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Momentum trading strategies on cryptocurrencies

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Abstract

Momentum trading strategies have been noted as the principal market anomaly that has the potential to successfully predict future market prices. Momentum trading strategies have formed part of a multitude of research, proving successful results across all traditional asset classes. Understanding the price predictability of momentum strategies on cryptocurrencies is important as they are a relatively new financial asset and are attracting institutional investors' attention. The objective of the study was to test whether momentum trading strategies would produce significant positive returns when applied to cryptocurrencies. The study tested time-series and cross-sectional momentum trading strategies across 15 cryptocurrencies over a 6 year period (2016-2022). The study found that momentum strategies generally produce positive returns when applied to the 15 cryptocurrencies over the sample period. However, the positive returns produced by the time series and cross-sectional momentum trading strategies were not significant. In addition, the study found that time-series momentum strategie applied to individual cryptocurrencies, in isolation, could be used to identify cryptocurrencies which produce significant returns.

Keywords

Cross-sectional momentum, Time-series momentum, Cryptocurrency, Efficient market hypothesis

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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Momentum trading strategies on cryptocurrencies

1.2 Research problem

Momentum trading strategies have been noted as the principal market anomaly that rejects the weak form of the efficient market hypothesis (EMH) (Fama & French, 2008). This indicates that momentum trading strategies have the potential to successfully predict future market prices. Research has also proven that successful momentum trading strategies exists across various traditional asset classes (Jegadeesh & Titman, 1993; Moskowitz et al., 2012). However, very little academic research has been done on the applicability of momentum trading strategies on cryptocurrencies, with thinly spread literature providing contradicting views. Urquhart (2016) identified that Bitcoin was inefficient (rejecting EMH), with Nadarajah and Chu (2017) indicating that Bitcoin is efficient (accepting EMH). Momentum testing has also been performed with contradictory results, with Grobys and Sapkota (2019) indicating that there are no significant returns present (accepting EMH), while Liu and Tsyvinski (2021) indicating that there are significant returns present (rejecting EMH). The contradictory results provide no clear indication as to whether the cryptocurrency market is efficient or not and whether momentum trading strategies would result in excess returns.

By testing momentum trading strategies on cryptocurrencies, a better understanding would be attained of its pricing predictability. The research done would also fill the gap in the literature.

1.3 Background

Cryptocurrencies are a recent financial instrument that has gained considerable interest globally. It is built on a new technology known as the blockchain, which is also gaining tremendous attention within the FinTech community (Cong et al., 2021).

The cryptocurrency market has rapidly gained global notoriety since its launch in 2009. The financial industry has been greatly impacted by cryptocurrencies which have created enormous exposures to risks and returns. This is evidenced by the large annual profit and losses seen in the market. Statistics showed that the top 10 highest cryptocurrencies' annual returns in 2022 ranged from 5200% to 15034% (Analytics Insight, 2022). While additional research has also indicated losses that amounted to negative returns in 2011 (-99%), 2012 (-56%), 2013 (-83%), 2018 (-84%), 2020(-50%) and 2021 (-52%) (Lisa, 2021).

Bitcoin has been noted as the first decentralised cryptocurrency to be introduced into the market (Ciaian et al., 2018; Maciel, 2021; Trimborn & Härdle, 2018). When bitcoin first became available for trading in 2009, the market price was marked at less than $0.01 (USD), and in 2021, it reached an all-time high of $61 374 (Statista, 2021). The sharp increase in bitcoin's price resulted in a growth rate of approximately 613739900% over 11 years.

To demonstrate the magnitude of this increase, a R10 (ZAR) investment into bitcoin in 2010 could have resulted in an estimated value of R12.8 million (ZAR) in 2021. The prices of bitcoin have remained impressively high with its price averaging over $30,000 (USD) as at the time of writing the report (Statista, 2021).

Cryptocurrencies have mostly been traded by individuals and have mainly been excluded from any financial institutional trading. As cryptocurrencies become part of our daily lives, it's gaining acceptance into the scope of institutional trading firms.

1.4 Theoretical need

Extensive research has been performed on momentum trading strategies and its usefulness in forecasting future prices. A review of the literature indicates that momentum is a useful tool when predicting future prices and that it exists across multiple asset classes (Baltussen et al., 2021; Moskowitz et al., 2012). Grinblatt et al. (2020) adds that institutional investors apply momentum trading strategies due to its simplicity and ease to implement.

Even though historical research has proven that momentum exists across traditional asset classes such as equities, interest rates, commodities and foreign exchange (Baltussen et al., 2021; Moskowitz et al., 2012), it does not confirm whether cryptocurrencies would react in the same manner. Additionally, no clear indication to whether momentum exists in cryptocurrencies has been found either.

Research has found contradicting results when applying momentum trading strategies on cryptocurrencies. According to Schilling and Uhlig (2019), cryptocurrency prices are unpredictable as it conscribes to a martingale. Grobys and Sapkota (2019) also support this notion, with their research finding that momentum does not exists within the cryptocurrency market. However, contradictory evidence is provided by Liu and Tsyvinski (2021) that momentum does exist in the short term cryptocurrency market. It is still unclear as to whether momentum occurs within the cryptocurrency market or not and this research aims to address that.

Cryptocurrencies have recently been classified into an independent asset class by Bianchi (2020) and Hairudin et al. (2020) with no clear indication of momentum trading strategies being a strong indicator of its price predictability (Grobys & Sapkota, 2019; Schilling & Uhlig, 2019). The question of whether momentum could be used to attain superior returns should be addressed. Testing the trading theory of momentum would also support and contribute to the current studies of momentum and cryptocurrencies, as well as identify whether the cryptocurrency market is efficient or not.

1.5 Business need

Predicting market prices allows any entity to make substantially better decisions (Brown et al., 2019). With the introduction of institutional traders into the cryptocurrency market, highlighted by Forbes (2021) and the Financial Times (2021), the need to investigate ways of predicting future market prices arises. Additionally, the Financial Times indicated that hedge funds could hold up to 7% of their assets under management in cryptocurrencies before 2026 (Financial Times, 2021).

Furthermore, Dragomirescu-Gaina et al. (2021) study provide observations into the decision-making techniques of investment managers. The study concludes that the techniques used by investors include a number of estimations and price predictions. Grinblatt et al. (2020) also add that momentum strategies are popular amongst institutional investors as price prediction tools seeing that they are easy to implement and execute on. This highlights the potential contribution that the research into momentum trading strategies could have for investors trading and entering the cryptocurrency market. Predicting future prices could also result in future sustainable profits for investors.

Given cryptocurrencies' high volatility and the introduction of institutional investors into the market, it is crucial to understand whether momentum strategies can predict future prices. Historical research of momentum on traditional asset classes could prove helpful, however it does not conclude that cryptocurrencies would react in a similar manner.

1.6 Aim

The research paper sets out to test whether momentum trading strategies could be used to attain excess returns within the cryptocurrency market. The objective would be to determine whether there is a significant difference in cryptocurrency returns when momentum strategies are used. Testing momentum on cryptocurrencies would also provide insights into the efficiency of the market.

1.7 Acronyms

AMEX	American Stock Exchange
CSM	Cross-Sectional Momentum
EMH	Efficient Market Hypothesis
HD	Holding (Holding period)
LB	Look-Back (Look-Back period)
NYCE	The New York Stock Exchange
TSM	Time-Series Momentum
USD	United Stated Dollar
ZAR	South-African Rand

2. Literature Review

2.1 Introduction

The literature on cryptocurrencies has expanded significantly over the past 5 years. This is indicated by Google Scholars' search results which provide more than 32 000 results, with more than 3000 of these articles being peer-reviewed. The latest scholarly research has provided tremendous insights into the operations and functionality of cryptocurrencies which forms part of the literature review.

In conjunction with cryptocurrencies, the technical style-based investment strategy, identified as momentum, also formed part of the research. Momentum is a well-researched and documented trading strategy which is used to predict future price movements by using historical time-series data. Most of the historical research done on momentum has been conducted on traditional asset classes such as equities, commodities, fixed income and currencies (Baltussen et al., 2021; Jegadeesh & Titman, 1993; Moskowitz et al., 2012). Therefore, the need for additional research has been noted on the feasibility of momentum trading strategies on cryptocurrencies.

