Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	09-01-2023 09:00 CET	**Termin:**	202310
Sluttdato:	03-07-2023 12:00 CEST	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202310||11184||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

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Informasjon fra deltaker

Tittel *:	Is Technical Analysis Viable In the Cryptocurrency Market?
Navn på veileder *:	Dagfinn Rime

Inneholder besvarelsen konfidensielt materiale?:	Nei	**Kan besvarelsen offentliggjøres?:**	Ja

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	12
Andre medlemmer i gruppen:	

GRA 19703 Master Thesis

Is Technical Analysis Viable In the Cryptocurrency Market?

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Master of Science in Business: Major in Finance

Handelshøyskolen BI

Oslo, Norway

July 2023

Acknowledgements

We would like to express our gratitude to our supervisor, Dagfinn Rime, for his excellent feedback and suggestion along the way throughout the entire process of completing this thesis. He always provided constructive and insightful comments, even on short notice.

We would also like to extend our gratefulness for the invaluable partnership we have enjoyed over the past two years, particularly in the collaboration of writing this master's thesis.

Abstract

This thesis examines the viability of technical analysis in the cryptocurrency market using two commonly used oscillators. The testing period extends from the inception of Bitcoin, XRP, and Ethereum until December 31, 2022. Six Relative Strength Index rules and three Moving Average Convergence Divergence rules are tested on four-hourly and daily returns. The methodology is heavily based on the influential paper by Brock et al. (1992). Our findings indicate that the examined trading strategies can generate occasional profits but do not outperform the buy-and-hold strategy when considering transaction costs.

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1 Introduction

For as long as financial markets have existed, there have been attempts to predict future price movements to generate excess returns. Practitioners have developed numerous techniques within fundamental and technical analysis to forecast time series of future price movements to decide when to buy or sell a financial asset. In contrast, academics focus on the behaviour and characteristics of the time series. They focus on whether any exploitable reliance exists in consecutive price changes that could be utilized through various trading techniques.

Technical analysis is a collective term widely used in different financial markets with the purpose of outperforming the market by studying past price data. The term stems back to Charles Dow in the early 1900s when the famous Dow theory originated. It involves examining the behaviour of price to determine how investors can profit from it.

Given the supportive findings of various studies (e.g., Brock et al. (1992), Bessembinder and Chan (1995), Dooley and Shafer (1976), Levich and Thomas (1993)) regarding the profitability of technical trading in financial markets, our study aims to explore the applicability of these findings in the specific context of the cryptocurrency market. We test some of the most common technical trading rules on some of the largest and longest existing cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH) and XRP. The trading rules' performance is tested by evaluating profitability using a student t-test, such as Brock et al. (1992). A significant danger often overlooked when testing and developing such trading rules is data snooping. This results from searching for trading rules that work and training them on a dataset. We emphasize that in our study, we have only backtested the predetermined rules to ensure that our results are not subject to problems regarding data snooping.

In recent times, behavioural finance has emerged as a theoretical foundation for much of the technical analysis employed in understanding investor behaviour, drawing insight from psychology and other behavioural theories. Technical analysis has proven to generate returns in periods for a long time. However, the adoption of technical trading rules for investment decisions remains a subject of controversy.

The efficient market hypothesis (EMH) addresses that it is not possible to gain information that can be used to forecast future price movements. However, the hypothesis can be separated into several parts in terms of efficiency, and it seems that in markets where traders can profit from technical analysis, the market might not be fully efficient. Outperforming the market contradicts studies supporting that the EMH holds, meaning that technical trading has no value. More recent research starkly contradicts earlier findings that supported the random walk hypothesis. Instead, the prevailing consensus now suggests that predictable variations in returns are minimal. As Brock et al. (1992) argue, older studies that supported the random walk hypothesis found that predictable variance in equity returns was low, starkly contrasting to more recent studies.

Additionally, Brock et al. (1992) bring forward two opposing explanations for claimed predictable variation in stock returns. First, there is the market inefficiency that causes prices to deviate from their base levels. Second, if markets are efficient, time-varying equilibrium returns can be used to explain the predictable fluctuation. Brock et al. (1992) claim that there exist no data that clearly separates these two conflicting hypotheses.

In this paper, the profitability of the Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI), two widely used trading indicators in the financial markets, are evaluated on daily and intraday level. We extend the investigation to test if such rules can generate excess returns beyond the buy-and-hold returns. Our study reveals that of the three cryptocurrencies, ETH is the only one that consistently generates significant profits and that it happens on an intraday level.

The remainder of the paper is organized as follows: In section 1, we provide our motivation for the choice of research area and introduce the cryptocurrency market. Section 2 presents some widely known theories about market efficiency and ties them up to the cryptocurrency market. Further, section 3 presents an overview of the academic literature on technical analysis and the trading rules utilized. Section 4 describes the data and our technical trading rules. Next, section 5 presents the empirical results from the different technical trading rules and their performance measures before discussing the thesis and its limitations. Finally, section 6 concludes with a brief outline of the entire thesis.

1.1 Motivation

The relative novelty and emerging nature of cryptocurrencies, which presents an intriguing area for investigation, served as our motivation for selecting this research topic. The limited amount of study that has been done on this topic until now underscores the necessity for thorough investigation even more. Additionally, the cryptocurrency market holds significant potential due to its dynamic characteristics, such as extreme volatility and innovative development. This warrants academic attention to explore the possibility of implementing technical analysis approaches.

The majority of current literature points to cryptocurrency's inefficiency. Very few studies propose practical strategies for capitalizing on these inefficiencies. As a result, the objective of our study is to empirically test a set of trading strategies to determine how well they work as an approach to exploit the identified inefficiencies. This study contributes to the academic understanding of this developing field by addressing the present research gap and offering insights into the prospective application of technical analysis in the cryptocurrency market.

1.2 Introduction to the cryptocurrency market

Cryptocurrencies are digital currencies that are decentralized and encrypted. Unlike traditional fiat currencies, such as the US dollar or Euro, cryptocurrencies operate independently without the need for a central bank. One notable difference is that cryptocurrencies have a predetermined supply limit that is set before the coin is released. Fiat currencies can be traded and printed based on market demand and are regulated by central banks. Central banks have the authority to control interest rates to manage inflation, whereas cryptocurrencies are not subject to such centralized regulation.

The first ever cryptocurrency was named Bitcoin. It was outlined in a *whitepaper*[1] in 2008 by the pseudonym Satoshi Nakamoto. The whitepaper was titled "Bitcoin - A Peer-to-Peer Electronic Cash System" and expressed as an electronic payment system based on cryptographic proof instead of trust (Forbes Advisor, 2022). In the whitepaper, he explains how Bitcoin can be used as an online payment to transfer value between parties (peer-to-peer) in a decentralized way, meaning without including a more centralized institution. This happens because every transaction happens in a verified and trackable way on a blockchain (Forbes Advisor, 2022).

A blockchain is a digital, decentralized distributed ledger that traces all transactions made on a network. In the case of Bitcoin, the blockchain validates and tracks transactions when one peer sends Bitcoin to another. This procedure assures the blockchain network's transaction history is transparent, secure and immutable.

This process involves a network of computers working together in order to verify the transaction. These computers are called nodes. After the transaction is verified, it is connected to a block. This block, including information about the transaction, is then connected to an existing block creating an immutable blockchain that records all transactions on the blockchain.

Creating new blocks to the existing blockchain is done by solving advanced mathematical problems using nodes, and the process is called mining. This process requires a lot of power and electricity. In order to compensate peers by using their electricity and computer power resources, they are rewarded with Bitcoins. This process is called proof-of-work (PoW).

The other method is a consensus mechanism used by other networks, such as Ethereum's Proof-of-Stake (PoS) mechanism. PoS relies on peers who can validate a transaction and create new blocks by *staking*[2]. The most significant difference from PoW is that it does not rely on energy-intensive mining. In 2022, Ethereum transitioned from a PoS network to a PoS consensus mechanism, resulting in a remarkable reduction of over 99% in energy consumption (Butts, 2023).

[1] A whitepaper is a document that covers the technical features of a project or blockchain technology. It describes the project's objectives, features, underlying technology, and potential use cases. It also serves as an important tool for investors and developers to evaluate and assess a project's viability.

[2] Staking is the process of holding and locking up cryptocurrencies as collateral to support the network. This is done as a security to validate incoming transactions. The more cryptocurrency a trader holds, the bigger the chance the trader gets to be a validator and your amount to be "staked". As a reward, the trader earns the transaction fee when the transaction is connected to the block and newly mined cryptocurrency.

Within the PoS consensus mechanism, there is a penalty mechanism called slashing. By staking cryptocurrency as collateral, it prevents validators from participating in harmful activities. Validators face penalties when they violate the rules, such as double-signing a conflicting block or attempting to manipulate the network. These penalties usually consist of a decrease in their stake or temporarily suspending their capability to work as a validator. This encourages validators to be truthful.

Cryptocurrencies have attracted increasing interest from investors and institutions, but due to the absence of transparent balance sheets, fundamental analysis is challenging. Technical analysis emerges as a viable approach, similar to trading foreign currencies. With the cryptocurrency market capitalization at around 1.1 Trillion USD dominated by Bitcoin (CoinMarketCap, 2023), the reliability and availability of historical price data become crucial factors. Being decentralized and running on blockchain technology, cryptocurrencies differ from traditional fiat currencies, and crypto exchange platforms serve as intermediaries for converting them into fiat cash.

The high volatility in the cryptocurrency market can significantly impact the effectiveness of the technical trading rule. When prices fluctuate extensively, technical trading rules may generate numerous trading signals, leading to increased transaction costs that can reduce a trader's profit. Therefore it is crucial to carefully select reliable and robust trading rules that can navigate the inherent volatility of the market effectively.

Another critical aspect is the efficiency in the crypto market. If the market is strong efficient, it can be hard to find any significant profit using technical analysis. As in other financial markets, unpredictable macroeconomic news can disrupt technical analysis as it is based on historical data and may not account for major market shifts caused by unforeseen economic events, such as government policies, geopolitical tension or news that affects the overall economic conditions.

Cryptocurrencies, like foreign currencies, are commonly quoted with respect to another currency, typically the US dollar due to their global acceptance and being the world reserve currency. The use of technical analysis for cryptocurrencies can be impacted by the trading pair used, such as BTC/USDC or BTC/USDT, as well as BTC/USD. The first two, BTC/USDC and BTC/USDT are two of the most common stablecoins of Bitcoin quoted against the US dollar. While stablecoins strive to maintain a 1:1 ratio with the US dollar, some variations may occur due to market demand and liquidity.

The selection of a trading pair can exert a considerable impact on the implementation of trading strategies. To ensure the acquisition of highly precise data for analysis, we employed an index pertaining to the particular cryptocurrency pairs under investigation. In this context, the prices were derived from the average valuation observed across prominent historical exchanges, including Coinbase, Bitstamp, Kraken, and others (TradingView, nd). However, it is worth noting that this trading pair is not practically viable during live trading scenarios. The sole objective of employing this approach was to mitigate instances of price anomalies that may arise on individual exchanges.

While the financial markets operate worldwide, their trading hours differ according to geographical areas and time zones. From a Norwegian perspective and with a 24-hour format, the New York Stock Exchange (NYSE) has trading hours between 09:30 and 16:00 (07:30 and 14:00 UTC). The London Stock Exchange (LSE) trades between 08:00 and 16:30 (06:00 and 14:30 UTC). The Norwegian Stock Exchange has trading hours between 09:00 and 16:20 (07:00 and 14:20 UTC). While the stock exchanges are usually open Monday to Friday, the foreign exchange markets are open 24/7 but rarely trade on weekends. As cryptocurrencies are traded around the clock, one might wonder where the closing prices are extracted from. To avoid confusing readers, we specify that the cryptocurrency market does not open and close like other markets. However, to track the performance, the opening time is commonly set to 02:00, and the closing time is 01:59 (00:00 and 23:59 UTC).

2 Market Efficiency

To what extent the market is efficient was early assessed and analyzed. One notable contribution was made by Eugene Fama in 1970, as evidenced by Fama (1970). This led to the formulation of the efficient market hypothesis that got further explored with the random walk theory. Later in the early 2000s, Lo (2004) introduced the adaptive market hypothesis with a different perspective than the previous theories. These theories have also been tested regarding the viability of technical analysis. Additionally, the cryptocurrency market has been tested with different perspectives and beliefs towards the efficiency.

2.1 The Efficient Market Hypothesis

The efficient market hypothesis (EMH) is a prominent theory in financial economics that asserts that market prices fully reflect all information available. According to Fama (1970) and subsequent empirical literature on the EMH, the market is efficient, rendering it impossible to achieve higher returns through trading strategies based on market analysis.

Fama (1970) categorized the EMH into three forms, each differing in its interpretation of information availability: weak, semi-strong and strong. The weak form suggests that prices reflect historical market information, while the semi-strong form implies that prices reflect all publicly available information. The strong form posits that prices reflect all relevant information (Fama, 1991). According to the weak form, technical analysis is futile as prices already incorporate historical data, making trading based on it unreliable. The EMH suggests that historical trends are likely random rather than driven by fundamentals, undermining the use of technical analysis for generating excess return (Lo et al., 2000).

However, technical analysis can be valuable in identifying unaccounted deviations, such as behavioural aspects, and profiting from them. The academic community remains divided on the evidence supporting technical analysis for excess return. To generate significant results, technical analysis would need to violate the weak form of the EMH by predicting future prices or patterns based on historical trends.

Empirical evidence suggests that technical analysis can generate excess returns in certain markets, but transaction costs make it challenging to achieve such returns (Park and Irwin, 2007). Technical analysis appears more effective in emerging markets, where accurately analyzing information is more complicated. In an efficient market, the expected return will be aligned with the investor's risk profile.

2.2 Random Walk

A notable component of the EMH is the widely recognized theory known as the Random Walk, first introduced by Burton G. Malkiel in 1973. According to this theory, a random walk refers to a situation where future steps or directions cannot be predicted based on historical data (Malkiel, 1973). The idea contends that because market prices already account for all publicly available information, it is impossible to generate excess returns. Thus, there are no exploitable price movements that can lead to profits.

