FOREIGN TRADE UNIVERSITY

HO CHI MINH CITY CAMPUS

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GRADUATION THESIS

Major: International Finance

THE EFFECTIVENESS OF TREND–FOLLOWING STRATEGY IN CRYTOCURRENCY MARKET

Student name: Phạm Hiền Điệp

Student ID: 2013316669

Class: K59CLC2

Intake: K59

Supervisor: Đỗ Duy Kiên, PhD

Ho Chi Minh City, May 2024

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THESIS REMARKS

Student's full name: Phạm Hiền Điệp Student code: 2013316669
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Name of the supervisor: Đỗ Duy Kiên, PhD
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DETAILED REMARKS

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Supervisor
(Signature with full name)

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LIST OF ABBREVIATIONS

No.	Abbreviation	Description
1	ADA	Cardano
2	BCH	Bitcoin Cash
3	BETC	Breakeven Transaction Cost
4	BH	Benjamin and Hochberg FDR controlling method
5	BNB	Binance Coin
6	BSV	Bitcoin SV
7	BTC	Bitcoin
8	BY	Benjamin and Yekutieli FDR controlling method
9	DAO	Decentralized Autonomous Organization
10	DeFi	Decentralized Finance
11	DOT	Polkadot
12	EMH	Efficient Market Hypothesis
13	EOS	EOS Network
14	ETF	Exchange Traded Fund
15	ETH	Ethereum
16	FDR	False Discovery Rate
17	FWER	Family Wise Error Rate
18	ICO	Initial Coin Offering
19	LINK	ChainLink
20	LSEG	London Stock Exchange Group
21	LTC	LiteCoin
22	MA	Moving Average
23	MACD	Moving Average Convergence Divergence
24	NFT	Non-Fungible Token
25	PoW	Proof-of-Work
26	RSI	Relative Strength Index
27	RWH	Random Walk Hypothesis
28	SOL	Solana
29	USDC	USD Coin
30	USDT	Tether
31	XMR	Monero
32	XRP	Ripple

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CHAPTER 1: INTRODUCTION

1.1 Rationale

Following the advent of Bitcoin by the anonymous Satoshi Nakamoto in 2008, a diverse ecosystem of thousands of cryptocurrencies with varying features and use cases have flooded the market. For example, in 2011, Litecoin emerged, offering faster block times and a different hashing algorithm compared to Bitcoin. Ripple (XRP) was introduced in 2012, designed for rapid cross-border transactions and integration with traditional banking systems. In 2015, Ethereum launched, providing a platform for smart contracts and decentralized applications, further expanding the possibilities of Blockchain technology.

This proliferation of cryptocurrencies, along with their own distinctive risk–return profile (Saksonova and Kuzmina-Merlino, 2019), has facilitated the acceptance of such digital asset class as a more mainstream alternative investment worldwide. Notable milestones, such as the launch of Bitcoin futures contracts in December 2017, the subsequent approval of Bitcoin futures ETFs in late 2021, and most recently, the acceptance of Bitcoin Spot ETF by the US Securities and Exchange Commission in Jan 2024 have further integrated Bitcoin into the global financial system. Moreover, Bitcoin's classification as a commodity under the Commodity Exchange Act, and its comparisons to gold as a safe-haven asset (Selmi, Mensi, Hammoudeh, & Bouoiyour, 2018) and as a tool for hedging against traditional investments, inflation, and currency depreciation, especially in regions plagued by economic instability and political turmoil (Dyhrberg, 2016), all underscore its growing acceptance.

According to Institutional Investor Digital Assets Study 2021 published by Fidelity Digital Assets, institutional investors, hedge funds, and high-net-worth individuals worldwide are increasingly allocating capital to cryptocurrencies as part of their investment portfolios, as they are recognizing benefits of such digital asset class as a potential source of diversification and alpha generation. In a recent study, Platanakis and Urquhart (2019) examined the out-of-sample benefits of including Bitcoin in eight popular asset allocation strategies within portfolios containing stocks and bonds. They discovered that incorporating Bitcoin significantly enhances risk-adjusted returns, a result that holds even after adjusting for transaction costs and including a commodity portfolio.

However, skeptics raise valid concerns about the promising nature of cryptocurrencies and the associated risks that have emerged throughout their establishment history. Regulatory uncertainty, market manipulation, and security vulnerabilities pose significant challenges to the widespread adoption and acceptance of these digital assets. High-profile incidents, such as exchange hacks, Ponzi schemes, and fraudulent initial coin offerings (ICOs), have highlighted the urgent need for robust regulatory oversight and investor protection measures (Cheah & Fry, 2015). Besides, the inherent volatility of cryptocurrency prices has led to accusations of speculative bubbles, drawing comparisons to historical financial crises like the Tulip Mania of the 17th century and the dot-com bubble of the late 1990s.

On the other hand, much criticism of Bitcoin and other cryptocurrencies centers on their lack of intrinsic value as well as sufficient reliable fundamental information for valuations, since their value is not derived from any tangible asset or any country's economy but rather on the security of algorithms that trace all transactions or investors' belief. Together with the current context that existing literature on finance concerning Bitcoin and other cryptocurrencies remains limited due to their relatively recent emergence as financial assets, presenting difficulties and challenges for market participants who wish to use fundamental analysis to develop effective trading strategies tailored to this market. Therefore, there is a pressing need for different investment strategies that can effectively navigate the cryptocurrency market's complexities, for instance, technical analysis, specifically the commonly used trend-following strategies provide critical tools in this regard (Zatwarnicki and Zatwarnicki, 2023; Gazizova et al, 2022; Kyriazis, 2019).

Within the realm of cryptocurrency trading strategies, trend-following or trend trading, which historically have generated a positive momentum risk premium as well as significantly positive returns over the past decade when tested across different asset classes (Rohrbach et al., 2017; Dobrynskaya and Dubrovskiy, 2023; Levy and Lopes, 2021; and Kroft, 2018), has emerged as a popular approach among investors seeking to exploit existing market inefficiencies (price momentum and market trends) and generate returns. This strategy is predicated on the notion that markets exhibit persistent trends and that prices tend to follow a certain direction for extended periods before a new catalyst shifting the sentiment and reversing course (Chan & Zhou, 2016). Apopo and Phiri (2021) conducted a robust analysis of the weak-form informational efficiency in the cryptocurrency market, assessing the effectiveness of various trading strategies, which suggests that certain trend-following strategies can capitalize on inefficiencies observed in daily and weekly market movements. Detzel et al. (2018) showed that the 5- to 100-day moving average rule, both in and out of sample, offers predictive power to investors, and trading strategies formulated on these rules generate substantial alphas, utility and Sharpe ratios while significantly reducing the severity of drawdowns relative to a buy-and-hold position in Bitcoin.

However, relatively speaking, the current literature and related empirical works tailored for testing the effectiveness of variety of technical trading strategies in cryptocurrency market over comprehensive scale and with reliable statistical approaches remains limited and inconclusive. For instance, while some studies suggest that trend following may yield positive returns in certain market conditions, others find mixed results or argue that the strategy is inherently flawed due to the efficient market hypothesis (EMH) and the random walk hypothesis (RWH) (Chen et al., 2019).

On the other hand, most existing academic works often focus on Bitcoin and a few large-cap cryptocurrencies, neglecting the growing interest in mid and small-cap non-Bitcoin cryptocurrencies which are gradually driving the market. Furthermore, previous studies examined almost just a single type of technical trading rule rather than a combination used in practice by investors in practice, potentially causing biases in statistical inference due to data mining (Shynkevich, 2012). Finally, methodological and data limitations, as well as sample selection biases further complicate the interpretation and reliability of implied results, for example, previous studies faced challenges to safeguard their implied findings against data-snooping bias that reduce their test power.

Given this above information, this thesis, "The effectiveness of Trend-following strategy in cryptocurrency market", aims to bridge the gap in the literature as well as contribute an up to date empirical evidence of trend-following trading strategies in the cryptocurrency market. By leveraging the technical trading strategies with total of 3,200 trend-following rules on 12 cryptocurrencies with robust statistical techniques, the author aims to evaluate the performance of trend-following strategies over nearly eight years back to the year 2017. The analysis will focus on key performance metrics, including return, risk-adjusted returns, and breakeven transaction costs, to assess the effectiveness and robustness of these strategies. The findings will contribute to a deeper understanding of cryptocurrency market dynamics and provide practical insights for investors aiming to optimize their trading strategies and enhance portfolio performance.

1.2 Research background

1.2.1 Trend-following strategies in traditional markets.

Trend-following strategies have been a cornerstone in traditional financial markets, particularly in forex and commodities trading (Neely, Weller, & Dittmar, 1997 and Miffre & Rallis, 2007), and later become popular in stock markets (Fama & Blume, 1966; Jegadeesh & Titman, 1993). Historical data from as early as the 1980s supports the profitability of these strategies, particularly in markets characterized by significant trends (Brock et al., 1992). Faber (2007) discusses the role of trend-following strategies in portfolio diversification, highlighting their ability to generate positive returns independently of traditional asset classes. By doing so, trend-following can significantly reduce overall portfolio risk and improve risk-adjusted returns, particularly during bear markets. A significant longitudinal analysis by Hurst, Ooi, and Pedersen (2017) examined trend-following strategies over a century, across various asset classes including commodities, equity indices, currencies, and bond markets. Their findings robustly support the effectiveness of trend-following, showing positive returns that are consistent over extended periods and across different economic conditions, challenges the notion that trend-following strategies are only effective in certain eras or market conditions.

However, the effectiveness of trend-following has been increasingly questioned. Notably, the research by Park and Irwin (2007) scrutinizes the common perception of profitable trend-following by analyzing the results of 24 different studies on commodity futures markets. Their meta-analysis reveals that although most studies report positive returns, the effect magnitude varies significantly, suggesting that the profitability may not be as robust or consistent as traditionally believed. Research covering periods such as 2003-2007 and after 2009, indicates a decline in the profitability of these strategies, suggesting that market efficiency may be diminishing their effectiveness (Szakmary et al., 2010). Critics also point to the issue of transaction costs erasing profits and the prevalence of data snooping biases in historical analyses, which may inflate the perceived success of these strategies (Fama & French, 2012).

Furthermore, the growing sophistication of financial markets and the advent of algorithmic trading have introduced new challenges for trend-following strategies. According to Hsieh and Sullivan (2016), the increased use of algorithms has contributed to faster price adjustments in the markets, thereby reducing the duration and predictability of profitable trends. In addition, transaction costs remain a critical factor that can undermine the profitability of trend-following strategies (Edwards, Caglayan, and Thomas, 2013). Even when trends are correctly identified, the costs associated with entering and exiting positions can be substantial enough to negate potential gains. This issue is particularly pronounced in markets where high-frequency trading is prevalent, leading to tighter spreads and increased costs for slower trading strategies. Lastly, the criticism regarding data snooping biases has been further validated by recent studies, such as those by Sullivan, Timmermann, and White (2001), who show that many successful back tests of trend-following strategies are largely a result of overfitting rather than genuine predictive power. These biases occur when strategies are excessively tailored to historical data, leading to inflated performance in theoretical models but poor performance in real-world trading.

1.2.2 Trend-following strategies in cryptocurrency markets

Cryptocurrencies, characterized by high volatility, lacking fundamental data, as well as continuous operation, present unique opportunities for applying trend-following strategies – which have been historically successful in traditional financial markets (James & Menzies, 2020). Early studies generally showed that trend-following could generate substantial returns and provide better risk-adjusted performance, even after accounting for transaction costs. Trend-following strategies are not limited to major cryptocurrencies like Bitcoin and Ethereum. Elendner et al. (2016) explore the application of these strategies across a variety of digital currencies, including altcoins, demonstrating that under certain market conditions, even lesser-known cryptocurrencies can be highly profitable.

Notwithstanding, subsequent analyses have provided a more nuanced picture, of which the success of trend following trading strategy in cryptocurrency market is driven by many factors. For instance, Krafft and Xiong (2018) found that while some trend following strategies yielded positive returns, the results varied greatly depending on the specific cryptocurrency and the market conditions during the study period. According to Larkin and Wong (2018), periods of high volatility in the cryptocurrency market can lead to more pronounced and longer-lasting trends, which are ideal for trend following strategies. This variation underscores the complexity inherent in the cryptocurrency market and suggests that a one-size-fits-all approach to trend following may not be effective across different cryptocurrencies or market environments.

Furthermore, the performance of trend following strategies in cryptocurrencies has also been shown to be highly sensitive to the timeframe over which they are applied. For example, Aste (2016), Cheng et al. (2019), and Tzouvanas et al. (2020) demonstrated that shorter timeframes might capture more volatile movements and offer more opportunities for profitable trades, whereas longer periods might smooth out such volatility, resulting in fewer trading signals but potentially more stable returns. Last but not least, the liquidity of the specific cryptocurrency plays a crucial role in the success of trend following strategies. As noted by Dyhrberg (2016), more liquid markets, such as Bitcoin, allow for quicker and more cost-effective trades, which can enhance the profitability of trend following strategies. In contrast, less liquid markets may impose higher transaction costs and offer less favorable execution prices, which can erode the gains from such strategies.

The author also observed that existing research often exhibits significant limitations in scope and methodology that impact the generalizability and applicability of their findings. Firstly, the studies often did not address potential data snooping biases adequately. Bajgrowicz, P. and Scaillet, O. (2012) provide a critical view on the prevalence of data snooping in technical trading studies, suggesting that many strategies that appear profitable are the result of overfitting. Second, most of these studies focused on a narrow range of cryptocurrencies, primarily Bitcoin and Ethereum on individual level, and utilized a limited set of technical indicators, thereby not fully capturing the complex dynamics of the broader cryptocurrency market. This focus limits the breadth and depth of the research, as these two cryptocurrencies, while popular, do not fully represent the diversity and variability found across the entire market. Cryptocurrencies like Ripple, Litecoin, and recent emerging tokens such as Solana, Binance Coin exhibit different volatility patterns and market behaviors, which might respond differently to trend following strategies. Therefore, the need for more comprehensive studies using more advanced quantitative approaches that consider a variety of cryptocurrencies and employ diverse trend following strategies is highlighted to better understand their effectiveness (Narayan et al.,2021).

Given the significant advances in cryptocurrency markets such as lower transaction costs, the introduction of futures, and mechanisms for short selling, it is crucial to re-evaluate the effectiveness of trend following strategies under these new conditions. The critical question for this thesis remains whether the findings from earlier studies are still applicable in today's context. This inquiry extends to Bitcoin as well as other emerging cryptocurrencies across various trading timeframes and different types of classical trend following strategies. More robust methodologies are needed to control data snooping biases to ensure that the strategies are not only historically effective but also predictive of future performance.

1.3 Research purpose

This study primarily aims to comprehensively assess the effectiveness of trend following strategies in the cryptocurrency market, including but not limited to:

- To conduct a thorough examination of the practice and outcomes of trend following strategies, enhancing the understanding of its efficacy in varying market conditions.
- To provide actionable recommendations for practitioners, derived from the analysis of empirical data and performance metrics within the scope of this research.
- To contribute to the existing body of literature on cryptocurrency and financial market trading strategies by offering a detailed investigation into trend following trading strategy by leveraging price data and typical technical indicators. This contribution is intended to strengthen the current literature, addressing gaps identified in previous studies which may lack comprehensive analysis.

1.4 Research scope and objectives

1.4.1 Research objects

The study focuses on 3,200 trading rules across four primary types of trends following strategies: Moving Average, Resistance & Support, Relative Strength Index (RSI) oscillator, and Moving Average Convergence Divergence. These strategies are chosen due to their prevalence, simplicity, and potential effectiveness in capturing market trends. Regarding the selection of studied cryptocurrencies, the author specifically targets the top 5 largest non-Stablecoin cryptocurrencies by market capitalization of each year, aggregating into total 12 currencies over the testing period. Finally, a key aspect of this research is to evaluate the effectiveness of common trend-following strategies within the cryptocurrency market and compare their performance to the Buy and Hold strategy.

1.4.2 Research scope

The study will examine price movements at daily intervals during the time frame spanning from January 1st, 2017 to April 29th 20224 to best capture a range of market conditions, including bull and bear markets, market corrections, and periods of relative stability given the availability of data. In addition, the study also considers two subperiods which are (1) Jan 1st, 2017 to June 30th, 2020 and (2) July 1st, 2017 to April 29th, 2024 which represent two market cycles, thus it is able to examine the effectiveness of trend following strategy through time. The observational space of this research includes the 12 largest non-Stablecoin cryptocurrencies, which collectively and consistently represent over 85% of the total market capitalization of the cryptocurrency market.

1.5 Research questions

The research questions are designed to probe the depth of strategy effectiveness and practicality across different market conditions and against more passive investment approaches like the Buy and Hold strategy:

Effectiveness of Trend Following Strategies:

For each of long-short combined strategies and long-only strategies:

- Are the positive returns generated by trend following strategies across the portfolios of selected cryptocurrencies statistically significant?
- How do risk-adjusted returns compare to those of the Buy and Hold strategy?
- How consistent are these strategies across different testing timeframes (from 01.2017 to 06.2020, from 07.2020 to 04.2024, and from 01.2017 to 04.2024) compared to the Buy and Hold strategy?

Financial Viability and Transaction Costs:

- What is the breakeven point in terms of transaction costs for these trend following strategies?

- Are these strategies financially viable considering typical transaction costs thresholds which might be observed in practical trading?

Robustness and Reliability of Findings:

- Do the positive results remain significant after adjustments for data snooping biases?

1.6 Research method and data

Research methods

This study employs a quantitative approach to systematically develop, back-test, and evaluate the performance of various trends following trading rules across different cryptocurrencies. The methodology combines both descriptive and inferential statistics to thoroughly analyze the data and provide a clear understanding of the results, specifically:

- Define 3,200 trends following trading rules derived from 4 popular trends following strategy class in daily interval. The analysis will span different market phases, considering key milestones that might impact overall results.
- For the evaluating trend following strategy performance, portfolio of currencies will be constructed under equally distributed mechanism for each individual trading rule. For reach trading rule's portfolio performance measurements such as cumulative return, annual average return, and risk adjusted return like Sharpe ratio, Sortino ratio, and Calmar ratio will be calculated. Finally, the effectiveness of trend following strategy will be evaluated through four trend-following strategy classes under two conditions: (i) long–short, and (2) long-only portfolios.
- Calculate breakeven transaction costs: an analysis to determine the breakeven transaction costs – the cost at which neither positive nor negative return will be generated by the trading rules. It is then compared with relevance transaction cost threshold provide insights into the financial practicality of implementing these strategies in actual trading scenarios.

- Hypotheses testing: the author will conduct tests to identify potential biases including data snooping bias due to multiple hypothesis testing, ensuring the robustness and reliability of the research findings. Regarding inferential statistics, a Shapiro-Wilk normality test will be applied, followed by a hypothesis test for mean positive returns using Stationary bootstrapping method on each individual trading rules portfolio.
- The analysis will also include checks for robustness, particularly addressing the potential data snooping biased raised from multiple hypothesis testing using Family-wise error rate (FWER) and False discovery rate (FDR) method. Besides, breakeven transaction cost will be calculated to examine the final profitability.

Data collection

To conduct the analysis, the author collected cryptocurrency market data from Refinitiv Eikon, a subsidiary of the London Stock Exchange Group (LSEG). The dataset includes daily dollar-based price over 3,050 days from January 1, 2016, to April 29, 2024. Since the study aims to analyze trend following strategies starting in 2017, the 2016 data will be trimmed after creating necessary technical indicators to ensure a complete time-series for the testing period from January 1, 2017, to April 29, 2024. This approach guarantees a smooth back-testing process. Although some cryptocurrencies entered the market later, their data was sufficient long before their inclusion in the back-testing portfolios, ensuring consistent and robust analysis.

1.7 Contribution and significance of the research

This paper significantly enhances the understanding of trend following strategies by providing a comprehensive and up-to-date empirical analysis of their effectiveness in the cryptocurrency market. By addressing gaps in the current literature and introducing novel insights into strategy performance, this research makes several key contributions.

Firstly, the study provides a comprehensive analysis of trend following strategies in cryptocurrency market. The study provides an exhaustive examination of nearly 3,200 trading rules across 4 classes of trends following strategies, including

Moving Averages, Support & Resistance, RSI oscillators, and Moving Average Convergence Divergence as applied to the cryptocurrency market. Unlike prior studies which often focus on a limited scope or older data, this research utilizes data spanning from January 2017 to the most recent time of April 2024, capturing a broad spectrum of market behaviors and trends. By doing so, it offers a refreshed and holistic view of the strategy's effectiveness during various market phases, including periods of high volatility and market corrections.

Secondly, this study makes significant contributions to our understanding of what drives the success of trend following strategies. The effectiveness of these strategies can be explained through various financial theories and insights. For instance, the Efficient Market Hypothesis (EMH) suggests that all known information is already reflected in asset prices, making it hard to consistently outperform the market. However, empirical evidence shows that trend following strategies can exploit market inefficiencies, suggesting that markets are not always perfectly efficient. On the other hand, behavioral finance offers another perspective, explaining how psychological biases can impact investor behavior and create opportunities for trend following strategies. For example, herding behavior, where investors follow the crowd, can create trends in asset prices. Overconfidence bias, where investors overestimate their knowledge and skills, often leads to excessive trading and market inefficiencies that trend followers can exploit. Similarly, the disposition effect, where investors hold onto losing investments for too long and sell winning ones too early, can create price trends that trend following strategies can leverage.

Third, advanced approaches and methodologies are deployed to bridge the technical biases or limitations faced in previous studies. A pivotal aspect of this research is its rigorous methodological approach, which includes comprehensive tests to safeguard against data snooping and data mining biases. By employing robust statistical techniques and validation methods such as transaction cost and multiple hypothesis testing, the study ensures that the results are not merely artifacts of model overfitting or excessive data optimization. This approach significantly strengthens the credibility of the findings, addressing a common critique in financial modeling highlighted by Bajgrowicz and Scaillet (2012), who argued that many apparent successes in financial markets trading strategies could be attributed to such biases.

The significance of this research lies in its potential to influence both academic discourse and practical applications in the field of financial trading:

- Academic Contribution: By thoroughly testing the effectiveness of trend following strategies in the cryptocurrency market, this paper adds valuable knowledge to existing financial literature. It challenges and expands upon previous findings by using a comprehensive dataset and advanced analytical techniques, thus paving the way for future studies to build upon a more solid foundation.
- Practical Implications: For practitioners, this research offers actionable insights that can enhance decision-making processes. The detailed analysis of different trading rules and their performance across various conditions provides traders and investors with refined tools and strategies that are better aligned with market realities. Additionally, the identification of breakeven points and transaction costs helps in assessing the financial viability of these strategies under current market conditions.

In conclusion, this paper not only extends the empirical evidence regarding the effectiveness of trend following strategies in cryptocurrencies but also enhances the understanding of their practical applications, thereby serving as a bridge between theoretical research and real-world trading practices.

1.8 Structure of the research

In addition to the introduction, conclusion, list of acronyms, list of tables, figures, list of references and appendices, the article is structured in 5 chapters as follows:

Chapter 1: INTRODUCTION

Chapter 2: LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Chapter 3: DATA COLLECTION AND METHODOLOGY

Chapter 4: EMPIRICAL RESULTS

Chapter 5: CONCLUSION AND RECOMMENDATIONS

Summary of Chapter 1

Chapter 1 introduces the thesis by detailing the rationale and significance of investigating trend-following strategies in the cryptocurrency market, highlighting the sector's rapid growth and inherent volatility. It reviews the historical application and success of these strategies in traditional markets and underscores the unique challenges and opportunities presented by cryptocurrencies. The chapter clearly defines the research purpose, scope, and objectives, emphasizing the need for robust trading strategies in this volatile market. In addition, the chapter sets clear overall technical processes to assess the performance of 3,200 trading rules on 12 major cryptocurrencies, addressing gaps in existing literature by incorporating robust statistical techniques to avoid biases and data snooping. Lastly, the significance of this research lies in its detailed empirical analysis, which aims to enhance the understanding of trend-following strategies' effectiveness, provide actionable insights for traders, and improve portfolio performance in the dynamic cryptocurrency market.

CHAPTER 2: LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Literature review

2.1.1 Theoretical background on Cryptocurrency market

2.1.1.1 Definition, classification, common use cases, and inherent characteristics of cryptocurrency assets

Blockchain technology has gained significant attention for its potential to transform various industries, especially finance. At its core, blockchain is a decentralized, distributed ledger system that records transactions securely and immutably (Iansiti & Lakhani, 2017), allowing users to conduct transactions without revealing personal identities and promoting trust through public verifiability (Narayanan et al., 2016). The technology eliminates the need for central authorities, enabling peer-to-peer transactions and fostering trust through consensus mechanisms. The success of Blockchain has given rise to the cryptocurrencies market, with a total market capitalization reaching trillions of dollars at its peak (CoinMarketCap, 2023). Investors and institutions view Blockchain and cryptocurrencies as transformative forces with the potential to reshape traditional business models and create new opportunities for innovation (Deloitte, 2020).

Underpinned by the technological power of Blockchain, cryptocurrencies are considered as digital assets that use cryptographic techniques operating on decentralized networks to secure transactions, control the creation of new units, and verify the transfer of assets. In particular, they can serve as a medium of exchange, store of value, and unit of account, enabling peer-to-peer transactions without the need for intermediaries like banks or governments (such as Bitcoin). Beyond those applications, empirical studies have shown that investors and the general public have increasingly perceived cryptocurrencies as a new and attractive investment asset class for hedging risk, generating alphas, and diversifying their overall investment portfolios (Baur & Lucey, 2010; Li & Wang, 2017). For example, Baur and Lucey (2010) conducted an early study on the diversification benefits of cryptocurrencies, focusing on Bitcoin's low correlation with traditional asset classes like stocks, bonds, and commodities. The study found that adding Bitcoin to a diversified portfolio could reduce overall risk due to its unique price dynamics. This low correlation means that Bitcoin's price movements are often independent of those in other markets, providing a potential hedge against volatility in traditional financial assets.

Cryptocurrencies are classified into two main categories: coins and tokens. Coins, like Bitcoin and Ethereum, operate on their own blockchains and are used as a medium of exchange or store of value (Ethereum Foundation, 2020). Tokens are issued on existing blockchains, often through smart contracts, and can represent various assets or grant specific rights (ICORating, 2018). Security tokens represent ownership in a company or asset, while utility tokens provide access to specific services or platforms.