The literature review on cryptocurrencies and momentum were dealt with in seven areas:

- Cryptocurrency background
- Cryptocurrencies classification
- Financial analysis methods
- Efficient market hypothesis
- Efficient market hypothesis and cryptocurrencies
- Momentum
- Literature findings

All the research that has been performed were concentrated on peer-reviewed journals and whitepapers.

2.2 Cryptocurrency background

Digital currencies are not a recent phenomenon and have been in use before the invention of cryptocurrencies. The online gaming industry has been noted as the trailblazers of virtual currencies, using these virtual currencies to purchase in-game modifications (Sifat, 2021). Additionally, previous attempts of failed virtual currencies include eCash by David Chaum, Beenz by Charles Cohen and Flooz by Robert Levitan (Peng et al., 2018). However, a new form a digital currency was introduced in 2009, with an innovative underlying technology, which would enable the digital currency to be scalable and secure (Nakamoto, 2008).

In 2008, Satoshi Nakamoto, a pseudo name for the creator of bitcoin, posted a whitepaper describing the concept of bitcoin. Bitcoin was also identified as the first official cryptocurrency utilising the blockchain (Nakamoto, 2008). Blockchain technology uses specialised cryptography to safeguard all transactions, it also controls the generation of extra units of the currencies being utilised (Chu et al., 2017).

The whitepaper further describes cryptocurrencies as a peer-to-peer version of digital currencies, with the main objective of the digital currency to enable direct payments between parties. The peer-to-peer payment system evidently bypasses financial institutions and follows the concept of decentralisation of the flow of cash (Nakamoto, 2008).

2.3 Cryptocurrencies classification

With the introduction of cryptocurrencies as a tradable instrument, their classification into an asset class is imperative. An asset class is defined as a collection of financial products with related characteristics. These characteristics include risk profiles, capacity for growth, and responses to market fluctuations (Chevalier & Darolles, 2019).

Traditional asset classes are generally classified into four categories which are known as fixed income (bonds), equities (stocks), foreign exchange (currencies) and commodities (brent and gold) (Chevalier & Darolles, 2019; Kurka, 2019). Asset classes are generated to group similar instruments together, which provides the ability to diversify the risk and return characteristics of a portfolio (Bianchi, 2020).

The starting point in classifying cryptocurrencies into an asset class would be to identify the definition of money. Literature identifies cryptocurrencies as a digital or virtual currency, creating the need to identify the attributes of money (Lo & Wang, 2014; Peng et al., 2018). By classifying cryptocurrencies as digital or virtual currencies indicates that it should have similar characteristics to normal currencies. This alludes to cryptocurrencies being seen as a form of currency which could be classified into the foreign exchange asset class.

Literature suggests that the traditional definition of money includes three attributes. Firstly it should be a measure of account, secondly a medium of trade and lastly be a store of wealth (Peng et al., 2018).

Further research identified multiple different views of whether cryptocurrencies adhere to the formal definition of money. Lo and Wang (2014) argued that cryptocurrencies do fulfil all three attributes required to be classified as money. However, Lo and Wang's (2014) classification of cryptocurrencies were challenged by Yermack (2013), who argued that the speculative nature of cryptocurrencies deviates from the core functionality of being a store of wealth. Therefore, Yermack (2013) suggests that cryptocurrencies should be classified as a speculative investment rather than being grouped into any of the traditional asset classes.

Dyhrberg (2016) further extends the understanding of the classification of cryptocurrencies as neither a currency nor a speculative investment, but rather identified that cryptocurrencies should be classified within a standalone asset class. Additionally, Dyhrberg (2016) explains that cryptocurrencies could be used independently as a medium of trade, similar to cash or as a store of wealth, such as gold. Hairudin et al. (2020) also adds that alternative assets, such as cryptocurrencies, typically act in a different way from conventional currencies. Hairudin et al. (2020) claims are supported by Bianchi, (2020) as they indicate that there is minimal correlation between cryptocurrencies and any of the traditional asset classes, including foreign currencies.

Hairudin et al. (2020) also confirmed that there had been calls to classify cryptocurrencies as an independent asset class rather than being classified into any of the traditional asset classes. This supports Dyhrberg's (2016) original suggestion of classifying cryptocurrencies into a standalone asset class. Hairudin et al. (2020) further highlight that cryptocurrencies have stylised factors that do not correspond to the traditional asset classes, which affirms the request for an independent asset class.

With cryptocurrencies being classified as an independent asset class, additional research was required to identify the risk and return characteristics of the newly classified asset class. As we know from Chevalier and Darolles (2019), the definition of an asset class is defined as a collection of financial products with related characteristics which do not correlate with other asset classes. Liu and Serletis (2019) conclude that there is a lack of empirical evidence within the literature regarding cryptocurrency's qualities of diversification, hedging, and safe haven properties when compared to other asset classes. Therefore, creating the need to further understand cryptocurrencies as their risk and return characteristics would not correspond to either of the traditional asset classes.

Thus, the question of whether conventional trading methods would function similarly for cryptocurrencies as they do for traditional asset classes is raised. Before identifying and testing any trading strategies, the appropriate analysis method for cryptocurrencies should be identified. The following section will investigate and identify the appropriate analysis methods which could be used for cryptocurrencies.

2.4 Financial analysis methods

Literature identifies two prominent financial analysis methods used within financial markets. The two analysis methods are known as fundamental analysis and technical analysis, and both of these methods are used to forecast the future performance of the instruments being analysed (Hilkevics & Hilkevica, 2018).

Fundamental and technical analysis are seen as two fundamentally different analysis methods. Hilkevics and Hilkevica (2018) classifies the two methods as independent methods. This means that the two analysis methods can be used independently from each other to identify inefficiencies in financial markets. By identifying inefficiencies in the market, investors could gain insights into the direction of price movements, or the perceived value of the financial product being analysed.

Due to the fundamentally different amounts of the two analysis methods, further investigation was required. Further investigation would provide insights to which analysis method would be best suited for cryptocurrencies. Therefore, a brief review of both analysis methods has been provided below.

2.4.1 Fundamental analysis

The first method examined was that of the fundamental analysis method. Fundamental analysis as described by (Sloan, 2019), is a method of assessing a financial instrument in the efforts to determine its value. Sloan (2019) further explains that this is done by analysing relevant financial and economic factors. Abarbanell and Bushee (1998) also emphasise that fundamental analysis uses accounting-based signals to predict future returns. Li and Mohanram (2019) expand the understanding of fundamental analysis and give insights that fundamental analysis provides an intrinsic value of the financial instruments being analysed.

2.4.2 Technical analysis

The second method examined was that of the technical analysis method. Technical analysis identifies trading opportunities by analysing the historical time-series of a financial instrument being investigated (Psaradellis et al., 2021). Studies have highlighted that technical analysis could be utilised across multiple asset classes such as equities (Baltussen et al., 2021; Bogomolov, 2013; Chevalier & Darolles, 2019; Psaradellis et al., 2021; Vincent et al., 2021), foreign exchange (Baltussen et al., 2021; Chevalier & Darolles, 2019; Gehrig & Menkhoff, 2004; Psaradellis et al., 2021) and commodities (Baltussen et al., 2021; Chevalier & Darolles, 2019; Levine & Pedersen, 2016; Psaradellis et al., 2021).

2.4.3 Appropriate analysis method for cryptocurrencies

After briefly investigating the two different analysis methods, the following conclusion has been made. By using the fundamental analysis method an investor would gain relevant insights by analysing accounting-based signals (Abarbanell & Bushee, 1998). These accounting-based signals would identify whether an instrument is undervalued or overvalued relative to the current market price. Due to cryptocurrencies not having any accounting-based information such as balance sheets or income statements, the fundamental analysis method has been dismissed from further research.

Therefore, the method best suited for the analysis of cryptocurrencies would be the technical analysis method. The technical analysis method uses historical time-series data to perform its analysis (Psaradellis et al., 2021). This is appropriate for cryptocurrencies as historical time-series is available for each cryptocurrency traded in the market. The decision was supported by the multitude of technical analysis research found on cryptocurrencies (Chu et al., 2020; Grobys & Sapkota, 2019; Shen et al., 2021).

