulting in a lower long-run CAGR compared to HODL or momentum.

Figure 4. Strategy comparison with daily data.

	HODling strategy	**MA 20 > MA 50 Momentum strategy**	**Mean reversion strategy (Bollinger Bands)**
Cumulative Return	678 %	385 %	-9.67 %
CAGR	32.65 %	24.28 %	-1.39 %
Volatility (ann.)	49.21 %	35.63 %	14.47 %
Sharpe Ratio	0.82	0.79	-0.02
Max Drawdown	-73.39 %	-38.40 %	-39.43 %

Figure 4 shows the strategy comparison when daily data was used. Over the sample period, the buy-and-hold (HODL) strategy generated a cumulative return of 678,24 % with an annualized volatility of 49,21 % and a Sharpe ratio of 0,82. The moving average crossover (MA20 > MA50) strategy produced a cumulative return of 384,78 %, with a lower volatility of 35,63 % and a Sharpe ratio of 0,79.

However, the maximum drawdown of the HODL strategy was substantially larger (-73,39 %) compared to the momentum strategy (-38,40 %), indicating that the active strategy mitigated the risk of a downturn during major market declines.

Mean reversion was implemented using Bollinger Bands: long positions were opened when Bitcoin closed below the 20-day lower band (indicating oversold conditions) and closed when price crossed above the middle band.

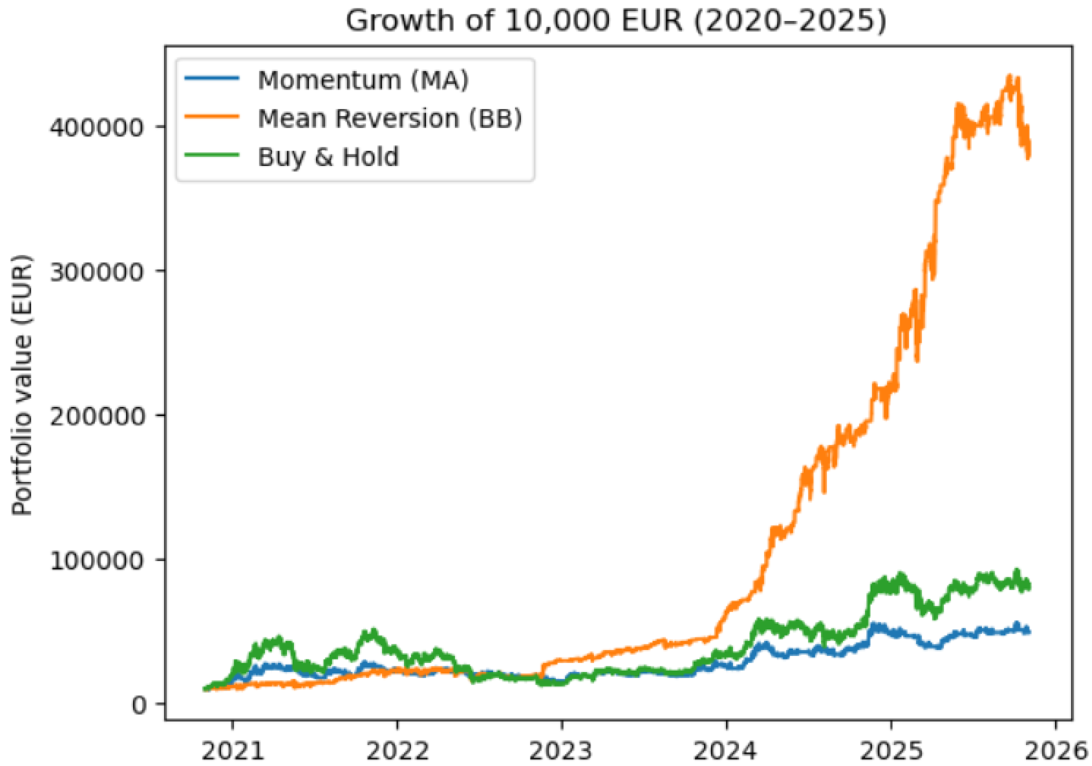
5.2 Strategy comparison with hourly data