The versatility of tokens has led to a diverse range of applications and use cases in the cryptocurrency ecosystem. Beyond serving as a means of exchange or payment, cryptocurrencies play a vital role in decentralized finance (DeFi), where they are used for lending, borrowing, and staking in peer-to-peer financial systems that operate without traditional intermediaries (ConsenSys, 2021). Cryptocurrencies are also integral to non-fungible tokens (NFTs), a form of digital asset that represents ownership of unique items like art, music, or collectibles. Popular platforms such as OpenSea and Rarible enable artists and creators to tokenize their work, offering new revenue streams and reshaping the creative industry (Athey et al., 2022).

In addition, cryptocurrencies play a central role in decentralized autonomous organizations (DAOs), which are community-driven groups with no central leadership. DAOs use smart contracts to govern decision-making, with token holders voting on proposals (Hassan & De Filippi, 2021). This structure allows for greater democratization and transparency in organizational governance, with notable examples including MakerDAO and Uniswap. Furthermore, cryptocurrencies are utilized in cross-border remittances, providing a faster and more cost-effective alternative to traditional methods. Projects like Stellar and Ripple are designed to facilitate international transactions, reducing fees and processing times (Schwartz et al., 2014). This use case has significant implications for global finance, particularly for unbanked populations and regions with limited access to conventional banking services.

The first cryptocurrency, Bitcoin, was introduced in 2009 by Satoshi Nakamoto, laying the foundation for decentralized digital currency (Nakamoto, 2008) and up to now remains the most prominent cryptocurrency, serving as a store of value and an increasingly adopted medium of exchange. Bitcoin's Proof-of-Work (PoW) consensus mechanism requires miners to solve complex mathematical puzzles to validate transactions and create new blocks, ensuring security and preventing double-spending (Antonopoulos, 2014). Bitcoin's finite supply of 21 million coins has led to its characterization as "digital gold," and it is often used as a store of value and hedge against traditional financial systems.

Beyond Bitcoin, notable cryptocurrencies have been flooded the market with varying features and use cases, reflecting the evolving nature of the cryptocurrency market. For instance, Ethereum is known for its smart contracts and decentralized applications, leading the DeFi movement (Buterin, 2013; ConsenSys, 2021). Ripple (XRP) focuses on fast and low-cost cross-border payments, using the Ripple Protocol Consensus Algorithm (RPCA) to achieve efficiency (Schwartz et al., 2014). Litecoin, created as a faster alternative to Bitcoin, employs a different hashing algorithm to enable quicker block generation (Litecoin Foundation, 2020). Cardano, launched in 2017, emphasizes scalability and sustainability through its Proof-of-Stake consensus mechanism (Hoskinson et al., 2017). Polkadot, designed for interoperability, allows different blockchains to communicate and share information, addressing a key limitation in the cryptocurrency ecosystem (Wood, 2016). Especially, there are evolving variants of cryptocurrencies that are designed for special purposes, for example, Stablecoins, like Tether (USDT) or USD Coin (USDC), a notable category of cryptocurrencies, are used to minimize price volatility, offering a stable value relative to a reference asset like the US dollar, gold, or other commodities (Adrian & Mancini-Griffoli, 2019). Unlike other cryptocurrencies, which can experience significant fluctuations, Stablecoins aim to maintain a consistent value, making them useful for transactions, remittances, and as a store of value.

However, despite the rapid growth and widespread adoption of cryptocurrencies, a critical issue that sets them apart from traditional assets is their characteristic of lacking inherent or fundamental value. Unlike stocks, which represent ownership in a company with potential dividends, or bonds, which yield interest based on the issuer's creditworthiness, most cryptocurrencies do not represent a claim on future cash flows or tangible assets (Yermack, 2015). This absence of intrinsic value creates a speculative environment where cryptocurrency prices are highly volatile, influenced by factors such as market sentiment, new events, media coverages, and changes in regulatory frameworks (Liu & Tsyvinski, 2021), posing investors with associated risks. For example, endorsements or criticisms by high-profile individuals, such as Elon Musk's tweets about Bitcoin and Dogecoin, can cause dramatic price fluctuations (CNBC, 2021).

In addition, during the ICO craze of 2017, numerous companies issued tokens to raise capital, often without a solid business model or viable product, leading to speculative bubbles and regulatory concerns (Zetsche et al., 2019). The collapse of the ICO bubble resulted in significant financial losses for investors and underscored the need for clear valuation metrics and regulatory oversight in the cryptocurrency market (FATF, 2019). Another instance, without traditional valuation anchors like earnings or dividends, Bitcoin's value largely depends on collective belief and speculation (Ciaian et al., 2016). This reliance on sentiment can lead to dramatic price fluctuations, with Bitcoin experiencing extreme highs and lows over short periods, reflecting the speculative nature of the market (Hendrickson et al., 2016). As a result, the unique characteristics of cryptocurrencies, such as their speculative nature, lack of intrinsic value, and ease of creation, require a more nuanced approach of establishing robust regulatory frameworks and effective trading strategies to protect investors and ensure market stability (Liu & Tsyvinski, 2021).

2.1.1.2 Cryptocurrencies markets at a glance

The cryptocurrency market has grown remarkably since the introduction of Bitcoin in 2009, with significant expansion in the number of coins and tokens, as well as the development of various cryptocurrency trading exchanges like Binance, Coinbase, Kraken, and Bitfinex. As of May 2024, the total market capitalization of all cryptocurrencies exceeded $2.5 trillion, with Bitcoin alone accounting for approximately $1.4 trillion of that total (CoinMarketCap, 2024), together with other leading cryptocurrencies like Ethereum, Binance Coin, Tether (XRP), Cardano, and Solana (CoinGecko, 2024). However, despite this rapid growth, cryptocurrencies are relatively small when compared with the combined market capitalization of traditional securities markets like the New York Stock Exchange (NYSE) and NASDAQ, which exceed $50 trillion (World Federation of Exchanges, 2024).

Investor engagement and market liquidity in the cryptocurrency market have seen substantial increases, driven by the expansion of trading platforms and the growing popularity of digital assets. For instance, the cryptocurrency exchange Binance reported over 28.6 million users as of 2022, with daily trading volumes regularly exceeding $20 billion (Binance, 2022). The cryptocurrency market is available 24 hours a day, 7 days a week because it is a decentralized market. Unlike buying and selling stocks and commodities, the cryptocurrency market is not only able to be traded centrally from a single location, on the other hand, cryptocurrency transactions can also take place decentralized, between individuals, in different venues across the world.

However, this surge in investor engagement comes with high volatility and risk. Historical returns on Bitcoin, the first cryptocurrency, demonstrate inherent volatility characteristics of such digital assets. Since its establishment in 2009, Bitcoin has experienced several significant bull runs, but each has been followed by substantial corrections. The high volatility and speculative nature of cryptocurrencies lead to substantial price fluctuations, with Bitcoin often experiencing daily price swings of over 5% (Liu & Tsyvinski, 2021). In terms of market efficiency (referring to the extent to which asset prices reflect all available information), cryptocurrencies, however, are often less efficient compared with traditional markets, as evidenced by the frequent occurrence of price anomalies and arbitrage opportunities. Urquhart (2016) found that Bitcoin exhibited signs of inefficiency, with price patterns suggesting that markets were not always fully integrating information. This inefficiency can lead to opportunities for arbitrage and speculative trading, in addition, it also indicates that prices may not always reflect fundamental value, resulting in increased risk for investors.

Globally, the distribution of cryptocurrency ownership varies, with major countries like the United States, China, and India having significant holdings. However, regulatory approaches differ widely. While some countries, like El Salvador, have accepted Bitcoin as legal tender, others, such as China, have imposed strict bans on cryptocurrency trading and mining (CNBC, 2021). Countries like the United States and the European Union are exploring regulatory frameworks to manage risks and ensure investor protection, reflecting the evolving regulatory landscape (European Central Bank, 2019; FATF, 2019).

2.1.1.3 Development of cryptocurrency markets

The cryptocurrency market has undergone significant evolution since the creation of Bitcoin in 2009, experiencing periods of rapid growth and sharp declines. The Initial Coin Offering (ICO) boom of 2017 marked a key milestone in the market's expansion. During this period, companies raised billions of dollars by issuing tokens to fund various projects, leading to a speculative frenzy and contributing to Bitcoin's dramatic price increase from around $1,000 in January 2017 to nearly $20,000 by December of the same year (Zetsche et al., 2019; CoinMarketCap, 2023). However, the ICO boom also triggered heightened regulatory scrutiny due to fraudulent schemes and investor protection concerns (FATF, 2019). The subsequent correction in 2018, when Bitcoin's price fell by over 80%, highlighted the high level of risk and volatility in the cryptocurrency market (CoinMarketCap, 2023).

In the years following the ICO boom, new trends emerged, contributing to the cryptocurrency market's recovery and expansion. The rise of decentralized finance (DeFi) and non-fungible tokens (NFTs) in 2020 attracted significant investment and mainstream attention, leading to another surge in cryptocurrency market capitalization (Coindesk, 2021). This resurgence culminated in 2021, with Bitcoin reaching an all-time high of nearly $69,000 in November and the total market capitalization exceeding $3 trillion (CoinMarketCap, 2023). This bull run was fueled by increased interest from institutional investors and broader adoption of cryptocurrencies and particularly innovative DeFi projects. However, the market downturn in 2022, triggered by a combination of regulatory developments, global economic uncertainty, and changing investor sentiment, demonstrated the ongoing volatility and unpredictability inherent in the cryptocurrency market (Liu & Tsyvinski, 2022).

A significant event affecting the cryptocurrency market is the Bitcoin halving, which reduces the block reward for miners by half approximately every four years (Antonopoulos, 2014). The halving event in May 2020 was believed to partly cause reduction of the reward from 12.5 to 6.25 Bitcoins, leading to increased speculation and contributing to the 2021 bull run. These halvings are integral to Bitcoin's design, ensuring a finite supply of 21 million coins, and contributing to Bitcoin's appeal as "digital gold" (Nakamoto, 2008; Li & Wang, 2017). Research shows that the anticipation of a halving event can drive Bitcoin prices upward in the months leading up to the event. The 2020 halving, for example, contributed to a significant bull run in 2021, with Bitcoin reaching nearly $69,000 in November, as reduced supply led to higher demand among speculators and institutional investors (Li & Wang, 2017; CoinMarketCap, 2023). This price rally also had a ripple effect on other cryptocurrencies, as increased interest in Bitcoin often leads to greater attention to the broader cryptocurrency market, resulting in price gains across various altcoins and tokens (Ciaian et al., 2016).

However, the speculative hype surrounding halvings can also lead to heightened market volatility, as seen after the ICO boom and the 2022 market downturn. While the reduced supply can drive up prices, the speculative fervor often subsides after the halving event, leading to significant corrections. This was evident after the 2016 halving, where Bitcoin's price initially surged but then fell sharply during the 2018 market downturn (CoinMarketCap, 2023). Similarly, the 2020 halving fueled the 2021 bull run, but the speculative nature of the rally resulted in a correction in 2022, highlighting the risks associated with these events (Liu & Tsyvinski, 2021). Most recently, Bitcoin again witnessed another halving event in

April 2024, thus it is interesting to re-visit cryptocurrency market and analyze their on-going behaviors.

2.1.2 Theoretical background on Trend-following trading strategies

2.1.2.1 Market Efficiency Theory

The Market Efficiency Theory, also known as the Efficient Market Hypothesis (EMH), is a cornerstone of modern finance, positing that in an efficient market, asset prices fully reflect all available information at any given time. This theory, introduced by Eugene Fama in the 1960s, has significantly influenced the understanding of financial markets and the development of investment strategies (Fama, 1970). According to the EMH, if markets are efficient, then all known information is quickly incorporated into asset prices, making it impossible to consistently outperform the market through arbitrage or trend-following strategies, which means that it becomes incredibly challenging for investors to consistently achieve returns that exceed the overall market without taking on additional risk.

The EMH is generally categorized into three forms: weak, semi-strong, and strong. In the weak form, all past price information is reflected in current prices, implying that technical analysis and trend-following strategies cannot generate consistent excess returns. The semi-strong form states that all publicly available information is incorporated into prices, suggesting that fundamental analysis would not lead to consistent outperformance. The strong form of efficiency claims that all information, including insider knowledge, is accounted for in asset prices, rendering all trading strategies ineffective for generating consistent alpha (Fama, 1970). Empirical studies generally support the weak and semi-strong forms of the EMH in traditional financial markets. Early research by Fama (1965) revealed that stock prices tend to follow a "random walk," suggesting that past price trends do not predict future price movements, aligning with the weak form of the EMH. Subsequent studies, like those by Fama and French (1993), demonstrated that asset prices in traditional markets adjust quickly to new publicly available information, consistent with the semi-strong form. These findings imply that trading strategies based on technical or fundamental analysis may not consistently yield excess returns in traditional markets.

Nevertheless, the EMH has been subject to criticism and debate over the years. Critics point out anomalies, behavioral biases, and market trends that suggest markets are not always perfectly efficient. For instance, phenomena such as the January effect, where stocks tend to experience higher returns in January, and the small-cap effect, where smaller companies tend to outperform larger ones, challenge the notion of perfect market efficiency (Banz, 1981; Keim, 1983). Behavioral economists argue that investors often behave irrationally, leading to market inefficiencies and pricing anomalies (Thaler, 1985). In the context of cryptocurrencies, the Efficient Market Hypothesis faces even greater challenges. Cryptocurrency markets are known for their high volatility, speculative nature, and inconsistent regulatory frameworks, which can lead to significant inefficiencies. Empirical studies have shown that these markets often display signs of inefficiency, with price patterns indicating opportunities for arbitrage and trend-following strategies (Urquhart, 2016). The rapid price swings and speculative sentiment in cryptocurrency markets further complicate the concept of market efficiency, suggesting that these markets operate under different dynamics compared to traditional financial markets.

2.1.2.2 Behavioral Finance in trading

Behavioral finance is a field of study that explores how psychological factors and cognitive biases influence investor behavior and financial markets. It emerged as a response to the Efficient Market Hypothesis (EMH), challenging the notion that markets are always rational and efficient. Behavioral finance examines the systematic errors in human decision-making and how these biases can lead to market anomalies, price inefficiencies, and irrational trading patterns (Thaler, 1985). This section delves into the core concepts of behavioral finance and their impact on trading strategies, particularly in the context of trend-following and cryptocurrency markets.

Behavioral finance identifies several cognitive biases and heuristics that can influence investor behavior. These biases often lead to irrational decision-making and contribute to market inefficiencies. Some of the most common biases include:

- *Overconfidence*: Investors often overestimate their knowledge and ability to predict market movements, leading to excessive trading and risk-taking (Barber & Odean, 2001). This overconfidence can create volatile market conditions and increase the likelihood of speculative trading.
- *Anchoring*: This bias occurs when investors rely too heavily on an initial piece of information, such as a stock's previous high price, and fail to adjust their expectations when market conditions change (Tversky & Kahneman, 1974). Anchoring can contribute to price rigidity and hinder market efficiency.
- *Herding*: Investors tend to follow the behavior of others, leading to herd mentality in trading. This bias can result in asset bubbles and rapid price corrections, as seen in the 2017 cryptocurrency's ICO boom and subsequent crash, exemplifies herding behavior, where investors flocked to new tokens despite minimal underlying value (Shiller, 2003).
- *Loss Aversion*: This concept, introduced by Kahneman and Tversky (1979), suggests that investors feel the pain of losses more acutely than the pleasure of gains. This aversion to loss can lead to risk-averse behavior and reluctance to cut losses, potentially exacerbating market downturns.

In cryptocurrency markets, behavioral finance plays an even more significant role due to the speculative nature and high volatility of these markets. The herding effect is particularly pronounced in cryptocurrencies, where social media trends, online communities, and public figures can drive large groups of investors to buy or sell (Urquhart, 2016). This behavior contributes to the rapid price swings and speculative sentiment often seen in cryptocurrencies, leading to market inefficiencies and challenging the traditional concepts of market efficiency. In addition, overconfidence is another common bias in cryptocurrency markets, with investors believing they can predict price movements or that certain cryptocurrencies will continue to rise indefinitely. This overconfidence can lead to speculative bubbles, as seen during the 2017 Initial Coin Offering (ICO) boom, where many investors bought into tokens with little underlying value (Zetsche et al., 2019).

2.1.2.3 Definition and philosophy of trend following strategies

Technical analysis is a method of evaluating financial assets based on historical price and volume data, which relies on the belief that historical price patterns can provide insights into future price movements (Murphy, 1999; Pring, 2002), rather than fundamental analysis, which focuses on a company's financial health and macroeconomic factors. This approach has a long history in financial markets, with its roots tracing back to the early 20th century when Charles Dow, co-founder of the Wall Street Journal, introduced the Dow Theory. This theory proposed that markets move in identifiable trends and that these trends can be used to predict future price movements (Dow, 1902).

Trend-following strategies, a subset of technical analysis, emerged from these early concepts and gained prominence as traders recognized that markets often exhibit consistent trends over time (Brock, Lakonishok, & LeBaron, 1992; Miffre & Rallis, 2007). The primary objective of trend-following is to identify and ride these trends, allowing traders to profit from sustained directional movements. These trends may be upward (bullish) or downward (bearish) consistent with in identifiable patterns, driven by market sentiment, investor behavior, or broader economic factors, and trend-following traders seek to identify and capitalize on these directional movements. A typical trend-following strategy involves buying assets when they are in an upward trend and selling when they are in a downward trend. Traders might also use stop-loss orders to limit potential losses if the trend reverses unexpectedly. The goal is to capture the bulk of a trend's movement while minimizing exposure to market noise and false signals. While the specific tools and indicators used in trend-following have evolved (technical indicators such as moving averages, trend lines, and momentum indicators, etc to more advanced statistical and machine learning models), the core philosophy remains consistent: follow the trend until it shows signs of reversal (Appel, 1979).

Within the diverse universe of different technical trading strategies, trend-following strategies differ from other approaches like momentum and mean reversion, though they share some common elements, such as the use of technical indicators. The essence of trend-following is to identify and ride established market trends—whether upward or downward—until there are clear signs of reversal (Jegadeesh & Titman, 1993; Poterba & Summers, 1988). This strategy tends to work well with longer timeframes and can be applied across different asset classes, such as stocks, commodities, and cryptocurrencies (Antonacci, 2014).

Momentum strategies – which involve frequently buying securities that have shown an upward price trend and selling those that have shown a downward price trend, while are quite similar to trend-following but focus more on the intensity and continued acceleration of asset price movements, within short to medium horizon. This approach typically involves shorter timeframes and is more aggressive in nature, as it seeks to capture rapid price increases, often without holding positions for long periods (Jegadeesh & Titman, 1993). In contrast, mean reversion strategies operate on the assumption that asset prices will eventually return to their average or mean levels. Traders following this strategy aim to capitalize on extreme price deviations by buying when prices are below their historical mean and selling when prices are above it, anticipating a reversion. This approach is inherently contrarian, expecting that market trends will eventually correct, unlike trend-following, which relies on trends persisting over time (Poterba & Summers, 1988).

Trend-following strategies often rely on various technical indicators to identify and confirm trends. These indicators are used to determine the direction of the trend, measure its strength, and identify potential reversal points. Some of the most commonly used indicators in trend-following include:

- *Moving Averages:* Moving averages smooth out price data over a specified period, helping to identify the overall trend. Traders often use simple moving averages (SMA) or exponential moving averages (EMA) to gauge trend direction. Crossovers, where a shorter-term moving average crosses above or below a longer-term moving average, are commonly used to signal trend changes (Murphy, 1999).
- *Relative Strength Index (RSI):* The RSI measures the speed and change of price movements to identify overbought or oversold conditions. An RSI above 70 typically indicates overbought conditions, while an RSI below 30 suggests oversold

conditions. This indicator can be used to confirm trends and spot potential reversals (Wilder, 1978).

• *Moving Average Convergence Divergence (MACD):* The MACD calculates the difference between two moving averages to identify trend momentum. Traders use MACD crossovers to signal changes in trend direction, while the histogram provides visual representation of momentum shifts (Appel, 1979).

• *Trend lines and Channels:* Trend lines connect significant price points to visualize the trend's direction. Channels, which are parallel trend lines, help identify areas of Resistance and Support which are the levels of price that are relatively more difficult to break through. These visual tools are useful for confirming trends and anticipating potential breakouts (Edwards & Magee, 1948).

Trend-following strategies are deeply intertwined with the concepts of market efficiency and behavioral finance. According to the Market Efficiency Theory, specifically the Efficient Market Hypothesis (EMH) introduced by Eugene Fama (1970), asset prices in an efficient market fully reflect all available information at any given time. This hypothesis suggests that it is impossible to consistently outperform the market through arbitrage or predictive strategies like trend-following, as prices already incorporate all known information. The strong and semi-strong forms of the EMH, which posits that current prices reflect all past market data, directly challenges the effectiveness of trend-following strategies since these strategies rely on historical price patterns to predict future movements (Fama, 1970). Empirical studies have shown mixed results regarding the EMH, with some supporting the hypothesis in traditional markets (Fama & French, 1993) while others highlight anomalies and market inefficiencies that can be exploited by trend-following strategies (Banz, 1981; Keim, 1983).

Behavioral finance offers a contrasting perspective by emphasizing how psychological factors and cognitive biases influence investor behavior and market dynamics. This field argues that markets are not always rational or efficient due to systematic errors in human decision-making (Thaler, 1985). Behavioral biases such as overconfidence, anchoring, herding, and loss aversion contribute to market inefficiencies, which trend-following strategies can exploit (Barber & Odean, 2001; Tversky & Kahneman, 1974; Shiller, 2003; Kahneman & Tversky, 1979). For instance, herding behavior can create prolonged market trends that trend-following strategies aim to capitalize on. In the context of cryptocurrencies, which exhibit high volatility and speculative behavior, the principles of behavioral finance are particularly relevant. Studies have shown that trends in cryptocurrency prices can often be attributed to investor psychology and social influences, providing fertile ground for trend-following strategies (Urquhart, 2016; Zetsche et al., 2019).

Trend-following strategies have been used in traditional financial markets, such as equities, commodities, and foreign exchange, where they have a history of success. In these markets, trend-following strategies typically focus on medium- to long-term trends, allowing traders to capitalize on persistent price movements (Miffre & Rallis, 2007). In emerging markets like cryptocurrencies, trend-following strategies can be especially appealing due to the high volatility and frequent price trends. However, the inherent risks associated with high volatility and rapid trend reversals require careful risk management and robust trading strategies (Urquhart, 2016).

Trend-following strategies, despite their potential benefits, face several limitations and challenges that can impact their effectiveness. Technical indicators, which are essential inputs to trend-following, may generate false signals in choppy or sideways markets, leading to premature entries or exits and resulting in losses for traders (Murphy, 1999). Market noise from high-frequency trading and short-term price fluctuations can further disrupt trend-following strategies, reducing their reliability, especially in highly volatile markets (Lo & MacKinlay, 1989).

Additionally, survivorship bias can skew the perceived success of trend-following strategies, as studies may focus on successful assets or strategies while overlooking failed ones, creating an overestimation of their effectiveness when conducting strategy research (Brown et al., 1992). Regulatory risks also pose a significant challenge; sudden changes in regulatory environments can abruptly alter market trends, requiring traders to adapt their strategies accordingly (FATF, 2019).

These limitations underscore the need for careful risk management and flexibility when implementing trend-following strategies in practice.

2.1.3 Empirical findings on effectiveness of Trend-following trading strategies in cryptocurrency markets

Empirical studies have provided insights into the effectiveness of trend-following strategies across a variety of financial markets, yielding implications for traders and investors. Trend-following relies on the concept that financial markets often display consistent trends, driven by underlying factors such as investor sentiment, market psychology, or broader economic conditions. The successful implementation of trend-following strategies can yield considerable returns, with evidence indicating positive risk-adjusted performance over various timeframes (Brock et al., 1992).

In the context of multi-asset investment, Geczy and Samonov (2017) revealed that trend-following strategies provided consistent returns over extended periods. This study's implication is that trend-following can be applied across different asset classes, offering a flexible approach to portfolio diversification. Given that these strategies worked across a range of assets, it suggests that trend-following is versatile and not confined to a single market type. Faber (2007) explored the use of moving averages in equity markets and found that trend-following strategies could help reduce drawdowns during significant market downturns, such as the dot-com bubble burst and the 2008 financial crisis. In commodities markets, Miffre and Rallis (2007) demonstrated that trend-following strategies outperformed traditional benchmarks, delivering positive risk-adjusted returns. This finding has significant implications for investors seeking alternative strategies beyond equities, suggesting that trend-following could offer diversification and reduce exposure to traditional market fluctuations. The ability of these strategies to generate returns in commodities markets, known for their cyclical nature, indicates that identifying and following trends could be an effective way to capitalize on broader economic patterns. These findings indicate that trend-following could serve as a protective strategy, reducing risk and minimizing losses during periods of market instability.

In cryptocurrency markets empirical evidence regarding the effectiveness of trend-following strategies presents a mixed picture. The broader cryptocurrency market, which includes altcoins and tokens, can offer additional opportunities for trend-following due to its diverse nature and tendency to follow Bitcoin's lead. Balcilar et al. (2017) found that trend-following strategies in the cryptocurrency market could yield positive returns, though with a higher risk profile compared to traditional financial markets. Another study by Leung, Chong, and Fung (2015) specifically examined the profitability of technical trading rules, including trend-following strategies, in the Bitcoin market. Their findings indicate that simple moving average and momentum-based strategies were able to generate positive returns over a significant portion of the study period. Moreover, the research conducted by Frydenberg, Johansen, and Sornette (2017) explored the performance of trend-following strategies across various cryptocurrencies, not just Bitcoin. Their empirical analysis revealed that these strategies could capture substantial profits, particularly during bull markets when prices exhibit strong upward trends. However, they also noted that the effectiveness of these strategies tends to diminish during bear markets or periods of extreme volatility, pressing the need for dynamic strategy adjustments to manage risks.