However, through the research process, literature identified a theory which rejects the use of technical analyst being used to predict future prices. The theory identified as the (EMH) by Fama (1970) will be discussed below.

2.5 Efficient market hypothesis

The EMH emerged from the research as a central theory, which rejects the possibility of using technical analysis for the use of predicting future market movements. According to Eugene Fama's thesis on the effect market hypothesis, markets are efficient when they adequately reflect all relevant information (Fama, 1970). Fama (1991) further concludes that instrument prices are fully representative of the information available to price them, which indicates that historical prices won’t be able to predict future price movements.

The EMH identifies three forms of market efficiency. The three levels of market efficiency are known as weak form, semi-strong form and strong from (Fama, 1970). The three forms of market efficiency will be discussed below.

2.5.1 Efficient market hypothesis – Weak form

The weak form of the market hypothesis identifies that market prices fully reflect all historical data (Fama, 1970), which indicates that investors cannot predict future prices by utilising technical analysis. Thus, strategies used to obtain positive returns by means of historical volumes and pricing data are not viable under the weak form of market hypothesis.

2.5.2 Efficient market hypothesis – Semi-strong form

The semi-strong form of market hypothesis states that all prices available in the market fully reflect all the publicly known information (Fama, 1970). This includes historical market data, which means that the semi-strong form encompasses the weak form as well (Fama, 1970). Thus, investors cannot obtain excess returns by means of technical or fundamental analysis.

2.5.3 Efficient market hypothesis – Strong form

The final form of market efficiency is known as the strong form of market efficiency. For the strong form, prices represent both public and private information, which indicates that the strong form encompasses both semi-strong and weak forms of market hypothesis (Fama, 1970). The strong form goes further and concludes that even insider trading wouldn't produce excess returns.

2.5.4 Efficient market hypothesis and cryptocurrencies

The EMH theory presented by Fama (1970) states that new information presented in the market is immediately reflected in the price of the financial instrument. This indicates that neither technical, at a weak form, nor fundamental analysis, at a semi-strong form, could provide excess returns (Malkiel, 2003).

However, inconsistencies in the market have been noted, resulting in the EMH not holding true in certain instances. One of these inconsistencies noted is the trading strategy of momentum (Fama & French, 2008). It has been argued that even with the EMH in play, the momentum trading strategies have been able to be profitable in excess of market returns (Baltussen et al., 2021; Vincent et al., 2021).

Additionally, all the traditional asset classes tested for momentum provided an opportunity for the investor to gain improved returns (Baltussen et al., 2021; Vincent et al., 2021).

It is therefore understood that the momentum trading strategy, which is a form of technical analysis, could potentially be utilised to predict future price movements in cryptocurrencies. Further research has therefore been performed on the momentum trading strategies which will be discussed below.

2.6 Momentum

Research on momentum as a trading strategy has been performed to identify whether it would suffice in predicting the future prices of cryptocurrencies. A great deal of evidence has been found which supports that traditional asset classes contain momentum (Fama & French, 2008; Moskowitz et al., 2012; Schmid & Wirth, 2021).

Momentum is described as an anomaly, where instruments with historically weak returns tend to continue with weak returns in the near future and where instruments with historically high returns tend to continue with high returns over the short term (Köseoglu et al., 2020; Levine & Pedersen, 2016). Eriksen (2019) and Levine and Pedersen (2016) further describe momentum as a trading strategy that capitalises on the continuation of historical market trends. The assumption that returns are durable and that past returns might aid in predicting future returns were supported by a sizable body of literature (Schmid & Wirth, 2021). These findings highlighted that momentum could disprove the weak form of the EMH. Research also indicated that momentum challenges financial theory and that the patterns that exist in the average historical returns cannot be explained by traditional asset pricing models (Eriksen, 2019; Schmid & Wirth, 2021). In conclusion, it is suggested that momentum trading strategies could suffice in predicting the future prices of cryptocurrencies.

Moskowitz et al. (2012) highlights that there are two predominant forms of momentum. The cross-sectional momentum (CSM), and time-series momentum (TSM). These two forms of momentum are discussed in detail below.

2.6.1 Cross-sectional momentum

CSM has been identified as a type of momentum which focuses on the historical performance of an instrument relative to other instruments or indices' historical performance. The first extensive investigation into CSM was carried out by Jegadeesh and Titman (1993), who also developed the framework that has been used and cited by many subsequent studies.

Jegadeesh and Titman (1993) study analysed the efficiency of the AMEX and NYSE stock market by assessing the excess returns of the market when employing their CSM strategy. The key findings were that the best performing instruments from the previous three to twelve months, grouped into portfolios, continued to outperform worst performing instruments that were grouped into portfolios in the following three to twelve months (Jegadeesh & Titman, 1993).

Jegadeesh and Titman's (1993) CSM trading strategies consisted of combinations of look-back (LB) and holding (HD) periods. LB periods were defined as the period used to calculate each instrument's historical returns. The HD periods were defined as the period for which the instrument will be held. The figure below represents a strategy with a (J) LB period and a (K) HD period.

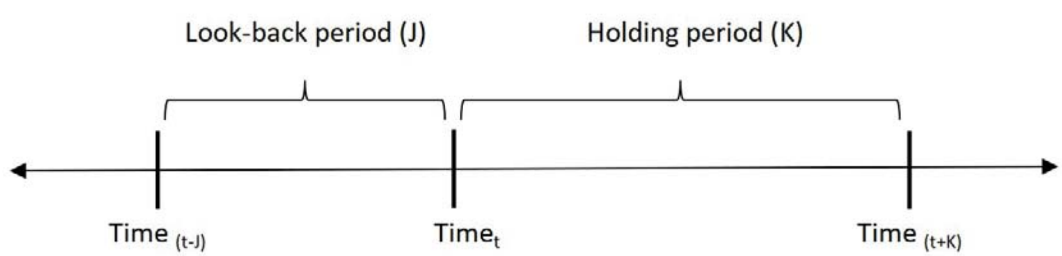

Figure 1: Look-back and Holding period schematic

The figure below summarises Jegadeesh and Titman's (1993) methodology when creating their best performing (Winner) and worst performing (Loser) portfolios. Their trading strategies included LB periods (J) of 3, 6, 9 and 12 months when identifying stock returns and HD periods (K) of 3, 6, 9 and 12 months for investment HD periods.

Process 1

Stock returns over J months	
Stock	**Return**
1	5%
2	4%
3	6%
4	8%
5	7%
6	1%
7	10%
8	2%
9	3%
10	9%

Process 2

Ranked according to return over J months		Assigning Deciles
Stock	**Return**	**Decile/Portfolio**
7	10%	1 "Winner"
10	9%	2
4	8%	3
5	7%	4
3	6%	5
1	5%	6
2	4%	7
9	3%	8
8	2%	9
6	1%	10 "Loser"

Process 3

Holding for K months	
Buy	"Winner"
Sell	"Loser"

Figure 2 : Jegadeesh & Titman (1993) investment process.

Additionally, Jegadeesh and Titman's (1993) strategy included a zero-cost strategy, where "Winning" portfolios were bought and "Loser" portfolios were sold. Jegadeesh and Titman (1993) confirmed that all their zero-cost strategies returned significant excess returns.

A look into Jegadeesh and Titman (1993) methodology provided deeper insights into the functionality and workings of their model. Their inputs used for the model have also indicated the viability of using cryptocurrency market prices to test for momentum.

2.7.2 Time-series momentum

Compared to CSM, TSM focuses on the absolute performance of the instrument being analysed instead of the relative performance. The first extensive investigation into TSM, across multiple asset classes, was carried out by Moskowitz et al. (2012).

Instead of following Jegadeesh and Titman's (1993) process of ranking instruments into "Winner" and "Loser" portfolios, Moskowitz et al. (2012) used the

LB periods returns for each instrument as an indicator to buy or sell the individual instrument. The strategy followed by Moskowitz et al. (2012) was to buy all instruments which attained positive returns over the LB period and to sell all instruments which attained negative returns over the LB period.

The figure below summarises the methodology used by Moskowitz et al. (2012) when deciding on their buying or selling strategies. Their trading strategies included LB periods (J) of 3, 6, 9, 12, 24, 36 and 48 months and HD periods (K) of 3, 6, 9, 12, 24, 36 and 48 months.