Analysis of the hourly data showed completely different results than of the daily data. The dramatic performance differences between daily and hourly testing suggest that Bitcoin behaves differently on different time scales, and that trading strategies interact with market structure in fundamentally different ways depending on frequency. When using daily candles, the buy-and-hold strategy performed best, while mean reversion showed poor results. On the contrary, when using hourly data, the mean reversion model performed significantly better than momentum and buy-and-hold strategies. This difference can be explained by several structural and behavioural factors in cryptocurrency price dynamics. At daily resolution, many of the profit opportunities of mean-reversion are statistically invisible, while in hourly data these short-term fluctuations are preserved. Figure 5 shows how the different strategies performed in the hourly based data analysis. Also, the final values from the initial sum of 10 000 € have been added to show how different trading strategies have been performed between 2020 and 2025.

Figure 5. Hourly data strategy comparison.

	Momentum (MA)	**Mean-reversion (BB)**	**HODLing**
Annual Return	37,5 %	106.8 %	51.3 %
Volatility	50 %	44.35 %	75.04 %
Sharpe Ratio	0.89	1.86	0.93
Max drawdown	-47.5 %	-35.6 %	-76 %
Profit factor	1.05	1.15	1.03
Final 10k value	49 413 €	382 096 €	79 792 €

The comparison of portfolio values with hourly data in picture 10 shows how the mean reversion strategy has outperformed momentum and HODLing strategies. The picture shows that the mean reversion strategy has accelerating compounding effects, especially from 2023 onwards, reflecting its ability to consistently benefit from short-term price movements. The buy-and-hold strategy benefits from significant uptrends, but lacks protection in downturns, resulting in slower asset returns. The momentum strategy produces gradual growth, but it does not match the performance of implementations based on reversal strategies.



Picture 10. Changes in portfolio's value with hourly data.

5.3 How trading fees affect the results

Transaction fees can significantly change the profitability of active strategies — especially those that trade often. In the data, transaction fees have not been taken into consideration and I will address them now separately. In figure 6 are shown the number of trades taken and how each strategy is affected by the fees.

Figure 6. The number of Bitcoin trades taken during the observation period.

Strategy	Trades	Market exposure	Fee sensitivity
Mean reversion	423	26.6 %	High
Momentum	138	52.3 %	Medium
HODLing	1	100 %	Minimal

Typical BTC trading fee is 0.04 % – 0.10 % per trade (if using limit orders + high volume tier), and typical retail trader fee for market orders is 0.15 % – 0.25 %. To make calculations easy, 0,1 % fee is used per trade.

Mean reversion: 423 trades × 0.1% =
423 × 0.001 = 0.423 = **42.3 %** of capital eroded by fees.

Momentum: 138 trades × 0.1% =
138 × 0.001 = 0.138 = **13.8 %**

HODLing: 1 trade × 0.1% =
The effect is insignificant.

The final value from the hourly data is used and the effect of the fees are calculated in figure 7. It shows the decline in annual return for mean reversion and momentum strategies when trading fees are added, but with or without fees, Bitcoin is more mean-reverting than trend-driven on hourly basis.

Figure 7. The effect of the trading fees to the final values.