While some studies highlight potential profitability, many others reveal significant limitations, critical challenges, and risks associated with these strategies. Given that trend-following strategies are often most effective in markets with clear and persistent trends, Brock et al., (1992) believes that such strategies tend to perform well only when market conditions are stable and exhibit a consistent directional movement. For example, Faber (2007) found that trend-following using moving averages reduced drawdowns in the U.S. stock market, suggesting that these strategies could provide stable returns during periods of sustained market trends. In contrast, in highly and more frequently volatile markets, such as cryptocurrencies markets, the effectiveness of trend-following strategies may be compromised. Specifically, the inherent high volatility characteristics of cryptocurrency markets often leads to rapid and unpredictable price swings or frequent trend reversals, undermining the core principle of trend-following strategies, which rely on sustained directional movements. For instance, Urquhart (2016) noted that while Bitcoin prices exhibit exploitable trends, the frequent and abrupt changes in these trends pose substantial risks for traders. This extreme volatility nature, driven by factors such as speculative trading, regulatory news, and market sentiment, can lead to substantial losses if not managed properly.

A study by Balcilar et al. (2017) supports these concerns, highlighting that although trend-following strategies can generate positive returns in the cryptocurrency market, they come with significantly higher risk compared to traditional financial markets. This increased risk is attributed to the market's heightened sensitivity to news and events, leading to sudden and severe price corrections. The study indicates that while trend-following strategies might capture some of the rapid price movements characteristic of cryptocurrencies, the frequent false signals and trend reversals can erode profits and increase the likelihood of losses. These findings suggest that the success of trend-following in cryptocurrency markets is highly contingent on effective risk management and the ability to adapt quickly to changing market conditions.

Another critical factor impacting the effectiveness of trend-following strategies in cryptocurrency markets is the presence of market noise, which can obscure genuine trends and generate false signals. According to Lo and MacKinlay (1989), high-frequency trading and short-term price fluctuations contribute to this noise, making it challenging to identify and follow sustained trends. Or even if the trends are properly detected, transaction cost can erode significantly to abnormal return. This issue is particularly pronounced in cryptocurrency markets, where speculative trading and the influence of social media can lead to erratic price movements. The resulting market noise complicates the application of traditional trend-following indicators, such as moving averages and momentum oscillators, leading to potential misinterpretations and premature trades.

Furthermore, the unique regulatory environment of cryptocurrency markets adds another layer of complexity. Regulatory announcements and changes can have a profound and immediate impact on market trends, often causing abrupt and significant price movements. The Financial Action Task Force (FATF, 2019) highlights the regulatory risks associated with cryptocurrencies, noting that sudden changes in the regulatory landscape can disrupt market stability and trend patterns. For trend-following strategies, this regulatory uncertainty can lead to unexpected trend reversals and increased volatility, undermining the reliability of these strategies.

On the other hand, survivorship bias presents a significant challenge in assessing the true effectiveness of trend-following strategies in cryptocurrency markets. This happens when studies only look at the strategies that have been successful and ignore the ones that have failed. As a result, the overall effectiveness of these strategies is often overestimated. Brown et al. (1992) emphasize that this bias can skew empirical findings, creating a misleading perception of trend-following success. In the volatile and nascent cryptocurrency market, where many trading strategies may fail due to rapid market shifts and high-risk exposure, accounting for survivorship bias is crucial in evaluating the genuine performance of trend-following strategies.

In addition to survivorship bias, data snooping poses another critical challenge. This occurs when researchers repeatedly test various models and strategies on the same dataset until they find one that appears to work, inadvertently capitalizing on random patterns rather than true predictive power. White (2000) explained that this practice can lead to over-fitted models, which seem great in historical tests but fall flat in real-world trading. In the crypto market, where data is both limited and highly volatile, the risk of data snooping is even higher. Sullivan, Timmermann, and White (2001) highlighted how this can result in strategies that look promising in back tests but fail miserably when applied in real trading. Thus, addressing both survivorship bias and data snooping is essential for accurately evaluating the effectiveness of trend-following strategies in the cryptocurrency market.

2.2 Hypothesis Development

Existing research on trend-following strategies within cryptocurrency markets provides a mixed picture of their effectiveness. Studies like those conducted by

Balcilar et al. (2017) and Leung et al. (2015) have shown that trend-following strategies can yield positive returns, although often accompanied by higher risk compared to traditional financial markets. For example, Balcilar et al. (2017) demonstrated that momentum-based trading strategies could be profitable in cryptocurrency markets, capitalizing on significant price movements. Similarly, Leung et al. (2015) found that simple moving average and momentum-based strategies were able to generate positive returns over a significant portion of the study period. Frydenberg, Johansen, and Sornette (2017) found that these strategies could capture substantial profits during bull markets, highlighting the potential of trend-following to exploit strong upward trends in cryptocurrencies.

Conversely, other studies such as those by Urquhart (2016) indicate that the high volatility and frequent trend reversals in cryptocurrency markets can undermine the effectiveness of trend-following strategies. This view is also supported by the efficient market hypothesis (EMH), which suggests that any apparent success of these strategies could be attributed to market inefficiencies that are temporary and often unpredictable. Critics argue that the highly speculative nature and the rapid price swings inherent in cryptocurrency markets pose significant challenges to the consistent profitability of trend-following strategies. Liu and Tsyvinski (2021) further argue that cryptocurrencies' extreme volatility and susceptibility to speculative bubbles significantly reduce the predictability required for successful trend-following strategies.

Hudson and Urquhart's (2019) study serves as a pivotal reference point for this thesis. They conducted a comprehensive empirical analysis focusing on technical trading rules where a major of them are trend-following rules within cryptocurrency markets from January 2017 to June 2020. Their research aimed to assess the profitability and statistical significance of various trading rules across, primarily centered on Bitcoin. By employing robust statistical tests and back-testing methodologies, they evaluated the performance of each trading rule in terms of profitability and predictive power, considering factors such as transaction costs, market liquidity, and slippage. The findings from Hudson and Urquhart's study provided compelling evidence regarding the potential profitability of trend following strategy to generate positive returns and offer outperforming risk-adjusted performance compared to buy and hold only, even after accounting for transaction cost and data snooping issues.

In addition, several key limitations of existing literature and empirical evidences surrounding this topic were also identified by Hudson and Urquhart's (2019) in their study. Firstly, previous research was confined to Bitcoin and some altcoin long term in the past, thereby narrowing the generalizability of their findings to other newly emerging cryptocurrencies which possess different price behaviors. Secondly, past studies mainly pick, hold, and evaluated a certain set of cryptocurrencies which were deemed to represent the market at the time the study was conducted, this potentially falls into survivorship biased since the choice on selected cryptocurrencies were made on the already-successful ones. Thirdly, the time period analyzed in previous studies rarely extended beyond 2018, which means significant market developments and volatility in subsequent years were not captured. Lastly, existing papers did not sufficiently address the issue of data snooping bias, which could lead to overestimating the effectiveness of the trading strategies. Hudson and Urquhart recommended that future research should include a broader range of cryptocurrencies, extend the analysis period to include more recent data, and employ more robust statistical techniques to address potential biases.

Building on the technical framework established by Hudson and Urquhart, this thesis seeks to bridge the gaps identified in their study through several methodological enhancements. Firstly, this research includes a diverse range of cryptocurrencies beyond Bitcoin, reselected into the trading rule's portfolio every year, thereby providing a more comprehensive view of the market while avoiding survivorship bias. By examining multiple cryptocurrencies assets, the study aims to generalize the findings and offer insights applicable to the wider cryptocurrency market. Secondly, the analysis extends over a more extended period, including data up to the most recent in April 2024, which captures a broader range of market conditions and market's quick evolvement, including the recent surge in institutional interest, regulatory changes, interest rate hike, and Bitcoin halving event. This allows for the assessment of strategy performance across different market phases, including bull and bear markets. Furthermore, this research employs robust statistical techniques such as the Family-Wise Error Rate (FWER) and False Discovery Rate (FDR) to ensure the reliability and validity of the findings. These methods help control the increased likelihood of Type I errors when multiple hypotheses are tested simultaneously, thereby addressing the issue of data snooping bias identified in previous studies. By applying these rigorous statistical techniques, the study aims to provide a more accurate assessment of the financial viability of trend-following strategies in cryptocurrency markets.

A key distinction between this research and Hudson and Urquhart’s study is the exclusive focus on trend-following strategies. While Hudson and Urquhart examined a broad spectrum of technical trading rules, this thesis narrows the focus to specifically evaluate trend-following strategies. This targeted approach allows for a deeper investigation into the nuances and performance of trend-following strategies, providing detailed insights into their effectiveness across various market conditions. This focus also addresses the recommendation by Hudson and Urquhart to conduct more specialized studies within the broader context of technical analysis.

The formulation of hypotheses is structured around three main objectives:

(1) Evaluating the standalone performance of each individual trend-following trading rules (which are Trend-following strategy with specific parameterization, and belongs to a trend-following strategy’s class or category);

(2) Assessing the performance of Trend-following strategy classes or categories (which are Trend-following strategy but using different trend detecting indicators, thus provides distinctive entry/exit signal from others);

(3) And examining the overall performance of trend-following strategies across different periods.

Each hypothesis is designed to test the robustness and effectiveness of these strategies in generating statistically significant positive returns:

- *H1: Each trading rule stand-alone generates statistically significant positive mean return over three tested periods of from January 2017 to June 2020, from July 2020 to April 2024, and from Jan 2017 to April 2024.*
- *H2: Each Trend-following strategy class or category generates statistically significant positive mean return over three tested periods of from January 2017 to June 2020, from July 2020 to April 2024, and from Jan 2017 to April 2024.*
- *H3: The overall trend following strategy generates statistically significant positive mean return over three tested periods of from January 2017 to June 2020, from July 2020 to April 2024, and from Jan 2017 to April 2024.*

The first hypothesis (H1) posits that each trading rule, when considered independently, generates a statistically significant positive mean return over the three tested periods: January 2017 to June 2020, July 2020 to April 2024, and January 2017 to April 2024. This hypothesis aims to validate the effectiveness of individual trading rules in generating positive returns across different market phases. By examining each rule independently, the research provides a granular analysis that can identify specific rules that consistently perform well, thereby addressing the gap in Hudson and Urquhart's study which:

(1) focused predominantly on some cryptocurrencies and potentially trapped by survivorship bias. Hudson and Urquhart selected them as successful currencies to represent the whole market at the time the research was conducted (in 2018-2019), then back-testing their performance in period 2015-2017 and might neglect the fact that, within 2015-2017, the selected currencies could not fully represent the whole market, or there might be more other cryptocurrencies that also significantly shared the same position as the selected currencies to represent the whole market, but then failed to maintain it until the time Hudson and Urquhart made the research. This biased could then overstate the results of Trend-following strategies since it focused on the currencies with relatively more sustainable uptrend.

(2) The study did not thoroughly extent beyond 2018 in which the whole cryptocurrency market witness a significant correction after rising ten to hundreds of times in 2016-2017 period.

This approach ensures that the findings are not only applicable to Bitcoin but also to other cryptocurrencies, offering a broader perspective on the effectiveness of trend-following strategies. Previous studies have highlighted the potential of individual trading rules such as moving averages and momentum indicators in capturing profitable trends in volatile markets. For instance, the moving average crossover strategy has been shown to be effective in identifying entry and exit points during trending market conditions (Zhou and Dong, 2020).

The second hypothesis (H2) suggests that each trading strategy category generates a statistically significant positive mean return over these same periods. This hypothesis seeks to evaluate the performance of broader strategy categories rather than individual rules, thereby providing insights into the effectiveness of different types of trend-following strategies. By categorizing the trading rules and evaluating their collective performance, this research followed technical framework and recommendations guided by Hudson and Urquhart's (2019) to bridge the gap in previous studies that often focused on single types of technical trading rules. It also considers the evolving nature of cryptocurrency markets and aims to identify strategy categories that are resilient across different market conditions. Studies by Faber (2007) and Moskowitz et al. (2012) have shown that combining multiple trend-following strategies can enhance performance and reduce risk by diversifying exposure to different market conditions.

The third hypothesis (H3) proposes that the overall trend-following strategy generates a statistically significant positive mean return over the three tested periods: January 2017 to June 2020, July 2020 to April 2024, and January 2017 to April 2024. This hypothesis evaluates the combined effectiveness of all trend-following strategies, providing a holistic view of their performance in the cryptocurrency market. By considering the overall performance, this research addresses the limitations of studies that focused only on short-term profitability without considering long-term sustainability, as well as provide the up to date assessment up to April 2024. This comprehensive approach aims to determine whether trend-following strategies can consistently generate positive returns over an extended period, thus enhancing the findings of Hudson and Urquhart by incorporating a broader currency and a longer timeframe. Studies by Hurst, Ooi, and Pedersen (2017) have demonstrated that trend-following strategies can be effective over long horizons, capturing persistent trends across various asset classes, including commodities, equities, and bonds.

Summary of Chapter 2

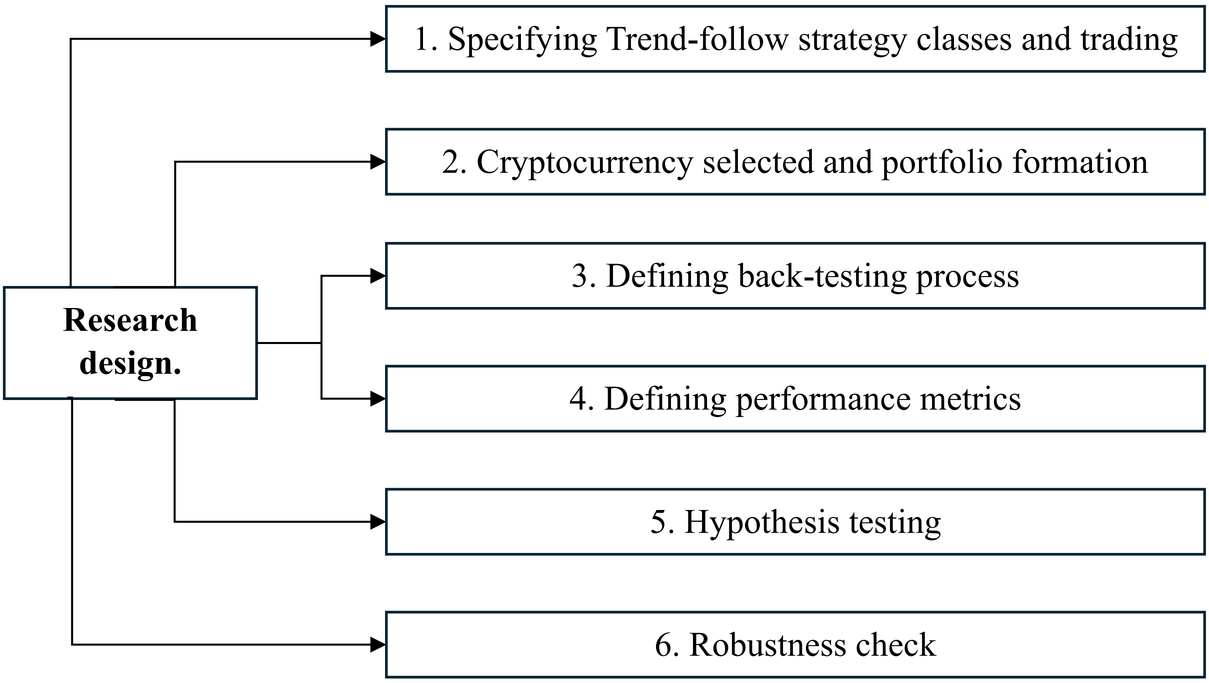
The cryptocurrency market, underpinned by blockchain technology, has transformed finance by enabling secure, decentralized transactions without intermediaries. Cryptocurrencies, classified into coins (e.g., Bitcoin, Ethereum) and tokens, serve as mediums of exchange, stores of value, and units of account, offering diversification and risk hedging opportunities. They have applications in decentralized finance (DeFi), non-fungible tokens (NFTs), decentralized autonomous organizations (DAOs), and cross-border remittances. However, cryptocurrencies are highly volatile, lack intrinsic value, and are influenced by market sentiment, regulatory changes, and speculative trading. Bitcoin, introduced in 2009, remains prominent, characterized by its finite supply and Proof-of-Work consensus mechanism. The market's capitalization exceeded $2.5 trillion by April 2024 but remains much smaller than traditional securities markets. Trend-following trading strategies, part of technical analysis, aim to capitalize on consistent market trends but face challenges in the volatile cryptocurrency market. Empirical studies show mixed results, with some indicating profitability during bull markets and others highlighting risks from frequent trend reversals. The Market Efficiency Theory (EMH) and behavioral finance offer contrasting views on market efficiency and cognitive biases in trading. Trend-following strategies use technical indicators like moving averages and momentum oscillators but face limitations in volatile markets in practical trading as well as potential data snooping, data mining, and survivorship biased in strategy research. Hudson and Urquhart's (2019) study on Bitcoin provides a framework, but further research is needed across more cryptocurrencies and time periods. This thesis will evaluate trend-following strategies in cryptocurrency markets, focusing on individual rules, strategy categories, and overall performance, testing if they can generate and maintain significant positive returns despite market challenges.

CHAPTER 3: DATA AND METHODOLY

3.1 Research design

To obtain the outcome of a trend-following strategy, it is essential to test the strategy on historical data. This research employs a well-established research design in common trading strategy research literature and was also likely adopted by Hudson and Urquhart (2019). The detailed research design was guided by Michael L. Halls-Moore (2010) in his published "Successful algorithm trading" which highlights six steps in trading strategy research and evaluation. These steps are well-suited to the objective of the study, which is to evaluate the effectiveness of the trading strategy systematically and thoroughly. Each step addresses a critical aspect of the strategy's development and testing, ensuring that the final assessment is thorough and reliable, as follows:

Figure 3.1: Research Design



(Sources: Michael L. Halls-Moore (2010), author's compilation)

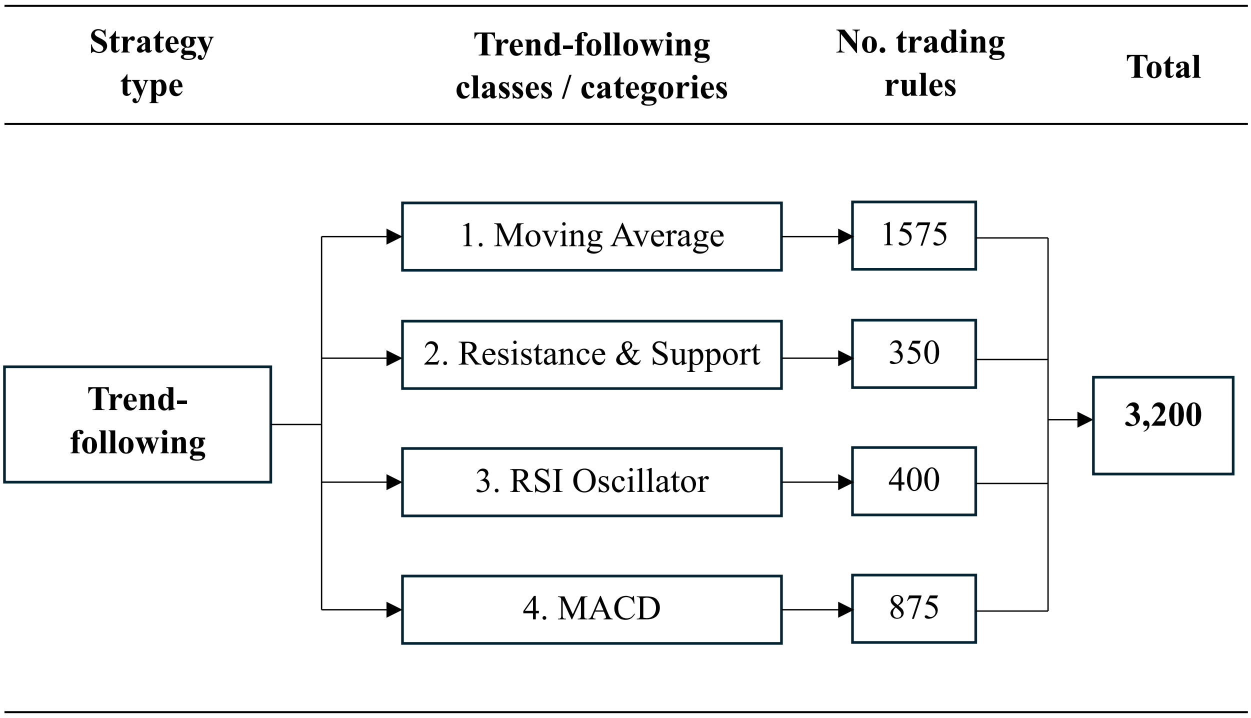
3.1.1 Specifying Trend-following strategy classes and trading rules.

A trading strategy is a set of instructions that defines when to enter and exit a trade in a financial instrument such as a stock, cryptocurrency, or commodity. These strategies are typically based on technical or fundamental analysis, or a combination of both. In recent decades, there has also been the emergence of more advanced trading approaches that are not strictly based on traditional technical or fundamental analysis, such as econometrics and machine learning-based strategies, which primarily rely on sophisticated statistical models and algorithms to learn from various kinds of data and improve over time. A crucial part of any trading rule is incorporating risk management techniques which involves setting stop-loss orders to automatically exit a trade if the price reaches a certain level to limit potential losses or taking profits at pre-defined levels to lock in gains. As each trading strategy is tied to different objectives, the trading strategy universe is very diverse, given by different underlying trading philosophies, asset classes, timeframes, and operational parameters of technical models behind the strategy.

This study refers the past studies of Hudson et al. (2019) and Hsu et al. (2016), who conducted a comprehensive test on the effectiveness of technical analysis in cryptocurrency market, but with a more focused look at trend-following strategies as recommended by them. The author employs 3,200 trend following trading rules derived from different plausible parameterizations of four common trend following classes in daily trading intervals.

The four classes of trend-following strategies include (1) Moving Average, which attempts to ride trends and identify imminent breaks in trends by examining the behavior of the price relative to a moving average of a given length; (2) Resistance – Support, which operates on the idea that breaking a support or resistance level (lower and upper bounds where the asset price faces difficulty to penetrate through) will prompt further rapid price movement in the same direction; (3) Relative Strength Index (RSI) oscillator, which measures the relative strength or momentum of the price or the strength of the trend characterized by its value oscillating around 0 to 100, where extreme values indicate overbought or oversold stages as an indication of imminent trend reversal; and (4) Moving Average Convergence Divergence (MACD), which is a trend-following momentum indicator that simultaneously helps identify the direction and momentum of a trend based on the relationship between two exponential moving averages of the currency price. The final 3,200 distinct trading rules include 1,575 moving average rules, 350 resistance – support rules, 400 RSI oscillator rules, and 875 MACD rules.

Figure 3.2: The Trend-following strategy employed under classification



(Source: Hudson and Urquhart (2019), author's compilation)

(1) Moving Average

The moving average indicator (MA) is a popular tool in technical analysis used to smooth out price data and identify trends by averaging the asset's price over a specified period. The moving average of an asset's price (commonly close price) over an n-period lookback window is simply the average of the asset's price over the past n days. Moving average trading rules are among the most widely used technical trading rules by traders (Taylor and Allen (1992)). These rules attempt to ride trends and identify imminent breaks in trends or the emergence of new trends. For example, the most basic moving average rule is that if the current price is higher (lower) than the moving average over n days, a buy (sell) signal is generated. However, traders often replace the current price with a short-term moving average or state that the short-term moving average must be greater than the long-term moving average by a certain percentage or must persist for a certain number of days.

Trading rules: If the moving average price with a shorter lookback window moves up at least x percent above the moving average price with a longer lookback window and remains so for d days, enter a long position and hold the position until the moving average price with the shorter lookback window moves down at least x percent below the moving average price with the longer lookback window and remains so for d days, at which time close the long position and enter a short position. If the moving average price with the shorter lookback window moves down at least x percent below the moving average price with the longer lookback window and remains so for d days, enter a short position and hold the position until the moving average price with the shorter lookback window moves up at least x percent above the moving average price with the longer lookback window and remains so for d days, at which time close the short position and enter a long position.

In the case where the lookback window is one, the moving average price is the close price of the asset itself. The author studies 1,575 Moving Average trading rules under different parameterizations regarding the length of n lookback window, x percentage, and d day.

The indicator's mathematical definition, trading signal generation, and parameterization settings for the Moving Average strategy class can be found in the Appendix.

(2) Resistance and Support

Resistance and Support trading strategies identify key levels on a price chart where an asset's historical price faces difficulty to rise above (resistance) or falling below (support). These levels act as psychological barriers for traders. The primary idea behind these strategies is that when the price breaks through these levels, it is likely to continue moving in the same direction. This concept is based on the psychology of market participants and the dynamics of supply and demand. For example, when a resistance level is breached, it may become a new support level as traders who initially missed the breakout look to buy at that level. Conversely, when a support level is broken, it may become a new resistance level as traders who missed selling at the higher price aim to sell at that level (Murphy, J.J. (1999) and Pring, M.J. (2002)). In this study, the author defines the Resistance and Support of an asset's price as the maximum/minimum asset's close price over the last *n* days lookback window.

The trading rule for Resistance and Support class would be: When the price moves up at least *x* percent above the resistance and remains so for *d* days, enter a long position, and hold it. If the price moves down at least *x* percent below the support and remains so for *d* days, close the previous position if it was long and then enter a short position. The author studies 350 Resistance & Support trading rules with different parameterizations in term of *n* lookback window, *x* percentage, and d day.

The indicator's mathematical definition, trading signal generation, and parameterization settings for the Resistance and Support strategy class can be found in the Appendix.

(3) RSI Oscillator

A type of technical trading rule popularly employed in the foreign exchange market is the oscillator indicator, which aims to indicate that the price movement in a particular direction has been too rapid and that a correction is imminent. One of the most popular oscillator rules is the Relative Strength Indicator (RSI), which is commonly calculated from asset's close price and attempts to measure the strength of 'up movements' relative to the strength of 'down movements' and is normalized to lie between 0 and 100 (Investopedia). Common values at which a particular currency is deemed to have been overbought (signaling an imminent downward correction) or oversold (signaling an imminent upward correction) are 70 and 30, respectively (see, e.g., Henderson, 2002). The RSI is a type of 'reversal' indicator since it is designed to anticipate a reversal in trend, but it can also be used to detect trend formation after the previous trend gets reversed.