Process 1

Buy/Sell decision based on Cryptocurrency returns over J months		
Cryptocurrency	Return	Holding for K months
1	-5%	Sell
2	4%	Buy
3	3%	Buy
4	-2%	Sell
5	6%	Buy
6	8%	Buy
7	7%	Buy
8	-3%	Sell
9	-1%	Sell
10	10%	Buy
11	2%	Buy
12	-7%	Sell
13	-8%	Sell
14	3%	Buy
15	-9%	Sell

Figure 3: Moskowitz et al. (2012) investment process.

Moskowitz et al.'s (2012) findings confirmed that TSM was present in the asset classes tested which included equities, currencies, commodities and fixed income.

2.7 Literature findings

Based on the research and literature reviewed, momentum could potentially be utilised to predict the future prices of cryptocurrencies. When searching the effects of momentum on cryptocurrencies, a mere 52 peer-reviewed articles were found, with only 3 quality peer-reviewed articles testing momentum trading independently on cryptocurrencies. Due to cryptocurrencies being a recent phenomenon, no consensus was present pertaining to the efficiency of the cryptocurrency market.

Research done by Urquhart (2016) was the first paper investigating the inefficiency of the cryptocurrency market. The research solely focused on Bitcoin over the horizon of six years (2010-2016), with multiple tests performed to identify inefficiency. The tests set out by Urquhart (2016) were performed to identify long range dependence, unit roots, autocorrelations and nonlinearities in Bitcoin returns. All the results were convincing and resulted in the rejection the weak form of market hypothesis, which indicates that momentum trading strategies could result in excess returns.

A follow up paper of Urquhart (2016) was presented by Nadarajah and Chu (2017) with addition investigations into the efficiency of Bitcoin. Their date range tested corresponded with the date range used by Urquhart (2016). However, their paper investigates three additional tests which included the Ljung-Box test, the runs test, and, lastly, the Bartel's test. Nadarajah and Chu (2017) concluded that Bitcoin was weakly efficient, resulting in accepting the weak form market hypothesis. Their results indicate that momentum trading strategies would not result in excess returns.

Bariviera (2017) also tests for market inefficiency of Bitcoin over six years (2011-2017). However, Bariviera (2017) does this by studying the long-range memory of Bitcoins returns, using the Hurst exponent. The findings indicate that the Bitcoin market was inefficient before 2014, whereafter Bitcoins' returns behaved efficiently. Rejecting the weak form of market hypothesis on data pre-2014 and accepting the weak form hypothesis for data post-2014. Indicating that momentum trading strategies would not result in excess returns after 2014.

Brauneis and Mestel (2018) identified that most of the academic research performed were solely done on Bitcoin. Brauneis and Mestel (2018) investigated, not only Bitcoin, but a larger sample of cryptocurrencies to identify whether the cryptocurrency market is inefficient or not. Their conclusion indicated that cryptocurrencies as a whole were efficient, with Bitcoin being the most efficient (Brauneis & Mestel, 2018). The test resulted in the cryptocurrency markets accepting the weak form market hypothesis.

Additional research performed by Zhang et al. (2018) extended on Bariviera's (2017), Nadarajah and Chu's (2017) and Urquhart's (2016) earlier research. This was achieved with efficiency tests such as the rolling windows analysis and the inefficiency index analysis on the top 20 cryptocurrencies by market capitalisation. Zhang et al.'s (2018) test concluded that all the cryptocurrencies tested from 2013 to 2018 were in fact inefficient. Rejecting the weak form of market hypothesis, which indicates that momentum trading strategies could result in excess returns.

The first momentum testing performed on cryptocurrencies was done by Grobys and Sapkota (2019). Grobys and Sapkota's (2019) test was performed with data ranging from 2014 to 2018, testing both CSM and TSM. Their results concluded that there was no evidence of significant momentum in the cryptocurrencies tested.

Lastly, Shen et al. (2021) concludes that Bitcoin showed significant returns when intraday time-series strategies were used. Liu and Tsyvinski (2021) also concluded that TSM was present within a shortened time frame.

Based on the literature reviewed, no conclusion could be made whether momentum strategies would be profitable or not. Therefore, additional testing could assist the body of literate in expanding its understanding to reach a general consensus.

3. Research Questions

According to the examined literature, there was no consensus on whether the cryptocurrency markets were efficient, resulting in no indication as to whether momentum trading strategies would result in positive excess returns or not. Additionally, Grobys and Sapkota's (2019) tests of momentum trading strategies were contradicted by Shen et al.'s (2021) findings on TSM.

In light of the lack of consensus found within the literature, this research paper aims to add to the breadth of research, assisting in building knowledge of the cryptocurrency market. Therefore, answering the questions raised in this report would broaden the understanding of the viability of momentum trading strategies on cryptocurrencies. For the research report, one research question was created with five sub-research questions.

Research question

The research paper sets out to test whether momentum trading strategies could be used to attain excess returns within the cryptocurrency market. The main research question to whether momentum trading strategies could attain excess returns were answered by investigating five sub-questions which are listed below.

Question 1: Would CSM trading strategies attain positive returns when applied to the sample set of cryptocurrencies?

Question 2: Would the returns of the CSM trading strategies applied to cryptocurrencies be significantly different from zero?

- H_0: CSM trading strategy returns (Winners-Losers) = 0
- H_A: CSM trading strategy returns (Winners-Losers) ≠ 0

Jegadeesh and Titman (1993) utilised their CSM trading strategies and proved that CSM trading strategies could attain significant returns over various asset classes. Research question 1 and 2 aims to build on the research done by Grobys and Sapkota (2019), who identified that CSM over a longer period did not produce significant returns. Additionally, the research questions would provide insights into the contradictory findings of (Nadarajah & Chu, 2017; Urquhart, 2016; Zhang et al., 2018)

Question 3: Would TSM trading strategies attain positive returns when applied to the sample set of cryptocurrencies?

Question 4: Would the returns of the TSM trading strategies applied to cryptocurrencies be significantly different from zero?

- H_0: TSM trading strategy returns = 0
- H_A: TSM trading strategy returns ≠ 0

Question 5: Would any of the returns of the TSM trading strategies applied to individual cryptocurrencies (above the overall average of the group) be significantly different from zero?

- H_0: TSM trading strategy individual returns = 0
- H_A: TSM trading strategy individual returns ≠ 0

Moskowitz et al. (2012) utilised their TSM trading strategies and proved that TSM trading strategies could attain significant returns over various asset classes. Research question 3, 4 and 5 aims to build on the research done by Grobys and Sapkota (2019), who identified that TSM over a longer period did not produce significant returns. Additionally, by testing the hypothesis, additional literature could be produced to support either Bariviera (2017), Brauneis and Mestel (2018) and Nadarajah and Chu (2017), who claimed that momentum strategies wouldn't produce significant returns or Liu and Tsyvinski (2021), Shen et al. (2021), Urquhart (2016) and Zhang et al. (2018) who alludes that momentum strategies could produce significant returns.

4. Research Methodology

4.1 Research design

A quantitative research methodology was utilised to better understand the returns of cryptocurrencies when applying momentum trading strategies. The chosen method would assist in determining whether momentum strategies attained significant returns when used.

The core research design was inspired by Jegadeesh and Titman (1993) and Moskowitz et al. (2012), with their cross-sectional and TSM models. As with Jegadeesh and Titman (1993) and Moskowitz et al. (2012), a positivist philosophy was utilised, removing human subjectivity and using a structured model to answer the research question.

The research paper employed a deductive approach to test momentum strategies and used highly structured, clearly defined, and empirically proven techniques. Additionally, deduction methods are used to test theoretical propositions (Saunders & Lewis, 2018, p. 112).

As with previous research done on momentum strategies, a mono method was employed to attain the pricing data (Grobys & Sapkota, 2019; Liu & Tsyvinski, 2021). The data utilised in testing the momentum strategies were secondary cryptocurrency price data retrieved from Coinmarketcap.com. Coinmarketcap was used as the data source as it corresponded to the data source used in the research done by both Grobys and Sapkota (2019) and Liu and Tsyvinski (2021).