Despite its recognition, the Random Walk theory has faced much criticism as some academics doubt the market's ability to adhere to all available information fully. The book "A Non-Random Walk Down Wall Street", by Andrew Lo and A. Craig Mackinlay, added to this discussion by examining the stock market's inclusion of predictable aspects. It concluded that the market is not entirely random (Lo and MacKinlay, 2002).

2.3 Adaptive Market Hypothesis

Lo (2004) proposed with a theoretical basis questioning the standard assumptions of the EMH. The Adaptive Market Hypothesis (AMH) acknowledges the dynamic nature of financial markets and emphasizes the significance of adaptive behaviour and evolutionary process in affecting market outcomes (Lo, 2004). Unlike the EMH, the AMH considers the diversity of market participants and combines concepts from biology, psychology and physics. It emphasizes the impact of cognitive bias, emotions and social interactions regarding the investor's behaviour. Further, the AMH recognizes dynamic market situations and the need for adaptable strategies as financial markets are argued to be adaptive.

Evidence supports the AMH over the EMH across several financial markets, including the stock and foreign exchange market. Urquhart and Hudson (2013) finds the AMH to be a better description of the behaviour of the stock market returns over the EMH. In the foreign exchange market, Neely et al. (2009) analyses the intertemporal stability of excess returns to technical trading rules. They argue that their results are more consistent with the AMH than the EMH.

2.4 Efficiency in the Cryptocurrency market

The empirical research on cryptocurrencies' weak-form efficiency has yielded mixed results. Various studies, including Nadarajah and Chu (2017), Brauneis and Mestel (2018) and Wei (2018), have failed to provide convincing evidence to support the EMH. These studies contend that a deviation from a random walk pattern in historical data analysis shows some predictability in cryptocurrency prices. It is important to remember that while these studies have revealed possible inefficiencies, they have not yet presented specific methods or strategies for reliably taking advantage of these inefficiencies to produce excess returns.

Several studies have also contributed with a particular emphasis on Bitcoin regarding market efficiency. Urquhart (2016), Jiang et al. (2018), Nan and Kaizoji (2019), Hu et al. (2019) and others have collectively shown that the market is inefficient. The fact that these inefficiencies are only sometimes present throughout historical periods is essential to mention.

Caporale et al. (2018) examines the persistence of four major cryptocurrencies from 2013 to 2017, notably Bitcoin, Litecoin, Ripple and Dash. Using two long-memory approaches, they find a positive correlation between past and future values. They conclude that their findings serve as proof of market inefficiency and that trend trading strategies can be profitable.

The paper "Efficiency in the markets of cryptocurrencies" by Tran and Leirvik (2020) demonstrates how the degree of market efficiency varies over time and across different currencies. In particular, they find the Bitcoin market largely inefficient until early 2017 and more efficient after 2017. This is in line with what Urquhart (2016) concludes. He argues that Bitcoin's inefficiency is rather severe. He points to one possible explanation: it was in its early stages when sharing traits with an emerging market. He concludes that the Bitcoin market is growing more efficient over time and that the early-stage inefficiency is not shocking.

3 Literature Review

This section will present a comprehensive overview of the literature on technical analysis and introduce the technical trading rules used in our thesis. Investors and traders can utilize two distinctive techniques to analyze financial market data and make investment decisions based on technical and fundamental analysis. While fundamental analysis evaluates the intrinsic value of an asset, technical analysis examines price movements and historical patterns to predict future movements.

3.1 Technical analysis in financial practice

Technical analysis is frequently employed alongside fundamental analysis by brokers, including investment banks and private equity firms, in their investment decision-making processes. Simply put, a technicalist focuses solely on an asset's price history, distinguishing them from a fundamentalist. The fundamentalist also investigates a firm's balance sheet to estimate future cash flow streams and dividends to calculate the assets intrinsic value.

By employing technical analysis, investors can actively identify market trends and determine optimal timing for entering or exiting positions. This comprehensive understanding enhances the ability to make more informed investment decisions as market dynamics can be better evaluated. Identifying potential opportunities can also be done based on a broad set of analytical tools.

3.2 Critique on technical analysis

Technical analysis, a well-known technique for a long time, traces its roots back to Charles Dow in the late 1800s with the development of the Dow Theory. This theory served as the foundation for various technical trading techniques aimed at identifying market inefficiencies that could result in abnormal returns. These techniques can range from relatively simple approaches to highly sophisticated methods. Despite its historical significance, technical analysis has faced ongoing criticism.

The study conducted by Osler and Chang (1995) surveyed seven prominent technical analysis manuals and found that these books lacked elements that would appeal to academically trained economists. The primary reason for this was the inability of these manuals to establish the validity of technical trading rules, primarily because the profitability of such rules was often assessed without considering opportunity costs or associated risks (Osler and Chang, 1995, p. 7).

As eloquently explained by Brock et al. (1992), academics hold a particular perspective towards the use of technical analysis. This sentiment is summarized effectively in section 6: "Technical Analysis and the Random-Walk Theory" of Burton G. Malkiel's book "A Random Walk Down Wall Street":

"Obviously, i am biased against the chartist. This is not only a personal predilection, but a professional one as well. Technical analysis is anathema to the academic world. We love to pick on it. Our bullying tactics are prompted by two considerations: (1) the method is patently false; and (2) it's easy to pick on. And while it may seem a bit unfair to pick on such a sorry target, just remember, it is your money we are trying to save" (Malkiel, 2019).

Despite the academic's scepticism, it is worth noting that technical analysis continues to be utilized on daily, either as a primary or complementary tool alongside fundamental analysis, by brokers and other market participants when evaluating the performance of assets.

3.3 The use of Technical Analysis in different markets

This section focuses on the utilization of technical analysis within diverse markets, highlighting its adaptability across various asset classes. Whether applied in the stock market, foreign exchange market, or other financial domains, traders employ a range of technical indicators as valuable aids for market participants. However, the employment of technical analysis remains a subject of conflicting findings among academic researchers. Numerous studies have sought to explore different aspects of the EMH.

3.3.1 Technical analysis in the equity market

Several papers in the Journal of Finance have investigated the topic of technical analysis. One notable study by Brock et al. (1992) focuses on the Dow Jones Index from 1897 to 1986. The authors examined moving averages (MA) and trading range breakout (TRB) as technical indicators. Their research, using statistical analysis techniques like t-tests and bootstrap methods, provided robust evidence supporting that these trading rules were more profitable during the early stage of the analyzed period, suggesting a less efficient market at that time.

Furthermore, the authors demonstrated that the predictability of technical trading rules contradicted the assumptions of a random walk. This finding challenged previous studies that had prematurely concluded the ineffectiveness of technical trading rules. Their pioneering application of bootstrap techniques enhanced the credibility of their research. Brock et al. (1992) also emphasize that transaction costs may offset the profitability of these trading rules.

Bessembinder and Chan (1995) conducted a study to explore the predictability of price movements in the Asian stock market, focusing on the utilization of trading rules proposed by Brock et al. (1992). Their research aimed to investigate the effectiveness of these technical trading rules, particularly in emerging markets such as Malaysia, Thailand and Taiwan. Across the six countries analyzed, which also include Japan, Hong Kong and South Korea, the assessed trading rules yielded a mean percentage change on buy days that surpassed the mean on sell days by 0.095% per day, corresponding to an annualized return of 26.8% (Bessembinder and Chan, 1995).

Bessembinder and Chan (1998) expanded upon the research of Brock et al. (1992), aiming to assess the economic importance of their findings and whether they indicated market inefficiencies. The authors acknowledged the potential for measurement errors resulting from nonsynchronous trading and emphasized that forecasting skills cannot be solely attributed to such errors. Nonsynchronous data can arise from trade impact or timing effects presenting challenges such as small inferred correlations and autocorrelation among risk factors.

The study's findings supported the effectiveness of technical analysis but did not necessarily contradict the EMH. The authors proposed that nonsynchronous trading and market inefficiency could coexist, and the exact source of the technical forecasting power identified by Brock et al. (1992) remained unclear.

Lo and MacKinlay (2002) discussed the findings of other studies that showed statistically significant profits produced by technical indicators. They argued that comprehending the economic source of these profits necessitated analysis within the framework of equilibrium pricing models. By employing such models, they discovered that specific technical patterns could offer additional information, particularly for stocks listed on Nasdaq. Notably, their findings did not suggest consistent excess returns from technical analysis, and traditional patterns were only occasionally optimal.

Park and Irwin (2007) conducted a comprehensive investigation into the profitability of technical analysis, aggregating data from high-quality studies. Their findings revealed profits ranging from 4-17% in the stock market (1897-1998), 5-10% in the foreign exchange market (1976-1991), and 4-6% in the futures market (1976-1986). These results were derived from examining seven trading strategies, highlighting the variety of approaches for achieving profitability. However, approximately 21% of the time, negative returns were observed, indicating challenges and potential limitations associated with the studied strategies.

Marshall et al. (2008) empirically investigated the profitability of 7846 popular technical trading rules across five rule families in the US equity market. These rule families included filtering, moving averages, support and resistance, channel breakout, and on-balance volume rules. The study specifically focused on intraday trading, utilizing 5-minute data from 2002-2003. Their analysis focused on assessing the profitability of the tested trading rules while accounting for data snooping. Prior to adjusting for data snooping bias, only a few rules showed profitability. However, after considering data snooping bias and utilizing White's reality check as an evaluation method, none of the trading rules demonstrated evidence of being beneficial.

Chong and Ng (2008) conducted a comprehensive study on the efficiency of the two trading rules, RSI and MACD. Their research spanned the period 1935 to 1994 and focused primarily on the London Stock Exchange. The results indicated that both RSI and MACD trading rules had the potential to outperform a pure buy-and-hold strategy. Additionally, the study revealed that the MACD trading rule displayed predictable characteristics, suggesting its utility as a trading tool.

In a subsequent study, Chong et al. (2014) revisited their earlier research and expanded their analysis to include five additional member countries of the Organisation for Economic Cooperation and Development (OECD). Their findings demonstrated promising performance of various RSI trading rules in different markets. Specifically, the RSI(21,50) rule exhibited favourable outcomes in the Mila Commit General Index, while the RSI(14, 30/70) rule proved profitable in the Dow Jones Industrial Index.

However, for the Nikkei 225 Stock Average, neither of the RSI rules surpassed the effectiveness of a simple buy-and-hold strategy. Furthermore, Chong et al. (2014) compared the performance of different RSI rules against each other and determined that the centerline crossover rule exhibited the highest performance across the examined markets.

3.3.2 Technical analysis in the foreign exchange market

The foreign exchange market possesses unique characteristics that differentiate it from equity markets, rendering it a significant and distinctive component of the global financial market. Notably, features like high liquidity, low bid-ask spreads, and continuous trading distinguish the foreign exchange market. Its immense size surpasses the combined turnover of even the largest stock exchanges.

A survey conducted by the Bank for International Settlements (BIS) provides a remarkable scale of global foreign exchange trading volume. The survey indicated a daily trading volume of $7.5 trillion in the global foreign exchange market (Jones and John, 2022). This substantial turnover underscores the significance and liquidity of the foreign exchange market.

Dooley and Shafer (1976) and Sweeney (1986) provide empirical evidence supporting the effectiveness of trading rules in the foreign exchange market. Sweeney (1986) suggests that the observed profits from certain technical trading rules can be rationalized by speculative risk, countering concerns of excessive returns or market inefficiency. However, these findings challenge the applicability of the Capital Asset Pricing Model (CAPM) to exchange markets and offer two possible explanations: market inefficiency or time-varying risk premium (Sweeney, 1986).

Levich and Thomas (1993) employed a bootstrap methodology to investigate the profitability of technical trading rules on currency futures contracts during the period from 1976 to 1990. The findings suggested that simple technical trading rules exhibited the ability to generate substantial returns. The sample was divided into three sub-samples, with statistically significant evidence of profitability observed for the trading rules. However, in the last sub-sample, a decline was observed in the effectiveness of some of the technical trading rules.

Neely and Weller (2003) conducted an investigation that accounts for transaction costs. Their study utilized a genetic program and an optimized linear forecasting model to assess the out-of-sample performance of intraday technical trading rules on various currency exchange rates. Contrary to expectations, their findings revealed no evidence of abnormal returns after considering transaction costs. This suggests that the application of trading rules, while explored extensively, may not yield significant profitability in currency markets.

Similarly, Olson (2004) conducted a study on the profitability of moving average rules in currency markets over an extended period from 1971 to 2000. Using out-of-sample analysis, the researcher aimed to examine any changes in profitability over time. The findings revealed that moving average rules generated statistically significant risk-adjusted profits during the 1970s but became statistically insignificant during the 1980s. By the 1990s, these rules yielded zero profits. These results suggest that market inefficiencies observed in earlier decades were corrected in the 1990s, leading to a decline in the profitability of these trading rules. Consequently, the profitability of trading rules in currency markets appears to have diminished over time.

Menkhoff and Taylor (2007) acknowledged the significance of technical analysis for currency traders. He recognized that technical analysis may possess some predictive power in the short term. However, he emphasized that the ability to generate excess return over the long term consistently is limited.

The evidence presented across various research papers challenges the notions of semi-strong and strong form of the EMH in financial markets. While the weak form of the EMH seems to hold more validity, debates persist among academics. Some investigations suggest that the observed significant returns may stem from factors attributed to luck rather than persistent market inefficiencies.

3.4 Overview of technical trading rules

Testing the viability of technical analysis in the cryptocurrency market will be done using some of the most well-known technical trading strategies: Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD). The time required to generate signals using trend-following indicators results in a low frequency of trades.

3.4.1 Relative Strength Index

Relative Strength Index (RSI) is a momentum indicator or oscillator for technical trading introduced by J. Welles Wilder, JR in 1978. The oscillator is one of the most common indicators often used in the stock or foreign exchange market to measure a price movement's direction. This is also called a trend-following indicator. RSI measures the speed and magnitude of asset price changes to evaluate whether the asset is overvalued or undervalued at the current price (Fernando, 2023).