Trading rules: If RSI is below $50 + v$ and then rises above $50 + v$ for at least *d* days, enter a long position and hold it. If RSI is above $50 - v$ and then subsequently drops below $50 - v$ for at least d days, close the previous position if it was long position, and enter a short position. The author studies 400 RSI Oscillator trading rules with different parameterizations in terms of n lookback window v premium/discount threshold, and d day.

The indicator's mathematical definition, trading signal generation, and parameterization settings for the RSI Oscillator strategy class can be found in the Appendix.

(4) MACD

Moving Average Convergence Divergence is another popular momentum indicator characterized by the MACD and MACD-Signal line, which forms the basis for identifying the direction of a trend and the speed of price changes in a specific direction. The MACD Line is simply the difference between an Exponential Moving Average (EMA) of the price over a period and another exponential moving average of the price over a shorter period, while the Signal Line is the moving average of the MACD Line. Thus, when the MACD line crosses above the MACD-Signal line, it is considered a rising price with potential strengthening momentum and a potential bullish trend emerging, and a larger gap between the two lines indicates stronger momentum in the upward direction. Conversely, a closer gap between the two lines suggests decreasing momentum as well as a trend reversal (Investopedia).

Trading rule: If MACD line moves up at least x percent above MACD-Signal line and remains so for d days, go long until MACD line moves down at least x percent below MACD-Signal and remains so for d days, at which time go short. If MACD moves down at least x percent below MACD-Signal and remains so for d days, go short until MACD moves up at least x percent above MACD-Signal line and remains so for d days, at which time go long. The author examined 875 MACD trading rules with different parameterizations in terms of n lookback window, x percentage, and d day.

3.1.2 Cryptocurrency selection and portfolio formation

The portfolio formation process involves constructing an investment portfolio through asset allocation, security selection, and diversification according to specific investment objectives and constraints. The process continues with risk management, portfolio rebalancing and optimization, and overall performance evaluation (CFA Institute, 2024). In the context of this study, the portfolio is formulated to evaluate the performance of each trend-following trading rule across various cryptocurrencies simultaneously. This ensures that the trend-following strategy is appropriately tested at the whole cryptocurrency market level rather than on stand-alone currencies. The process involves (1) Cryptocurrency selection, (2) Capital allocation, (3) Trend-following strategy application, and (4) Defining benchmark.

1. Cryptocurrency selection: In this study, the author selects the five largest non-stablecoin cryptocurrencies, which represent over 85% of the market's capitalization when they were incorporated into the portfolios. Aggregately, there are 12 cryptocurrencies examined throughout the testing timeframes. The list of cryptocurrencies as portfolio components with their market-relative capitalization is reported in the Appendix.

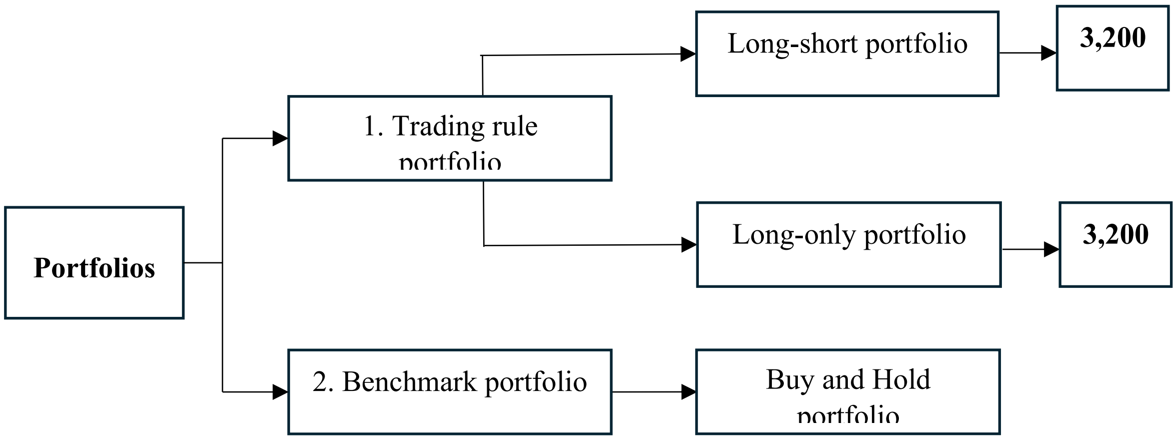
2. Capital allocation: For simplicity, the author aims to form a trading rule portfolio in an equally distributed style, rebalancing at the beginning of each year. This indicates that each of the five cryptocurrencies will be assigned an equal weight of 20% on January 1st of every year, starting from 2017. On January 1st of each subsequent year, the portfolio will then: (i) Re-select the currencies to ensure that they are the top five largest non-Stablecoins in terms of capitalization. This process may maintain or drop some currencies that are already in the portfolio to meet the market capitalization conditions; and (ii) Rebalance the newly selected currencies to ensure an equal weight distribution of 20%. Additionally, the price index of portfolio is also calculated with the base of 1,000 points on the beginning of January 1st, 2017 to serve further portfolio performance measurement.

3. Trend-following strategy application: Each trading rule will be applied and tested on a portfolio of currencies formed above in both long-short and long-only

styles. In other words, the process will create 3,200 long-short portfolios corresponding to 3,200 trend-following trading rules, where both long and short orders are allowed, and another 3,200 portfolios where only long orders are allowed. This process is expected to provide more insight into evaluating each trading rule's performance.

4. Defining the benchmark: Following the past study by Hudson and Urquhart (2019) and common literature in the cryptocurrency market, the author utilizes the buy-and-hold strategy as the benchmark to compare with the trend-following strategy, thus forming a buy-and-hold portfolio with the same components and properties as the trading rule portfolios defined above.

Figure 3.3: Portfolio formation structure

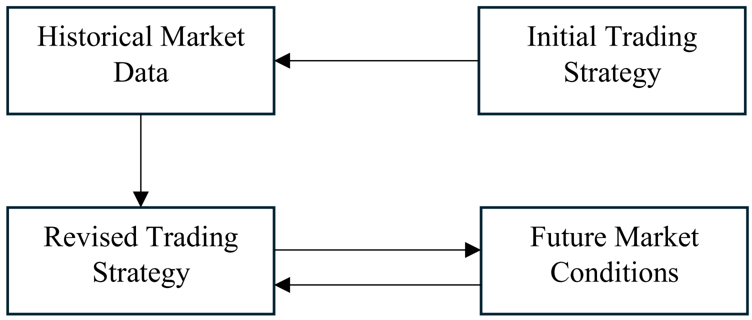


(Sources: Author's analysis)

3.1.3 Defining back-testing process

Back-testing, in the context of trading strategy research, is the process of simulating how a predictive model or trading strategy would have performed based on historical data to determine its accuracy. The logic behind this is that if the strategy performed poorly in the past, it is unlikely to perform well in the future due to continuous changes in market conditions. During the back-testing process, analyzing the overall profitability and the level of risk taken is essential for further strategy development before being applied in real-world trading. While the market usually does not move exactly as it did historically, back-testing first relies on the assumption that stocks move in similar patterns as they did historically. Then, it continuously monitors and analyzes factors that could cause this assumption to deviate and repetitively revises the trading strategy or predictive model to adapt to new market conditions (Corporate Finance Institute, 2024).

Figure 3.4: Back-testing process



(Source: Corporate Finance Institute, 2024)

Based on various research, the author defines three common back-testing techniques: Historical Simulation, Walk-Forward Optimization, and Monte Carlo Simulation. The core idea of Historical Simulation is to simulate how a strategy would have performed in the past by simply applying it to historical input data required by the strategy such as price, volume, specific events, or other market indicators. To the author's knowledge, this is the simplest and most realistic back-testing method and is largely employed in the literature, as it serves as the very first step in testing how any trading rule would perform, typically done before any other methods.

Walk-Forward Optimization, first proposed by Robert E. Pardo in 1992, focuses on enhancing a strategy's robustness regarding parameter optimization and overfitting avoidance. Strategy optimization involves adjusting the parameter settings to achieve the best possible performance of a strategy, but this may lead to overfitting bias as a strategy might be excessively optimized to fit the specific quirks and noise of historical data, resulting in a model that performs well in historical back-testing but poorly in real-world scenarios. The Walk-Forward Optimization technique helps avoid overfitting by dividing the historical data into two sets called in-sample and out-of-sample. The in-sample dataset is used to define and optimize the trading strategy with the best parameterization, while the trading strategy results are analyzed on the out-of-sample data to ensure minimized overfitting bias. The process of defining, optimizing, and evaluating is repeated with an iteratively moving in-sample and out-of-sample window through the historical dataset. Lastly, all the recorded results from the out-of-sample set are used to assess the trading strategy.

The final technique, Monte Carlo Simulation, first conceived by Stanislaw Ulam in 1946, utilizes historical data and its statistical properties to generate numerous random market scenarios. The trading rule is then tested in simulated markets to analyze its behavior under diverse market conditions, not limited to historical data. This kind of back-testing method is also sometimes referred to as scenario analysis and has the advantage of testing strategy robustness and risk management, but it demands substantial computational power.

Given that this research objective is to test the effectiveness of the Trend-following strategy as an extension of Hudson and Urquhart's research in 2019, the author adopts the first back-testing approach, which is Historical Simulation, to be consistent with the base research. On the other hand, it is unnecessary to carry out the optimization or overfitting avoidance steps highlighted by Walk-Forward Optimization since the study aims to test many Trend-following rules with different parameterizations and does not focus on optimizing or further developing any single trading rule. Moreover, Monte Carlo Simulation may be overwhelming as it is computationally intensive and more focused on the very final steps of strategy development.

3.1.4 Defining performance evaluation metrics.

Performance metrics are quantifiable measures used to assess how effective a trading strategy is and how well it meets its objectives in terms of risk and return. These metrics provide a standardized way to compare portfolio performance over time or against a benchmark. As there is no single best metric, using a combination of metrics offers a more comprehensive view of a strategy's performance. In this research, the author utilized the performance metrics pre-defined by Hudson and Urquhart (2019), which consist of three aspects:

(1) Strategy return, using daily and annual average return.

(2) Risk-adjusted return to evaluate the strategy's return considering volatility, downside deviation, and trading drawdown. Three risk-adjusted return ratios will be assessed: the Sharpe ratio, Sortino ratio, and Calmar ratio.

(3) Trade analysis, considering average return per trade, per long/short order, and the percentage of trading rules that generate a positive return among all trading rules.

These measurements will be calculated for each individual trading rule. The performance measurement of a Trend-following class is obtained by taking the arithmetic average of all trading rule portfolios' respective measurements within the class. Finally, the performance measurement of the whole Trend-following strategy is the weighted average of the four strategy classes, with the weights being the number of trading rules within each class.

Return

The author applies simple return to assess the portfolio performance such that:

$$r_t = \frac{P_t - P_{t-1}}{P_t} \qquad (1)$$

Where r_t is the return at time t of the portfolio, P_t is the price index of the portfolio at time t and P_{t-1} is the price index of the portfolio at time t−1. The first performance metric to be evaluated is the daily geometric mean return. This is the simplest performance measure and quantifies the average return generated by each trading rule in a day. The daily mean return of j^{th} trading rule portfolio is defined as:

$$R_j = \left[\prod_{t=0}^{d-1} (1 + r_t)\right]^{\frac{1}{d}} - 1 \qquad (2)$$

Where R_j is the daily mean return of trading rule portfolio j^{th}, d is the number of trading days in the testing timeframes or periods, and r_t is the simple return of the portfolio at time t. The author also reports the annualized mean return which is the annualizing daily mean return. Since the cryptocurrency market is traded 24/7, 365 is used in the annualization.

Risk adjusted return.

Sharpe ratio

Return measures along shows limitation as it does not account for the risk associated with the trading rule portfolio, particularly in terms of return volatility, to generate such return. To address this, the Sharpe ratio is calculated. Sharpe ratio, named by Wiliam F. Sharpe (1996), is a widely used performance metric in the finance industry as it measures the average excess return per unit of risk, with risk being quantified by the standard deviation of excess returns. The Sharpe ratio for the j^{th} trading rule portfolio is defined as follows:

$$S_j = \frac{R_j - rf}{\sigma_j} \qquad (3)$$

Where S_j is the daily Sharpe ratio of trading rule portfolio j^{th} and rf is the daily Vietnam risk free rate which is obtained by averaging three years Vietnam 10-year government bond yield. The author takes the annualized risk-free rate of 3.00%. Lastly, σ_j is the standard deviation of daily excess returns generated by the j^{th} trading rule portfolio.

Sortino ratio

The Sharpe ratio, in its nature, includes both downside volatility as well as upside volatility in the denominator, while investors may only be aversed to the downside risk as the upside provides them with greater returns. Thus, the author also calculates the Sortino ratio which is first proposed by Frank A. Sortino in 1980. Sortino ratio measures the risk-adjusted return of an investment or a trading strategy similarly to Sharpe ratio but focuses specifically on downside risk, which is the standard deviation of negative excess returns. Thus, Sortino ratio helps provide a clearer picture of a portfolio's downside risk rather than its total volatility (Corporate Finance Institute, 2024).

$$SO_j = \frac{R_j - rf}{DR_j} \qquad (4)$$

Where SO_j is the Sortino ratio of the j^{th} trading rule portfolio, and DR_j is the downside risk.

Calmar ratio

The Calmar ratio is a significant metric for investment banks and the hedge fund industry (Psaradellis et al., 2019). It measures the average annual return of an investment relative to its maximum drawdown, making it particularly valuable for those using momentum strategies that may experience significant drawdowns. Maximum drawdown (MDD) quantifies the largest peak-to-trough decline in the value of an investment or portfolio over the entire investment period, thus, it also give insight into the maximum leverage on the investment. (Hudson and Urquhart (2019)). The Calmar ratio for the j^{th} trading rule portfolio is defined as:

$$CR_j = \frac{R_j}{MDD_j} \qquad (5)$$

Where CR_j Calmar ratio for trading rule portfolio j^{th}, and MDD_j is the annualized maximum drawdown of the returns generated by the portfolio in the testing timeframe, and R_j is mean return of portfolio j^{th} expressed in annualized form.

Average return per trade

Average return per trade refers to the return generated by each trade or unit of trading activity within a trading rule portfolio. It helps traders understand how many profits would be made on average when conducting another trade activity in comparison to the cost incurred when making that trade. Thus, this measure provides insight on the scalability of the trading strategy.

$$AT_j = (1 + HPR)^{\frac{1}{n}} - 1 \qquad (6)$$

Where AT_j is average return per trade of trading rule j^{th}, and HPR is the holding period return of portfolio j^{th}. n is the total number of trades closed within the portfolio, which includes both long and short orders closed off across every cryptocurrency under the portfolio. Similarly, the author also reports Average return per long order and Average return per short order with the HPR is determined as if the portfolio is long-only and short-only respectively.

Testing period

The author evaluated the strategy performance across over seven years, from 2017 to April 2024, to ensure a most up-to-date analysis. The author picked 2017 as the starting year given the availability of the data, and the year itself marks significant exponential growth in the cryptocurrency market such as increased trading volume, the rise of AltCoins, and the introduction of the first cryptocurrency futures contract by the Chicago Mercantile Exchange (CME). To provide a clearer picture on how Trend-following strategy behavior over time, it is be tested over two periods: January 1, 2017, to June 30, 2020, and July 1, 2020, to April 30, 2024. June 2020 is chosen as a separator due to two reasons: (1) it coincides with the third Bitcoin halving event, which reduces the block reward for miners, making Bitcoin scarcer and often leading to bullish trends; and (2) it marks a significant increase in institutional investor interest, which has likely impacted market structure and efficiency. In 2020, the Office of the Comptroller of the Currency (OCC) in the U.S. allowed national banks to hold cryptocurrency assets and offer custodial services, providing a clearer regulatory framework. Fidelity reported that 27% of U.S. institutional investors held digital assets in 2020, up from 21% in 2019. These two subperiods also encompass full cycles of market ups and downs, minimizing bias toward any market regime and providing a robust basis for evaluating the effectiveness of trend-following strategies.

3.1.5 Hypothesis testing

Hypothesis testing

As this research is structured around evaluating the effectiveness of Trend-following strategies in cryptocurrency under different contexts - such as standalone trading rules, trend-following classes, and the aggregate Trend-following strategy - different methodologies will be appropriately applied to each hypothesis testing layer.

Firstly, to test the hypothesis that each standalone trend-following trading rule generates a significant positive mean return, the author utilized the stationary bootstrapping method introduced by Politis and Romano (1994) to calculate the p-value. This method is preferred over parametric tests like the t-test to address issues such as non-normality, autocorrelation, and heteroskedasticity, which are commonly observed in financial time series data (Hudson and Urquhart, 2019). The advantage of the stationary bootstrap method over traditional bootstrapping methods lies in its ability to preserve the underlying structure of the original sample, including autocorrelation, dependencies, and potential stationarity. A key feature of the stationary bootstrap process is resampling with blocks of random length based on a geometric distribution, which captures the original sample's statistical properties. In this study, the author used the stationary bootstrap with 10,000 iterations, specifying an expected block size equivalent to 5% of the original length. This results in the probabilities of starting a new block in the bootstrapping process being 1.6%, 1.4%, and 0.7% respectively. After the significant of standalone trading rule, the author reports the percentage of trading rule portfolio that provides statistically significant positive return at the 5% level.

Secondly, to test whether a strategy class or the entire Trend-following strategy generates a significant positive return, the author followed the methodology of Hudson and Urquhart (2019). This involved conducting a t-test on the sample, which is the record of the daily mean returns of every trading rule within the strategy class, assuming a normal distribution. The author then reports whether each trading class and the overall Trend-following strategy can generate a significant positive mean return at the 1%, 5%, or 10% significance level.

3.1.6 Robustness check

Transaction cost

Any analysis of trading strategies should be concerned with transaction costs since if the returns from a trading strategy are not positive after taking account of transaction costs, the strategy is worthless to an investor. In cryptocurrency trading, transaction costs can come from multiple sources which are incurred either directly or indirectly by the traders (Investopedia, 2024):

(1) Brokerage fees and commissions are usually quoted explicitly as fixed fees or a percentage of trade value and may vary across different brokers and different trading values carried out by the manager. Brokerage fee commissions in cryptocurrency trading are typically charged based on different trading value tiers, with average percentage fees ranging from 0.10% to 0.6% of trading value directly charged to traders (CoinBase, 2024).

(2) Bid-Ask spread, which is the difference between the highest price a buyer is willing to pay and the lowest price a seller is willing to sell an asset. The spread is also considered a direct cost as it represents the immediate loss incurred when buying at the ask price and selling at the bid price. At the time the author conducted this research, the bid-ask spread of Bitcoin on the top five largest crypto exchanges by volume ranged from less than 1bps to 10bps (TheBlock.co, 2024). However, the bid-ask spread may vary significantly across different currencies with different liquidity and is sensitive to market volatility.

(3) Slippage, which is the difference between the expected price of a trade and the actual price at which the trade is executed. The impact of slippage is usually larger under volatile market conditions, with low liquidity assets, or large order sizes as it becomes more difficult to execute the trade at the expected price (Investopedia, 2024).

(4) Other indirect and harder to estimate sources of transaction costs in cryptocurrency trading may come from latency, which is the time delay between sending a trade order and its execution caused by a “slow” operating system; and the potential adverse impact of the trend on the asset's market price.

Taking careful consideration of transaction costs is especially important since many papers have found that technical trading rules are profitable for investors, but once transaction costs are accounted for, many rules are no longer profitable. For instance, Timmermann and Granger (2004) provided evidence that technical trading rules may predict cryptocurrency movements in the sense of generating significant returns but still not be profitable once the excess returns are adjusted for transaction costs. Most recently, Trinh Le and Ruthnah (2023) also reported that transaction costs erode part of the excess returns associated with their constructed trend-following portfolio because the high volatility of crypto assets, such as BTC and ETH, requires frequent portfolio rebalancing.

Since the estimation of actual transaction costs poses a significant challenge given the variety of cryptocurrencies examined over a long-time range and the complexity of transaction cost sources and structures, the author aims to properly account for these costs by calculating the breakeven transaction cost for each trading rule portfolio. The breakeven transaction cost (BETC), expressed as a percentage, is simply the transaction cost that offsets all positive returns of a trading rule. In other words, it is the minimum return that either a trade open or a trade close order must generate to make the trading rule profitable. For simplicity, the author assumes the transaction cost incurred is always a variable cost, thus BETC calculation is quite straightforward:

$$BETC_j = (1 + HPR)^{\frac{1}{2n}} - 1 \qquad (7)$$

Additionally, the author also reports the proportion of trend-following rules that have BETC above the 50-basis point threshold, consistent with Hudson and Urquhart. (2019). The 50-basis points threshold was first proposed by Lintilhac and Tourin (2017), who aimed to study Bitcoin's actual transaction costs. They showed that the transaction fee per number of Bitcoins traded is \$0.0025, while the bid-ask spread is 0.005 as a fraction of the USD price, equivalent to 50bps. Finally, comparing this proportion of "50bps outperform" trading rules to the proportion of trading rules that generate positive returns before accounting for transaction costs illustrates the impact of transaction costs on trend-following strategies.

Data snooping issues

Since this research is designed to evaluate various trading rules simultaneously, simply comparing the mean returns of different strategies is inadequate due to the problem of data snooping bias. Data snooping bias refers to the tendency to draw misleading conclusions from data analysis when multiple hypotheses are tested, as is the case in this research with 3,200 hypotheses on 3,200 trading rules on standalone condition without proper statistical controls.

When researchers or traders test numerous trading rules or strategies, they are more likely to incorrectly reject the null hypothesis (conclude a strategy is profitable when it is not). This is because the probability of making at least one Type I error increases significantly as the number of hypotheses tested increases. In other words, the likelihood of incorrectly rejecting the hypothesis that the trend-following strategy class generates zero or negative mean returns is as high as $1 - (1 - \alpha)^M$, rather than just 1 – (1 - α) as in tests for individual trading rules. Here, α is the significance level threshold for each hypothesis, and n is the number of hypotheses tested within the set.

Chordia et al. (2018) demonstrated this phenomenon by testing many trading strategies and applying various multiple hypothesis testing techniques. They found that many strategies that appeared to outperform under single hypothesis testing were likely false positives. Furthermore, “surviving” strategies often lacked theoretical foundations, indicating the presence of "p-hacking," where researchers selectively report statistically significant results.

To address the issue of multiple hypothesis testing, researchers often utilize two broad approaches: family-wise error rate (FWER) and false discovery rate (FDR). FWER controls the probability of making at least one Type I error across all tested hypotheses, while FDR controls the proportion of false discoveries among all rejected hypotheses. Implementing these statistical controls helps mitigate data snooping bias and ensures more robust conclusions from data analysis.

Family Wise Error Rate (FWER)

The strictest multiple hypothesis test is to try and avoid any false rejections. This translates to control the FWER, which is defined as the probability of rejecting even one of the true null hypotheses and therefore the FWER measures the probability of even one false discovery. The author implements two main FWER tests, which are Bonferroni method and Holm method.

Bonferroni Method

The Bonferroni technique, published by Carlo Emilio Bonferroni in 1936, is a one-step process, that compares each p-values of each trading rule portfolio with a single Bonferroni-adjusted critical value. This single Bonferroni-adjusted critical value is α/M, where M is the number of rules examined and α is the selected critical value. This change results in an extremely small Bonferroni-adjusted critical if M is large, making it overly conservative and losing power. The lack of power stems from the study's implicit treatment of all test statistics as independent, hence disregarding cross-correlation among trend-following rules.

Holm method

The Holm method is a stepwise adjustment that that rejects the null hypothesis of no outperforming rules if:

$$\text{p-value}_i \leq \alpha / (M - i + 1) \text{ with } i = 1, \ldots m \text{ is the ascending rank of p-value}$$

When testing many hypotheses, the Holm technique is relatively less stringent than the Bonferroni approach. As a result, compared to the Bonferroni technique, the Holm method usually rejects more hypotheses and has greater power. Nevertheless, Holm correction method also ignores the dependent nature of each individual trading rule.

False Discovery Rate (FDR)

Instead of controlling the number of false rejections, one can manage the percentage of false rejections known as the False Discovery Rate (FDR). FDR measures and controls the expected FDR among all discoveries. A multiple hypothesis testing method is considered to control the FDR at a level q if FDR ≡ E(FDR) ≤ q, where q is a user-defined threshold.

BH method

One of the earliest methods for controlling the False Discovery Rate was introduced by Benjamini and Hochberg in 1995. This method is a stepwise procedure that operates by ranking all individual p-values in ascending order, each p-value from the smallest to the largest then being respectively compared with BH-adjusted p-value:

$$j = \text{Max}\left(j : p \leq \frac{j \text{ x } q}{M}\right) \qquad (8)$$

Where all hypothesis H_1, H_2,…H_j will be rejected.

BY method

Although Benjamini and Hochberg (1995) demonstrated that their method controls the FDR if the p-values are mutually independent, Benjamini and Yekutieli (2001) showed that a more general control of the FDR can be achieved under a broader dependence structure of p-values by modifying the definition of j. With C_M in the denominator equivalent to log(M) + 0.5:

$$j = \text{Max}\left(j : p \leq \frac{j \text{ x } q}{M \text{ x } C_M}\right) \qquad (9)$$

However, this method is less powerful than the BH method and remains quite conservative.

The author applies these four multiple hypothesis testing correction procedures to the individual p-values of each trading rule, previously obtained using the Stationary bootstrapping method by Politis and Romano (1994), as mentioned in the Hypothesis Testing section.

3.2 Data collection

To conduct the analysis, the author collected cryptocurrency market data from Refinitiv Eikon, a market intelligence firm that is a subsidiary of the London Stock Exchange Group (LSEG). The dataset includes daily OHLCV (open, high, low, close, volume) and market capitalization data for 12 cryptocurrency tickers over a period of 3,050 days, from January 1, 2016, to April 29, 2024. Since cryptocurrency markets trade 24/7, the dataset includes observations for every day, including weekends and holidays, ensuring a complete time-series.

Given that the study focuses on trend-following strategies over a period starting from 2017, data from 2016 will be used only for creating necessary technical indicators and then trimmed to ensure no missing data during the testing period from January 1, 2017, to April 29, 2024. This approach ensures a smooth and complete dataset for the back-testing process.