The research was performed on longitudinal data. This allowed for returns to be tracked over time, capturing the returns more accurately and ensuring that excess returns were not temporary. Testing data on a longitudinal time horizon were also supported by Köhler et al. (2017), who identified that a longitudinal design could remove the inconsistencies in data taken at one point in time.

Two independent models were built to perform the research. The CSM model was build in accordance to the model used by Jegadeesh and Titman (1993) and the TSM model was built in accordance with the model used by Moskowitz et al. (2012). The model sections below contain the descriptions of the CSM and TSM excel models that were built by the researcher to conduct the analysis.

Cross-sectional momentum model

The CSM methodology used was comparable to that of Jegadeesh and Titman's (1993) model when testing their zero-cost strategies.

The CSM model that was built utilised the 15 cryptocurrencies with their date ranges of 1 September 2016 to 31 August 2022. Additionally, out-of-scope data for the month of 1 August 2016 was included in the model to accommodate the initial LB period at the start of the sample.

The first process of the model calculates the daily returns of each cryptocurrency over the sample period. The calculated daily returns were used to identify the HD period returns for each quintile. The daily returns were calculated by means of log returns as presented below.

$$Daily\ Returns = In\ (\frac{Price_t}{Price_{t-1}})$$

The second process of the model calculates the LB period returns of each cryptocurrency. The LB period returns were utilised in the ranking process, which placed each cryptocurrency in its respective quintile over the specified HD period. The LB period returns were calculated in the same manner as the daily returns in the first process.

The third process of the model assigned a rank to each of the LB period returns. Ranking each return enabled the identification of which cryptocurrency was to be allocated to which quintile. The returns were ranked from best performing LB period returns (rank = 1) to the worst performing LB period returns (rank = 15).

After ranking each cryptocurrency based on its LB period return, the cryptocurrencies were then placed into equally weighted quintiles. The three best performing cryptocurrencies were grouped into the first quintile, named "Winners", and the three worst performing cryptocurrencies were grouped into the fifth quintile, named "Losers".

After identifying and allocating each cryptocurrency to a quintile, the daily log returns which were calculated in the first process were used to calculate the HD period returns for each cryptocurrency over the specified HD period. The returns for each quintile were made up of the three cryptocurrencies' combined average returns over the HD period.

At the end of each HD period the process was repeated over the sample period of the data, which provided the cumulative returns for each quintile.

The final process of the model subtracted the "Loser" returns from the "Winner" returns. The spread of the two returns was the measurement that formed part of the hypothesis testing.

The figure below represents the process followed to obtain the returns for the CSM trading strategies, repeated over the selected sample period.

Identify look-back period return

Cryptocurrency returns (look-back period)	
Cryptocurrency	**Return**
1	5%
2	4%
3	3%
4	2%
5	6%
6	8%
7	7%
8	3%
9	1%
10	10%
11	2%
12	7%
13	8%
14	3%
15	9%

Rank each cryptocurrency according to look-back period return

Ranked according to look-back period returns		Quintile
Cryptocurrency	**Return**	**Quintile/Portfolio**
10	10%	1 "Winner"
15	9%	
6	8%	
13	8%	2
7	7%	
12	7%	
5	6%	3
1	5%	
2	4%	
8	3%	4
3	3%	
14	3%	
4	2%	5 "Losers"
11	2%	
9	1%	

Record holding period returns

Holding period
Winner
Loser

Figure 4: Student methodology for cross-sectional momentum

Time-series momentum model

The TSM methodology used was comparable to that of Moskowitz et al's (2012) model. As with the CSM model, the TSM model utilised the identified 15 cryptocurrencies with their date ranges of 1 September 2016 to 31 August 2022. The out-of-scope data for the month of 1 August 2016 was included in the model to accommodate the initial LB period at the start of the sample.

The first process of the model calculates the daily returns of each cryptocurrency over the testing period. The calculated daily returns were used to identify the HD period returns for the “Buy” and “Sell” portfolios. The daily returns were calculated by means of log returns as presented below.

$$Daily\ Returns = In\ (\frac{Price_t}{Price_{t-1}})$$

The second process of the model calculates each cryptocurrency's LB period returns. The LB period returns were used to flag each cryptocurrency into the “Buy” or “Sell” portfolios. Cryptocurrencies with positive LB period returns were flagged as “Buy” and cryptocurrencies with negative LB period returns were flagged as “Sell”. The LB period returns were calculated in the same manner as the daily returns in the first process.

Following the allocation of each cryptocurrency, the model calculated the HD period returns for the "Buy" and "Sell" portfolios. The average returns of all the bought cryptocurrencies formed the “Buy” portfolio returns and the average returns of all the sold cryptocurrencies formed the “Sell” portfolio returns. At the end of each HD period, all the process was repeated over the time horizon of the data.

The final process averaged the returns from the “Buy” and the “Sell” portfolios, providing the returns for each strategy. In addition, the cumulative daily returns of a “Buy-and-Hold” strategy of all 15 cryptocurrencies were produced. This provided an indication to whether the TSM strategy outperformed the "Buy-and-Hold" strategy. The spread of the two returns was the measurement that formed part of the hypothesis testing.

The figure below represents the process followed to obtain the returns for the TSM trading strategies, repeated over the selected sample period.

Identify look-back period return

Cryptocurrency returns (look-back period)	
Cryptocurrency	**Return**
1	-5%
2	4%
3	3%
4	-2%
5	6%
6	8%
7	7%
8	-3%
9	-1%
10	10%
11	2%
12	-7%
13	-8%
14	3%
15	-9%

Allocate each cryptocurrency according to look-back period return

Allocate according to look-back period returns		"Buy" or "Sell"
Cryptocurrency	**Return**	**Portfolio**
1	-5%	Sell
2	4%	Buy
3	3%	Buy
4	-2%	Sell
5	6%	Buy
6	8%	Buy
7	7%	Buy
8	-3%	Sell
9	-1%	Sell
10	10%	Buy
11	2%	Buy
12	-7%	Sell
13	-8%	Sell
14	3%	Buy
15	-9%	Sell

Record holding period returns

Holding period
Buy
Sell

Figure 5: Student methodology for time-series momentum

Trading costs

A transaction cost of 25 basis points was levied throughout each entry and close-out at the beginning and end of the HD period. This was in line with the research done by Brauneis and Mestel (2018), who identified that Kraken, one of the biggest cryptocurrency exchanges, charged a fee of 25 basis points for each trade.

4.2 Universe

The universe of the study included all the cryptocurrencies that were present on the Coinmarketcap database. The Coinmarketcap database was utilised as the universe due to its stringent requirements for exchanges and cryptocurrencies to be listed. This resulted in only listed cryptocurrencies traded on exchanges and listed on Coinmarketcap. At the time of the research, Coinmarketcap had more than 500 exchanges listed with over 21 000 cryptocurrencies present. Additionally, when reviewing literature it was noted that Coinmarketcap was the preferred database (Ciaian et al., 2018; Gerritsen et al., 2020; Grobys & Sapkota, 2019; J. Liu & Serletis, 2019; W. Liu, 2019; Y. Liu & Tsyvinski, 2021; Maciel, 2021).

4.3 Sampling

Judgement sampling was used when selecting currencies to be analysed. Firstly, cryptocurrencies which were pegged to the USD were removed from the universe. Pegged cryptocurrencies do not have any daily movement as they constantly trade at a 1-to-1 exchange rate to the USD. Making these cryptocurrencies ineffective for exploring on momentum strategies.

Secondly, a similar method used by Grobys and Sapkota (2019) was used to identify the top cryptocurrencies. Cryptocurrencies were ranked by their market capitalisation, and the top 15 cryptocurrencies were selected as the sample for the research. Additionally, the sample of cryptocurrencies selected for the research expands on the samples used by Nadarajah and Chu (2017), Shen et al. (2021) and Urquhart (2016), as their samples only included bitcoin.

Each of the 15 cryptocurrencies that formed part of the sample had at least 6 years of times-series data and a market capitalisation of USD 100 million. Resulting in the sample period being selected from 1 September 2016 to 31 August 2022.