The RSI scales from 0 to 100, indicating whether an asset is overbought or oversold. The RSI oscillator can be calculated as done by Menkhoff and Taylor (2007):

$$RSI_t = 100\frac{U_t}{U_t - D_t} \tag{1}$$

where

$$U_t = \sum_{i=1}^{m} \tau(s_{t-i} - s_{t-i-1} > 0)(s_{t-i} - s_{t-i-1}) \qquad (2)$$

$$D_t = \sum_{i=1}^{m} \tau(s_{t-i} - s_{t-i-1} < 0)|s_{t-i} - s_{t-i-1}|, \qquad (3)$$

where τ takes the value one when the statement in parenthesis is true and otherwise zero. The U_t denotes the cumulated movement upwards over a certain period. This means the exchange rate has a higher closing price than the previous period. D_t denotes the cumulated movement downwards over a certain period. This means the exchange rate has a lower closing price than the previous period. The periods are usually the same for up-and-down movement and are typically set to fourteen days (Menkhoff and Taylor, 2007).

If the RSI value is greater than 70, it indicates that the asset price is overbought and a possible sell signal. If the value is lower than 30, it indicates that the asset price is oversold and a possible buy signal. If the price is between 30 and 70, it typically indicates that it is in a range. To help identify a possible breakout, other technical tools can be used.

3.4.2 Moving Average Convergence Divergence

Moving Average Convergence Divergence (MACD) is a well-known indicator in technical analysis first introduced by Gerald Appel in the late 1970 (Appel and Dobson, 2007). MACD is used to pinpoint elements of an asset's general trend and includes the MACD line and a signal line. The MACD line, which shows the trend direction and duration, is set as an indicator that uses the moving average of two different periods.

The signal line is served as a selected-length EMA. This signal line is seen as a bullish signal when the MACD line crosses above the signal line, signalling an upward change in momentum. It is considered a bearish signal when the MACD line crosses below the signal line, signalling a downward shift in momentum. The exponential moving average is calculated as done by Chong et al. (2014):

$$\text{EMA}_{,}(N) = [\frac{2}{N} \cdot (P_t - \text{EMA}_{t-1}(N))] + \text{EMA}_{t-1}(N) \tag{4}$$

Where EMA,(N) is the exponential average at time t, N is the window length of the EMA, and P_t is the value of the index at time t. MACD is a trend-following momentum oscillator or indicator that shows the relationship between two EMA's (Dolan, 2023). The MACD is calculated by subtracting a long-term EMA from a short-term EMA:

$$\text{MACD} = \text{Short-term EMA} - \text{Long-term EMA} \tag{5}$$

4 Data and methodology

In this section, we introduce the utilized methods in determining profitability and offer a comprehensive explanation of the trading strategies employed to evaluate its performance.

Given the broad variations in technical trading rules, we adopt multiple approaches for our thesis. In particular, we implement trading strategies in Python for the RSI and MACD indicators. Backtesting is conducted to assess the profitability of these strategies. To address any econometric problems, the resulting returns are carefully analyzed and statistically tested. We compute the logarithmic returns, which are further backtested and significance tested using t-statistic such as done by Brock et al. (1992). This approach provides valuable insight into the effectiveness of these oscillators in cryptocurrency trading.

4.1 Technical Trading Strategy Rules

The technical trading strategies employed in this study are among the widely utilized approaches in technical analysis across various markets. Previous research, such as Brock et al. (1992) and Chong et al. (2014), has demonstrated the potential for significant excess returns through these strategies in the stock market.

4.1.1 Relative Strength Index (RSI) Rules

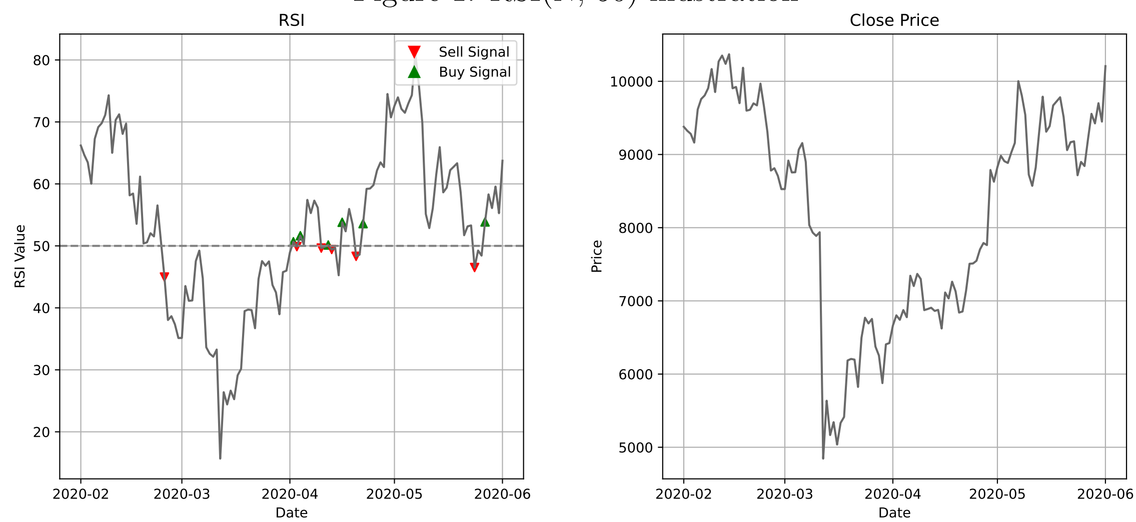
We employ two distinct RSI rules to generate trading signals: RSI(N, 50) and RSI(N, 30/70).

Rule 1: RSI(N, 50) :

Buy signals are triggered when the RSI crosses the centerline(RSI=50) from below. Likewise sell signals are obtained when RSI crosses the centerline from above. We will operate with close prices, which are denoted C.

Buy signal: Buy @ C_t if $\{RSI_t > 50 \ \& \ RSI_{t-1} \leq 50\}$
Sell signal: Sell @ C_t if $\{RSI_t < 50 \ \& \ RSI_{t-1} \geq 50\}$

Figure 1: RSI(N, 50) illustration



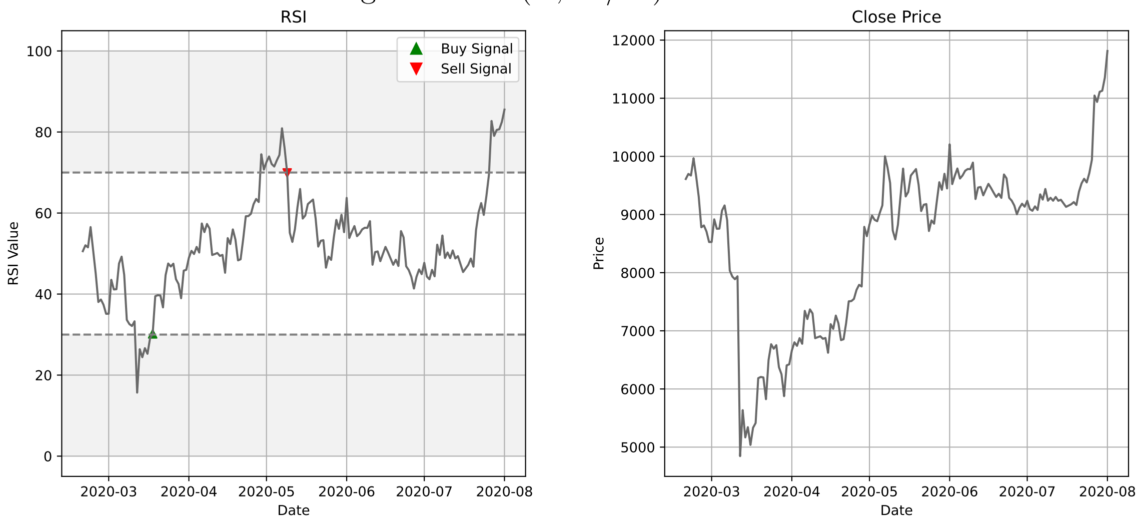
Rule 2: RSI(N, 30/70) :

This rule is based on the notion that RSI can enter overbought and oversold zones. These zones are traditionally regarded to be RSI < 30 for the oversold zone and RSI > 70 for the overbought zone. The buy signal occurs when the RSI exits the oversold zone (RSI > 30), and the sell signal occurs when the RSI exits the overbought area (RSI < 70). This is in accordance with Welles

(1978).

Buy signal: Buy @ C_t if $\{RSI_t > 30$ & $RSI_{t+1} \leq 30\}$
Sell signal: Sell @ C_t if $\{RSI_t < 70$ & $RSI_{t+1} \geq 70\}$

Figure 2: RSI(N, 30/70) illustration



4.1.2 Moving Average Convergence Divergence (MACD) Rules

For the MACD trading strategy, three different rules have been used to produce results. All MACD rules must contain a short EMA (EMA_{short}) and a long EMA (EMA_{long}) to calculate the MACD. As per Chong et al. (2014), we will utilize two different signals, the 9-day EMA (Sign(9)) and 0.

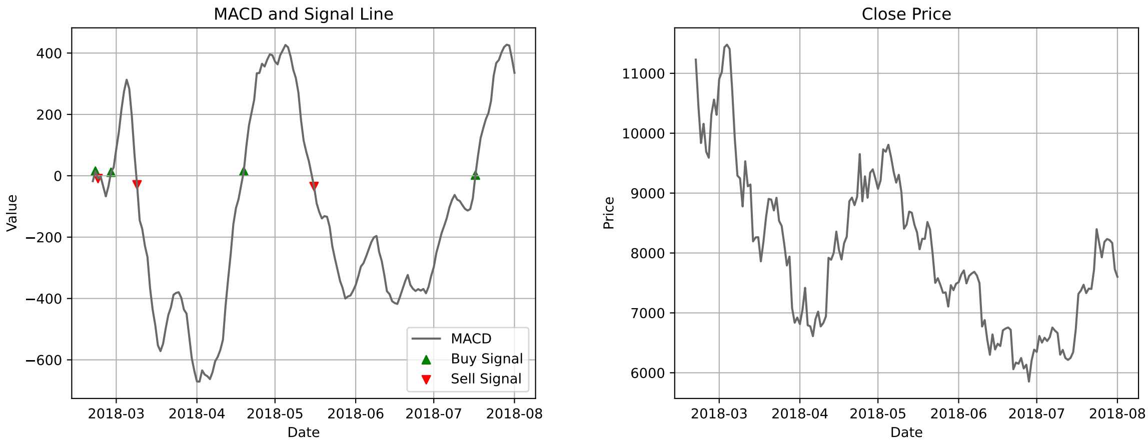
Sign(n) = EMA_n

Rule 3: MACD(EMA_{short}, EMA_{long}, 0)

The signal 0 will be used in the MACD(12, 26, 0) strategy, which means that buy signals will occur when the MACD goes from negative to positive and sell signal from positive to negative.

Buy signal: Buy @ C_t if $\{MACD_t > 0 \quad \& \quad MACD_{t-1} < 0\}$
Sell signal: Sell @ C_t if $\{MACD_t < 0 \quad \& \quad MACD_{t-1} > 0\}$

Figure 3: MACD(EMA_{short}, EMA_{long}, 0 illustration

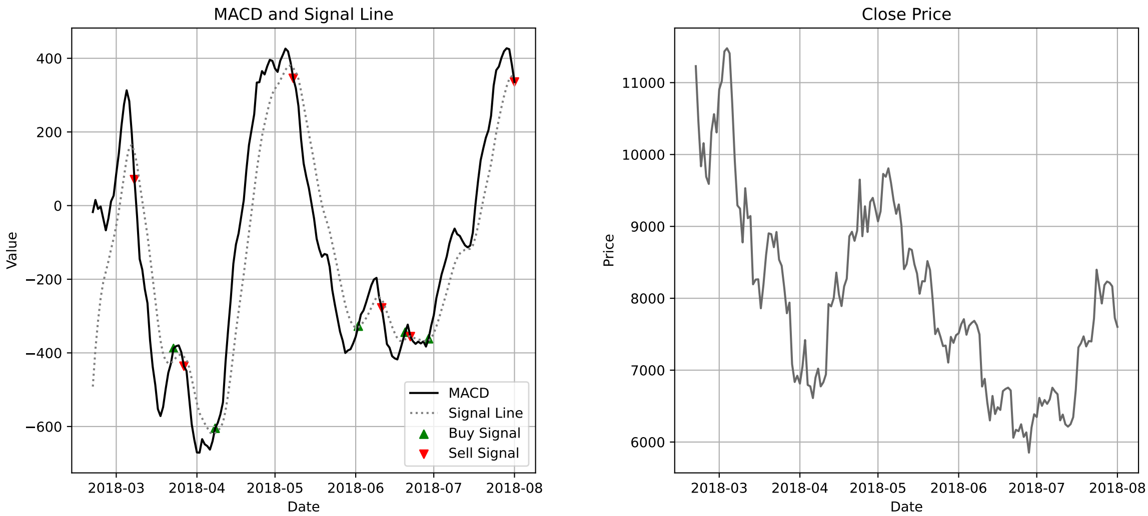


Rule 4: MACD(EMA_{short}, EMA_{long}, Sign(9))

The 9-day EMA will be used as the signal in the MACD(12, 26, 9) and MACD(8, 17, 9) strategy. Buys signals will therefore occur when the MACD crosses the sign (9) from below and sells will occur when it crosses the signal (9) from above.

Buy signal: Buy @ C_t if $\{MACD_t > Sign(9)_t \quad \& \quad MACD_{t-1} < Sign(9)\}$
Sell signal: Sell @ C_t if $\{MACD_t < Sign(9)_t \quad \& \quad MACD_{t-1} > Sign(9)\}$

Figure 4: MACD(EMA_{short}, EMA_{long}, Sign(9)) illustration



4.2 Development Of The Trading Algorithm

To facilitate this research, it was imperative to develop an algorithm capable of calculating the profitability achieved by each trading strategy for various cryptocurrencies. The algorithm was implemented using the Python programming language.

The initial stage involved acquiring and importing the requisite data. TradingView served as the primary data source for acquiring comprehensive market information across various time frames, including daily and intraday perspectives. TradingView, a widely adopted charting platform with a user base exceeding 50 million (Tradingview, 2023), provided access to accurate daily and four-hourly data spanning a substantial historical period. Using their "Export Chart Data" functionality, we obtained ".csv" files containing the requisite data for analysis. Consequently, the algorithm encompasses 4,536 data points for daily data and 21,863 for four-hourly data.