Additionally, while some cryptocurrencies may have entered the market later than others and thus have different start dates, this does not impact the back-testing process. The data for each cryptocurrency is sufficient before its inclusion in the back-testing portfolios. Visualizations of the price movements for each cryptocurrency are provided in the Appendix.

Summary of Chapter 3

This research evaluates the effectiveness of trend-following strategies in the cryptocurrency market through a six-step back-testing approach: specifying trading strategies, selecting cryptocurrencies, and forming portfolios, back-testing, performance evaluation, hypothesis testing, and robustness checks. The study focuses on 3,200 rules across four classes—Moving Average, Resistance-Support, RSI Oscillator, and MACD—each with various parameterizations. Portfolios are constructed from the five largest non-Stablecoin cryptocurrencies, rebalanced annually, with a Buy and Hold portfolio as a benchmark. Back-testing uses the Historical Simulation method, and performance is measured by returns, Sharpe ratio, Sortino ratio, Calmar ratio, and average return per trade, including breakeven transaction costs. Hypotheses are tested with stationary bootstrap methods to handle data non-normality and autocorrelation, using multiple hypothesis testing approaches like Bonferroni, Holm, BH, and BY to mitigate data snooping bias. Data from Refinitiv Eikon includes daily OHLCV and market capitalization for 12 cryptocurrencies from January 1, 2016, to April 29, 2024. This comprehensive analysis provides insights into the profitability and risk management of trend-following strategies in the volatile cryptocurrency market.

CHAPTER 4: EMPIRICAL RESULTS

4.1 Descriptive statistics

Table 4.1: Descriptive statistics and normality test for examined cryptocurrency from the start of available data in Jan 2017 – April 2024 period

Ticker	No. Obs	Mean	Std.Dev	Max	Min	Skewness	Kurtosis	Shapiro p_value
BTC	2684	0.0023	0.0387	0.2556	-0.3918	-0.1367	7.3651	3.834E-10
ETH	2684	0.0035	0.0512	0.2951	-0.4455	0.1633	5.9880	1.826E-11
BNB	2372	0.0039	0.0565	0.6997	-0.4396	1.9646	25.3637	5.762E-16
SOL	1388	0.0060	0.0728	0.6486	-0.4235	0.8991	8.4425	4.223E-13
XRP	2684	0.0041	0.0765	1.7955	-0.4797	6.7562	128.3821	9.376E-19
ADA	2320	0.0014	0.0564	0.4173	-0.4156	0.5575	5.6749	1.926E-09
LINK	2287	0.0035	0.0647	0.6087	-0.4712	0.5751	7.1790	1.689E-07
BCH	2470	0.0023	0.0667	0.5827	-0.4499	1.6808	15.6212	7.704E-13
EOS	2502	0.0016	0.0653	0.5618	-0.4199	0.9358	9.8874	1.305E-12
BSV	1997	0.0022	0.0721	1.4545	-0.4635	5.8791	98.3965	7.203E-18
LTC	2684	0.0027	0.0590	0.8349	-0.3854	2.0966	25.0089	3.852E-16
XMR	2684	0.0023	0.0546	0.5456	-0.4146	0.4819	11.5047	5.655E-12

(Sources: Author's analysis, CoinMarketCap)

The descriptive statistics table summarizes the features of 12 cryptocurrency return series, providing insights into the market performance over time. All examined cryptocurrencies show positive daily mean returns, ranging from approximately 0.2% to 0.4%, except for Solana (SOL), which has the highest daily mean return at 0.60%. In contrast, Cardano (ADA) has the lowest mean return at 0.14%.

However, these currencies exhibit high return dispersion, with standard deviations ranging from 3% to 8% over the testing period, highlighting the cryptocurrency market's heavy volatility. This volatility is also evident in the maximum and minimum daily returns for each currency. For instance, Ripple (XRP) and Bitcoin SV (BSV) once surged nearly 180% and 145% in a single trading day, respectively. Other cryptocurrencies also experienced "skyrocketing" days with returns as high as 50%-60%. Only Bitcoin (BTC) and Ethereum (ETH), the two largest cryptocurrencies by market capitalization, showed relatively less volatility, with their best return days capped at around 30% during the examined period.

Despite the potential for substantial daily gains, the worst daily returns for all cryptocurrencies range from -30% to -40%, indicating a fast developing yet still very risky market. Additionally, the daily return distributions for all cryptocurrencies are clearly not normally distributed, exhibiting extreme skewness and kurtosis. This is formally evidenced by Shapiro-Wilk test p-values close to zero. Bitcoin, due to its largest market capitalization and popularity, shows a slightly more "normal" distribution compared to the heavily fluctuating alternative cryptocurrencies.

4.2 Empirical results

4.2.1 Long-short portfolio

The author summarizes the performance of the Trend Following strategy across four different classes with various parameters in **Table 4.2**. Initially, it appears that all strategy classes generate positive returns at the 1% significance level. Most trading rules within each class yield positive returns, with many showing statistically significant positive daily mean returns individually. However, the Buy and Hold portfolio proves more effective over time in terms of both risk and risk-adjusted returns, although some trading rules still offer better risk-adjusted returns than Buy and Hold. Furthermore, the performance of all strategies weakens over time. While the effectiveness of the Buy and Hold portfolio declines slightly, other Trend Following strategies experience significant deterioration, potentially indicating a stronger form of market efficiency.

Overall, it is worth noting that investing in cryptocurrency, whether passively or actively, can yield substantial returns but comes with significant risks. The Annual Sharpe ratio is less than one, indicating that each risky dollar does not generate one dollar of excess return. Additionally, investments can suffer drawdowns as large as the returns generated.

Particularly, all trend-following strategy classes yield positive mean returns at the 1% significance level, with an average annual return of 57.21%. Whereas 94.05% of all rules end up with positive return, and 70.76% are individually statistically significant at the 5% level over the period from January 2017 to April 2024. Among the classes, MACD and Resistance & Support stand out with the highest returns and better risk-adjusted statistics. Notably, nearly 100% of MACD and Resistance & Support trading rules end with positive returns, with 95.7% and 71.7% individually rules respectively being statistically significant during this period. These classes also maintain above-average statistics in other subperiods, indicating their consistency. In contrast, RSI Oscillator and Moving Average classes show inferior performance, with returns, return-adjusted statistics, and the percentage of statistically significant positive trading rules always below average.

Despite this, the Buy and Hold portfolio remains the most effective strategy. This passive strategy yields an average annual return of 111.8% from 2017 to the present, with annual Sharpe, Sortino, and Calmar ratios of 0.82, 1.19, and 1.22 respectively (**Table 4.3**). In comparison, the best trend-following class, Resistance & Support, yields only a 71.76% return with ratios of 0.59, 0.86, and 0.94 respectively.

Given that each trend-following strategy class average includes various trading rules with different parameterizations, the author also reports the portion of trading rules within each class that outperforms the Buy and Hold strategy in **Table 4.4**. Across the examined period, only 3.04% of rules generate better returns than the Buy and Hold strategy from January 2017 to April 2024. Although the portion of rules outperforming Buy and Hold increases when considering downside risk-adjusted returns like Sortino and Calmar ratios, it remains limited to less than 20%.

Table 4.2: The performance of Trend-following portfolios versus Buy and Hold portfolio over three periods

Trend following trading rule	No. Rules	Avg. Daily return	Avg. Annual return	% + Ret	% Sig. ret
2017-01-01 - 2024-04-29	**3,200**	**0.1174%*****	**57.21%**	**94.05%**	**70.76%**
MACD	875	0.1254%***	60.08%	99.31%	94.74%
Moving Average	1,575	0.1155%***	56.47%	92.93%	57.96%
RSI Oscillator*	400	0.0768%***	38.86%	77.90%	56.16%
Support & Resistance	350	0.1451%***	71.76%	100.00%	71.71%
Buy and Hold	1	0.2058%***	111.75%		
2017-01-01 - 2020-06-30	**3,200**	**0.1638%*****	**92.23%**	**91.83%**	**48.45%**
MACD	875	0.1893%***	104.44%	100.00%	74.97%
Moving Average	1,575	0.1587%***	89.65%	91.52%	33.65%
RSI Oscillator*	400	0.0827%***	50.62%	61.40%	34.93%
Support & Resistance	350	0.1922%***	109.87%	99.14%	50.00%
Buy and Hold	1	0.2440%***	143.36%		
2020-07-01 - 2024-04-29	**3,200**	**0.0756%*****	**34.42%**	**92.06%**	**38.25%**
MACD	875	0.0671%***	29.57%	90.29%	54.17%
Moving Average	1,575	0.0762%***	34.64%	94.07%	27.09%
RSI Oscillator*	400	0.0759%***	36.51%	85.23%	37.12%
Support & Resistance	350	0.1021%***	48.18%	95.43%	43.71%
Buy and Hold	1	0.1709%***	86.50%		

(Sources: Author's analysis)

The "No.Rules" denotes the total number of trading rules and equivalent to the total number of portfolio examined under four trend-following classes. "Avg. Daily return" represents the average return of the strategy class (geometric mean return), and *** represents a 1% statistically significant. "% + Ret" and "% Sig. ret" show the percentage of trading rule portfolios end up with positive return, and is significant positive at 5% significance level respectively.

*For RSI Oscillator class, only 276 portfolios equal to 276 parameterization sets out of 400 were meaningful and able to generate any long/short signal. Thus, in fact only 276 portfolios were in calculation.

Table 4.3: The risk-adjusted performance of trend-following portfolios over three periods

Trend following trading rule	Sharpe	Ann. Sharpe	Sortino	Ann. Sortino	Calmar
2017-01-01 - 2024-04-29	**0.0241**	**0.4608**	**0.0354**	**0.6761**	**0.7968**
MACD	0.0255	0.4881	0.0383	0.7320	0.8852
Moving Average	0.0241	0.4608	0.0347	0.6633	0.7600
RSI Oscillator	0.0138	0.2644	0.0211	0.4035	0.5661
Support & Resistance	0.0307	0.5858	0.0448	0.8550	0.9438
Buy and Hold	0.0431	0.8234	0.0625	1.1945	1.2243
2017-01-01 - 2020-06-30	**0.0285**	**0.5452**	**0.0446**	**0.8524**	**1.4745**
MACD	0.0327	0.6240	0.0520	0.9942	1.6585
Moving Average	0.0284	0.5432	0.0433	0.8277	1.4466
RSI Oscillator	0.0101	0.1939	0.0191	0.3650	0.8752
Support & Resistance	0.0352	0.6734	0.0541	1.0337	1.6509
Buy and Hold	0.0449	0.8579	0.0667	1.2748	1.5705
2020-07-01 - 2024-04-29	**0.0171**	**0.3275**	**0.0237**	**0.4527**	**0.5510**
MACD	0.0145	0.2778	0.0202	0.3859	0.4889
Moving Average	0.0173	0.3301	0.0237	0.4534	0.5415
RSI Oscillator	0.0172	0.3293	0.0242	0.4627	0.6123
Support & Resistance	0.0256	0.4891	0.0354	0.6757	0.7554
Buy and Hold	0.0421	0.8037	0.0592	1.1301	1.0425

(Sources: Author's analysis)

The trend-following strategy results in this study are similar but relatively weaker compared to the findings of Hudson and Urquhart (2019). Hudson and Urquhart tested over 15,000 technical trading rules, found that a significant portion (around 30%-40%) of these rules, including trend-following rules, outperformed the Buy and Hold strategy when considering downside risk-adjusted returns, which were notably better than one.

The weaker performance in this study is likely due to the different market conditions. Hudson and Urquhart conducted their tests before 2018, during a period of continuous upward rally in the cryptocurrency market. In contrast, the period from

January 2017 to April 2024 experienced significant growth with many ups and downs, indicating a more efficient market where trend-following strategies have lost some effectiveness over time. Therefore, it is important to observe how these strategies perform over different sub-periods.

Table 4.4: The percentage of portfolios within total Trend-following portfolios that outperform the Buy and Hold portfolio based on different metrics.

Trend following trading rule	% outpert. Ret	% outpert. Sharpe	% outpert. Sortino	% outpert. Calmar
2017-01-01 - 2024-04-29	**3.04%**	**4.49%**	**6.80%**	**19.88%**
MACD	2.40%	2.74%	4.34%	20.80%
Moving Average	2.87%	4.78%	7.52%	18.98%
RSI Oscillator	2.54%	5.07%	7.61%	18.48%
Support & Resistance	6.86%	8.57%	10.86%	23.14%
2017-01-01 - 2020-06-30	**20.18%**	**17.63%**	**24.64%**	**43.48%**
MACD	20.69%	15.43%	25.83%	53.71%
Moving Average	20.78%	18.48%	25.05%	39.26%
RSI Oscillator	5.88%	7.72%	9.56%	28.68%
Support & Resistance	31.43%	32.29%	35.43%	46.86%
2020-07-01 - 2024-04-29	**3.81%**	**5.43%**	**5.27%**	**14.66%**
MACD	0.34%	0.69%	0.80%	7.66%
Moving Average	2.42%	3.25%	3.06%	14.21%
RSI Oscillator	13.26%	15.15%	15.15%	23.48%
Support & Resistance	13.14%	23.43%	22.29%	32.29%

(Sources: Author's analysis)

As noticing the performance of these strategies across two subperiods, from January 1, 2017, to June 30, 2020, and from July 1, 2020, to April 29, 2024, it is unsurprising that both the Buy and Hold and trend-following strategies weakened. However, trend-following rules showed greater sensitivity and deterioration across all metrics. For example, the Buy and Hold portfolio's annual return and Sharpe ratio decreased from 143.4% and 0.86 in the first subperiod to 86.5% and 0.80 in the second subperiod. In contrast, trend-following rules experienced a sharper decline, with annual returns dropping from 92.23% to 34.42% and Sharpe ratios from 0.55 to 0.33. Additionally, the percentage of trend-following rules outperforming the Buy and Hold strategy decreased two to three times across return and risk-adjusted return metrics. This consistent decline across all trend-following strategy classes indicates a loss of effectiveness. The overall optimistic performance for the entire period from 2017 to 2024 is mainly attributed to the subperiod from 2017 to 2020 when cryptocurrency experienced a dramatic surge.

For a deeper analysis, the author also reports the performance of these strategies by breaking down them into long and short order separately, along with their daily average returns as if the strategy is long-only or short-only in **Table 4.5**. The statistics show that nearly all trend-following portfolio positive returns were generated by long orders, with an average return of 0.17% a day created by long order from 2017 to 2024, while short order resulted in an average loss of 0.05% per day. Notably, short orders consistently generated negative returns across all strategy classes throughout the examined periods, and only a very small portion, around 2.99%, of short order contributed positively to trend-following strategy final return. Given this, it might be necessary to evaluate the performance of long-only portfolios, considering the cryptocurrency market is relatively young and fast-developing, potentially favoring a long-only trading strategy.

Table 4.5: The performance of trend-following broken down into long-only and short-only portfolios over three periods.

Trend following trading rule	Avg. Daily ret Long	% + Long ret	Avg. Daily ret Short	% + Short ret
2017-01-01 - 2024-04-29	**0.1704%***	**98.29%**	**-0.0530%**	**2.99%**
MACD	0.1946%***	100.00%	-0.0691%	2.63%
Moving Average	0.1643%***	98.66%	-0.0487%	0.25%
RSI Oscillator	0.1253%***	89.86%	-0.0484%	1.45%
Support & Resistance	0.1685%***	100.00%	-0.0234%	21.14%
2017-01-01 - 2020-06-30	**0.2418%***	**94.22%**	**-0.0779%**	**4.19%**
MACD	0.2797%***	100.00%	-0.0902%	4.57%
Moving Average	0.2376%***	93.05%	-0.0788%	0.38%
RSI Oscillator	0.1640%***	76.84%	-0.0812%	0.74%
Support & Resistance	0.2173%***	100.00%	-0.0251%	27.71%
2020-07-01 - 2024-04-29	**0.1099%***	**99.10%**	**-0.0343%**	**17.62%**
MACD	0.1221%***	100.00%	-0.0550%	3.89%
Moving Average	0.1015%***	99.87%	-0.0252%	20.65%
RSI Oscillator	0.0991%***	92.05%	-0.0231%	29.55%
Support & Resistance	0.1255%***	100.00%	-0.0234%	36.86%

(Sources: Author's analysis)

The author reports the "Avg. Daily ret Long", "Avg. Daily ret Short" as the daily geometric mean return of the portfolio as if it were evaluated by long and short order separately. While "% + Long ret" and "% + Short ret" are the proportion of Long/Short only portfolio that end up with positive return.

4.1.2 Long-only portfolio

Compared to trend-following strategies portfolios that allow both long and short orders, long-only trading rules lead to a significantly improved result. **Table 4.6** indicates that long-only rules generate an annual return of 89.48% and an annual Sharpe ratio of 0.80 for the period from 2017 to 2024. This is much better than the 57.21% return and 0.46 Sharpe ratio of long-short portfolios (examined in the previous section). Furthermore, the percentage of individual rules that have statistically significant positive return increases notably from 70.76% to 85.76%.

The MACD class benefits the most from eliminating short orders, with its annual return and Sharpe ratio increasing from 60.08% and 0.49 to 105.04% and 0.93 respectively, which even outperform the Buy and Hold strategy. Its average downside risk-adjusted metrics, like the Sortino ratio and the Calmar ratio even impressively above Buy and Hold for the 2017-2024 period, thanks to its strong performance in 2017-2020. While other strategy class which are Moving Average, RSI Oscillator, and Resistance & Support also improve performance, Resistance & Support class could not maintain their top position indicating this class would be relatively more benefited from short order compared to other. For instance, in long-short portfolio, they have the best Sortino and Calmar ratios compared to the other three on average, but in long-only portfolio, purely trend-following classes like Moving Average have better outcomes. Indeed, **Table 4.5** clearly shows that in 2017 till 2024 period, 21.14% of short-only Resistance & Support portfolios end up with positive return, while this number is less than 3% for other trend-following classes.

More interesting, it is seen that risk-adjusted measurement such as Calmar ratio increasing significant from 0.7996 for long-short portfolios to 1.4896 for long-only portfolio indicates that the risk, or the drawdowns were mainly due to short orders, which bet on downturns, but they turned out with an unexpected reversion then. Furthermore, **Table 4.7** shows a consistent improvement in the percentage of rules outperforming the Buy and Hold portfolio across all classes during the three examined periods.

Table 4.6: The risk-adjusted performance of long-only trading rules portfolio over three periods

Trend following trading rule	Ann. Return	Ann. Sharpe	Ann. Sortino	Calmar	% + Ret	% Sig. ret
2017-01-01 - 2024-04-29	**0.8948*** **	**0.8002**	**1.2264**	**1.4896**	**98.29%**	**85.76%**
MACD	1.0504***	0.9272	1.4812	1.8482	100.00%	100.00%
Moving Average	0.8517***	0.7707	1.1489	1.3897	98.66%	77.64%
RSI Oscillator	0.6518***	0.5740	0.8693	1.1143	89.86%	69.93%
Support & Resistance	0.8482***	0.7635	1.1438	1.1781	100.00%	97.50%
Buy and Hold	1.1175***	0.8234	1.1945	1.2243		
2017-01-01 - 2020-06-30	**1.4936*** **	**0.8781**	**1.4569**	**3.2231**	**94.22%**	**86.49%**
MACD	1.7659***	1.0132	1.7886	4.3566	100.00%	100.00%
Moving Average	1.4663***	0.8634	1.3683	2.9406	93.05%	90.18%
RSI Oscillator	1.0139***	0.5731	0.9597	2.2179	76.84%	62.50%
Support & Resistance	1.2115***	0.8216	1.3181	1.8503	100.00%	45.25%
Buy and Hold	1.4336***	0.8579	1.2748	1.5705		
2020-07-01 - 2024-04-29	**0.5133*** **	**0.6679**	**0.9042**	**0.9006**	**99.10%**	**58.91%**
MACD	0.5822***	0.7746	1.0607	1.0315	100.00%	89.22%
Moving Average	0.4648***	0.6064	0.8147	0.8208	99.87%	41.36%
RSI Oscillator	0.4623***	0.5797	0.7796	0.8212	92.05%	52.27%
Support & Resistance	0.5890***	0.7227	0.9746	0.9591	100.00%	54.00%
Buy and Hold	0.8650***	0.8037	1.1301	1.0425		

(Sources: Author's analysis)

Table 4.7: The percentage of long-only portfolios within total trend-following portfolio that outperform the Buy and Hold portfolio based on different metrics.

Trend following trading rule	% outper. Ret	% outper. Sharpe	% outper. Sortino	% outper. Calmar
2017-01-01 - 2024-04-29	**14.87%**	**44.44%**	**41.23%**	**46.23%**
MACD	21.94%	70.93%	57.71%	65.96%
Moving Average	13.65%	31.85%	33.25%	38.85%
RSI Oscillator	10.39%	39.30%	40.13%	37.44%
Support & Resistance	1.32%	24.38%	27.19%	25.94%
2017-01-01 - 2020-06-30	**42.96%**	**52.98%**	**43.71%**	**54.81%**
MACD	59.49%	62.24%	58.68%	71.43%
Moving Average	37.05%	53.92%	37.42%	51.59%
RSI Oscillator	38.18%	33.74%	33.52%	35.90%
Support & Resistance	21.61%	36.61%	36.17%	34.50%
2020-07-01 - 2024-04-29	**0.31%**	**19.03%**	**15.82%**	**23.04%**
MACD	0.67%	28.14%	24.05%	35.04%
Moving Average	0.00%	13.94%	11.67%	15.60%
RSI Oscillator	0.89%	16.67%	13.99%	21.92%
Support & Resistance	0.00%	17.03%	11.17%	22.17%

(Sources: Author's analysis)

Overall, despite the obvious improvement of long-only trend-following strategies, especially the MACD class, it is important to note that long-only trend-following performance is being deteriorating through time and is observed with underperforming performance comparing to Buy and Hold strategy across all metrics in the most recent subperiod, from Jan 2020 to April 2024. They exhibit the same pattern of diminishing effectiveness over time, reinforcing the idea of a more efficient cryptocurrency market where Trend-following strategies cannot "beat" the market.

Additionally, even the Buy and Hold strategy, while yielding substantial annual returns, does not sufficiently compensate for the risk investors bear. Its risk-adjusted returns, such as the Annual Sharpe ratio, remain modest, decreasing from 0.86 in 2017-2020 to 0.80 in 2020-2024. Other downside risk-adjusted measurements like the Annual Sortino ratio and Calmar ratio also decrease and remain barely above one, making them unattractive. The next section will provide further analysis on how Trend Following strategies perform when considering transaction costs and data snooping.

4.3 Robustness test

4.3.1 Transaction cost

The analysis has assumed zero transaction costs up to this point. However, in practice, these costs can be significantly high in cryptocurrency trading. Timmermann and Granger (2004) noted that technical trading rules may predict cryptocurrency movements and generate significant returns but might not remain profitable once excess returns are adjusted for transaction costs. On the other hand, the transaction costs for cryptocurrencies vary depending on the specific cryptocurrency and the exchange used, and estimating the transaction costs is challenging as they also vary significantly over time among various cryptocurrencies. Thus, to properly account for transaction costs, the author follows past studies to calculate the breakeven transaction cost (BETC) for each trend following rules which is the minimum return required per trade to open or close a position, assuming transaction cost is the only variable cost.

Additionally, given that Lintilhac and Tourin (2017) found the transaction cost of Bitcoin is around 50 basis points, the author also reports the percentage of trend-following rules with a BETC above the 50-basis points threshold together with the BETC and the average return per trade carried out by the portfolio under each trend following rule. While actual transaction costs might include fixed brokerage fees and vary across exchanges and currencies, using a 50-basis points threshold for BETC aligns with Hudson and Urquhart (2019) and provides a clearer view of strategy effectiveness when considering transaction costs.

Table 4.8: Breakeven transaction cost (BTEC) and the proportion of long-short portfolio that have positive returns considering 50bsp threshold.

Trend following trading rule	Ave no. Trades	Avg. Trade return	BETC	% > 50bsp
2017-01-01 - 2024-04-29	**420**	**0.8085%**	**0.4034%**	**17.94%**
MACD	449	0.7885%	0.3935%	15.84%
Moving Average	418	0.8072%	0.4028%	19.54%
RSI Oscillator	330	0.7481%	0.3734%	14.96%
Support & Resistance	426	0.9570%	0.4774%	20.15%
2017-01-01 - 2020-06-30	**197**	**1.1555%**	**0.5761%**	**30.66%**
MACD	209	1.2041%	0.6002%	29.48%
Moving Average	195	1.1527%	0.5747%	32.54%
RSI Oscillator	159	0.9041%	0.4510%	17.56%
Support & Resistance	204	1.2830%	0.6394%	39.57%
2020-07-01 - 2024-04-29	**223**	**0.5384%**	**0.2688%**	**7.96%**
MACD	240	0.4324%	0.2160%	4.59%
Moving Average	222	0.5368%	0.2681%	7.60%
RSI Oscillator	171	0.7303%	0.3645%	14.01%
Support & Resistance	222	0.7098%	0.3543%	15.11%

(Sources: Author's analysis)

The results indicate that each class of trend-following rules generates a moderate proportion of rules with a BETC above 50 basis points, ranging from approximately 15% to 20% for long-short portfolios and 46% to 56% for long-only portfolios over the entire sample period. However, the number of rules outperforming the transaction cost is declining. For example, from January 2017 to June 2020, 30.66% of long-short trend-following portfolios had a breakeven cost above 50 basis points, but this proportion dropped to 7.96% from July 2020 to April 2024. Similarly, for long-only portfolios, the proportion decreased from 54.29% to 31.78% across the same periods. This trend suggests that fewer trend-following rules can generate positive returns over time, with most positive returns being wiped out by the hypothesized transaction cost of 50 basis points.

Table 4.9: Breakeven transaction cost (BETC) and the percentage of long-only portfolio that have positive returns considering 50bsp threshold.