The sample of the 15 cryptocurrencies selected represented 96% of the market capitalisation in 2016 and had a market capitalisation of 85% at the time of the research. The table below presents each cryptocurrency which formed part of the sample. Representing each cryptocurrencies name, code, price and market capitalisation as of the 31st of August 2022.

Cryptocurrency	Code	Price (USD)	Market capitilisation (USD)
Bitcoin	BTC	21 769.26	416 840 289 162
Ethereum	ETH	1 761.80	215 523 920 726
XRP	XRP	0.36	17 694 152 749
Dogecoin	DOGE	0.06	8 452 981 187
Ethereum Classic	ETC	38.49	5 266 558 381
Litecoin	LTC	62.24	4 428 570 474
Stellar	XLM	0.11	2 896 290 608
Monero	XMR	158.86	2 886 991 192
Dash	DASH	48.31	526 942 028
Decred	DCR	29.96	429 653 063
NEM	XEM	0.05	419 769 833
Siacoin	SC	0.00	218 341 288
DigiByte	DGB	0.01	168 892 905
Lisk	LSK	1.08	139 642 471
Syscoin	SYS	0.18	120 281 378

Table 1: Sample cryptocurrencies used in the study

4.4 Unit of analysis

The unit of analysis was the sample of 15 cryptocurrencies with a market capitalisation of no less than $100 million and a time-series form 1 September 2016 to 31 August 2022.

4.5 Measurement

The measurement that formed part of the study was the excess monthly log returns attained from the equally weighted portfolios for both CSM and TSM strategies.

The measurement utilised in the CSM model was similar to the measurement used by Grobys and Sapkota (2019) and Jegadeesh and Titman (1993). The measure used the spread between the cumulative “Winner” and “Loser” returns. The spread represented the excess returns which were achieved by implementing the zero-cost strategy. The spread was calculated by subtracting the “Loser” cumulative returns from the “Winner” cumulative returns, as presented below.

$$Spread_{CSM} = Winner_{returns} - Loser_{Returns}$$

The measurement utilised in the TSM model was similar to the measurement used by Grobys and Sapkota (2019) and Moskowitz et al. (2012). The measure used was the spread between the average returns obtained from the “Buy” and “Sell” portfolios and a “Buy-and-Hold” strategy. The “Buy-and-Hold” strategy consisted of buying and holding the 15 cryptocurrencies over the period of the test. Therefore, the spread represented the excess returns which were achieved by implementing the TSM strategy. The spread was calculated by subtracting the returns obtained by the TSM strategy and the returns of the “Buy-and-Hold” portfolio, as presented below.

$$Spread_{TSM} = TSM\ Strategy_{returns} - Buy\ and\ Hold_{Returns}$$

4.2 Secondary data source

The research's source for the cryptocurrency pricing information was Coinmarketcap.com. Liu and Tsyvinski (2021) cite Coinmarketcap as a major source of information on cryptocurrency prices. Additionally, numerous research publications have used Coinmarketcap as their source of data (Brauneis & Mestel, 2018; Grobys & Sapkota, 2019; J. Liu & Serletis, 2019; Zhang et al., 2018).

Coinmarketcap compiles more than 500 exchanges' prices. It offers details on each listed cryptocurrency's pricing, trading activity, and market value. The usage of Coinmarketcaps' volume-weighted average pricing technique for all of their published prices supports the accuracy of their pricing data. Cryptocurrency prices are more indicative of the market according to the volume-weighted average pricing approach, which also lessens the impact of miss-trades or price spikes on individual exchanges. Furthermore, a cryptocurrency cannot be featured on Coinmarketcap until it has an API that reports the most recent prices and trading volumes and is registered on a public exchange with non-zero trading volumes. Coinmarketcap had more than 21 000 cryptocurrencies listed with a market value of around $937 billion when performing the research. (Coinmarketcap, n.d.)

5. Results

5.1 Introduction

Chapter five presents the results for each question raised in chapter three. Both the models described in chapter four were used to attain the results. Additionally, graphs of the best and worst-performing strategies were provided under each subsection to illustrate the results obtained visually.

5.2 CSM trading strategy returns

Question 1: Would CSM trading strategies attain positive returns when applied to the sample set of cryptocurrencies?

Question one aimed to identify whether trading strategies utilising the CSM model resulted in positive excess returns. 25 CSM strategies were applied to the sample of 15 cryptocurrencies to determine whether positive returns were attained. Strategies included LB periods of 3, 6, 9, 15 and 30 days with HD periods of 3, 6, 9, 15 and 30 days. The results were presented according to each HD period timeframe.

HD period of 3 days

The first test consisted of five cross-sectional momentum strategies. Each with a HD period of 3 days. The five strategies had LB periods of 3, 6, 9, 15, and 30 days.

The table below shows the average monthly returns for each strategy. The monthly returns were calculated by subtracting the "Loser" (quintile 5) returns from the "Winner" (quintile 1) returns.

Strategy	Average Monthly Returns (Winner - Loser)
(3:3)	-3.14%
(6:3)	-2.79%
(9:3)	3.47%
(15:3)	4.07%
(30:3)	-2.22%

Table 2: CSM trading strategy results with a holding period of 3 days

The best performing 3 day HD period strategy was the strategy that contained a 15 day LB period. This strategy resulted in a 4.07% average monthly return when subtracting "Loser" portfolio returns from "Winner" portfolio returns.

The chart below presents the (15:3) strategy's daily cumulative returns of quintile 1 "Winners", quintile 5 "Losers" and the spread between the two quintiles. The spread represents the returns obtained from the (15:3) strategy across the 6 years tested.

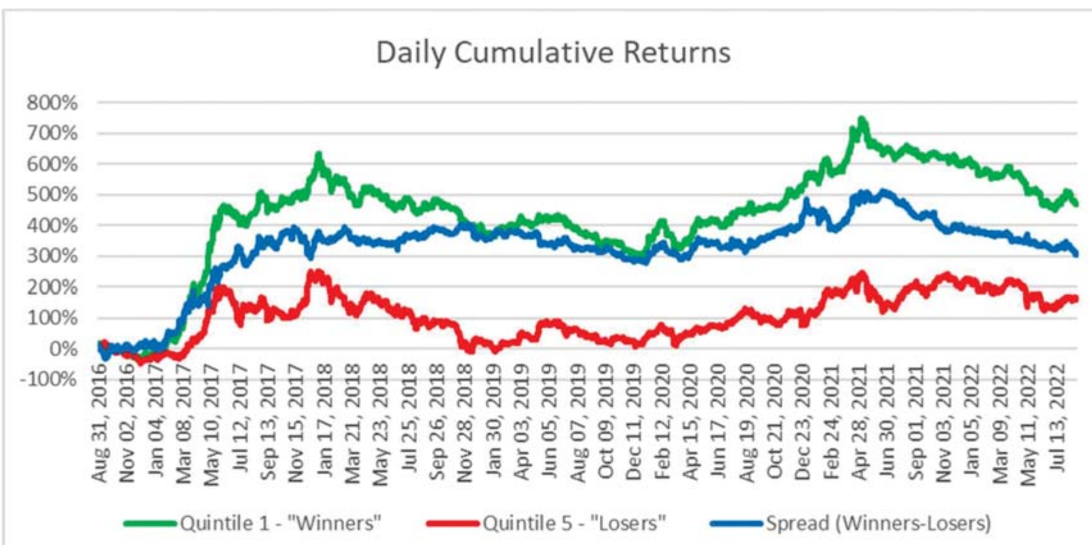

Figure 6: CSM trading strategy daily cumulative returns (15:3)

The chart shows the spread significantly increased from early 2017 to early 2018, following which it remained relatively flat for the remainder of the time under consideration.

The worst performing 3 day HD period strategy was the strategy that contained a 3 day LB period. This strategy resulted in a -3.14% average monthly return when subtracting "loser" portfolio returns from "winner" portfolio returns.

The chart below presents the (3:3) daily cumulative returns of quintile 1 “Winners”, quintile 5 “Losers” and the spread between the two quintiles. The spread represents the returns obtained from the (3:3) strategy across the six years tested.