The development of the algorithm itself is as complex as the trading rules described in section 4.1. As the signals describe, a trade is opened when the indicators have confirmed a close above/below the pre-determined level. The entry price of this trade becomes the close price on the same day of the confirmed close. This approach ensures that trades are not prematurely triggered by transient signal level crossings, which can occur multiple times within a day. The same principles apply to the four-hourly rules.

The trading rules classify trades as either buy (b) or sell (s) and determine the returns after h periods, with P denoting the price. The computation of the return will depend on whether it is a buy or sell and is calculated as follows:

$$r^{\mathrm{b}}_{\mathrm{t\,+\,h}} = \frac{(P_{t+h} - P_t)}{P_t} \tag{6}$$

$$r^{\mathrm{s}}_{\mathrm{t\,+\,h}} = \frac{(P_t - P_{t+h})}{P_t} \tag{7}$$

Note that when a signal is issued, other signals will be ignored until the trade is closed. Therefore, only one trade can be open at any given moment.

4.3 Transaction Costs

To accurately assess the returns of each trading strategy, the inclusion of transaction costs is imperative. Historical bid-ask spread data, which plays a crucial role in this regard, was obtained from Bitcoinity.org. This platform offers comprehensive historical data on the bid-ask spread for BTC, collected from multiple reputable exchanges. Data extraction was limited to renowned exchanges such as Bitfinex, Bitstamp, Coinbase, and Gemini (Bitcoinity, nd) to ensure reliability and mitigate biased results stemming from fraudulent exchanges.

Our study places significant emphasis on meticulously accounting for transaction costs to achieve more precise returns. Unlike many existing papers in the field of technical analysis that often rely on proxies or standard fees, we acknowledge the significance of considering the dynamic nature of transaction costs.

The cryptocurrency market is notorious for its high volatility, resulting in fluctuating bid-ask spreads. Employing a fixed, averaged fee could lead to erroneous conclusions and distort the actual impact of transaction costs on trading strategy returns. We adopt a more realistic approach to address this concern by incorporating transaction costs based on actual historical bid-ask spreads. This methodology aims to provide a more accurate assessment of our trading strategies, avoiding potential overestimations or underestimations arising from a static spread assumption.

The transaction costs encompass the dynamic bid-ask spread and a constant commission fee in the form of a maker fee. Makers are traders who place limit orders in the order book, while takers are traders who execute orders immediately with existing orders in the order book. The maker fee, set at 0.10%, is levied by the exchange on every transaction and aligns with the fees charged by industry-leading exchanges like Bybit and Binance (Bybit, 2023).

Due to challenges in obtaining historical data for bid-ask spreads of ETH and XRP, we employ the bid-ask spreads of BTC as proxies. Considering the intrinsic correlation observed in the cryptocurrency market, we posit that BTC bid-ask spreads serve as a suitable approximation. However, it is essential to note that using a proxy introduces certain inaccuracies. Nevertheless, this approach presents a practical solution to our data limitations, enabling valuable insights.

Figure 5 below shows the bid-ask spread for Bitcoin from 2013 to 2023. Initially, in 2013, the spread stood at approximately 0.7% and subsequently decreased to below 0.1% by mid-2016. The following year exhibited sporadic spikes, with the spread surpassing 0.5%, notably reaching nearly 0.9% in mid-2016 before declining back to around 0.1%. These findings suggest that there may have been limited liquidity and trading activity during BTC's early stages, resulting in wider spreads. However, in the period after 2016, particularly after 2018, the spread remained relatively consistent, aside from a spike in mid-2018 and another in early 2020.

The stability after 2016 indicates a certain level of market efficiency and liquidity attributed to a more mature market. Given that reliable bid-ask spread data is only available from 2013. Although, historical BTC data extends back to its inception in 2010, we deem it appropriate to set the bid-ask spread in this period to 1% to reflect the prevailing market conditions.

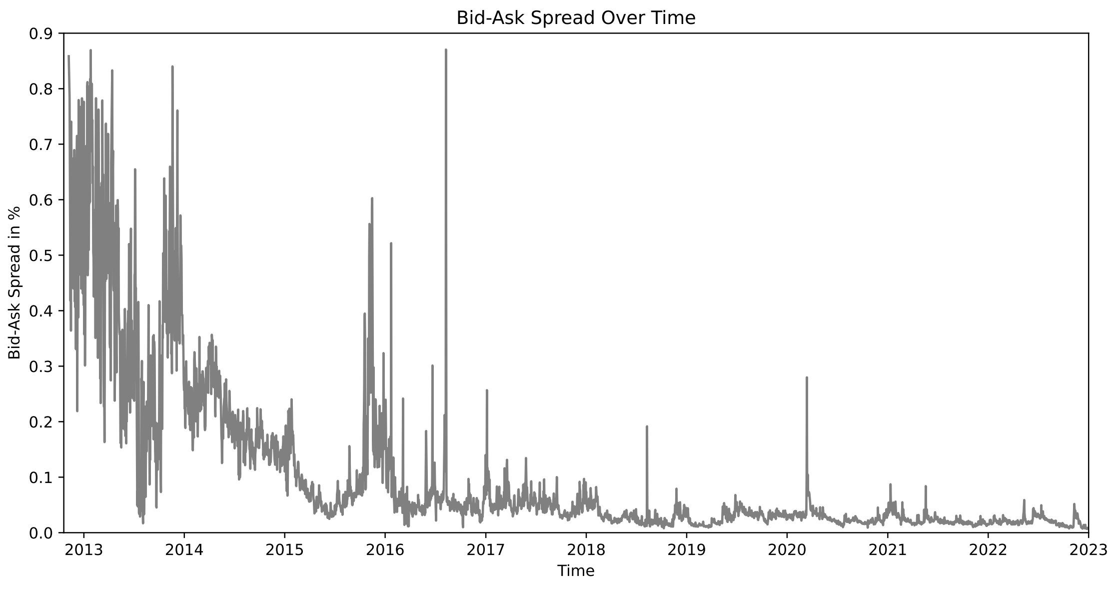


Figure 5: Bid-Ask spread

An investigation into a potential linear relationship between the bid-ask spread, and returns was conducted; however, no evidence was found to support such a trend. Although the spread was notably higher at the beginning of the period, it did not exhibit a linear decrease. Instead, it experienced a rapid decline to approximately 0.1%. The observed higher spread at the inception aligns with empirical evidence suggesting that developing markets are not fully efficient due to lower liquidity, reduced transparency, and higher transaction costs.

4.4 Data Snooping

In technical analysis, data snooping can occur when traders use past data on prices to create trading techniques without considering the likelihood of chance correlation. When a data set is used several times to find a suitable model, the trader might use the most satisfactory model, indicating that the results from the model do not come from the inherent merit in the model used to generate the results. This can cause models to be overfitted, meaning they perform well on historical data but poorly on new data. By avoiding data snooping, it is more probable to avoid incorrect conclusions leading to poor trading decisions.

Data snooping, emphasized by Sullivan et al. (1999), is a critically important problem that frequently arises but is rarely considered when examining technical trading rules. When it occurs, there is always a danger that any positive results are attributable to chance rather than the trading rules' efficiency. Jensen and Benington (1970) acknowledged data snooping as a "selection bias" issue that might influence on the performance of technical trading rules.

Brock et al. (1992) highlight the inherent risk of uncovering spurious patterns when employing the same dataset to discover and test of trading strategies. In the context of this thesis, it is crucial to emphasize that the surveyed strategies were not trained on the data. Instead, widely recognized technical trading rules were utilized and backtested on the historical price data of the three cryptocurrencies at daily and intraday frequencies to assess their profitability.

5 Empirical Results

5.1 Buy-and-Hold

In recent years, cryptocurrencies such as BTC, ETH, and XRP have gained significant popularity and widespread trading activity. Like any investment asset, investors are keen to identify strategies that can generate positive returns over time. One such strategy is the buy-and-hold approach, which involves purchasing and retaining an asset for an extended duration.

The buy-and-hold strategy is relatively straightforward to implement, as it requires traders to simply acquire the asset and maintain a long-term holding position. This strategy offers certain advantages, such as reduced emphasis on market timing, and lower transaction costs. . Identifying optimal entry points and determining the bullish or bearish nature of the asset can be challenging. Entering a trade at an unfavourable position may cause stress for traders. Conducting more trades also entails increased transaction costs potentially offsetting the returns. The buy-and-hold strategy aims for long-term profitability, regardless of the market's bullish or bearish structure. It is important to note that outperforming this strategy is not always straightforward. Allen and Karjalainen (1999) conclude that generating excess returns compared to the buy-and-hold strategy, particularly after accounting for transaction costs, is often unattainable.

Following the approach outlined by Brock et al. (1992), we employ the nonoverlapping unconditional mean return as the buy-and-hold strategy, with BTC as our chosen reference asset due to its significant dominance within the cryptocurrency market. Our analysis yields a daily unconditional mean return of 0.268% with a standard deviation of 5.19%, while the four-hourly yields a mean return of 0.046% and a standard deviation of 2.41%. Furthermore, the daily return skewness is significantly negative at the 1% level (-0.43), and the kurtosis is 13.85. The skewness is reduced but still significant for the four-hourly returns, while the kurtosis increases to 66.38.

Table 1 contains summary statistics for the entire sample and eight subperiods, divided in market cycles, for daily and four-hour returns on BTC. Panel A presents the results from the daily returns. These returns are strongly leptokurtic for the entire sample and all the subsamples. This is in line with findings in Brock et al. (1992) and Chong et al. (2014), where they study the traditional market indexes Dow Jones Industrials (DJI) and DAX 30 respectively. Volatility is most prominent for the earliest market cycles, after that steadily decreasing for the following subsamples. Serial correlation in the daily returns is not very prevalent, except for some large values in the fourth bull market. Panel B reports the four-hourly returns for the full sample and subsamples. A substantial increase in leptokurtosis, skewness and serial correlation can be observed for the four-hour returns. The results below are represented for the full sample and the nonoverlapping subsamples that are divided between bull & bear periods. Following Brock et al. (1992), $p(i)$ is the estimated autocorrelation for each period at lag (i).

The returns r are calculated using the logarithmic difference on both the daily and four-hour close prices as:

$$r = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{8}$$

where P_t is the price at time t and P_{t-1} is the price at the previous time period.

Notably, our examination reveals that all three cryptocurrency series exhibit significantly negative skewness, indicating a higher likelihood of upward movements than downward movements. Despite the inherent volatility of cryptocurrencies, the buy-and-hold strategy can still generate positive returns over time. Historical data demonstrates that holding BTC, ETH, and XRP for extended periods can lead to substantial investment growth. For instance, an investor who purchased BTC in 2010 and maintained their position until 2021 would have witnessed an over 13 million percentage appreciation.

However, it is important to acknowledge the risks associated with the buy-and-hold strategy in the cryptocurrency market. Cryptocurrencies represent a relatively new asset class, and their future remains uncertain. Additionally, the value of cryptocurrencies can be influenced by various factors, including regulatory changes, security concerns, and market sentiment. Consequently, investors adopting a buy-and-hold strategy in the cryptocurrency market must be prepared to withstand volatility and adopt a long-term perspective on their investments.

Table 1: Panel A: Daily Returns

	Full Sample	**Bull 1**	**Bear 1**	**Bull 2**	**Bear 2**	**Bull 3**	**Bear 3**	**Bull 4**	**Bear 4**
N	4535	325	156	740	619	854	365	1058	418
Mean	0.00268	0.01797	-0.01711	0.00865	-0.00251	0.00504	-0.00494	0.00288	-0.00336
S.D	0.0519	0.0904	0.0967	0.0555	0.0466	0.0385	0.0447	0.0410	0.0336
Skewness	-0.43**	0.40**	-1.29**	-0.26**	-0.66**	-0.32**	-0.41**	-1.53**	-0.59**
Kurtosis	13.85**	4.46**	5.71**	11.50**	9.60**	8.35**	1.78**	21.48**	3.86**
p(1)	0.019	0.069	-0.007	0.083*	-0.035	-0.010	-0.058	-0.115**	-0.022
p(2)	-0.017	-0.014	-0.186**	0.009	-0.101**	-0.046	0.057	0.064**	-0.008
p(3)	0.001	0.052	-0.045	-0.001	-0.040	-0.001	0.064	-0.031	0.014
p(4)	0.002	-0.034	-0.045	0.009	0.016	0.003	-0.109	0.075**	-0.021
p(5)	0.052**	0.047	0.019	0.090**	-0.031	0.016	0.066	-0.001	-0.021
Panel B: Four-hourly returns									
	Full Sample	**Bull 1**	**Bear 1**	**Bull 2**	**Bear 2**	**Bull 3**	**Bear 3**	**Bull 4**	**Bear 4**
N	26994	1745	936	4433	3714	5124	2191	6349	2509
Mean	0.00046	0.00352	-0.00270	0.00141	-0.00039	0.00082	-0.00077	0.00047	-0.00055
S.D	0.0241	0.0560	0.0388	0.0265	0.0198	0.0158	0.0195	0.0162	0.0134
Skewness	-0.13**	0.61**	0.41**	-2.86**	-0.73**	-0.89**	-0.02**	-0.69**	-0.28**
Kurtosis	66.38**	20.26**	14.50**	63.84**	40.92**	34.12**	6.59**	16.62**	5.54**
p(1)	-0.102**	-0.269**	0.087**	-0.011	-0.053**	-0.058**	-0.038	-0.041	0.016
p(2)	-0.022**	-0.005	-0.128**	-0.036*	-0.036*	-0.012	-0.002	0.008	0.002
p(3)	0.013*	0.032	-0.034	-0.037*	0.001	0.012	0.001	0.069	0.011
p(4)	0.003	-0.083**	0.040	0.035*	0.062**	0.068**	0.116**	-0.007	0.012
p(5)	0.042**	0.027	0.088**	0.086**	0.028	0.034	0.023	-0.008	0.003

**: Indicates significance at the 1% level;*: Indicates significance at the 5% level.

5.2 Market cycles

Murphy (1999) emphasizes the significance of prioritizing the long-term perspective when utilizing technical analysis to study market cycles. Long-term cycles can span several years and play a pivotal role in determining the overall market trend. According to the Dow Theory, the market structure is characterized as either bullish or bearish, with distinct stages that reflect investor sentiments. Trading volume tends to align with the prevailing trend, indicating that in an upward trend, volume should increase as prices rise and decrease as prices decline.