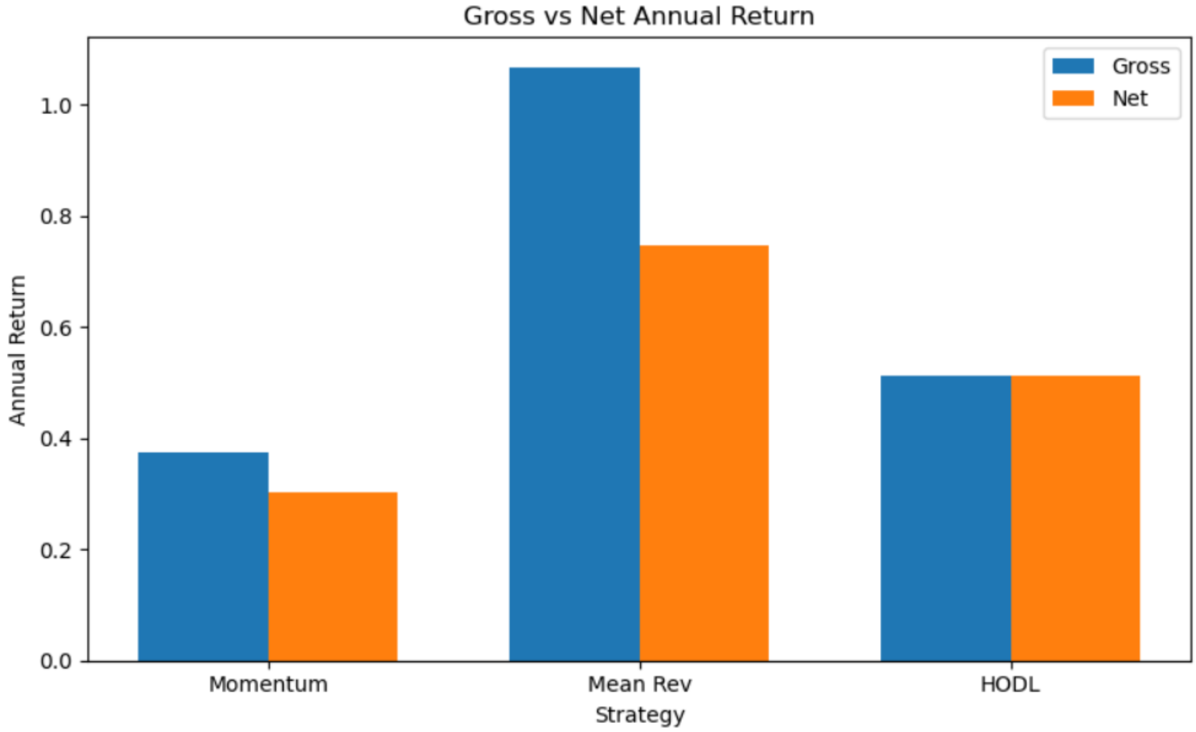
Strategy	Final value	After fees	Loss due to fees
Mean reversion	382 096 €	~221 000 €	-161 000 €
Momentum	49 413 €	~42 300 €	-7 100 €
HODLing	79 792 €	~79 700 €	Insignificant

An important limitation of this evaluation is that the reported results in hourly and daily data do not include transaction fees. Since the mean reversion strategy executed 423 trades during the sample period, even a modest fee of 0.1% per trade would result in a significant decrease in total returns. In contrast, the HODLing strategy, which only charges fees upon initial purchase, is essentially unaffected by trading costs. Therefore, after adjusting for realistic trading fees, the relative advantage of the mean reversion approach is likely to be reduced, although its performance would still remain competitive based on its inherent risk-adjusted characteristics. This highlights the importance of incorporating cost assumptions when evaluating high-frequency trading strategies. Figure 8 shows the percentual annual return without (Gross) and with (Net) the trading fees.

Figure 8. How the annual return is affected by trading fees. Hourly data was used.