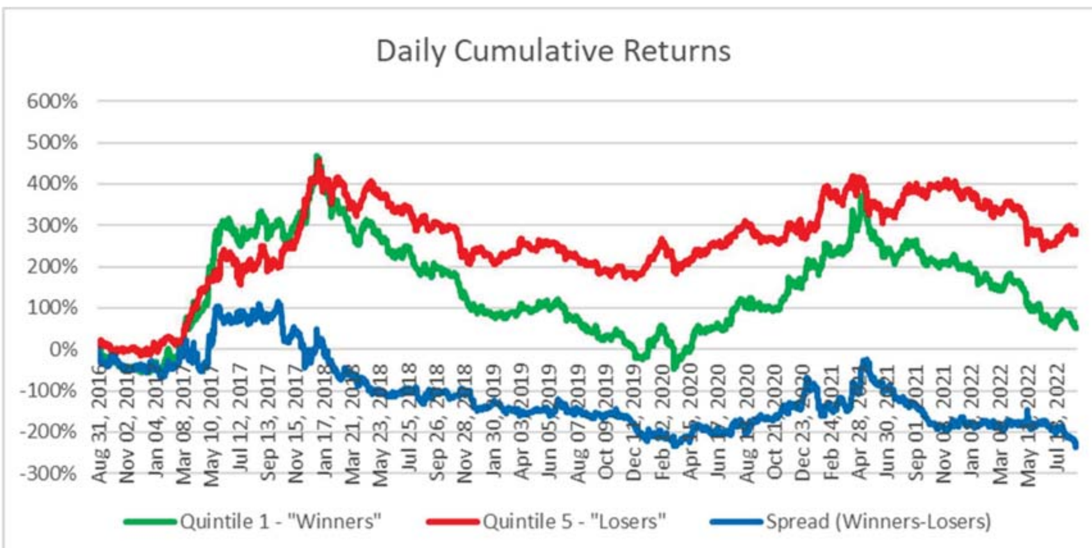

Figure 7: CSM trading strategy daily cumulative returns (3:3)

The chart shows a decrease in the spread at the beginning of 2018. The spread decreased until mid-2020 when it saw a modest uptick in 2021 before returning to its prior levels.

HD period of 6 days

The second test consisted of five cross-sectional momentum strategies. Each with a HD period of 6 days. The five strategies had LB periods of 3, 6, 9, 15, and 30 days.

The table below shows the average monthly returns for each strategy. The monthly returns were calculated by subtracting the "Loser" (quintile 5) returns from the "Winner" (quintile 1) returns.

Strategy	Average Monthly Returns (Winner - Loser)
(3:6)	-2.31%
(6:6)	4.47%
(9:6)	5.13%
(15:6)	5.86%
(30:6)	0.52%

Table 3: CSM trading strategy results holding period of 6 days

The best performing 6 day HD period strategy aligned with the best performing 3 day HD period strategy with a LB period of 15 days. This strategy resulted in a 5.86% average monthly return when subtracting "Loser" portfolio returns from "winner" portfolio returns.

The chart below presents the daily cumulative returns of quintile 1 “Winners”, quintile 5 “Losers” and the spread between the two quintiles. The spread represents the returns obtained from the (15:6) strategy across the 6 years tested.

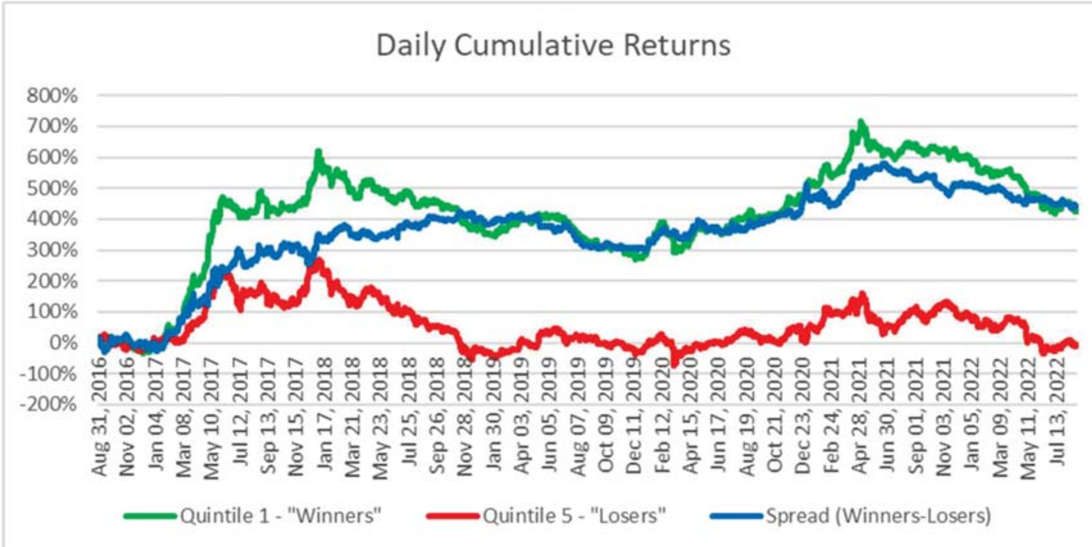

Figure 8: CSM trading strategy daily cumulative returns (15:6)

The graph shows a significant increase in the spread up until the beginning of 2019, after which it decreased marginally. The spread then resumes its upward trajectory.

The worst performing 6 day HD period strategy aligned to the worst performing 3 day HD period strategy with a LB period of 3 days. This strategy resulted in a -2.31% average monthly return when subtracting "Loser" portfolio returns from "Winner" portfolio returns.

The chart below presents the daily cumulative returns of quintile 1 “Winners”, quintile 5 “Losers” and the spread between the two quintiles. The spread represents the returns obtained from the (3:6) strategy across the six years tested.

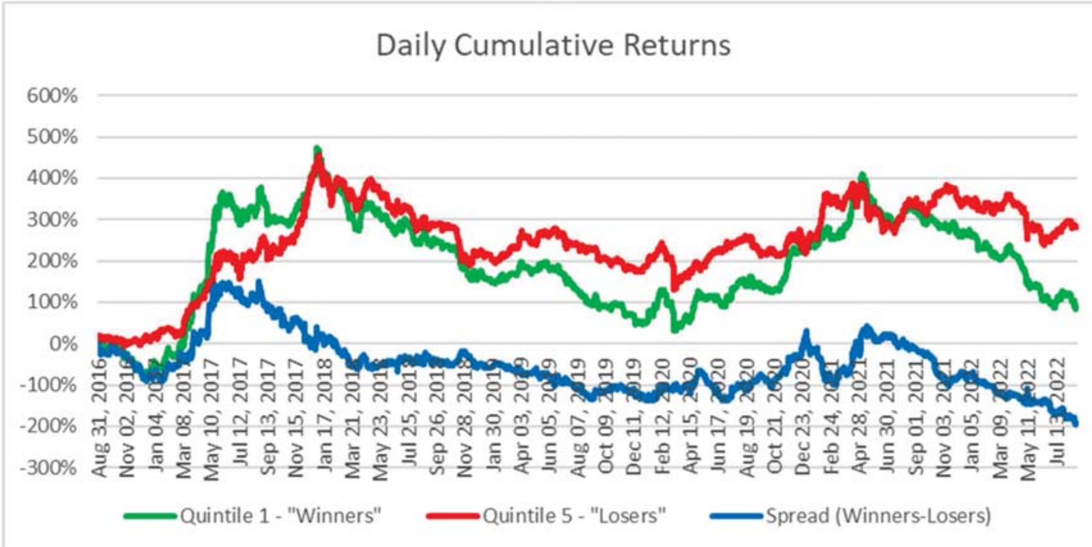

Figure 9: CSM trading strategy daily cumulative returns (3:6)

The chart shows a similar pattern to the (3:3) strategy, with a decrease in the spread in mid-2017. It remained fairly flat despite a modest uptick in 2021 before returning to its prior levels.

HD period of 9 days

The third test consisted of five cross-sectional momentum strategies. Each with a HD period of 9 days. The five strategies had LB periods of 3, 6, 9, 15, and 30 days.

The table below shows the average monthly returns for each strategy. The monthly returns were calculated by subtracting the "Loser" (quintile 5) returns from the "Winner" (quintile 1) returns.