The market cycles are graphically presented below in figure 6, illustrating the unconditional intraday periods with nonoverlapping intervals. Each sub-period is divided into respective bull and bear market cycles, visually depicted with a mean line indicating whether the market cycle points upwards (bullish) or downwards (bearish). The table summarizes the total period divided into bull and bear markets, providing the percentage return for each cycle, cycle length, as well as the low and high prices. The total period spans 4550 days from the start date to the end date, equivalent to 149 months and 14 days.

Figure 6: **Market cycles during the study period**

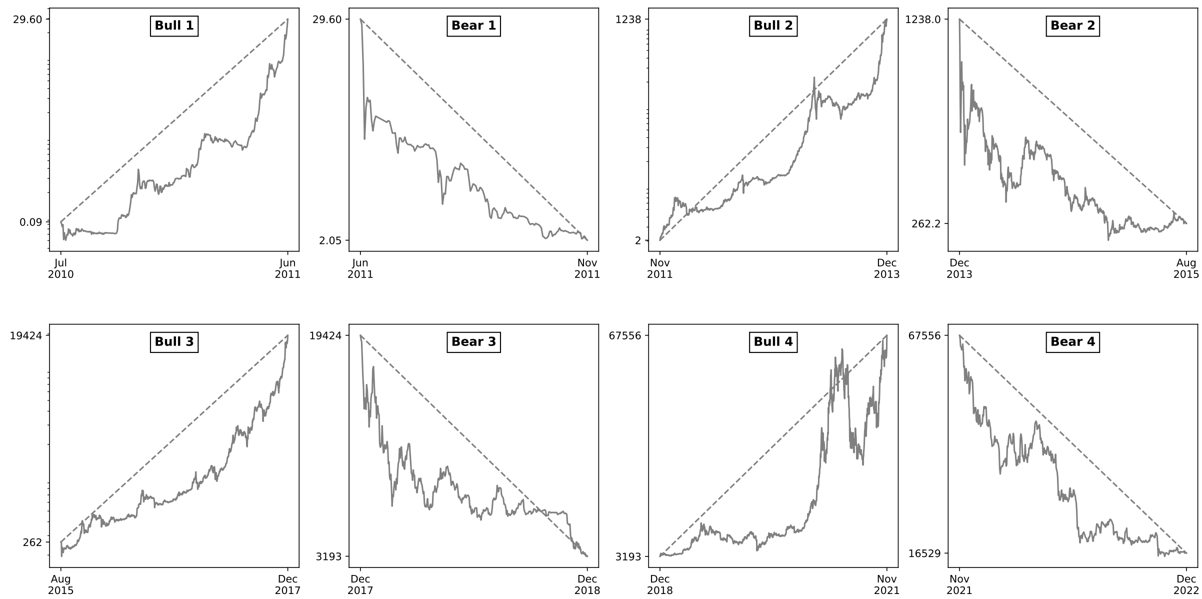


Table 2: Market cycles with percentage change returns

Start	End	% Change	Cycle	Months	Low (High)	High (Low)
2010-07	2011-06	160500	Bull	11	0.02	32.12
2011-06	2011-11	-93.73	Bear	5	31.91	2.00
2011-11	2013-12	61900	Bull	25	2.00	1242.00
2013-12	2015-08	-86.96	Bear	20	1242.00	162.00
2015-08	2017-12	12124.84	Bull	28	162	19804
2017-12	2018-12	-84.24	Bear	12	19804	3124
2018-12	2021-11	2108.27	Bull	35	3124	68997
2021-11	2022-12	-76	Bear*	14	68997	16332

*: The bear market is still ongoing. However, because our data only runs until 22-12-31, our analysis shows that the bear market has a duration of 14 months. In reality, because the market is still bearish, the actual number of months is 19 and still increasing as of May 2023.

The percentage change for each bull period demonstrates a substantial decrease with each cycle. However, the percentage change remains relatively high. In bear markets, the percentage change also declines for each bear period but with a more consistent reduction. Without delving into the high volatility inherent in the cryptocurrency market, this observation could indicate a rapid increase in market efficiency over the years. Furthermore, it is noteworthy that bull periods consistently exhibit longer durations than bear periods.

5.3 Traditional Tests

The method for the obtained results is explained before presenting the summary of the different RSI and MACD trading rules. The t-statistics that is presented in parenthesis below each return are the reported t-statistics. This tests the null hypothesis of equality between the return by the trading rule (μ_r, where r denotes buy/sell) and the buy-and-hold return (μ). A sell signal producing a negative return implies that the profit is positive.

Following Brock et al. (1992), the t-statistic for buy or sell returns is computed as:

$$t_r = \frac{\mu_r - \mu}{\sqrt{\left(\frac{\sigma^2}{N_r}\right) + \left(\frac{\sigma^2}{N}\right)}} \tag{9}$$

where μ_r and N_r are the mean return and number of buy/sell signals. μ is the unconditional mean, N represents the number of observations, whilst σ^2 represents the estimated variance for the entire sample. The same goes for the buy-sell t-statistic that Brock et al. (1992) computed as:

$$t_{buy-sell} = \frac{\mu_b - \mu_s}{\sqrt{(\frac{\sigma^2}{N_b}) + (\frac{\sigma^2}{N_s})}} \tag{10}$$

where μ_b is the mean return for the buy signals and N_b are the number of a buy signals. μ_s are the mean return for the sell signals and N_s are the number of sell signals.

To test the statistic significance on any of the trading rules we compare the excess returns with the unconditional mean return, also called the buy-and-hold return, which is used as a benchmark.

Hypothesis	H_0	H_A
Buy-Unconditional Return	$\mu_B - \mu_U = 0$	$\mu_B - \mu_U \neq 0$
Sell-Unconditional Return	$\mu_S - \mu_U = 0$	$\mu_S - \mu_U \neq 0$
Buy and Sell Fractions	Buy $> 0 =$ Sell > 0	Buy $> 0 \neq$ Sell > 0
Buy-Sell Return	$\mu_B - \mu_S = 0$	$\mu_B - \mu_S \neq 0$

where μ_B and μ_S represents the mean return for buy and sell respectively. μ_U represents the unconditional mean.

Under the null hypothesis, trading rules should not provide useful signals. Therefore the positive returns fraction should be the same for buys and sells. A binomial test was conducted to see if significant differences existed between the ratio of positive returns in buys and sells. In contrast to the findings in Brock et al. (1992), the null hypotheses were not consistently rejected in this study. A notable majority of the employed strategies failed to provide conclusive evidence against the null hypothesis, suggesting that these strategies lack the ability to yield meaningful signals in cryptocurrencies.

A normal distribution is not skewed and has a kurtosis equal to three. It will also have a zero coefficient of excess return. The Jarque-Bera test is used to examine this, with the null hypothesis stating that the distribution is symmetric and mesokurtic. The null hypothesis is of normality, and it is rejected if the residuals are significantly skewed, leptokurtic/platykurtic, or both (Brooks, 2019).

5.4 Trading Rules

The following tables present the results for the daily data and four-hourly data for the sample period. The daily sample period is 07.2010 - 12.2022, while the four-hour sample period starts in 2013 due to unavailable data before this year. Additionally, XRP and ETH were created in 2012 and 2015 (Investopedia, 2023), which reduces the respective sample period. "Ticker" identifies which cryptocurrency the strategy has been tested on, and "Frequency" reports whether it is the daily or four-hourly strategy. "N(Buy)" and "N(Sell) are the number of buy and sell signals produced during the sample period. "Buy" and "Sell" are the mean returns produced by the strategy. "Buy > 0" and "Sell > 0" are the fraction of buy and sell returns greater than 0. "Buy-Sell" is the mean sell returns subtracted from mean buy returns.

The numbers in parentheses are standard t-statistics testing the difference between the mean buy and mean sell from the unconditional mean and buy-sell from zero. The t-statistics for daily strategies are computed using the unconditional daily return of 0.268% with a standard deviation of 5.19%. The t-statistic for four-hourly strategies is computed using the unconditional four-hour return of 0.0468% with a standard deviation of 2.36%.

All the trading strategies will employ a one-period holding period for the trades, as done in Brock et al. (1992). This implies that the daily strategy trades will be open one day before closing, and the four-hourly trades will be open for four hours. The studied strategies were further examined across various subsamples to assess their susceptibility to market conditions. However, as shown in the "Strategy Returns" section of the Appendix, no discernible dependence on market conditions was observed. Nonetheless, specific strategies did exhibit intermittent profitability, followed by subsequent periods of unprofitability. If solely influenced by market conditions, this cyclic pattern would be expected to repeat consistently throughout each market cycle. However, the observed data suggests otherwise, as the pattern does not consistently repeat in a cyclical manner. Furthermore, the obtained results were subjected to a similar analysis for the full sample, and no significant deviations in outcomes were observed.

The calculation of the t-statistic reveals that the mean buy and sell returns can attain statistical significance solely when surpassing the returns achieved through the buy-and-hold strategy. This suggests that the returns may exhibit significant profitability when evaluated independently, excluding the comparison with the buy-and-hold strategy.

5.4.1 Rule 1 RSI (N, 50)

The following tables show the obtained results from the RSI(N, 50) strategy. **: Indicates significance at the 5% level;*: Indicates significance at the 10% level.

Table 3: **Average Returns for RSI(7, 50)**

Data	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
BTC 1D	306	306	0.0008	0.0018	0.5523	0.4804	-0.001
			(-0.61)	(1.46)			(-0.24)
ETH 1D	193	193	0.0009	0.0037	0.5492	0.4508	-0.0028
			(-0.47)	(1.67*)			(-0.53)
XRP 1D	235	235	-0.002	0.007	0.4851	0.434	-0.009
			(-1.35)	(2.78**)			(-1.88*)
BTC 4H	1564	1564	0.0002	0.0006	0.5332	0.5153	-0.0004
			(-0.44)	(1.74*)			(-0.47)
ETH 4H	1384	1385	0.0018	0.0001	0.5419	0.504	0.0017
			(2.04**)	(0.87)			(1.89*)
XRP 4H	1279	1281	0.001	-0.0003	0.4871	0.4949	0.0013
			(0.79)	(0.25)			(1.39)

All the buy returns are positive except the daily XRP returns. The only significant buy returns come from ETH´s 4H, while three sell strategy returns are statistically significant. The 1D strategy for XRP is the only one to provide significant negative profit at the 10% level. 4H XRP and 4H ETH are the only strategies to produce positive returns for the combined buy and sell, but only ETH´s 0.17% mean returns are significant. Only the ETH 4H significantly differed the fraction of positive returns in buys and sells.

Table 4: **Average Returns for RSI(14, 50)**

Data	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
BTC 1D	198	198	0.0021	0.0012	0.5455	0.4293	0.0009
			(-0.15)	(1.03)			(0.17)
ETH 1D	112	112	0.0059	-0.0053	0.5893	0.375	0.0112
			(0.65)	(-0.53)			(1.61)
XRP 1D	152	152	-0.0041	0.0108	0.5	0.4079	-0.0149
			(-1.58)	(3.15**)			(-2.5**)
BTC 4H	1033	1033	0.0007	0.0001	0.546	0.4734	0.0006
			(0.31)	(0.76)			(0.58)
ETH 4H	900	903	0.0024	-0.0019	0.5344	0.474	0.0043
			(2.41**)	(-1.79*)			(3.86**)
XRP 4H	867	869	0.0007	0.0004	0.4717	0.4776	0.0003
			(0.28)	(1.06)			(0.26)

The RSI(14, 50) provides significant negative returns at the 5% level for the 1D XRP, where most of the negative return comes from negative profits on the sell side of the strategy. The strategy provides a significant return at the 5% level for 4H ETH buy-sell strategy with a mean return of 0.43%. The application of the binomial test reveals a statistically significant disparity in the number of positive return trades generated by the strategies employed in both BTC and ETH.

Table 5: **Average Returns for RSI(21, 50)**

Data	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
BTC 1D	152	152	0.0042	0.0016	0.5921	0.4605	0.0026
			(0.35)	(1.0)			(0.44)
ETH 1D	93	93	0.0154	-0.0003	0.5806	0.3763	0.0157
			(2.34**)	(0.44)			(2.06**)
XRP 1D	129	129	0.0062	0.005	0.6047	0.4109	0.0012
			(0.76)	(1.66*)			(0.19)
BTC 4H	809	809	0.0001	-0.0002	0.5266	0.4784	0.0003
			(-0.44)	(0.32)			(0.25)
ETH 4H	703	706	0.0019	-0.0014	0.532	0.4674	0.0033
			(1.58)	(-1.03)			(2.62**)
XRP 4H	612	614	-0.0012	0.0011	0.4624	0.4886	-0.0023
			(-1.72*)	(1.62)			(-1.7*)

For the RSI(21, 50) rule, both frequencies provide significant positive returns for ETH´s buy-sell strategy. XRP´s 4H generates a significant negative return at the 10% level. Only the four-hour strategy in BTC and XRP had an insignificant difference in the ratio of positive return buy and sell trades.

5.4.2 Rule 2 RSI (N, 30/70)

The following tables present the outcomes of implementing the RSI (N, 30/70) strategy, wherein RSI lengths of 7, 14, and 21 have been examined. Notably, these strategies consistently generate a greater number of sell signals compared to buy signals, indicating a predominance of overbought conditions in the cryptocurrency market. This observation aligns with the prevailing market trend, characterized by an upward trajectory for most of the time.

Table 6: **Average Returns for RSI(7, 30/70)**

Data	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
BTC 1D	148	189	0.0036	0.0125	0.5676	0.6032	-0.0089
			(0.21)	(3.94**)			(-1.56)
ETH 1D	89	128	-0.0066	0.017	0.5281	0.5312	-0.0236
			(-1.67*)	(4.23**)			(-3.29**)
XRP 1D	151	126	-0.0072	0.0142	0.5232	0.3968	-0.0214
			(-2.3**)	(3.6**)			(-3.42**)
BTC 4H	665	934	-0.0011	0.0019	0.5203	0.5236	-0.003
			(-1.69*)	(3.01**)			(-2.5**)
ETH 4H	567	592	0.0017	0.0008	0.478	0.5051	0.0009
			(1.23)	(1.29)			(0.65)
XRP 4H	826	639	-0.0002	0.003	0.4528	0.5603	-0.0032
			(-0.8)	(3.66**)			(-2.57**)

The RSI(7, 30/70) rule generates significant negative returns in four of the six tests, where the majority originates from negative profits on the sell side. Among the examined assets, only XRP exhibited a statistically significant dissimilarity in the number of positive return trades generated between buy and sell trades.