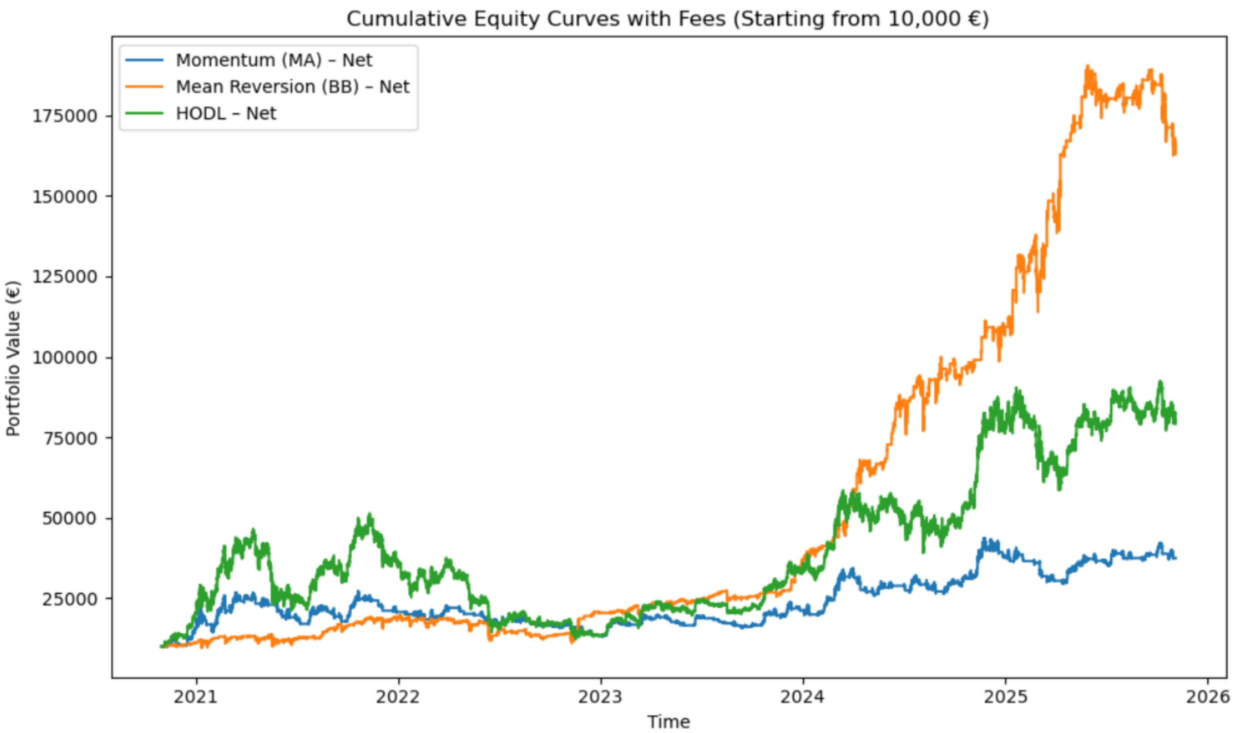
Strategy	Gross	Net
Mean reversion	106.8 %	74.8 %
Momentum	37.5 %	30.2 %
HODLing	51.3 %	51.3 %

By adding a transaction cost of 0.1% per trade significantly affected the results of the active strategies, particularly the mean reversion model, which executed 423 trades during the test period. As expected, the annual return of the mean reversion strategy declined from 106,8 % to 74,8 % and Sharpe Ratio from 1.86 to 1.48, reflecting the cumulative impact of transaction costs. The momentum model, with only 138 trades, experienced a more moderate reduction in profitability, while the buy-and-hold approach remained almost entirely unaffected. Notably, even after accounting for fees, the mean reversion strategy continued to outperform both alternatives on a risk-adjusted basis, demonstrating robustness against realistic execution costs. Picture 11 shows the annual return for each strategy with and without the trading fees.



Picture 11. Gross and Net annual return for each strategy.

In the picture 12 is shown the equity curves with fees included for each strategy. Hourly data was used, and the initial trading sum was 10 000 €.



Picture 12. Equity curves with fees for each strategy.

5.4 Comparison between daily and hourly strategy performance

Interestingly, the ranking of strategy effectiveness reverses when moving from daily to hourly data. When evaluated on hourly observations, the mean reversion strategy clearly dominates, producing the highest annual return (106,8 %), the strongest risk-adjusted performance (Sharpe Ratio 1.86), the lowest volatility (44,35 %), and the smallest maximum drawdown (-35,6 %). In comparison, HODLing yields an annual return of 51,3 % and a Sharpe Ratio of only 0.93, while momentum performs the worst of the active strategies with an annual return of 37,5 %. The profit factor follows the same pattern, with mean reversion achieving 1.15 versus 1.05 for momentum and 1.04 for buy-and-hold. The annualized volatility values were approximately 50 % for the momentum strategy, 44.4 % for the mean reversion strategy, and 75 % for buy-and-hold. The significantly lower volatility of the mean-reversion model continues to support its superior risk-adjusted performance, as reflected in its significantly higher Sharpe ratio.