Trend following trading rule	Ave no. Long	Avg. Long return	BETC	% > 50bsp
2017-01-01 - 2024-04-29	**209**	**2.3128%**	**1.1498%**	**52.62%**
MACD	225	2.4201%	1.2028%	53.54%
Moving Average	206	2.2734%	1.1303%	55.81%
RSI Oscillator	168	2.2661%	1.1267%	39.56%
Support & Resistance	212	2.1970%	1.0925%	46.65%
2017-01-01 - 2020-06-30	**98**	**3.2859%**	**1.6297%**	**54.29%**
MACD	106	3.4131%	1.6922%	61.46%
Moving Average	96	3.3381%	1.6554%	52.74%
RSI Oscillator	81	3.0853%	1.5309%	39.48%
Support & Resistance	102	2.7705%	1.3758%	53.93%
2020-07-01 - 2024-04-29	**110**	**1.5142%**	**0.7542%**	**31.78%**
MACD	119	1.5530%	0.7735%	26.25%
Moving Average	109	1.4061%	0.7006%	37.25%
RSI Oscillator	87	1.7556%	0.8740%	31.76%
Support & Resistance	110	1.6932%	0.8430%	21.63%

(Sources: Author's analysis)

Interestingly, even when a strategy class has an average BETC significantly greater than 50 basis points, the proportion of rules outperforming this threshold are not substantial in both long-short and long-only strategies. For instance, in the January 2017 to June 2020 period, Long-only portfolios had an average BETC of 1.63%, well above 0.5% (50 basis points), yet only over half of total rules outperformed the BETC threshold. This suggests that only a small subset of trend-following rules with specific parameterizations deliver superior performance, while the majority perform poorly, skewing the distribution.

Overall, the findings of this study are weaker compared to Hudson and Urquhart (2019), who found that around 20%-50% of technical rules had a BETC above 50 basis points. This study reaffirms that the effectiveness of trend-following strategies diminishes over time, with positive returns likely being erased by transaction costs.

4.3.2 Data snooping

So far, it has been proven that only a portion of trend-following strategies generate positive returns after accounting for transaction costs. However, even the issue of data mining, where searching among many competing rules leads to generating significant results by chance, has not been properly addressed. In this paper, we examined a total of 3,200 trend-following rules, following the model of Hudson and Urquhart (2019). This raises the probability of incorrectly rejecting the null hypothesis to $(1-(1-0.05)^{3,200})$ which is nearly 1.

To address this issue consistently with previous studies, we adopted Family-wise error rate (FWER) and False Discovery Rate (FDR) multiple hypothesis testing correction methods, requiring bootstrapping p-values for each individual rule. **Table 4.10** presents the percentage of trend-following rules that still generate statistically significant positive mean returns at 5% after correction by Bonferroni, Holm, BH, and BY procedures for both long-short and long-only rules.

Table 4.10: The of long-short trading rules that remains significant at 5% after four multiple hypotheses correction methods.

Trend following trading rule	Bonferroni	Holm	BH	BY
2017-01-01 - 2024-04-29	**0.10%**	**0.15%**	**0.56%**	**0.20%**
MACD	0.16%	0.16%	0.95%	0.32%
Moving Average	0.00%	0.05%	0.21%	0.05%
RSI Oscillator	0.00%	0.25%	0.50%	0.25%
Support & Resistance	0.57%	0.57%	1.14%	0.57%
2017-01-01 - 2020-06-30	**0.05%**	**0.13%**	**0.23%**	**0.15%**
MACD	0.00%	0.16%	0.32%	0.24%
Moving Average	0.00%	0.05%	0.05%	0.05%
RSI Oscillator	0.00%	0.00%	0.25%	0.00%
Support & Resistance	0.57%	0.57%	0.86%	0.57%
2020-07-01 - 2024-04-29	**0.00%**	**0.00%**	**0.13%**	**0.00%**
MACD	0.00%	0.00%	0.08%	0.00%
Moving Average	0.00%	0.00%	0.10%	0.00%
RSI Oscillator	0.00%	0.00%	0.25%	0.00%
Support & Resistance	0.00%	0.00%	0.29%	0.00%

(Sources: Author's analysis)

The results are conclusive: very few trading rules, for both long-short and long-only strategies remain significant after accounting for multiple hypothesis testing across different classes in all three examined periods. The highest percentage of "surviving" rules was found under the Holm procedure (the least stringent correction method among the four), with the long-only Resistance & Support class in the 2017-2024 period having 4.71%, equivalent to only 16 out of 350 rules as indicated by **Table 4.11**. This implies that almost all initially identified significant results were likely false positives or Type I errors.

This finding contrasts with the previous study by Hudson and Urquhart (2019), which concluded that around 20% to 50% of technical rules survived across four multiple hypothesis correction procedures. However, it confirms that trend-following rules have lost significant power as the cryptocurrency market has evolved with many ups and downs, different from the pre-2018 period observed by Hudson's study. Once again, the results support the fact that trend-following strategies can hardly generate significant positive returns and cannot "beat" the market.

Table 4.11: The percentage of long-only trading rules that remains significant at 5% after four multiple hypotheses correction methods

Trend following trading rule	Bonferroni	Holm	BH	BY
2017-01-01 - 2024-04-29	**0.33%**	**0.94%**	**1.90%**	**0.94%**
MACD	0.48%	1.77%	2.98%	1.77%
Moving Average	0.00%	0.00%	0.62%	0.00%
RSI Oscillator	0.75%	0.75%	1.50%	1.00%
Support & Resistance	1.14%	4.29%	4.71%	4.29%
2017-01-01 - 2020-06-30	**0.23%**	**0.99%**	**1.63%**	**1.04%**
MACD	0.32%	1.27%	2.22%	1.35%
Moving Average	0.10%	0.78%	1.04%	0.78%
RSI Oscillator	0.25%	0.25%	1.25%	0.50%
Support & Resistance	0.57%	2.00%	2.86%	2.00%
2020-07-01 - 2024-04-29	**0.18%**	**0.43%**	**1.19%**	**0.51%**
MACD	0.48%	0.71%	1.27%	0.79%
Moving Average	0.05%	0.21%	0.42%	0.21%
RSI Oscillator	0.00%	0.50%	2.50%	0.75%
Support & Resistance	0.00%	0.57%	3.71%	0.86%

(Sources: Author’s analysis)

Summary of Chapter 04

Chapter 4 examines the performance of Trend-following strategies in the cryptocurrency market, focusing on both long-short and long-only portfolios across various periods. Initially, all Trend-following strategy classes generate positive returns at a 1% significance level, with many rules showing statistically significant daily mean returns. However, the Buy and Hold portfolio consistently outperforms major part of Trend-following strategies over time for both risk and risk-adjusted returns. The effectiveness of Trend-following strategies diminishes over time, indicating increased market efficiency.

Long-only portfolios, however, perform much better than long-Short portfolios. They achieve an annual return of 89.48% and a Sharpe ratio of 0.80, considerably better than the long-short portfolios' 57.21% return and 0.46 Sharpe ratio. Whereas the MACD class benefits the most from eliminating short orders, with improved returns and Sharpe ratios, even outperforming the Buy and Hold strategy in some metrics.

Nevertheless, the inclusion transaction costs significantly impact profitability. The author calculates the average breakeven transaction cost (BETC) for each strategy. Results show that fewer Trend Following rules exceed the 50 basis points BETC threshold over time. From January 2017 to June 2020, 30.66% of long-short portfolios had a breakeven cost above 50 basis points, but this fell to 7.96% from July 2020 to April 2024. Similarly, for long-only portfolios, the proportion dropped from 54.29% to 31.78%.

Compared to previous studies like Hudson et al. (2019), this study finds Trend-following strategy effectiveness less powerful, suggesting that Trend-following strategies have lost power as the cryptocurrency market has matured. Very scarce trading rules significant after multiple hypothesis testing corrections. The highest percentage of surviving rules, under the Holm procedure, was just 4.71% for the long-only Resistance & Support class in the 2017-2024 period. Overall, Trend-following strategies can hardly "beat" the market, aligning with broader trends in market efficiency.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions of findings

5.1.1 Summary of key findings

The increasing popularity and volatility of the cryptocurrency market have made it a fertile ground for exploring various trading strategies. Among these, trend following strategies have garnered significant attention due to their historical success in traditional markets. The research evaluates the effectiveness of trend-following strategies in the cryptocurrency market, focusing on long-short combined strategies and long-only strategies. The analysis covers the period from January 1, 2017, to April 29, 2024, providing a comprehensive examination of these strategies' performance, statistical significance, and consistency across different timeframes and compared to the Buy and Hold strategy.

The first key finding of this study is the statistical significance of returns generated by trend following strategies. For the long-short portfolio, all strategy classes generate positive returns at a 1% significance level. Additionally, around 70% of these strategies individually show significant positive returns at a 5% level. The Moving Average Convergence Divergence (MACD) and Resistance and Support (RS) strategies stand out for their high returns and risk-adjusted returns, as well as a large proportion of individually significant strategies. Conversely, Moving Average (MA) and Relative Strength Index (RSI) strategies are relatively inferior. These findings suggest that while trend-following strategies can be effective, their performance varies significantly by strategy class. In the context of the long-short portfolio, the positive returns at a 1% significance level align with the findings of Hudson and Urquhart (2019), and Trinh Le (2023), who demonstrated the effectiveness of trend following in generating positive return in cryptocurrency market**.** Similarly, Hurst, Ooi, and Pedersen (2017) found that trend-following strategies across various asset classes yield consistent positive returns over extended periods. The high effectiveness of MACD and RS strategies is supported by their historical success in capturing market momentum and exploiting price levels, respectively. However, the relatively lower performance of MA and RSI strategies echoes the sentiments of Brock, Lakonishok, and LeBaron (1992), who noted that not all technical indicators perform equally well across different market conditions.

More optimistically, the long-only portfolio demonstrates more robust performance. All strategy classes generate positive returns at the 1% significance level, and approximately 86% of the trading rules individually show significant positive returns at the 5% level. MACD remains the most effective strategy, while RS strategies are less effective due to their reliance on short orders. The MA strategy shows improved effectiveness compared to the long-short portfolio, whereas RSI remains the least effective. This indicates a generally higher reliability of long-only strategies in generating statistically significant returns in the cryptocurrency market. The robustness of the long-only strategies in the fast growth cryptocurrency market is consistent with the findings of Moskowitz, Ooi, and Pedersen (2012), who highlighted that time-series momentum strategies perform better in up trending markets. The higher effectiveness of MACD and MA strategies in the long-only portfolio can be attributed to their ability to capture upward trends more reliably, as noted by Jegadeesh and Titman (1993). The lesser effectiveness of RS strategies in a long-only context may result from their design, which traditionally benefits from both upward and downward price movements, limiting their utility in an exclusively long context.

Another critical aspect of this study is the comparison of trend-following strategies and the Buy and Hold strategy. In the long-short portfolio, all strategy classes consistently underperform the Buy and Hold strategy across all metrics, including return, risk-adjusted return (Sharpe ratio, Sortino ratio, and Calmar ratio). Only a modest 20% of the strategies outperform the Buy and Hold strategy, and this outperformance shows a decreasing trend over time. This underperformance is consistent with the findings of Fama and French (2012), who argued that the profitability of technical trading strategies has declined over time due to increasing market efficiency. The modest outperformance of a few strategies may be attributed to specific market anomalies or periods of inefficiency, as suggested by Szakmary et al. (2010).

The long-only portfolio presents a more positive picture. On average, trend-following strategies provide slightly better risk-adjusted returns than the Buy and Hold strategy, with a Sharpe ratio of 0.800, Sortino ratio of 1.226, and Calmar ratio of 1.490, compared to the Buy and Hold's Sharpe ratio of 0.823, Sortino ratio of 1.195, and Calmar ratio of 1.224. Approximately 41-46% of the long-only strategies outperform the Buy and Hold strategy in risk-adjusted returns, with MACD and MA being the main drivers of this outperformance. These findings highlight the potential for long-only trend-following strategies to offer better risk-adjusted returns, although this outperformance is not overwhelmingly significant and appears long time in the past and could not maintain to recent period. The slight outperformance of long-only strategies is supported by the findings of Narayan, Bannigidadmath, and Popp (2017), who noted that certain trend following strategies can outperform passive strategies during specific market conditions. The role of MACD and MA as main drivers of outperformance aligns with their historical effectiveness in identifying and capitalizing on market trends, as evidenced by prior research (Detzel et al., 2018).

The consistency of trend-following strategies across different timeframes compared to the Buy and Hold strategy is another crucial consideration. The effectiveness of these strategies diminishes over time for both long-short and long-only portfolios. While the average performance for the entire period from 2017 to 2024 is positive, the subperiods of 2020-2024 show contrasting results. Most of the positive outcomes from 2017 to 2024 are driven by the 2017-2020 period, during which the market experienced frenzy growth. In the 2020-2024 period, both long-short and long-only strategies underperform the Buy and Hold strategy across all metrics. This inconsistency suggests that the effectiveness of trend following strategies is highly contingent on specific market conditions and periods of high market volatility. The declining effectiveness over time is consistent with findings by Neely et al. (1997), who noted that the profitability of technical trading rules has decreased in more recent periods due to increasing market efficiency. Similarly, the study by Lo, Mamaysky, and Wang (2000) indicated that the predictability of technical indicators diminishes over time as market participants become more sophisticated and adapt to these strategies.

Examining the financial viability and impact of transaction costs on these strategies provides further insights. The impact of transaction costs on the profitability of trend-following strategies is very notable and significantly impacts on their positive returns entirely. Considering current and fluctuating transaction costs, the financial viability of these strategies remains unattractive. The impact of transaction costs is a critical factor that has been highlighted in numerous studies. For instance, Edwards, Caglayan, and Thomas (2013) found that high transaction costs can significantly erode the profitability of technical trading strategies. This aligns with our findings, suggesting that while trend-following strategies can be profitable, their net returns may be significantly reduced by transaction costs, making them less attractive compared to the Buy and Hold strategy.

The robustness and reliability of the findings were tested for potential data snooping biases. The positive results of trend following strategies do not remain statistically significant after adjustments for data snooping biases. Only a small fraction of the strategies, both long-short and long-only, survive robustness tests, indicating that their performance may be due more to chance. This highlights the importance of considering potential biases in evaluating trading strategies. The potential for data snooping bias is a well-documented issue in financial research. Sullivan, Timmermann, and White (2001) emphasized the need for rigorous testing to avoid overfitting and ensure that observed patterns are not simply artifacts of historical data. Our findings corroborate this perspective, indicating that many of the observed positive returns may be the result of data mining rather than genuine predictive power.

5.1.2 Implications of the research

The findings have several critical implications for investors. Firstly, while trend-following strategies can generate statistically significant positive returns, their effectiveness is highly variable. This aligns with the findings of Park and Irwin (2007), who conducted a meta-analysis of technical trading strategies and found that while some strategies can be profitable, their performance is highly inconsistent. This does not support the recommendation for diversification when using trend-following strategies in investment portfolios especially when utilizing such simple and popular technical trading rules only in asset price data as examined by the author. Investors need to be aware that most of these strategies does not consistently outperform more passive approaches like the Buy and Hold strategy, especially when accounting for risk and transaction costs. This suggests that investors should exercise a significant cautious attitude toward trend following strategies.

The research underscores the importance of adaptability in trading strategies. The diminishing effectiveness of trend following strategies over time underscores the importance of adaptability. Investors and traders should recognize that the performance of these strategies is heavily influenced by specific market conditions. During periods of high market growth, such as 2017-2020, trend-following strategies may yield positive results. However, in less favorable conditions, like those observed from 2020-2024, these strategies are likely to underperform. This implies that continuous monitoring and adjustment of trading strategies are necessary to maintain their effectiveness. The importance of adaptability is emphasized by studies such as those by Geczy and Samonov (2017), who noted that the performance of trend following strategies is not uniform across different market conditions. Their research supports the need for a dynamic approach to strategy implementation, adapting to changing market environments to optimize performance.

In summary, the comprehensive analysis of trend-following strategies in the cryptocurrency market indicates that while these strategies can generate statistically significant returns, their effectiveness is highly variable, often diminishes over time, and unlikely maintaining sufficient effectiveness given evolving market efficiency against technical trend-following strategy. Long-only strategies show more promise than long-short strategies, particularly in terms of risk-adjusted returns. However, when compared to the Buy and Hold strategy, trend-following strategies generally underperform, especially after accounting for transaction costs. Furthermore, the robustness tests suggest that the observed positive performance of these strategies may largely be due to chance. Therefore, it is recommended to exercise significant caution when considering trend-following strategies for cryptocurrency trading.

Investors should be aware of the decreasing effectiveness over time and the significant impact of transaction costs.

To navigate these challenges, investors should not rely on trend-following strategies especially when using simple and popular technical trading rules only on price data as examined in the study. If necessary, only incorporating them as part of a broader, diversified investment portfolio with continuous monitoring and improvement. Additionally, it is important to account for transaction costs when evaluating the performance of trend-following strategies, as transaction costs can significantly erode potential positive returns. Implementing robust risk management techniques to mitigate the risks associated with trend-following strategies is vital, particularly in highly volatile markets like cryptocurrencies. Lastly, focusing on long-only trend-following strategies may be more beneficial, as they tend to perform better in terms of risk-adjusted returns compared to long-short strategies. By adhering to these recommendations, investors can better navigate the complexities of the cryptocurrency market and optimize the potential benefits of trend-following strategies while mitigating associated risks.

5.2 Limitations and recommendations for further research

5.2.1 Limitations of the research

Although this study carefully evaluates the effectiveness of a broad range of Trend-following strategies, it does not completely avoid any drawbacks and limitations. First, it focuses exclusively on 14 cryptocurrencies using daily historical data from January 2017 to April 2024. This does not completely guarantee or generalize of the findings to other cryptocurrencies in different time intervals (such as intraday frequency or lower frequency such as weekly), or future performance of examined currencies, given the continuously changing and likely non-stationary market conditions.

Second, the Trend-following strategies evaluated are based on specific, relatively simple technical indicators like MACD, Moving Average, Resistance-Support, and RSI due to their popularity; and exercised them solely on price data.

These models' simplicity and popularity may limit the results, which could differ if more advanced technical indicators or sophisticated models on different kinds of data were used to develop alpha capturing the "remaining" inefficiency of the market.

Thirdly, the author examined this strategy's effectiveness under equally distributed portfolio rebalancing each year for simplicity. This may not be the case in reality to treat small and risky altcoin such as Solana the same Bitcoin which consistent dominates over 40% of the whole cryptocurrency market capitalization. This equal treatment shifts the trend-following strategy portfolio performance toward non-Bitcoin currencies which may not achieve the market-efficient-degree as Bitcoin, thus overstate the results. Moreover, the study assumes a long-short mechanism was accessible to all currencies across examined period from January 2017 while in reality some currencies were not.

Lastly, the study assumes variable transaction costs in calculating the breakeven transaction cost and evaluates them based on a 50-basis point transaction cost threshold over the examined period. However, actual transaction costs contain both fixed and variables cost, and they vary widely depending on the exchange, trading volume, currency liquidity, and evolving market conditions. This assumption may oversimplify real-world trading conditions and affect the accuracy of the results.

5.2.2 Recommendations for further research

To address the limitations identified, the author also proposed several recommendations for future study to enhance the robustness and applicability of Trend-following strategies in cryptocurrency markets. First, it is advisable to use different time intervals, such as hourly or weekly to better capture the nuances of Trend-following strategies. Research by Moskowitz et al. (2012) suggests that trend following, and momentum strategies can be more effective when implemented over different research intervals compared to daily intervals. Gao et ak. (2018) also found that intraday momentum strategies generate higher returns than daily momentum strategies. This is due to the ability of intraday data to capture more granular price movements and trends that are often missed in daily data. Employing these intervals could provide a more comprehensive understanding of strategy performance across different time frames.

Second, instead of using simple and popular technical indicators whose effectiveness were arbitraged away, incorporating more advanced time series models or machine learning algorithms may significantly improve the detection and utilization of market trends. For instance, time series models like ARIMA (AutoRegressive Integrated Moving Average) or GARCH (Generalized Autoregressive Conditional Heteroskedasticity) can be used to predict price movement, thus may effectiveness confirm the trend, volatility, and provide more accurate entry/exit signal (Pai & Lin. 2005). Additionally, machine learning models such as LSTM (Long Short-Term Memory) networks or reinforcement learning algorithms have been shown to effectively predict and capitalize on market trends (Fischer & Krauss. 2018). These sophisticated methods can offer a more robust framework compared to simple technical indicators like MACD or RSI.

Third, instead of using an equally distributed portfolio, employing a market capitalization-weighted portfolio would more accurately reflect the actual market conditions. A market cap-weighted approach ensures that larger, more influential cryptocurrencies like Bitcoin have a proportionate impact on the portfolio, thereby providing a more realistic assessment of the strategy's performance. Furthermore, considering broad Altcoin index such as the S&P Cryptocurrency LargeCap Ex-MegaCap Index provided by S&P Global instead of individual altcoins for the portfolio can capture a full market performance and provide a more holistic view of the market dynamics. This approach can mitigate the risks associated with smaller, more volatile altcoins and offer a more balanced portfolio.

Lastly, it is crucial to account for transaction costs more realistically. Instead of a fixed 50-basis point transaction cost, future studies should incorporate both fixed and variable costs, accounting for their variation across exchange and the currency. Utilizing a dynamic model to estimate transaction costs would provide a more accurate and practical evaluation of strategy performance. For example, adopting a sliding scale for transaction costs based on trading volume and market conditions can better reflect the real-world trading environment (Kissell. 2016).

Summary of Chapter 5

The increasing popularity and volatility of the cryptocurrency market have made it a fertile ground for exploring various trading strategies, particularly trend following strategies. This study evaluates the effectiveness of such strategies in the cryptocurrency market from January 1, 2017, to April 29, 2024, focusing on both long-short and long-only strategies.

The key findings reveal that trend following strategies generate statistically significant returns, with the long-short portfolio showing all strategy classes producing positive returns at a 1% significance level and around 70% of them remaining individually significant at 5% level. Among these, MACD and Resistance and Support (RS) strategies stand out for their high returns. This aligns with Faber (2007) and Hurst, Ooi, and Pedersen (2017), who highlighted the effectiveness of trend following in various markets. The long-only portfolio demonstrates more robust performance, with all strategy classes generating positive returns at the 1% significance level and approximately 86% of them are individually significant at 5% level, particularly highlighting the effectiveness of MACD strategies. However, when comparing risk-adjusted returns with the Buy and Hold strategy, the long-short strategies underperform, whereas the long-only strategies show slightly better risk-adjusted returns but could not maintain it until recent.

This modest performance is consistent with Narayan, Bannigidadmath, and Popp (2017), who noted that certain trend-following strategies could outperform during specific market conditions. However, the effectiveness of these strategies diminishes over time, particularly in the 2020-2024 period, indicating their performance is highly contingent on market conditions. Transaction costs, although not entirely negating positive returns, does significantly affect profitability, as suggested by Edwards, Caglayan, and Thomas (2013). Robustness tests indicate potential positive performance are subjected to chance, highlighting the need for caution. The findings suggest that trend following, especially when utilizing such simple and popular technical rules as examined in this study, their performance is variable, diminishes over time, and unlikely effectiveness given the market was observed to be more efficient against technical trend following rules. Therefore, investors should not consider these strategies as part of a diversified portfolio, and if necessary, take them with significant caution.

REFERENCES

Abreu, M., Mendes, V., & Urquhart, A., 2022. 'Market efficiency and cryptocurrency: Evidence from a multiscale analysis.' *Journal of International Financial Markets*, Institutions and Money, 70, pp. 1-14.

Adrian, T. & Mancini-Griffoli, T., 2019. 'The rise of digital money.' IMF FinTech Notes, 19(1), pp. 1-20.

Antonacci, G., 2014. Dual Momentum Investing: An Innovative Strategy for Higher Returns with Lower Risk. *New York: McGraw-Hill Education*.

Antonopoulos, A.M., 2014. Mastering Bitcoin: Unlocking Digital Cryptocurrencies. *Sebastopol: O'Reilly Media*.

Appel, G., 1979. The Moving Average Convergence Divergence Trading Method. *Great Neck: Signalert.*

Aste, T., 2016. 'Cryptocurrency market efficiency and anomalous returns.' Physica A: Statistical Mechanics and its Applications, 462, pp. 423-434.

Athey, S., Parashkevov, I., Sarukkai, V., & Xia, J., 2022. 'Bitcoin pricing, adoption, and usage: Theory and evidence.' *SSRN Electronic Journal. Available at: https://ssrn.com/abstract=2826674*

Bajgrowicz, P. & Scaillet, O., 2012. 'Technical trading revisited: False discoveries, persistence tests, and transaction costs.' *Journal of Financial Economics*, 106(3), pp. 473-491.

Balcilar, M., Demirer, R., Hammoudeh, S., & Nguyen, D.K., 2017. 'Bitcoin return predictability: Can the barriers of market efficiency be captured?' *Finance Research Letters*, 23, pp. 212-221.

Banz, R.W., 1981. 'The relationship between return and market value of common stocks.' *Journal of Financial Economics*, 9(1), pp. 3-18.

Barber, B.M. & Odean, T., 2001. 'Boys will be boys: Gender, overconfidence, and common stock investment.' *Quarterly Journal of Economics*, 116(1), pp. 261-292.

Baur, D.G. & Lucey, B.M., 2010. 'Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold.' *Financial Revie*w, 45(2), pp. 217-229.

Benjamini, Y. and Hochberg, Y. (1995) 'Controlling the false discovery rate: A practical and powerful approach to multiple testing', Jou*rnal of the Royal Statistical Society, Series* B, 57, pp. 289-300.

Benjamini, Y. and Yekutieli, D. (2001) 'The control of the false discovery rate in multiple testing under dependency', *Annals of Statistics*, 29, pp. 1165-1188.

Brock, W., Lakonishok, J., & LeBaron, B., 1992. 'Simple technical trading rules and the stochastic properties of stock returns.' *Journal of Finance*, 47(5), pp. 1731-1764.

Brown, S.J., Goetzmann, W.N., Ibbotson, R.G., & Ross, S.A., 1992. 'Survivorship bias in performance studies.' *Review of Financial Studies*, 5(4), pp. 553-580.