Table 7: **Average Returns for RSI(14, 30/70)**

Data	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
BTC 1D	55	108	0.0123	0.0093	0.5455	0.5	0.003
			(1.37)	(2.37**)			(0.35)
ETH 1D	28	75	0.008	0.02	0.6071	0.5333	-0.012
			(0.54)	(3.75**)			(-1.04)
XRP 1D	58	51	0.0151	0.0408	0.5172	0.6078	-0.0257
			(1.81*)	(5.95**)			(-2.58**)
BTC 4H	321	463	-0.0008	0.0027	0.5389	0.5076	-0.0035
			(-0.95)	(2.86**)			(-2.04**)
ETH 4H	189	296	0.003	-0.0008	0.5026	0.4797	0.0038
			(1.47)	(-0.24)			(1.72*)
XRP 4H	349	328	-0.0012	0.0023	0.4212	0.5091	-0.0035
			(-1.31)	(2.11**)			(-1.92*)

Increasing the length from 7 to 14 appears to have some impact on the results. Three of the six strategies generate negative profits, while ETH 4H strategy now generate significant positive returns at the 10% level. XRP 4H is the only strategy to yield a significant difference between the fraction of positive buy and sell returns.

Table 8: **Average Returns for RSI(21, 30/70)**

Data	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
BTC 1D	23	79	0.0357	0.0162	0.5652	0.5696	0.0195
			(3.04**)	(3.2**)			(1.59)
ETH 1D	17	34	0.0037	0.0377	0.5882	0.6471	-0.034
			(0.08)	(4.52**)			(-2.21**)
XRP 1D	19	33	0.0146	0.0689	0.5263	0.5152	-0.0543
			(1.0)	(7.89**)			(-3.63**)
BTC 4H	132	332	0.0038	0.0013	0.5455	0.5422	0.0025
			(1.61)	(1.35)			(1.03)
ETH 4H	74	196	0.0077	0.0019	0.5405	0.4847	0.0058
			(2.62**)	(1.4)			(1.8*)
XRP 4H	205	188	0.0031	0.0016	0.4537	0.5213	0.0015
			(1.59)	(1.19)			(0.63)

Increasing the length further to 21 leads to only two strategies generating significant negative returns, while ETH 4H maintain its profitability compared to the buy-and-hold strategy. All the strategies fail to reject the null hypotheses that there is no significant difference between the proportions of positive returns for both buys and sells.

5.4.3 Rule 3 MACD

The following tables summarizes the results from the MACD rules.

Table 9: **Average Returns for MACD(12, 26, 9)**

Data	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
BTC 1D	139	139	0.0	-0.0054	0.4604	0.518	0.0054
			(-0.6)	(-0.61)			(0.87)
ETH 1D	90	90	0.0115	0.0061	0.5222	0.5889	0.0054
			(1.6)	(1.59)			(0.7)
XRP 1D	101	101	0.0116	0.0019	0.4455	0.5149	0.0097
			(1.71)	(0.88)			(1.33)
BTC 4H	798	798	0.0013	0.0005	0.5113	0.5702	0.0008
			(0.98)	(1.14)			(0.68)
ETH 4H	588	588	-0.0012	0.0012	0.4609	0.5629	-0.0024
			(-1.69)	(1.69)			(-1.74)
XRP 4H	762	762	0.0007	0.0001	0.4974	0.5066	0.0006
			(0.27)	(0.65)			(0.49)

The MACD(12, 26, 9) buy-sell strategy is not able to generate any significant positive returns. ETH 4H generate significant negative returns, while XRP 1D manages to outperform the buy-and-hold strategy on the buy trades. The four-hour strategy for BTC and ETH are the only ones to reject the null hypothesis of no difference between the fraction of positive buy and sell returns.

Table 10: **Average Returns for MACD(8, 17, 9)**

Data	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
BTC 1D	135	135	0.016	0.0091	0.563	0.6222	0.0069
			(2.94**)	(2.6**)			(1.09)
ETH 1D	76	76	0.0059	0.0042	0.5395	0.4737	0.0017
			(0.54)	(1.15)			(0.2)
XRP 1D	81	81	0.0099	-0.0042	0.4198	0.5432	0.0141
			(1.24)	(-0.26)			(1.73*)
BTC 4H	479	478	0.0019	0.0013	0.4781	0.5209	0.0006
			(1.31)	(1.62)			(0.39)
ETH 4H	278	277	0.0025	0.0021	0.5252	0.4801	0.0004
			(1.42)	(1.8*)			(0.2)
XRP 4H	430	430	0.0015	-0.0014	0.486	0.4744	0.0029
			(0.9)	(-0.81)			(1.8*)

The application of the MACD(8, 17, 9) strategy in BTC's daily trading strategies yields significant positive returns on the buy side. However, when considering the combined strategy, the significance diminishes due to significant negative profits observed on the sell side. In the case of XRP, both the 1D and 4H strategies exhibit significant positive returns at the 10% significance level for buy-sell. None of the strategies reject the null hypothesis of no difference between the fractions of positive buy and sell returns.

Table 11: **Average Returns for MACD(12, 26, 0)**

Data	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
BTC 1D	55	55	0.0084	0.0184	0.4545	0.5273	-0.01
			(0.81)	(2.99**)			(-1.01)
ETH 1D	33	33	-0.0073	-0.0055	0.303	0.5455	-0.0018
			(-1.1)	(-0.31)			(-0.14)
XRP 1D	52	52	-0.0223	0.0151	0.3462	0.5962	-0.0374
			(-3.45**)	(2.46**)			(-3.67**)
BTC 4H	335	335	0.0013	0.0009	0.4806	0.5582	0.0004
			(0.64)	(1.05)			(0.22)
ETH 4H	251	251	0.0001	-0.0005	0.4343	0.5418	0.0006
			(-0.25)	(-0.02)			(0.28)
XRP 4H	341	341	0.0004	-0.0003	0.4839	0.4897	0.0007
			(-0.05)	(0.13)			(0.39)

The MACD(12, 26, 0) strategy produces significant negative returns for the combined buy-sell strategy, where both the buy and sell trades contribute significantly to the result. All strategies besides BTC 1D and XRP 4H reject the null hypothesis of no difference between the fraction of positive buy and sell returns.

5.4.4 Results

Upon examining the buy and sell performances separately, it becomes evident that the sell performance, on only one occasion, yields a significantly positive return when compared to the buy-and-hold strategy. Conversely, it is observed that the sell performance frequently leads to statistically negative profits. As a result, it can be concluded that the sell trades do not have the capacity to generate significant profits beyond those achieved through the buy-and-hold strategy. On the other hand, the buy trades do yield some significantly profitable trades beyond the buy-and-hold strategy, albeit with a relatively low frequency overall. Based on the limited frequency with which buy returns occur, it can be inferred that these signals are unable to outperform the buy-and-hold strategy. Based on the subpar individual performance of both buy and sell returns compared to the buy-and-hold strategy, it is reasonable to assert that the combined strategy would also be unable to surpass the performance of the buy-and-hold approach.

5.5 Performance Measures

We calculate the Sharpe and Sortino ratios to test the strategies' performance. In order to calculate the Sharpe ratio, we need the mean excess return for each trading rule and divide it by the volatility. The mean excess return is the difference between the mean return for each trading rule and the risk-free rate. We deliberately eliminate the consideration of the risk-free rate as an opportunity to trading and therefore do not subtract it from the mean return to obtain the mean excess return. This decision comes as a result of being in a trading environment where maintaining liquidity is needed to invest in new trading signals.

5.5.1 Sharpe Ratio

As a result of this, the Sharpe ratio is calculated as follows:

$$\text{Sharpe Ratio} = \frac{R}{\sigma_R} \tag{11}$$

where R is the trading strategy returns and σ_R is the standard deviation for the trading strategies returns. A higher Sharpe Ratio indicates a higher risk-adjusted performance. The Sharpe ratio comes with some limitations. It assumes that the return and standard deviation are normally distributed, which is not always true for financial markets. Additionally, the financial markets tend to reveal skewness, fat tails in the distribution and to be leptokurtic.

5.5.2 Sortino Ratio

The Sortino ratio differentiates from the Sharpe ratio by emphasizing downside volatility as a risk measure. The Sortino ratio focuses on the downside risk by evaluating the risk-adjusted performance where mitigating the downside risk is critical. Additionally, it assesses the ability to generate positive returns relative to its downside risk. By measuring the Sortino ratio, we can evaluate the strategies focusing on the downside risk, enabling us to analyze and interpret the result more appropriately. A higher Sortino ratio implies that the strategy has achieved greater success returns relative to its downside volatility. It is calculated as follows:

$$\text{Sortino Ratio} = \frac{R}{\sigma_D} \tag{12}$$

where R is the trading strategy returns and σ_D is the standard deviation for the trading strategies negative returns.

5.5.3 Performance Analysis

In order to make these ratios comparable at different timeframes, they are annualized as detailed in Harvey and Liu (2014):

$$\text{Annualized Sharpe-/Sortino Ratio} = SR * \sqrt{N} \tag{13}$$

In this case, N denotes the number of realized returns in a year. The corresponding t-statistic is $SR * \sqrt{N \times \text{Number of Years}}$.

In our study, it is crucial to consider the possibility that the observed significant ratios could be purely due to chance when testing multiple strategies. We employ the Bonferroni multiple-testing method to address this concern and mitigate the risk of false positives. This method involves adjusting the p-value cutoff for critical values to account for the number of tests conducted.

In this particular study, we conduct a total of 18 tests. Consequently, the chosen significance levels need to be divided by this number to ensure appropriate adjustment. Initially, we operate with significance levels of 0.05 and 0.10. However, after applying the Bonferroni correction, these significance levels are transformed to 0.00277 and 0.0055, respectively.

To illustrate the impact of this adjustment, let us consider a trading strategy that generates 100 trades. In the original scenario, a t-statistic exceeding approximately 1.984 would be considered significant at 95% certainty. However, the new threshold is approximately 3.2 under the Bonferroni-corrected significance level. Thus, for our adjusted analysis, the t-statistic generated by the trading strategy must surpass this higher threshold to be deemed statistically significant at the 5% level. The Sharpe- and Sortino ratios as reported in table 12 and 13.

Table 12: Daily Performance Metrics

Strategy 1D	BTC		ETH		XRP	
	Sharpe	Sortino	Sharpe	Sortino	Sharpe	Sortino
RSI(7, 50)	-0.17	-0.22	-0.36	-0.45	-1.04	-0.97
RSI(14, 50)	0.14	0.18	1.31**	1.80**	-1.20	-1.13
RSI(21, 50)	0.29	0.38	1.49**	2.18**	0.09	0.08
RSI(7, 30/70)	-0.75	-0.91	-1.82	-1.93	-1.27	-1.13
RSI(14, 30/70)	0.18	0.23	-0.62	-0.73	-0.77	-0.77
RSI(21, 30/70)	0.82*	1.01	-1.04	-1.39	-0.84	-0.78
MACD(12, 26, 0)	-0.52	-0.57	-0.10	-0.23	-1.49	-1.64
MACD(12, 26, 9)	0.49	0.74	0.51	0.77	0.54	0.92
MACD (8, 17, 9)	0.49	0.80	0.13	0.17	0.76	1.55**

**: Indicates significance at the 5% level; *: Indicates significance at the 10% level.

In relation to the daily data, a limited number of strategies have demonstrated notable Sharpe and Sortino ratios. Specifically, the RSI(14, 50) and RSI(21, 50) strategies employed for ETH exhibited statistical significance for both the Sharpe and Sortino ratios at a confidence level of 5%. Conversely, for BTC, solely the Sharpe ratio associated with the RSI(21, 30/70) strategy displayed significance, albeit at a confidence level of 10%. However, due to the lack of significance in the Sortino ratio, it can be inferred that this strategy resulted in excessive downside volatility. Conversely, when considering XRP, only the Sortino ratio for MACD(8, 17, 9) exhibited statistical significance, indicating that the overall volatility was excessive, thereby preventing the achievement of a significant Sharpe ratio.

Table 13: Four-Hourly Performance Metrics

Strategy 4H	BTC		ETH		XRP	
	Sharpe	Sortino	Sharpe	Sortino	Sharpe	Sortino
RSI(7, 50)	-0.44	-0.55	1.29**	1.71**	0.83	1.15
RSI(14, 50)	0.55	0.72	2.55**	3.99**	0.15	0.21
RSI(21, 50)	0.22	0.25	1.65**	2.36**	-1.02	-1.23
RSI(7, 30/70)	-1.88	-2.08	0.36	0.54	-1.37	-1.67
RSI(14, 30/70)	-1.24	-1.24	1.10*	1.65**	-0.93	-1.14
RSI(21, 30/70)	0.61	0.98	1.04*	1.52*	0.24	0.32
MACD(12, 26, 0)	0.21	0.32	0.22	0.32	0.29	0.39
MACD(12, 26, 9)	0.58	0.74	-1.19	-1.33	0.32	0.36
MACD (8, 17, 9)	0.25	0.36	0.11	0.11	0.98*	1.33*

**: Indicates significance at the 5% level; *: Indicates significance at the 10% level.

The analysis reveals that the four-hour strategies exhibit superior performance compared to the daily strategies, particularly in the case of ETH. A substantial proportion of these strategies yield statistically significant Sharpe and Sortino ratios for ETH, with over half of the strategies demonstrating significance. Notably, these significant ratios are observed exclusively within the RSI strategies, while the MACD strategies fail to exhibit significance. Furthermore, when considering XRP on the four-hour frequency, the MACD(8, 17, 9) strategy demonstrates both a statistically significant Sharpe ratio and Sortino ratio, indicating its favorable performance.