These hourly results are in stark contrast with the daily-level analysis, where buy-and-hold was the most profitable and mean reversion performed poorly. The difference can be explained by the price dynamics observed at different time resolutions. Hourly price developments are characterized by frequent overextensions and rapid micro-reversals, a structure that favours mean-reversion strategies. On the contrary, daily sampling compresses hourly changes into a single data point, thereby masking many profitable short-lived reversals and instead capturing longer-term directional behaviour — which naturally benefits buy-and-hold and trend-following strategies.

Essentially, Bitcoin's behaviour is mean-reverting at high frequency and trend-following at low frequency. Thus, strategy performance is not a universal property but rather a function of the sampling interval. This observation highlights the importance of adapting the trading model to the appropriate market timeframe. It also shows that conclusions drawn from daily data cannot be directly generalized to intraday trading environments.

5.5 Limitations of the study

There are several methodological and structural limitations to this study that need to be considered when interpreting the results. First, while previous academic studies (including earlier master's theses) have used minute-level data, this study uses hourly price observations. Hourly data captures more intraday dynamics than daily data, but it still captures smaller price movements and the microstructure of the bid-ask spread within each hour. As a result, very short-term price changes that occur less than an hour apart may be missed. Similarly, certain noise patterns and volatility bursts observed in minute-data may not be visible in the hourly time series.

An additional limitation is that the model assumes zero slippage, meaning that each trade is executed at exactly the signal price. In practice, especially during periods of rapid price movements or liquidity imbalances, the execution price is typically less favourable, leading to hidden costs that can reduce the ultimate profitability. Transaction fees were included in the net return analysis at 0.1% per trade, but this is still a generalized assumption — actual fees will vary by exchange, trade volume, order type, and reward level.

It is also important to note that Bitcoin is fundamentally different from equity instruments: the value of the underlying company does not change from minute to minute or hour to hour, even if the share price fluctuates. Bitcoin has no underlying cash flows, assets, returns, or internal valuation anchors.

Its price is determined solely by sentiment, liquidity, and speculative demand. This makes Bitcoin particularly vulnerable to sudden intraday price shocks — dynamics that may amplify or distort the signals detected by mean-reversion strategies.

Furthermore, this study only tests one configuration of each strategy (one pair of moving average lengths, and one Bollinger band parameter set). Different parameter choices can lead to significantly different results. No cross-validation or systematic hyperparameter optimization was performed to prevent data-snooping biases. Data-snooping bias refers to the risk of overfitting a model to historical data by selectively choosing parameters that perform best in a given sample. This study sought to mitigate this effect by using standard parameter choices without iterative optimization. In addition, only long-side positions were considered — shorting Bitcoin can materially alter the performance of trend- and volatility-based strategies.

Another limitation is that the results are derived from historical back testing and do not guarantee future performance. Market behaviour evolves over time, and structural changes may reduce the persistence of the inefficiencies observed.

This analysis focuses exclusively on Bitcoin. While Bitcoin is the most liquid cryptocurrency, other digital assets may have different microstructural characteristics, trend dynamics, or sensitivity to noise and liquidity shocks. Therefore, the findings should not be automatically generalized to the broader cryptocurrency market.

While these limitations limit the scope of the current analysis, they also highlight several future research opportunities including higher-frequency data in the analysis, expanding strategy parameterization, and applying these methods to other cryptocurrencies could help validate whether the observed intraday mean-reversion behaviour represents a persistent and exploitable market inefficiency, or whether it is specific to the sample period and dataset used here.

5.6 Importance of continuous data for trading strategy analysis

The reliability and accuracy of technical trading strategies depend strongly on the structure of the underlying time series. Uninterrupted, evenly distributed data is essential for generating meaningful signals, especially for strategies based on moving averages, and other rolling indicators. When timestamps are missing or irregular, even a small gap can distort the calculations of key indicators, leading to misleading trading signals and incorrect performance results.