Buterin, V., 2013. 'Ethereum: A next-generation smart contract and decentralized application platform.' *Ethereum Whitepaper. Available at:* *https://ethereum.org/en/whitepaper/*

CFA Institute, 2024. 'Portfolio Management: An Overview', CFA Institute. *Available at: https://www.cfainstitute.org/en/membership/professional-development/refresher-readings/portfolio-management-overview.*

Corporate Finance Institute (2023) 'Backtesting'. *Available at: https://corporatefinanceinstitute.com/resources/data-science/backtesting/.*

Chabot, B., Ghysels, E., and Jagannathan, R. (2008). Price Momentum in Stocks: Insights from Victorian Age Data. *Journal of Financial Economics*, 82(3), pp. 679-706.

Chan, L.K.C. & Zhou, G., 2016. 'The illiquidity premium: International evidence.' *Journal of Financial Economics*, 120(3), pp. 614-638.

Cheah, E.-T. & Fry, J., 2015. 'Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin.' *Economics Letters*, 130, pp. 32-36.

Cheng, Q., Liu, X., and Zhu, X., 2019. Cryptocurrency momentum effect: DFA and MF-DFA analysis. Physica A: Statistical Mechanics and its Applications.

Ciaian, P., Rajcaniova, M., & Kancs, d'A., 2016. 'The economics of BitCoin price formation.' *Applied Economics*, 48(19), pp. 1799-1815.

CoinDesk, 2021. 'Crypto markets see massive inflow of institutional investors.' *Available at: https://www.coindesk.com/institutional-investors-crypto-market-growth/*

CoinMarketCap, 2023. 'Cryptocurrency market capitalization charts.' *Available at: https://coinmarketcap.com/charts/*

ConsenSys, 2021. 'The rise of decentralized finance (DeFi).' ConsenSys Blog. *Available at: https://consensys.net/blog/news/the-rise-of-decentralized-finance-defi/*

Deloitte, 2020. 'Deloitte’s 2020 global blockchain survey.' *Available at: https://www2.deloitte.com/global/en/pages/technology/articles/gx-deloitte-blockchain-survey.html*

Detzel, A., Liu, L.X., Strauss, J., Zhou, G., & Zhu, Y., 2018. 'Bitcoin momentum: Implications for returns and risk.' *Journal of Financial Economics*, 129(3), pp. 685-706.

Detzel, A., Liu, Q., Strauss, J., Zhou, G., and Zhu, Y., 2018. The Value of FORECASTS: Can the Financial Market Predict Aggregate Real Activity?. *Journal of Financial Economics*, 130(2), pp. 367-392.

Dobrynskaya, V., Dubrovskiy, M., 2023. "Cryptocurrencies meet equities: Risk factors and asset-pricing relationships." Fintech, Pandemic, and the Financial Crisis. *Emerald Publishing.*

Dow, C., 1902. Dow Theory Unplugged: Charles Dow's Original Editorials and Their Relevance Today. *Great Neck: Signalert.*

Dyhrberg, A.H., 2016. 'Bitcoin, gold and the dollar – A GARCH volatility analysis.' *Finance Research Letters*, 16, pp. 85-92.

Edwards, F.R., Caglayan, M.O., & Thomas, J.P., 2013. 'Hedge fund performance and manager skill.' *Journal of Portfolio Management*, 39(1), pp. 35-47.

Edwards, R.D. & Magee, J., 1948. Technical Analysis of Stock Trends. *Springfield: Edwards and Magee.*

Elendner, H., Trimborn, S., Ong, B., & Lee, T.M., 2016. 'The cross-section of cryptocurrency returns.' *SSRN Electronic Journal. Available at: https://ssrn.com/abstract=2892301*

European Central Bank, 2019. 'Crypto-assets: Implications for financial stability, monetary policy, and payments and market infrastructures.' ECB Occasional Paper Series. *Available at: https://www.ecb.europa.eu/pub/pdf/scpops/ecb.op223~3ce14e986c.en.pdf*

Faber, M.T., 2007. 'A quantitative approach to tactical asset allocation.' *Journal of Wealth Management*, 9(4), pp. 69-79.

Fama, E. F. (1991). Efficient Capital Markets: II. *Journal of Finance*, 46(5), pp. 1575-1617.

Fama, E.F. & Blume, M., 1966. 'Filter rules and stock market trading.' *Journal of Business*, 39(1), pp. 226-241.

Fama, E.F. & French, K.R., 1993. 'Common risk factors in the returns on stocks and bonds.' *Journal of Financial Economics*, 33(1), pp. 3-56.

Fama, E.F. & French, K.R., 2012. 'Size, value, and momentum in international stock returns.' *Journal of Financial Economics*, 105(3), pp. 457-472.

Fama, E.F., 1970. 'Efficient capital markets: A review of theory and empirical work.' *Journal of Finance*, 25(2), pp. 383-417.

Financial Action Task Force (FATF), 2019. 'Guidance for a risk-based approach to virtual assets and virtual asset service providers.' *Available at: https://www.fatf-gafi.org/publications/fatfrecommendations/documents/guidance-rba-virtual-assets.html*

Frydenberg, S., Johansen, A., & Sornette, D., 2017. 'A robust trend-following strategy for trading the cryptocurrency market.' *Finance Research Letters*, 26, pp. 1-6.

Geczy, C., and Samonov, M. (2017). Two Centuries of Trend Following. *SSRN Electronic Journal. Available at: https://ssrn.com/abstract=2993026 (Accessed: 23 May 2024).*

Geczy, C.C. & Samonov, M., 2017. 'Two centuries of trend following.' *Journal of Investing*, 26(4), pp. 42-59.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M.C., & Siering, M., 2014. 'Bitcoin – Asset or currency? Revealing users' hidden intentions.' *SSRN Electronic Journal. Available at: https://ssrn.com/abstract=2425247*

Hassan, S. & De Filippi, P., 2021. 'Decentralized autonomous organizations.' *Internet Policy Review*, 10(2), pp. 1-20.

Hendrickson, J.R., Hogan, T.L., & Luther, W.J., 2016. 'The political economy of Bitcoin.' *Economic Inquiry*, 54(2), pp. 925-939.

Hsieh, D.A. & Sullivan, R.N., 2016. 'Trend-following strategies in commodity futures: A reexamination.' *Journal of Investment Management*, 14(2), pp. 41-60.

Hudson, R. & Urquhart, A., 2019. 'Technical trading and cryptocurrencies.' *Finance Research Letters*, 29, pp. 145-150.

Hurst, B., Ooi, Y.H., & Pedersen, L.H., 2017. 'A century of evidence on trend-following investing.' *Journal of Portfolio Management*, 44(1), pp. 15-29.

Iansiti, M. & Lakhani, K.R., 2017. 'The truth about blockchain.' *Harvard Business Review,* 95(1), pp. 118-127.

ICORating, 2018. 'ICO market research Q2 2018.' *Available at: https://icorating.com/report/ico-market-research-q2-2018/*

Investopedia, 2023. 'Monte Carlo Simulation'. *Available at: https://www.investopedia.com/terms/m/montecarlosimulation.asp.*

Investopedia, 2024. 'Moving Average Convergence Divergence (MACD)', Investopedia. *Available at: https://www.investopedia.com/terms/m/macd.asp.*

Investopedia, 2024. 'Relative Strength Index (RSI)', Investopedia. *Available at: https://www.investopedia.com/terms/r/rsi.asp*.

Investopedia, 2023 Transaction Costs. *Available at: https://www.investopedia.com/terms/t/transactioncosts.asp.*

James, D. & Menzies, G., 2020. 'The case for trend following in cryptocurrencies.' *Journal of Behavioral and Experimental Finance*, 26, pp. 100287.

Jegadeesh, N. & Titman, S., 1993. 'Returns to buying winners and selling losers: Implications for stock market efficiency.' *Journal of Finance*, 48(1), pp. 65-91.

Jegadeesh, N., and Titman, S., 2001. Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *Journal of Finance*, 56(2), pp. 699-720.

Kahneman, D. & Tversky, A., 1979. 'Prospect theory: An analysis of decision under risk.' *Econometrica*, 47(2), pp. 263-291.

Keim, D.B., 1983. 'Size-related anomalies and stock return seasonality: Further empirical evidence.' *Journal of Financial Economics*, 12(1), pp. 13-32.

Krafft, M. & Xiong, J., 2018. 'Cryptocurrencies and trend following.' *Journal of Investment Strategies*, 7(1), pp. 39-50.

Kroft, L.C. van der (2018). "Price momentum in the cryptocurrency markets." Master's *Thesis, Erasmus University.*

Kyriazis, N.A., 2019. 'A survey on efficiency and profitable trading opportunities in cryptocurrency markets.' *Journal of Risk and Financial Management*, 12(2), pp. 67-79.

Larkin, M. & Wong, W.-K., 2018. 'Risk and return in the cryptocurrency market. *Journal of Risk and Financial Management*, 11(4), pp. 63-80.

Leung, P.L., Chong, T.T.L., & Fung, J.K.W., 2015. 'Technical analysis and the London stock exchange: Testing the MACD and RSI rules using the FT30.' *Applied Economics Letters*, 7(2), pp. 111-117.

Levy, B.P.C., Lopes, H.F., 2021. "Trend-Following Strategies via Dynamic Momentum Learning." *arXiv preprint arXiv:2106.08420.*

Li, X. & Wang, C.A., 2017. 'The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin.' *Decision Support Systems*, 95, pp. 49-60.

Litecoin Foundation, 2020. 'Litecoin: A peer-to-peer internet currency.' *Available at: https://litecoin.org/*

Liu, Y. & Tsyvinski, A., 2021. 'Risks and returns of cryptocurrency.' *Review of Financial Studies*, 34(6), pp. 2689-2727.

Lo, A. W., Mamaysky, H., and Wang, J., 2000. Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation. *Journal of Finance,* 55(4), pp. 1705-1765.

Lo, A.W. & MacKinlay, A.C., 1989. 'Data-snooping biases in tests of financial asset pricing models.' *Review of Financial Studies*, 3(3), pp. 431-467.

Malkiel, B. G., 2003. The Efficient Market Hypothesis and Its Critics. *Journal of Economic Perspectives*, 17(1), pp. 59-82.

Michael. L Halls-Moore, 2010. Successful Algorithm Trading. *John Wiley & Sons*. pp. 15-20.

Miffre, J. & Rallis, G., 2007. 'Momentum strategies in commodity futures markets.' *Journal of Banking & Finance*, 31(6), pp. 1863-1886.

Moskowitz, T.J., Ooi, Y.H., & Pedersen, L.H., 2012. 'Time series momentum.' *Journal of Financial Economics*, 104(2), pp. 228-250.

Murphy, J.J., 1999. Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications. *New York: New York Institute of Finance*.

Nakamoto, S., 2008. 'Bitcoin: A peer-to-peer electronic cash system.' *Bitcoin Whitepaper. Available at: https://bitcoin.org/bitcoin.pdf*

Narayan, P. K., Bannigidadmath, D., and Popp, S., 2017. Do Financial Market Variables Predict Changes in Fundamentals? Evidence from Panel Data. *Economic Modelling*, 64, pp. 46-61.

Narayan, P.K., Narayan, S., & Phan, D.H.B., 2021. 'Trading cryptocurrencies: A triple heuristic investment approach.' *Journal of Financial Markets*, 55, pp. 100619.

Narayanan, A., Bonneau, J., Felten, E., Miller, A., & Goldfeder, S., 2016. Bitcoin and Cryptocurrency Technologies: A Comprehensive Introduction. *Princeton: Princeton University Press.*

Neely, C. J., Weller, P. A., and Dittmar, R., 1997. Is Technical Analysis in the Foreign Exchange Market Profitable? A Genetic Programming Approach. *Journal of Financial and Quantitative Analysis*, 32(4), pp. 405-426.

Neureuter, J., 2021. Institutional Investor Digital Assets Study. Fidelity Digital Assets. Avail*able at:* *https://www.fidelitydigitalassets.com/sites/g/files/djuvja3256/files/acquiadam/993307.2.0_2021%20Institutional%20Investor%20Digital%20Assets%20Study%20Report.pdf*

Nguyen, C.C., Hoang, L.T., Phan, T.L., & Le, M.C., 2022. 'The impact of COVID-19 on cryptocurrency markets.' *Finance Research Letters*, 45, pp. 102221.

Park, C.H. & Irwin, S.H., 2007. 'What do we know about the profitability of technical analysis?' *Journal of Economic Surveys*, 21(4), pp. 786-826.

Platanakis, E. & Urquhart, A., 2019. 'Should investors include Bitcoin in their portfolios? A portfolio theory approach.' *Applied Economics Letters*, 26(7), pp. 467-473.

Politis, D.N. and Romano, J.P. (1994) 'The stationary bootstrap', *Journal of the American Statistical Association*, 89, pp. 1303-1313.

Poterba, J.M. & Summers, L.H., 1988. 'Mean reversion in stock prices: Evidence and implications.' *Journal of Financial Economics*, 22(1), pp. 27-59.

Pring, M.J., 2002. Technical Analysis Explained: The Successful Investor's Guide to Spotting Investment Trends and Turning Points. New *York: McGraw-Hill Education*.

Rohrbach, J., Suremann, S., 2017. "Momentum and trend following trading strategies for currencies revisited-combining academia and industry." *SSRN.*

Rouwenhorst, K. G., 1998. International Momentum Strategies. *Journal of Finance*, 53(1), pp. 267-284.

Saksonova, S. & Kuzmina-Merlino, I., 2019. 'Cryptocurrencies as an investment tool: A comparative analysis.' *Procedia Computer Science*, 156, pp. 407-416.

Schwartz, D., Youngs, N., & Britto, A., 2014. 'The Ripple protocol consensus algorithm.' *Ripple Labs Whitepaper. Available at: https://ripple.com/files/ripple_consensus_whitepaper.pdf*

Selmi, R., Mensi, W., Hammoudeh, S., & Bouoiyour, J., 2018. 'Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold.' *Energy Economics*, 74, pp. 787-801.

Shiller, R.J., 2003. 'From efficient markets theory to behavioral finance.' *Journal of Economic Perspectives*, 17(1), pp. 83-104.

Shynkevich, A., 2012. 'Performance of technical analysis in growth and small cap segments of the US equity market.' *Journal of Financial Markets*, 15(1), pp. 173-202.

StrategyQuant (2015) Walk-Forward Optimization. *Available at: https://strategyquant.com/doc/strategyquant/walk-forward-optimization/ (Accessed: 29 May 2024).*

Sullivan, R., Timmermann, A., & White, H., 2001. 'Data-snooping, technical trading rule performance, and the bootstrap.' *Journal of Finance*, 54(5), pp. 1647-1691.

Sullivan, R., Timmermann, A., and White, H. (2001). Dangers of Data Mining: The Case of Calendar Effects in Stock Returns. *Journal of Econometrics*, 105(1), pp. 249-286.

Szakmary, A.C., Shen, Q., & Sharma, S.C., 2010. 'Trend-following strategies in commodity futures: A re-examination.' *Journal of Banking & Finance*, 34(2), pp. 409-426.

Taylor, M.P. & Allen, H., 1992. 'The use of technical analysis in the foreign exchange market.' *Journal of International Money and Finance*, 11(3), pp. 304-314.

Thaler, R.H., 1985. 'Mental accounting and consumer choice.' *Marketing Science*, 4(3), pp. 199-214.

The Block, 2023. 'Bid-Ask Spread (BTC/USD, BPS)'. *Available at: https://www.theblock.co/data/crypto-markets/spot/bid-ask-spread-btc-usd.*

Tversky, A. & Kahneman, D., 1974. 'Judgment under uncertainty: Heuristics and biases.' *Science*, 185(4157), pp. 1124-1131.

Tzouvanas, P., Kizys, R., and Tsend-Ayush, B. (2020). Momentum trading in cryptocurrencies: Short-term returns and diversification benefits. *Economics Letters*.

Urquhart, A., 2016. 'The inefficiency of Bitcoin.' *Economics Letters*, 148, pp. 80-82.

White, H. (2000). "A Reality Check for Data Snooping". *Econometrica*, 68(5), 1097-1126.

Wilder, J.W., 1978. New Concepts in Technical Trading Systems. *Greensboro: Trend Research.*

Wood, G., 2016. 'Polkadot: Vision for a heterogeneous multi-chain framework.' *Polkadot Whitepaper. Available at: https://polkadot.network/PolkaDotPaper.pdf*

World Federation of Exchanges, 2023. 'Monthly report: Global markets performance.' *Available at: https://www.world-exchanges.org/*

Yermack, D., 2015. 'Is Bitcoin a real currency? An economic appraisal.' *Handbook of Digital Currency: Bitcoin, Innovation, Financial Instruments, and Big Data*, pp. 31-43.

Zetsche, D.A., Buckley, R.P., Arner, D.W., & Barberis, J.N., 2019. 'The rise of ICOs: Lessons and opportunities.' *Duke Law Journal*, 68(5), pp. 101-136.

Zhou, Y. & Dong, X., 2020. 'Moving average strategies in cryptocurrency markets: An empirical analysis.' *Journal of Financial Markets*, 47, pp. 100486.

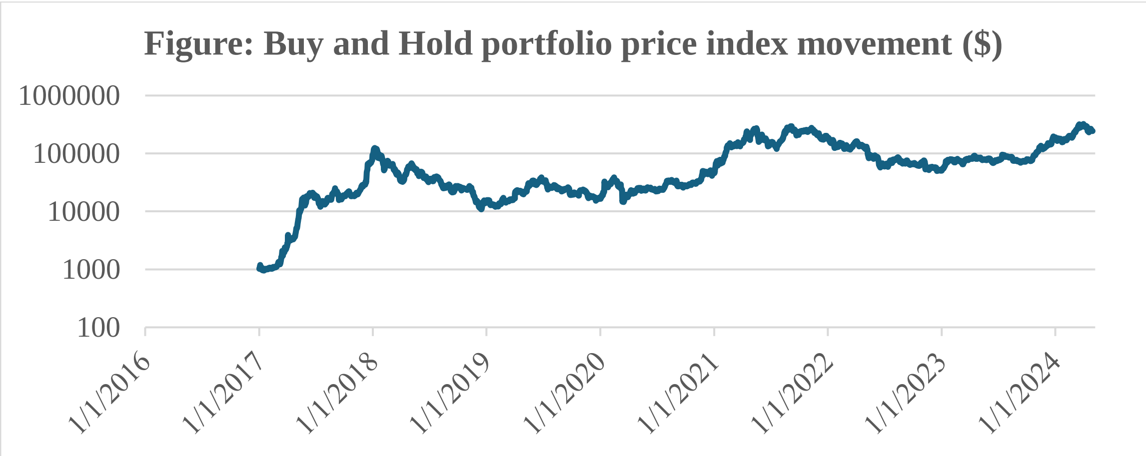
APPENDIX

Table: Portfolio components over testing year and their market capitalization

Cryptocurrency	Ticker	Market.cap ($Bn)	% total market.cap
2017-2018		16.453	96.84%
Bitcoin	BTC	14.905	87.73%
Ethereum	ETH	0.943	5.55%
Ripple	XRP	0.247	1.45%
LiteCoin	LTC	0.19	1.12%
Monero	XMR	0.168	0.99%
2018-2019		396.46	78.16%
Bitcoin	BTC	195.089	38.46%
Ethereum	ETH	101.943	20.10%
Ripple	XRP	53.463	10.54%
Bitcoin Cash	BCH	30.068	5.93%
Cardano	ADA	15.897	3.13%
2019-2020		92.976	76.21%
Bitcoin	BTC	62.99	51.63%
Ripple	XRP	13.181	10.80%
Ethereum	ETH	12.483	10.23%
Bitcoin Cash	BCH	2.177	1.78%
EOS Network	ADA	2.145	1.76%
2020-2021		197.947	82.82%
Bitcoin	BTC	158.194	66.19%
Ethereum	ETH	18.257	7.64%
Ripple	XRP	10.284	4.30%
Bitcoin Cash	BCH	6.167	2.58%
Bitcoin SV	BSV	5.045	2.11%
2021-2022		797.292	77.41%
Bitcoin	BTC	600.888	58.34%
Ethereum	ETH	159.184	15.45%
Ripple	XRP	16.268	1.58%
Cardano	ADA	11.01	1.07%
ChainLink	LINK	9.942	0.97%
2022-2023		1121.774	84.13%
Bitcoin	BTC	687.012	51.53%
Ethereum	ETH	302.389	22.68%
Binance Coin	BNB	63.393	4.75%

Cardano	ADA	37.644	2.82%
Solana	SOL	31.336	2.35%
2023-2024		676.411	85.26%
Bitcoin	BTC	402.234	50.70%
Ethereum	ETH	189.982	23.95%
Binance Coin	BNB	48.319	6.09%
Ripple	XRP	19.518	2.46%
Solana	SOL	16.358	2.06%

(*Sources: CoinMarketcap)*



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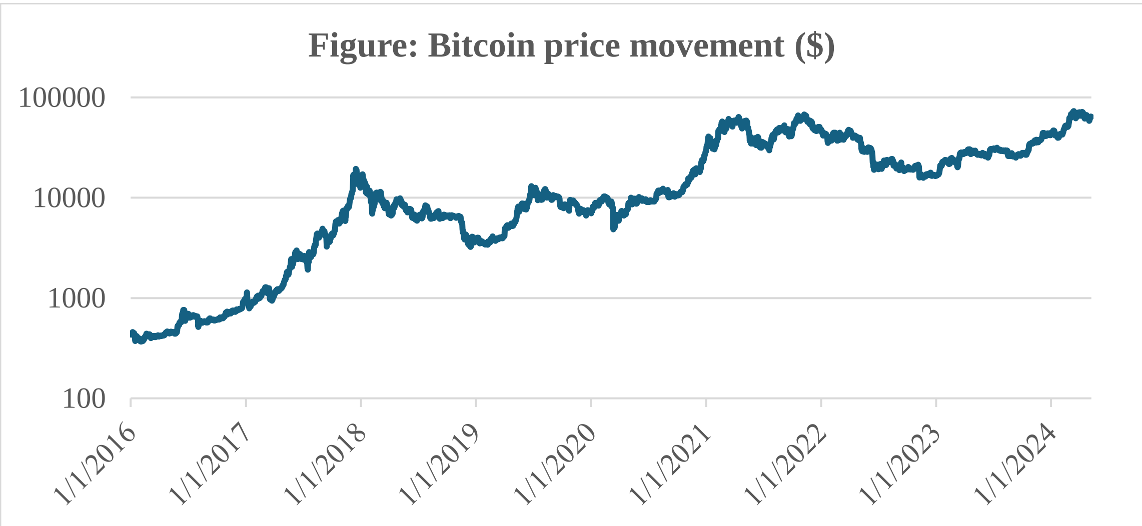

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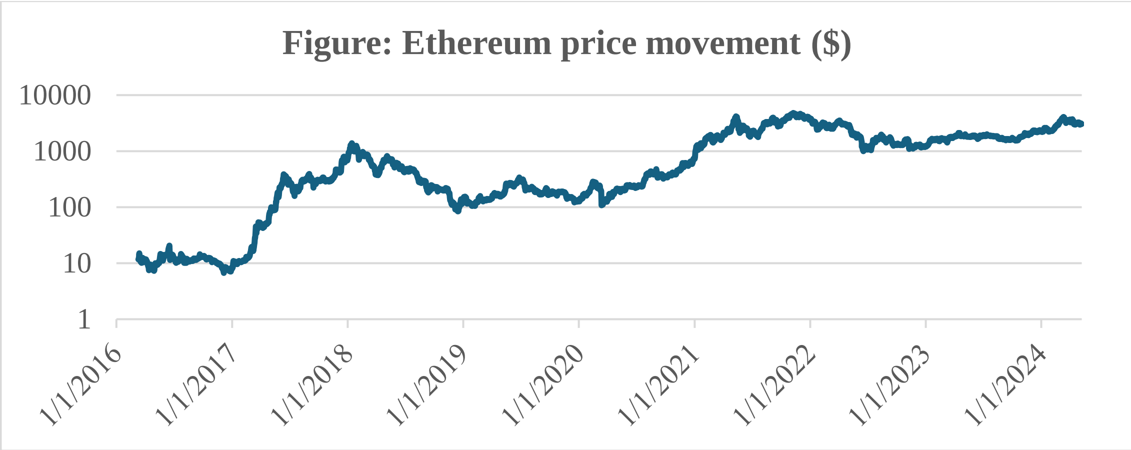

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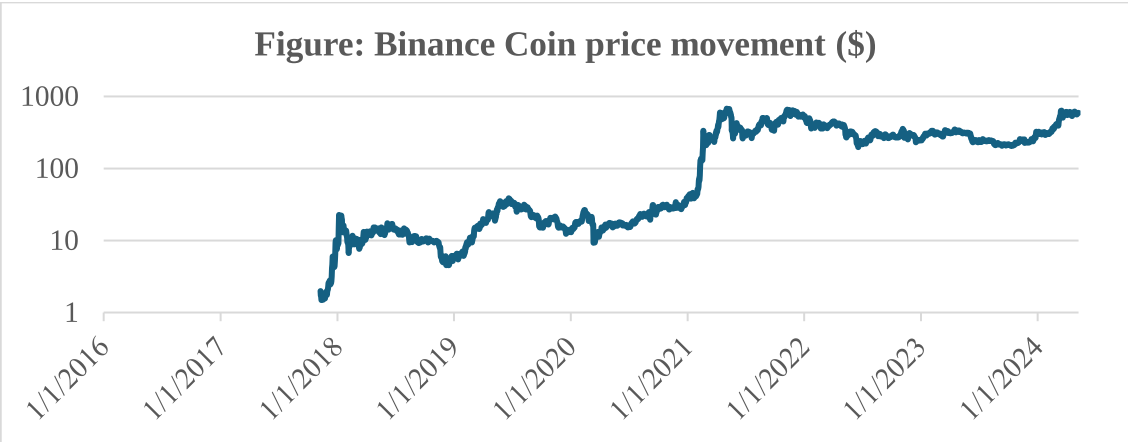