5.6 Discussion and Limitations

This thesis entails certain limitations that can impede the determination of the viability of technical analysis in the cryptocurrency domain. Firstly, we have examined some of the most commonly utilized trading rules, which have demonstrated the ability to generate excess returns in other financial markets. The prevalence of these rules in practical applications suggests their underlying rationale. However, a broader range of rules could have been tested to identify those that yield significantly superior returns.

Secondly, adhering to the academic literature investigating the feasibility of technical trading rules, as exemplified by Brock et al. (1992), the study reveals that as markets mature and become more efficient, trading rules no longer generate profits. This possibility also applies to our study, implying that rules proven to be profitable in historical data might not hold true for future market conditions, particularly considering the indications of market features aligning with increased market efficiency beyond the testing period.

This notion aligns with our discovery that only the youngest one, ETH, demonstrated significant excess returns through technical analysis among the examined cryptocurrencies. Furthermore, it is worth noting that a substantial portion of these returns occurred during the early stages of ETH's existence.

This research focuses on a limited number of the largest cryptocurrencies, neglecting the vast majority of available options. Expanding the analysis to encompass a broader range of currencies and incorporating multiple trading rules would enhance the robustness and reliability of the findings regarding performance. Additionally, it is crucial to emphasize that our results are derived from historical data, and it is imperative to recognize that historical performance does not guarantee future outcomes.

As a simplification, we applied the bid-ask spread for BTC to all three cryptocurrencies due to challenges in obtaining the actual bid-ask spread for XRP and ETH. However, it is important to acknowledge that this simplification may lead to varying returns for the different strategies, potentially resulting in either lower or higher returns. Furthermore, our analysis solely focused on the buy-and-hold strategy applied to BTC. However, it is crucial to acknowledge that employing the buy-and-hold strategies of ETH and XRP to their respective strategies, may lead to a different conclusions regarding their potential to outperform the buy-and-hold approach.

The employment of the Sharpe ratio and Sortino ratio as measures of returns has faced valid criticism. These metrics assume a normal distribution, which is not always applicable in financial practice. Moreover, they do not account for fat-tailed distributions or skewness pertinent to this thesis. Nonetheless, using the Sharpe and Sortino ratios, which assume normality, allows for easy comparison of ratios among different strategies, despite potential deviation from the assumptions inherent in our results.

While the presented options are intriguing, they exceed the scope of this thesis. Future research endeavours could incorporate some of these options and expand our investigation to attain greater reliability. Further exploration of more complex trading strategies may yield improvements in profitability, as evidenced by the findings of Hsu and Kuan (2005) in the stock market.

6 Conclusion

This thesis uses popular technical trading rules to investigate the potential for generating excess returns in the cryptocurrency market. Specifically, we examined nine variations of the RSI and MACD indicators, which have been extensively studied in traditional financial markets. The analysis was conducted at both daily and four-hour intervals to explore potential differences between daily and intraday trading strategies. The findings revealed comparable results between the daily and intraday strategies for BTC and XRP, while ETH exhibited greater profitability with the four-hourly RSI strategy. A considerable number of the examined strategies were found to generate an overall positive trading profit. However, it is important to note that the primary objective of this study was to evaluate the strategies' ability to generate profits surpassing those achieved through the buy-and-hold strategy.

The MACD strategies, consistent with the findings of Chong and Ng (2008) and Chong et al. (2014), failed to consistently generate excess significant positive profits across the evaluated cryptocurrencies. On the other hand, the RSI strategies demonstrated more profitable trades, with ETH being the only cryptocurrency to yield significant profits with this strategy when compared to the buy-and-hold.

Among the BTC strategies, the daily RSI(21, 30/70) strategy produced notable buy-sell profits, albeit not statistically significant. However, the associated volatility was low, compensating for the lack of significance and resulting in significant Sharpe- and Sortino ratios. The Sharpe and Sortino ratios provide evidence that the buy-sell trading strategies have the potential to generate significant profits. However, when these strategies are compared to the buy-and-hold approach, a different narrative emerges, suggesting that the buy-and-hold strategy may still outperform them in terms of overall profitability.

Examining buy and sell performances separately reveals that sell transactions rarely yield significantly positive returns compared to the buy-and-hold strategy. Conversely, sell transactions frequently result in statistically negative profits. This indicates that sell transactions lack the capacity to generate significant profits beyond the buy-and-hold strategy. On the other hand, buy transactions occasionally produce significantly profitable trades beyond the buy-and-hold approach, albeit with low overall frequency. Given the infrequent occurrence of profitable buy signals and the underperformance of both buy and sell transactions against the buy-and-hold strategy, it is reasonable to conclude that the combined strategy would also fail to outperform the buy-and-hold approach.

Additionally, this study examined the impact of different subsamples on the trading strategies. The subsamples were divided into the bull and bear markets observed throughout Bitcoin's history. The objective was to determine whether the strategies exhibited dependency on market conditions and if the maturity of the cryptocurrency market influenced the results. The findings suggest that these strategies have minimal dependence on market sentiment, although some appear to suddenly become ineffective in 2017. Specifically, the four-hourly BTC and ETH RSI (N, 50) strategies performed well during the earlier years of cryptocurrencies, potentially supporting weak-form market efficiency. However, drawing conclusive findings necessitates further research involving a broader range of cryptocurrencies.

Prior literature has presented mixed results regarding market efficiency in financial markets. The widespread use of technical analysis, both independently and as a complement to fundamental analysis, raises questions about the extent of market efficiency.

In summary, while the viability of technical trading rules in making investment decisions remains a topic of controversy, our study does not provide definitive answers. The answer to whether technical analysis is viable in the cryptocurrency market is nuanced and multifaceted. This complexity arises from the aforementioned factors. Moreover, our results indicate that it is not possible to consistently produce excess returns beyond the buy-and-hold strategy.