For momentum strategies, such as moving average crossovers, any break in the time series can change the slope or position of the moving averages. This can shift buy or sell signals forward or backward in time, artificially improving or weakening the strategy's apparent profitability. Since momentum trading is based on the detection of trend strength and direction, uninterrupted data ensures that price trends are accurately captured.

The effects of missing data can be even more significant in mean-reversion strategies. These strategies are based on moving averages and standard deviations, which require a stable observation window to be valid. Data gaps can cause the moving average to jump unexpectedly. This may result in false signals.

Uninterrupted data is also critical for calculating the risk metrics. Metrics such as volatility, Sharpe ratio, and maximum drawdown assume consistent time intervals. Missing observations can mask intraday price swings, overestimate returns, or underestimate risk. For example, a gap during a significant price movement may completely hide the actual drawdown, leading to an overly optimistic estimate of strategy performance.

To make sure that the dataset is free of gaps — which was confirmed in this study by timestamp checking and time-difference analysis — helps maintain the integrity of the results. It ensures that technical indicators, risk calculations, and simulated trades reflect real market conditions and are not artifacts created by missing data. As a result, the strategy analysis becomes more robust and transparent.

6 Conclusion

The objective of this study was to evaluate and compare the performance of momentum-based and mean-reversion trading strategies on Bitcoin, as well as to assess their profitability, risk characteristics, and sustainability over different analytical timeframes (daily and hourly). These objectives were successfully achieved: both strategies were implemented, tested, and evaluated on hourly data, and their performance was also contrasted against daily results and the passive buy-and-hold (HODL) benchmark index.

The main output of this thesis is an empirical performance comparison, supported by metrics such as annual return, Sharpe ratio, maximum drawdown, volatility and profit factor, as well as an examination of how transaction fees affect the real profitability. Whether or not the strategy depends entirely on the timeframe. The same strategy can succeed at one time span and fail at another. The strikingly different results between daily and hourly analyses demonstrate that Bitcoin price behaviour shows characteristics that are dependent on timescale. At the daily level, trend continuity, making HODLing the most effective strategy. On hourly data analysis, however, price movements are characterized by frequent short-term overreactions making mean-reversion significantly more profitable.

After adding a 0.1% transaction fee per trade, the mean reversion strategy maintained its strong returns, but its absolute profitability decreased significantly due to its high trading frequency. On the contrary, the HODLing strategy was barely affected by transaction costs, while the momentum strategy's returns decreased only slightly.

From a practical point of view, while the mean reversion strategy offers excellent gross returns, its implementation would require low-fee trading platforms to minimize trading costs. On the other hand, HODLing remains more suitable for casual investors who are maybe sensitive to costs and complex implementation models.

The successes in this research include effective data handling and preprocessing, verification of missing timestamps, correct implementation of trading strategies, and the ability to transform raw data testing results into clear analytical conclusions. Issues encountered during the process included data formatting issues in the original CSV file, missing column parsing and incorrect column naming. These issues were resolved through careful data cleaning, standardization of column names, and verification of time indexing.

However, the results of this study should be interpreted with caution due to several limitations, including the lack of slippage modelling, the use of hourly instead of minute-by-minute data, fixed parameter settings, and the focus on Bitcoin alone. Despite these limitations, the mean reversion strategy continues to outperform the market after deducting all trading costs.

All in all, this research advances our understanding of the microstructural behaviour of cryptocurrencies and provides empirical evidence that active trading strategies can outperform passive strategies. Further research using finer time resolution, broader asset coverage and realistic execution models will help validate and extend the insights developed here.

The process of conducting this study yielded many valuable insights. One important lesson was the recognition that Bitcoin does not behave like a traditional equity instrument with the underlying fundamental value remaining stable over short timeframes. Instead, Bitcoin's price is entirely driven by sentiment, liquidity, speculation, and order flow, leading to more volatile microstructure behaviour. Another lesson is the importance of choosing the right time resolution: the same market can appear trend-following on the daily scale and mean-reverting at intraday scale — meaning that the "truth" of the market depends on perspective. This study reveals exploitable inefficiencies in Bitcoin's intraday price dynamics and provides a foundation for more sophisticated crypto trading research in the future.

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