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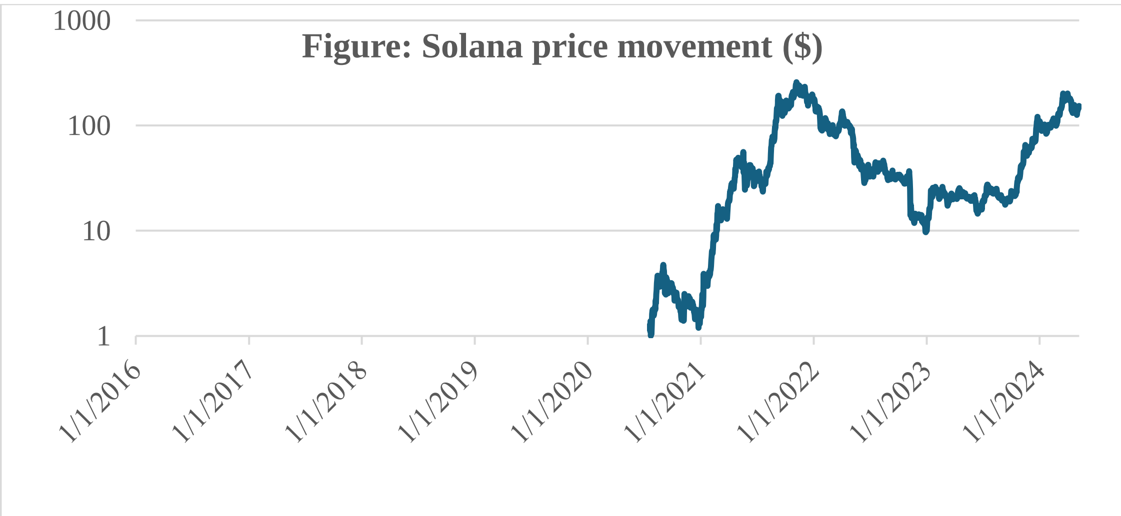

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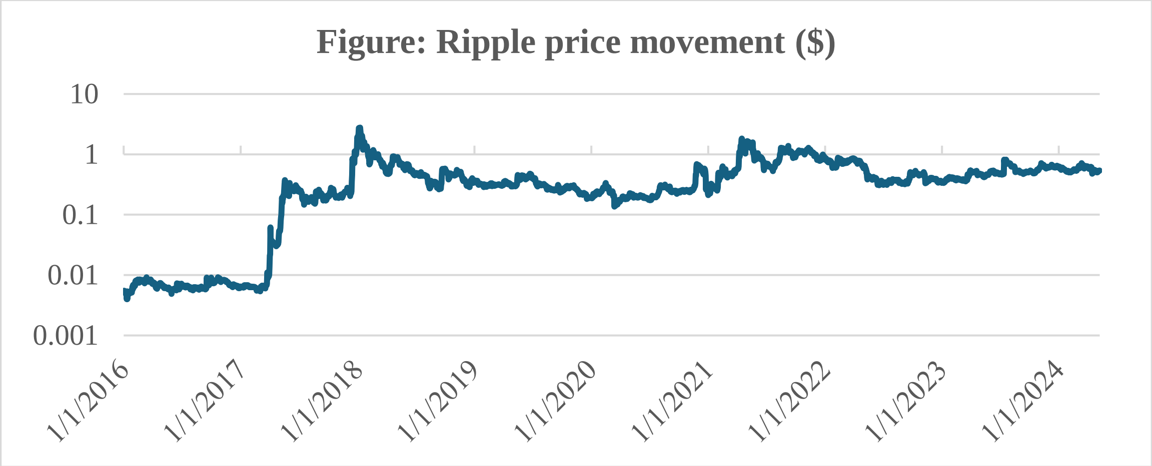

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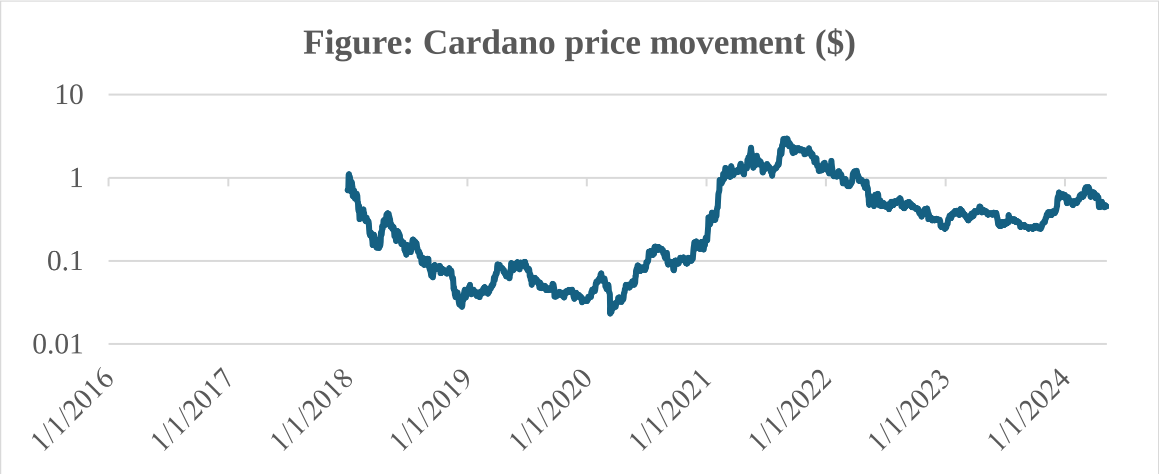

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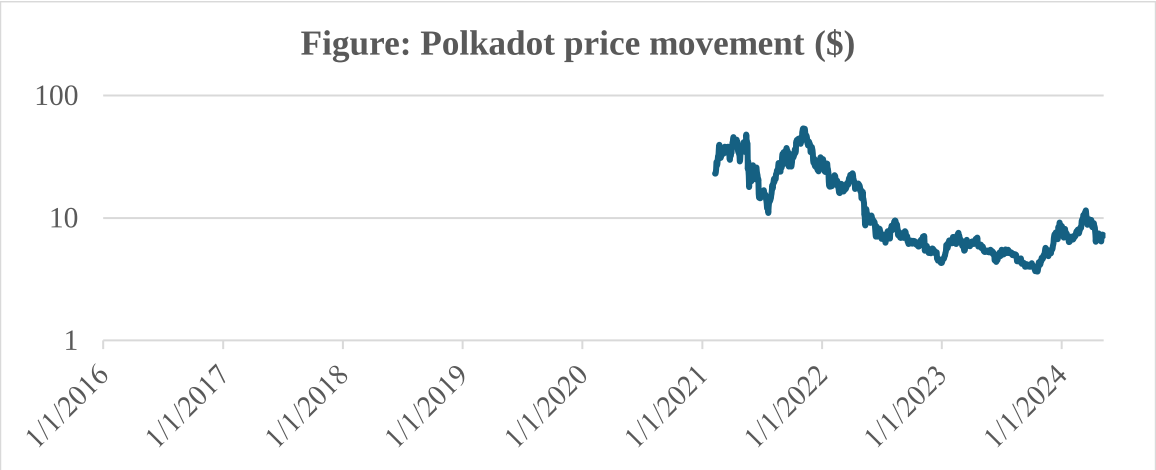

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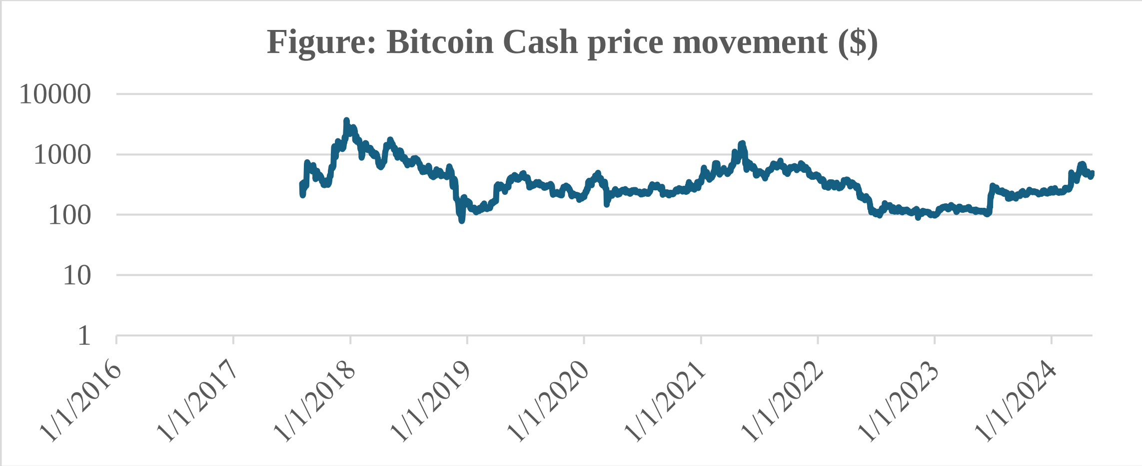

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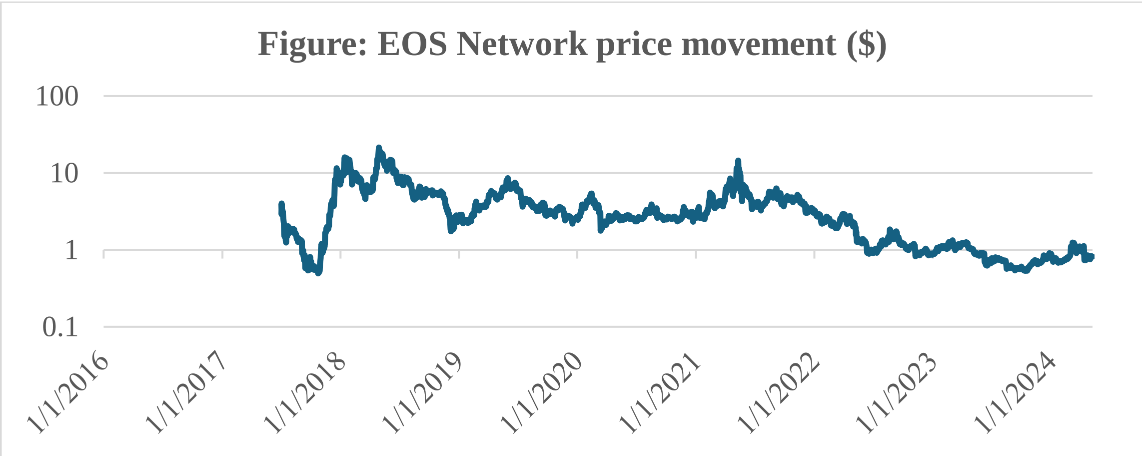

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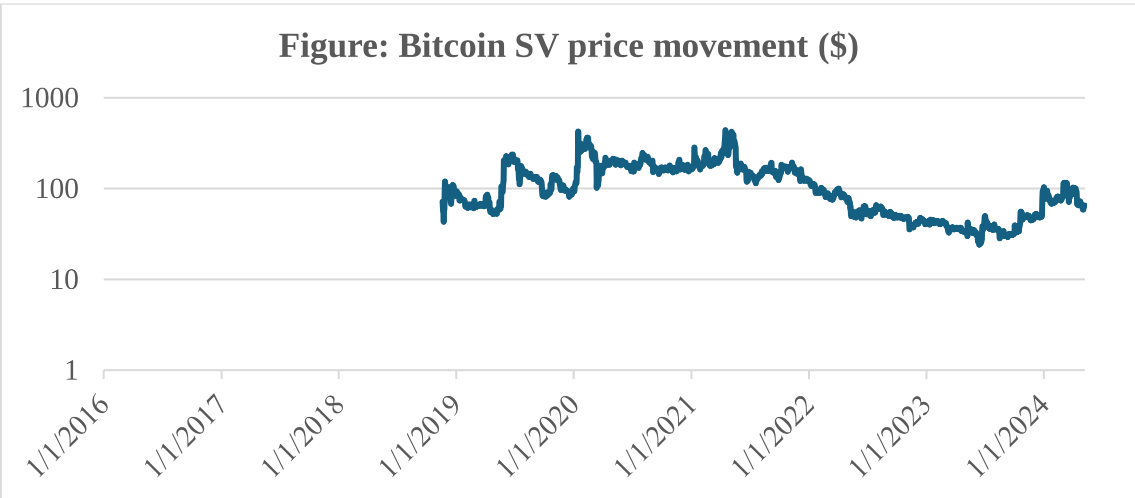

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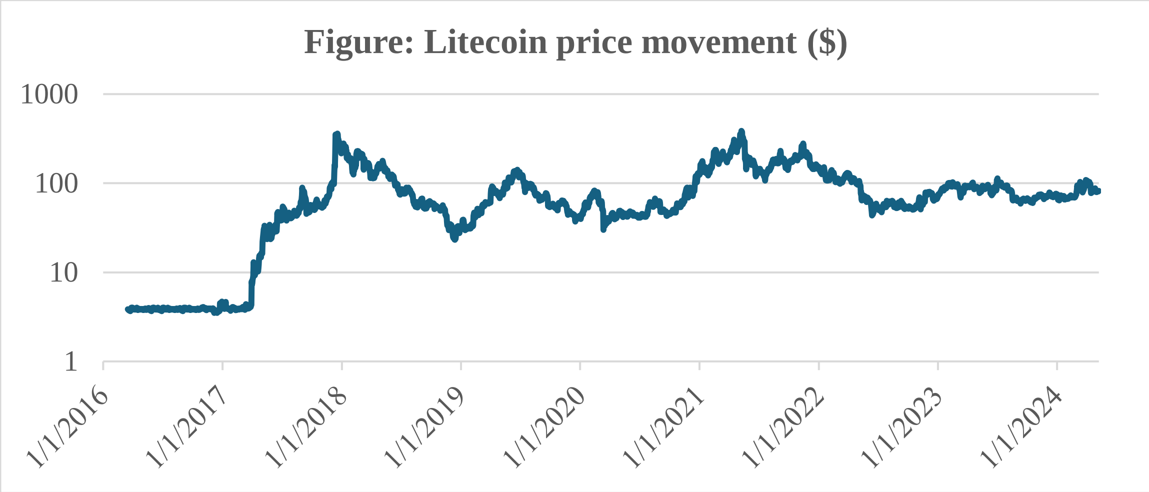

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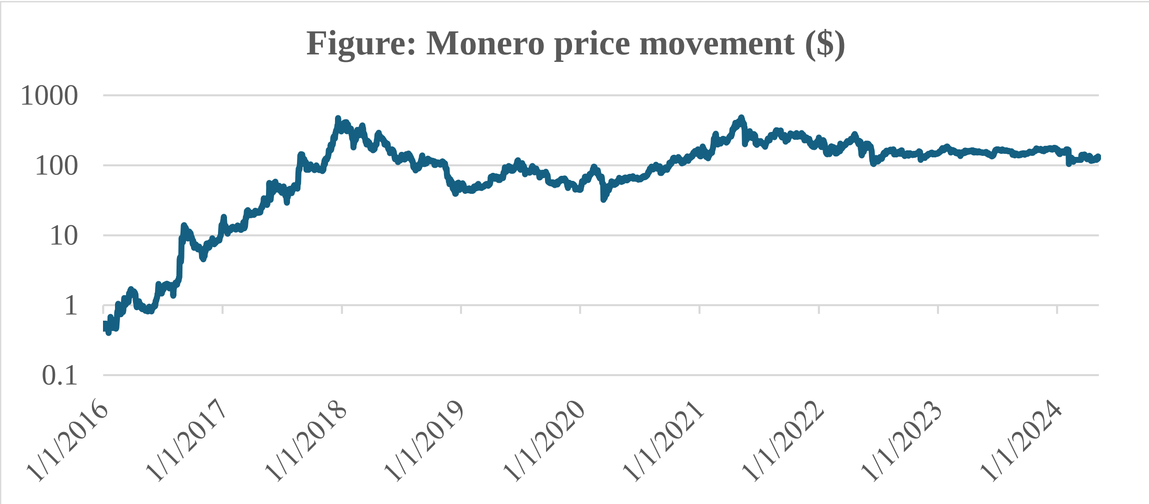

(*Sources: Refinitiv Eikon)*

Specifying trading strategy

(1) Moving Average

In this study, the author utilized Simple moving average to generate trading signal. Simple moving average is defined as:

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

MA_t (n): n day Simple moving average at time t

P_{t-i}: The closing price at time t-1

n: The length of value

Trading rules: If $MA_t(n_{short})$ moves up at least *x* percent above $MA_t(n_{long})$ and remains so for *d* periods, go long until $MA_t(n_{short})$ moves down at least *x* percent below $MA_t(n_{long})$ and remains so for *d* periods, at which time go short. If $MA_t(n_{short})$ moves down at least *x* percent below $MA_t(n_{long})$ and remains so for *d* periods, go short until $MA_t(n_{short})$ moves up at least *x* percent above $MA_t(n_{long})$ and remains so for *d* periods, at which time go long. n_{short} is less than n_{long}. In this case, n = 1 implicate the close price of the assets itself. (Investopedia, Hudson and Urquhart, 2019). The trading signal can be expressed as:

$$Signal_t = \begin{cases} 1 & \mid Diff_{t-i}\,[MA(n_{short}), MA(n_{long})] \geq x\% \\ -1 & \mid Diff_{t-i}\,[MA(n_{short}), MA(n_{long})] \leq -x\% \\ 0 & \mid Others\ cases \end{cases}$$

$i = \{0, 1, 2, \ldots, d\text{-}1\}$

(Sources: Author's analysis and compilation)

Where:

$Signal_t$: The buy or sell signal at time t

$Diff_t$ [MA(n_{short}), MA(n_{long})]: the percentage different between MA_t (n_{short}) over MA_t (n_{long})

The signal with value of one indicates a there is a long position while the value of negative one indicates there is a short position. The value of zero means there is no position.

The author considers several different parameter specifications, namely:

$n_{short} \in \{1, 2, 5, 10, 15, 20, 25, 50, 100, 150\}$ (day) $|\# n_{short} = 10$

$n_{long} \in \{2, 5, 10, 15, 20, 25, 50, 100, 150, 200\}$ (day) $| \# n_{long} = 10$

$x \in \{0, 0.01, 0.05, 0.1, 0.5, 1, 5\}$ (%) $| \#x = 7$

$d \in \{1, 2, 3, 4, 5\}$ (day) $| \#d = 5$

Therefore, the author studies 1575 trading rule under following number of parameterizations:

Number of different parameterization $= \#(n_{long} > n_{short}) \times \#x \times \#d = 45 \times 7 \times 5 = 1575$

(2) Resistance-support

The trading signal for Resistance & Support indicator can be expressed as:

$$Signal_t = \begin{cases} 1 & | \ Diff_t\,(P, R) \geq x\% \\ -1 & | \ Diff_t\,(P, S) \leq -x\% \\ 0 & | \ Others\ cases \end{cases}$$

$i = \{0, 1, 2, \ldots, d\text{-}1\}$

(Sources: Author's analysis and compilation)

Where:

$Signal_t$: The buy or sell signal at time t

R_t: The Resistance value at time t

S_t: The Support value at time t

The signal with value of one indicates a there is a long position while the value of negative one indicates there is a short position. The value of zero means there is no position.

The resistance level at time t is defined as the highest price, and the support is the lowest price of over n previous days, so it also called as "moving resistance/support". However, technically, if the price penetrating to the through the resistance/support at t-1, the price would immediately become the resistance / support at time t so the we cannot examine that if it can remain x percent above/below the previous resistance/support for x percentage for d days. So the resistance/support at time t should be re-defined as the highest/lowest price over n previous period, but if in the last d days from time t, the price has penetrating through the resistance/support for at least one time, the resistance/support at time t should remain its value in t-1. The main idea is that the resistance/support value should maintain static, not moving when the price is "testing" it before forming a new trend (Hudson and Urquhart, 2019, Author's compilation)

$$R_t = \begin{cases} R_t & \mid Or[\, Diff_t(P, R), Diff_{t-1}(P, R), \dots , Diff_{t-d}(P, R) \mid \geq x\% \,] \\ Max_t(P, n) & \mid Other\ case \end{cases}$$

$$S_t = \begin{cases} S_t & \mid Or[\, Diff_t(P, S), Diff_{t-1}(P, S), \dots , Diff_{t-d}(P, S) \mid \leq -x\% \,] \\ Min_t(P, n) & \mid Other\ case \end{cases}$$

(Sources: Author's analysis and compilation)

Where:

$Diff_t$ (P, R): The percentage difference between the P_t and R_t at time t

Max_t (P, n): The max close price over n period at time t

Min_t (P, n): The min close price over n period at time t

Or[$Diff_t$ (P, R), $Diff_{t-1}$ (P, R),… , $Diff_{t-d}$ (P, R) | ≥ x%]: Being True if in previous d days from t, the price have rise above the resistance for at least x percentage for at least one time

Or[$Diff_t$ (P, S), $Diff_{t-1}$ (P, S),… , $Diff_{t-d}$ (P, S) | ≤ -x%]: Being True if in previous d days from t, the price have fall below the support for at least x percentage for at least one time

The author considers several different parameter specifications, namely:

$n \in \{2, 5, 10, 15, 20, 25, 50, 100, 150, 200\}$ (day) | #n = 10

$x \in \{0, 0.01, 0.05, 0.1, 0.5, 1, 5\}$ (%) | #x = 7

$d \in \{1, 2, 3, 4, 5\}$ (day) | #d = 5

Therefore, the author study the 350 Resistance & Support trading rule with different number of parameterizations per rule:

Number of Resistance – Support rules = #n × #x × #d = 10 × 7 × 5 = 350

(3) RSI Oscillator

The Relative Strength Index (RSI) indicator is defined as:

$$RSI_t(n) = 100\left[\frac{U_t(n)}{U_t(n) + D_t(n)}\right]$$

$$U_t(n) = \sum_{i=0}^{n} a\,(P_{t-i} - P_{t-1-i} > 0)\,(P_{t-i} - P_{t-1-i})$$

$$D_t(n) = \sum_{i=0}^{n} a\,(P_{t-i} - P_{t-1-i} < 0)\,|P_{t-i} - P_{t-1-i}|$$

(Sources: Author's analysis and compilation)

Where:

RSI_t (n): The relative strength index at time t with lookback window n period

U_t (n): The cumulated 'up movement' at time t (i.e. the close-to-close increase when the price has closed higher than the previous interval's closing rate) over the previous n days

D_t (n) denotes the cumulated absolute 'down movement' at time t (the absolute close-to-close decrease on an interval when the price has closed lower than the previous interval's closing rate) over the same period.

a(.): is an indicator variable that takes the value one when the statement in parentheses is true and zero otherwise.

Trading rules: If RSI_t (n) moves below 50 - v then subsequently moves above 50 – v for at least d periods, go long. If RSI_t (n) moves above 50 + v and then subsequently moves below 50 + v for at least d periods, go short. The trading signal can be expressed as:

$$Signal_t = \begin{cases} 1 & | \ RSI_t\,(n) < 50 - v \text{ and } RSI_{t-i}\,(n) > 50 - v \\ -1 & | \ RSI_t\,(n) > 50 + v \text{ and } RSI_{t-i}\,(n) < 50 + v \\ 0 & | \ \text{Others cases} \end{cases}$$

$i = \{0, 1, 2, \ldots, d-1\}$

(Sources: Author's analysis and compilation)

The signal with value of one indicates a there is a long position while the value of negative one indicates there is a short position. The value of zero means there is no position.

The author considers several different parameter specifications, namely:

$n \in \{2, 5, 10, 15, 20, 25, 50, 100, 150, 200\}$ *(day)* | $\#n = 10$

$v \in \{2, 5, 10, 15, 20, 25, 30, 40\}$ *(%)* | $\#v = 8$

$d \in \{1, 2, 3, 4, 5\}$ *(day)* | $\#d = 5$

Therefore, the author studies 400 RSI Oscillator trading rule with different parameterizations per rule:

The number of RSI oscillator with different parameterization

Number of RSI Oscillator rules = $\#n \times \#v \times \#d = 10 \times 8 \times 5 = 400$

(4) MACD

Moving Average Convergence Divergence (MACD) indicator is defined as:

$$EMA_t(n) = (P_t \times \frac{2}{n+1}) + EMA_{t-1}(n) \times (1 - \frac{2}{n+1})$$

$$MACD_t = EMA_t(n_s) - EMA_t(n_l)$$

$$MACD\text{-}Signal_t(m) = \frac{1}{n}\sum_{i=0}^{m-1} MACD_{t-i}$$

(Sources: Author's analysis and compilation)

Whereas:

EMA_t (n): The n day Exponential moving average at time t

$MACD_t$: The MACD line at time t, which are the difference between EMA with shorter window and the EMA with longer window.

MACD-$Signal_t$ (m): The m day moving average of MACD line at time t. m is less than n. Since $MACD_t$ can be negative, MACD-$Signal_t$ (m) can also be negative.

Trading rule: If $MACD_t$ moves up at least x percent above MACD-$Signal_r$ and remains so for d periods, go long until $MACD_t$ moves down at least x percent below MACD-$Signal_r$ and remains so for d periods, at which time go short. If $MACD_t$ moves down at least x percent below MACD-$Signal_r$ and remains so for d periods, go short until $MACD_t$ moves up at least x percent above MACD-$Signal_r$ and remains so for d periods, at which time go long. The trading signal can be expressed as:

$$Signal_t = \begin{cases} 1 & | \; Diff_{t-i}\,[\, MACD_t,\ |MACD\text{-}Signal_t(m)|\,] \geq x\% \\ -1 & | \; Diff_{t-i}\,[MACD_t,\ |MACD\text{-}Signal_t(m)|\,] \leq -x\% \\ 0 & | \; Others\ cases \end{cases}$$

$$i = \{0, 1, 2, \ldots, d-1\}$$

(Sources: Author's analysis and compilation)

The author considers several different parameter specifications, namely:

$n_{short} \in \{1, 2, 5, 10, 20, 25, 50\}$ *(day)* $|\# n_{short} = 7$

$n_{long} \in \{2, 5, 10, 15, 20, 25, 50, 100\}$ *(day)* $|\# n_{long} = 7$

$m \in \{2, 5, 10, 20, 25\} \mid \#m = 5$

$x \in \{0, 0.01, 0.05, 0.1, 0.5, 1, 5\}$ *(%)* $\mid \#x = 7$

$d \in \{1, 2, 3, 4, 5\}$ *(day)* $\mid \#d = 5$

Therefore, the author studies the 875 MACD trading rules with different number of parameterizations per rule:

Number of MACD rules $= \#(n_{long} > n_{short}$ *and* $n_{short} > m) \times \#x \times \#d = 25 \times 7 \times 5 = 875$