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7 Appendix

Strategy returns

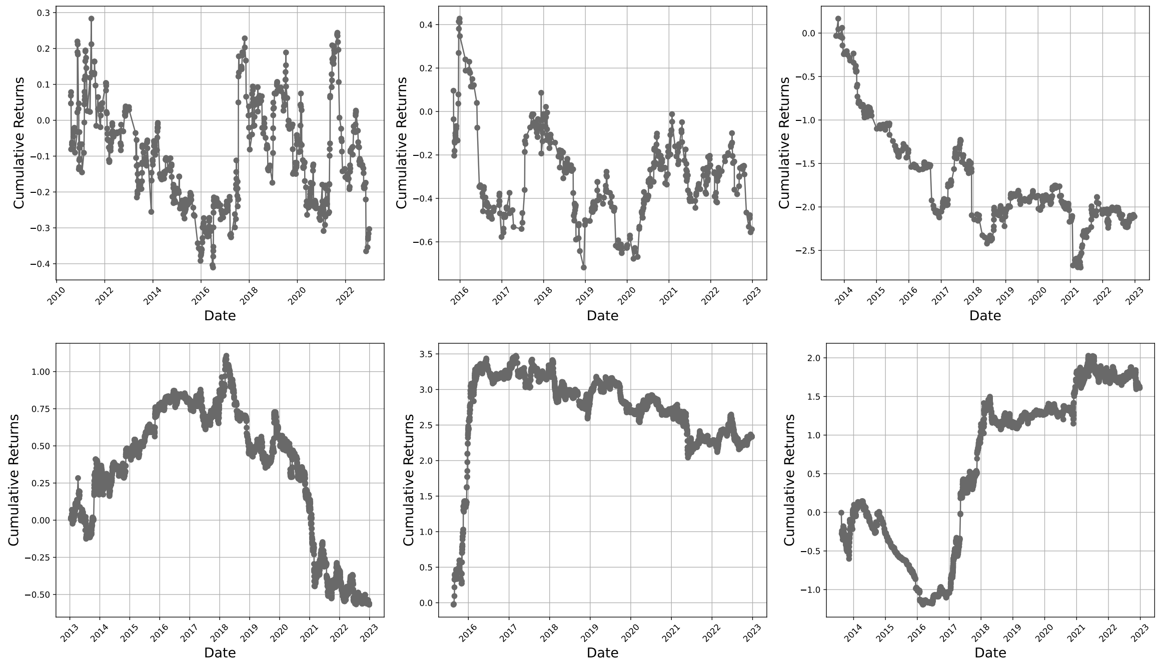

Figure 7: RSI (7, 50) Strategy returns

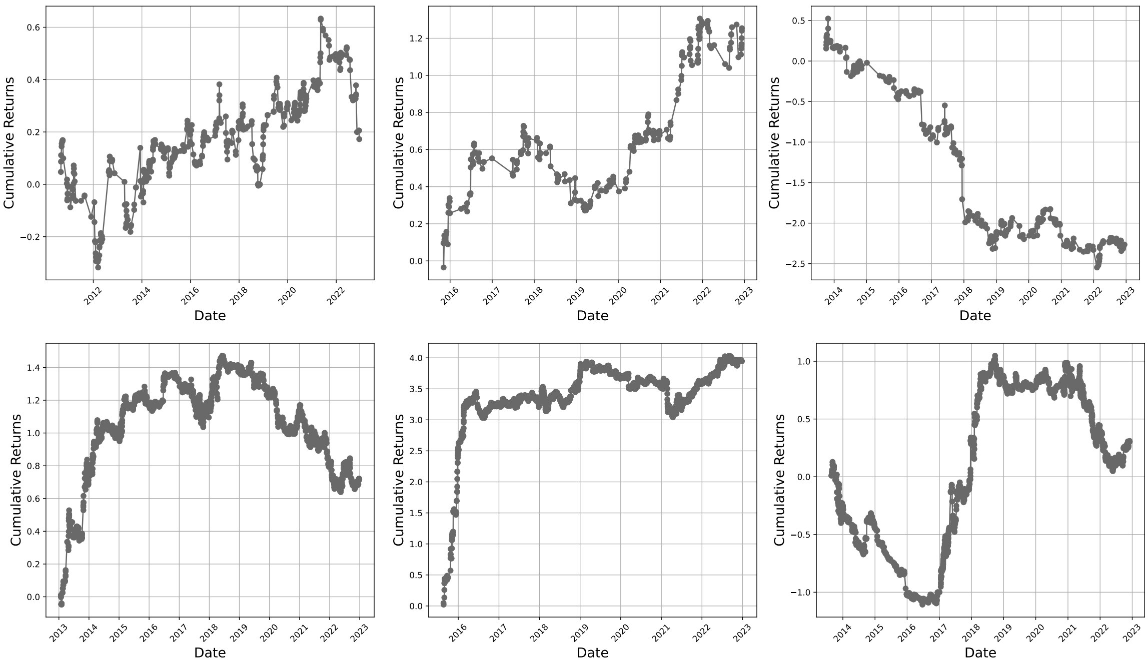

Figure 8: RSI (14, 50) Strategy returns

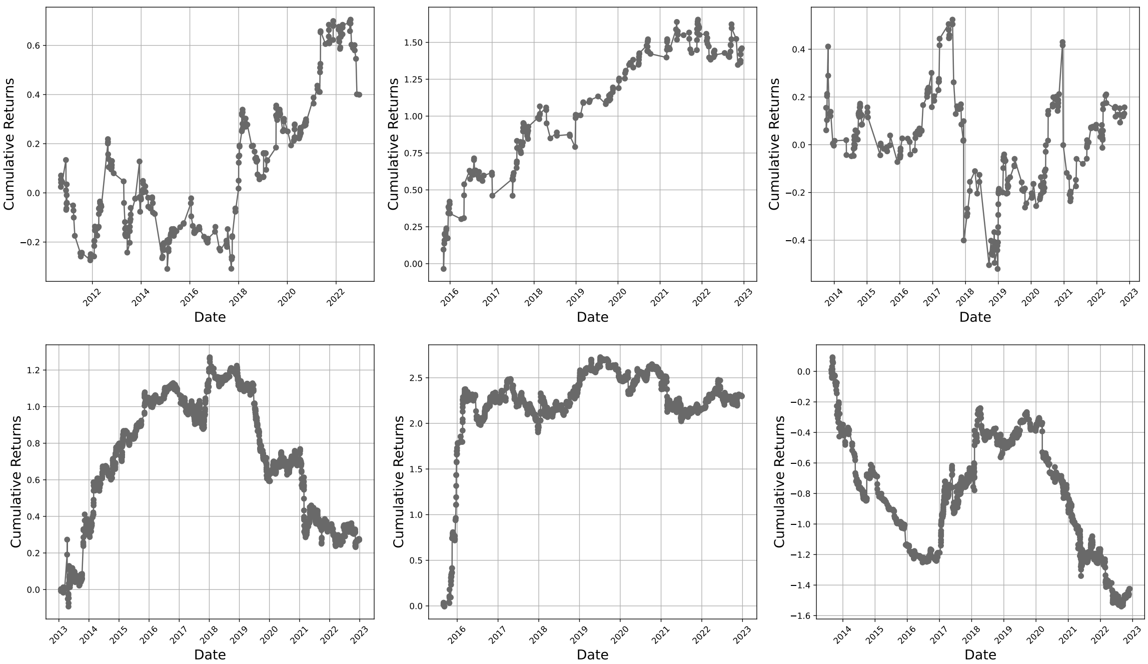

Figure 9: RSI (21, 50) Strategy returns

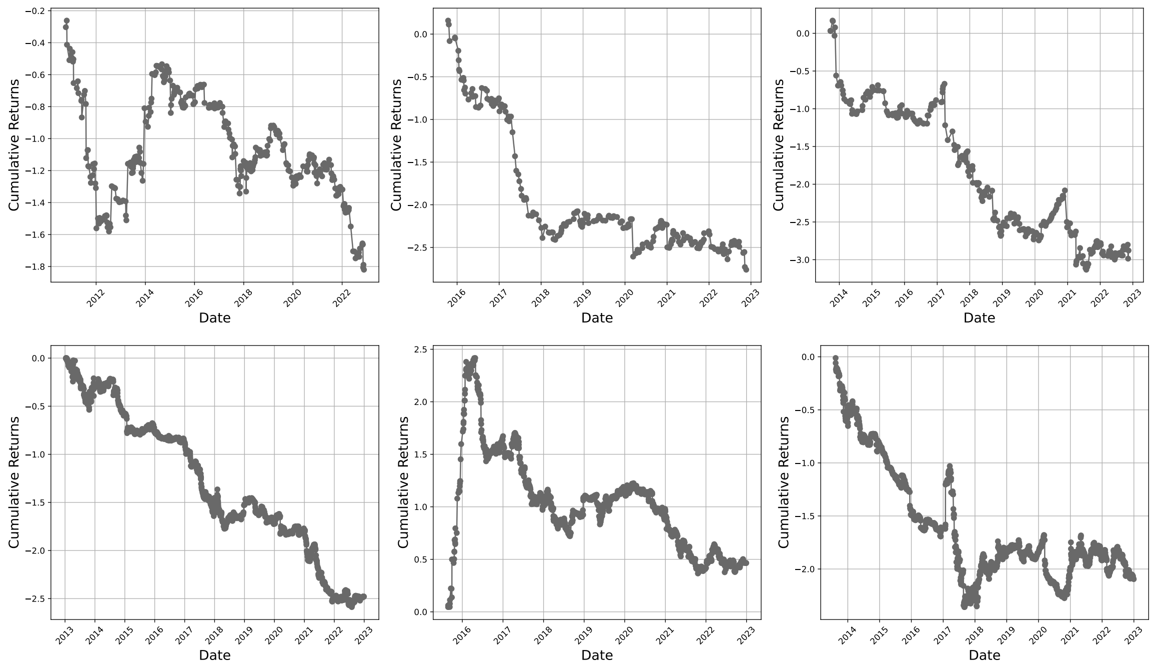

Figure 10: RSI (7, 30/70) Strategy returns

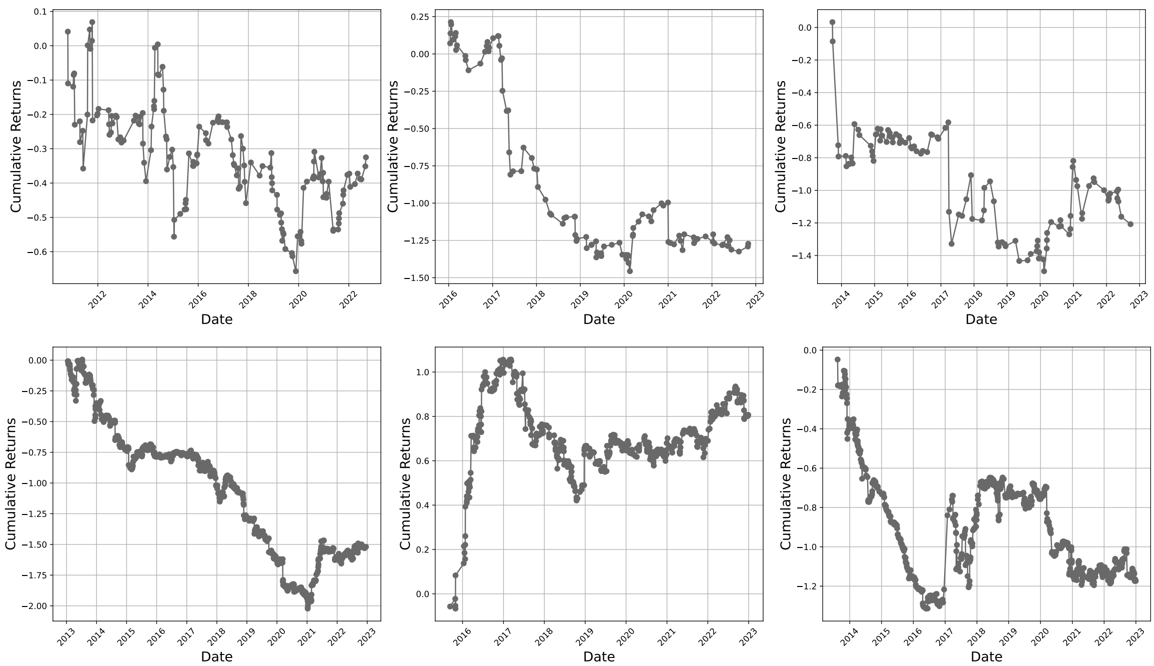

Figure 11: RSI (14, 30/70) Strategy returns

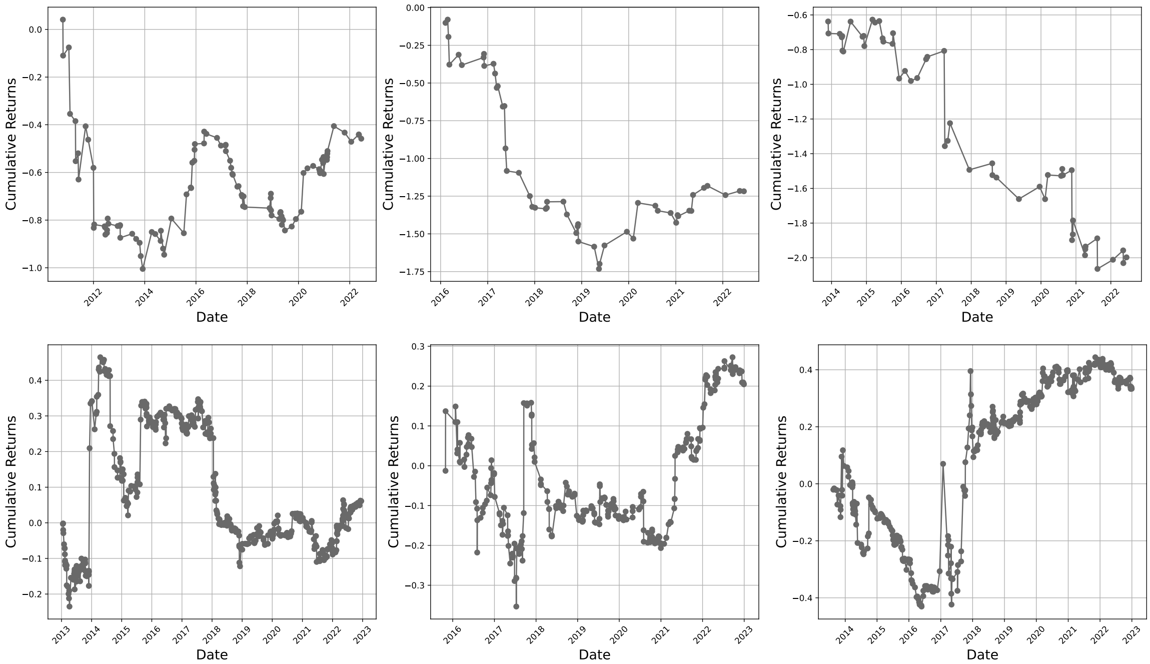

Figure 12: RSI (21, 30/70) Strategy

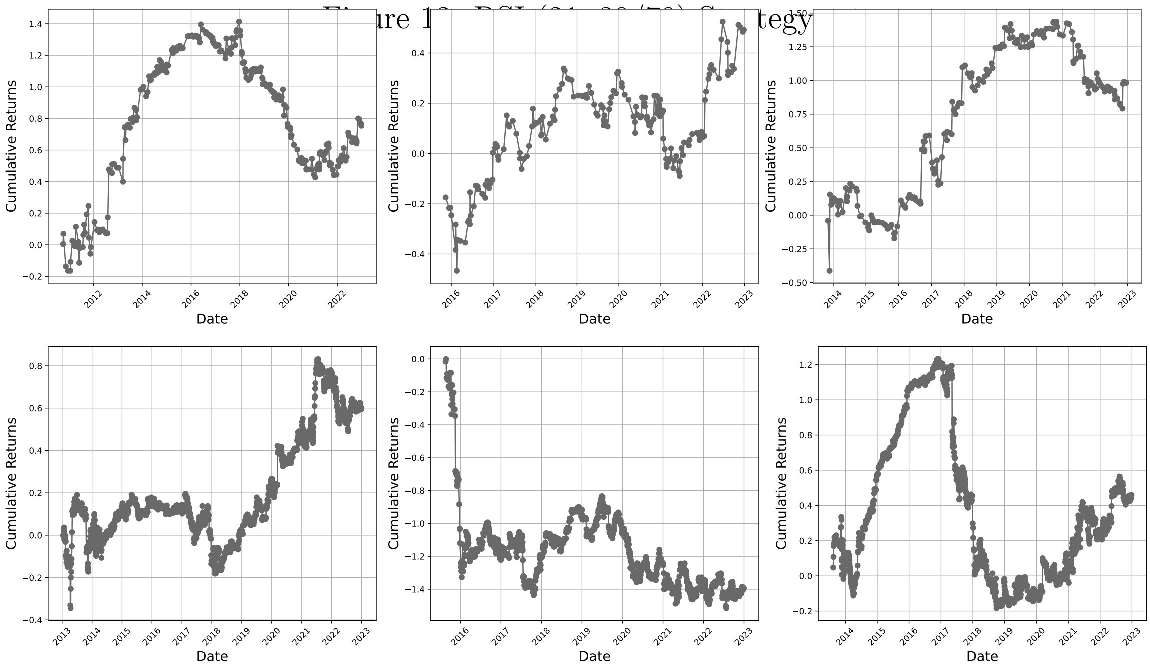

Figure 13: MACD(12, 26, 9) Strategy returns

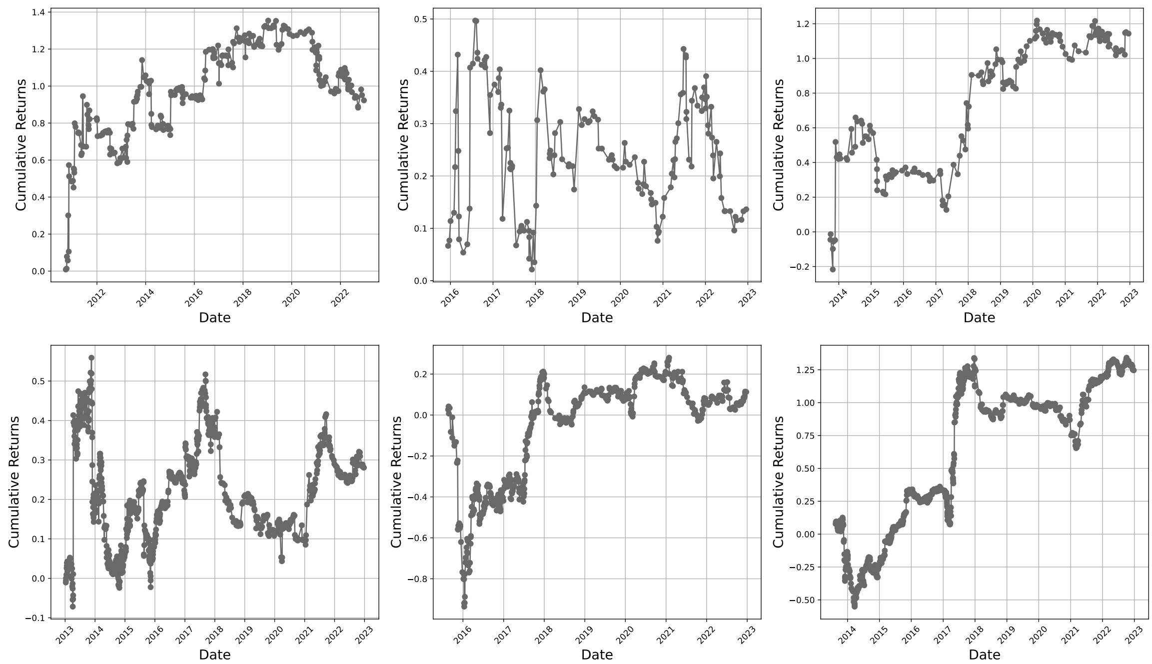

Figure 14: MACD(8, 17, 9) Strategy returns

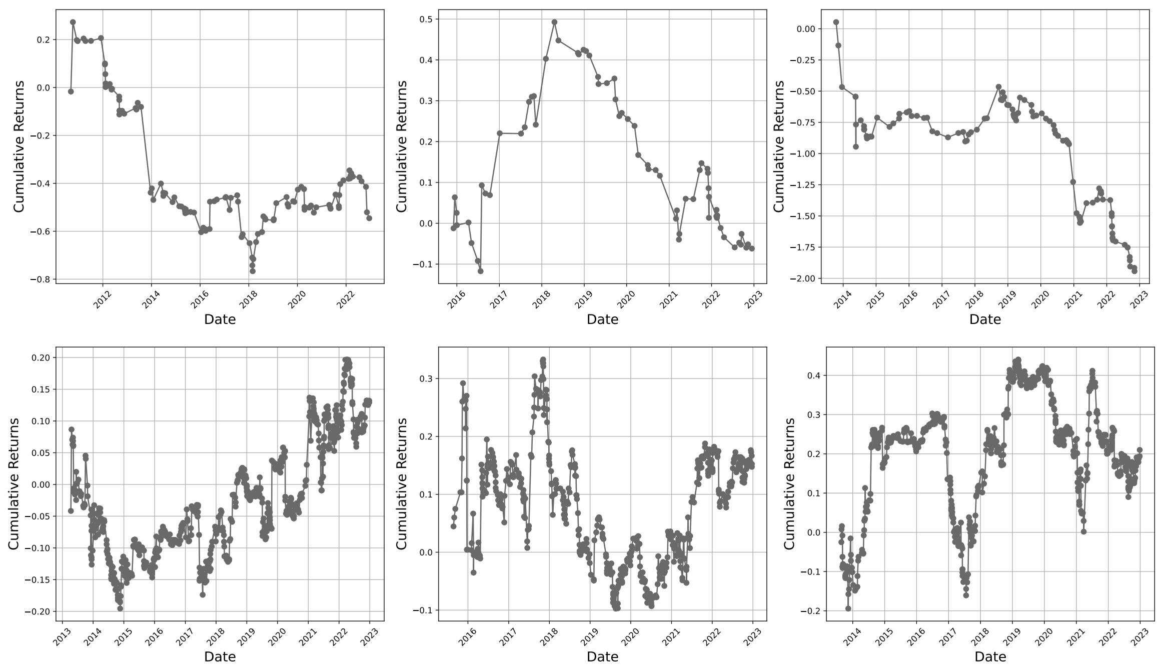

Figure 15: MACD(12, 26, 0) Strategy returns