Strategy	Average Monthly Returns (Winner - Loser)
(3:9)	-0.89%
(6:9)	1.10%
(9:9)	1.45%
(15:9)	1.48%
(30:9)	-0.79%

Table 4: CSM trading strategy results holding period of 9 days

The best performing 9 day HD period strategy aligned with the best performing 3 and 6 day HD period strategy with a LB period of 15 days. This strategy resulted in a 1.48% average monthly return when subtracting "Loser" portfolio returns from "Winner" portfolio returns.

The chart below presents the daily cumulative returns of quintile 1 “Winners”, quintile 5 “Losers” and the spread between the two quintiles. The spread represents the returns obtained from the (15:9) strategy across the six years tested.

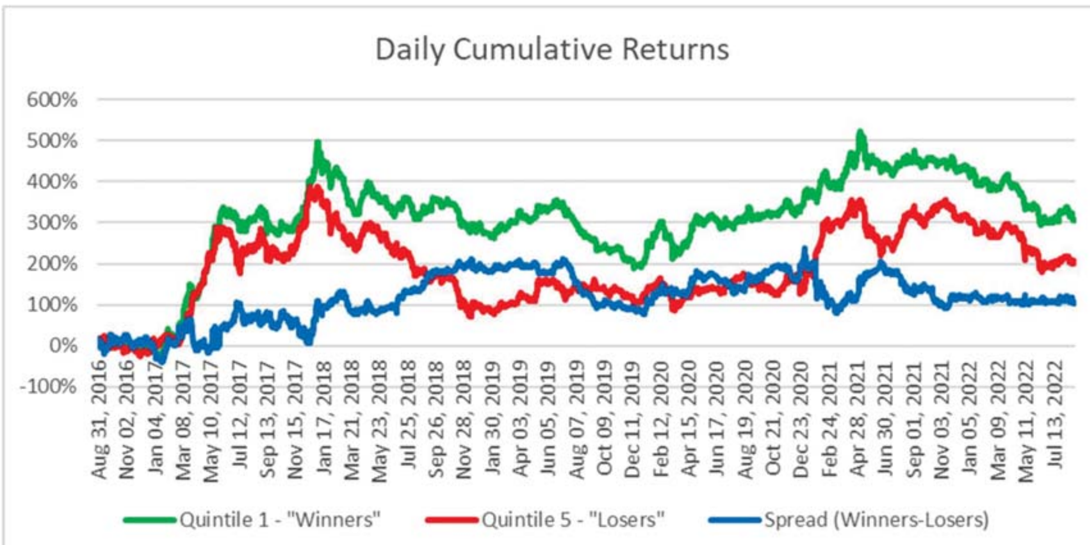

Figure 10: CSM trading strategy daily cumulative returns (15:9)

The chart shows a gradual uptick in the spread from 2016 to 2019, which it remained flat for the remainder of the period.

The worst performing 9 day HD period strategy aligned to the worst performing 3 day and 6 day HD period strategy with a LB period of 3 days. This strategy resulted in a -0.89% average monthly return when subtracting "Loser" portfolio returns from "Winner" portfolio returns.

The chart below presents the daily cumulative returns of quintile 1 “Winners”, quintile 5 “Losers” and the spread between the two quintiles. The spread represents the returns obtained from the (3:9) strategy across the six years tested.

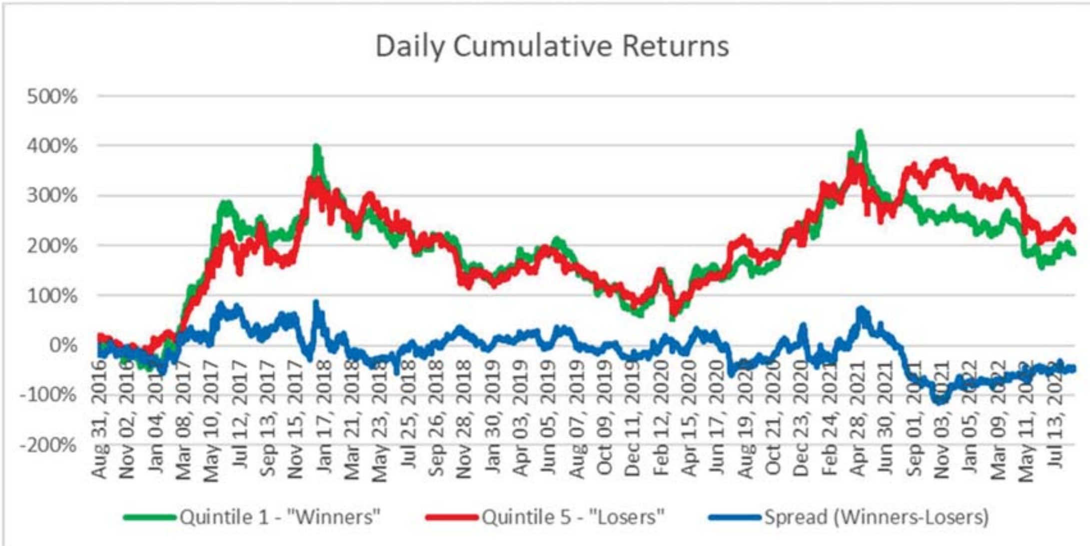

Figure 11: CSM trading strategy daily cumulative returns (3:9)

The chart shows the spread moving between the 100% and -100% range across the period tested, indicating minimal volatility in the returns obtained.

HD period of 15 days

The third test consisted of five cross-sectional momentum strategies. Each with a HD period of 15 days. The five strategies had LB periods of 3, 6, 9, 15, and 30 days.

The table below shows the average monthly returns for each strategy. The monthly returns were calculated by subtracting the "Loser" (quintile 5) returns from the "Winner" (quintile 1) returns.

Strategy	Average Monthly Returns (Winner - Loser)
(3:15)	3.39%
(6:15)	2.97%
(9:15)	5.75%
(15:15)	0.09%
(30:15)	-1.08%

Table 5: CSM trading strategy results holding period of 15 days

The best performing 15 day HD period strategy had a LB period of 15 days. This strategy resulted in a 5.75% average monthly return when subtracting "Loser" portfolio returns from "Winner" portfolio returns.

The chart below presents the daily cumulative returns of quintile 1 “Winners”, quintile 5 “Losers” and the spread between the two quintiles. The spread represents the returns obtained from the (9:15) strategy across the six years tested.

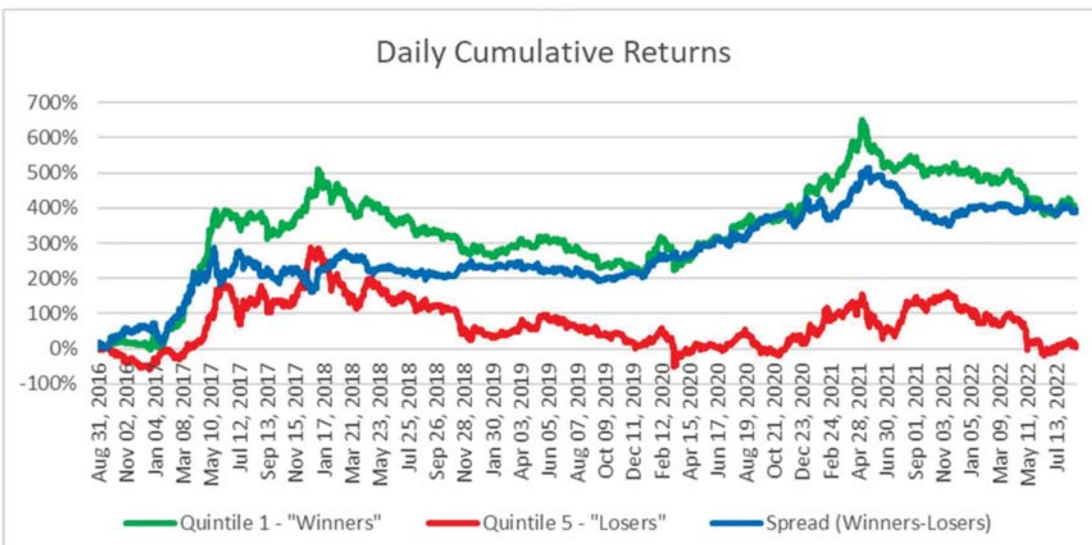

Figure 12: CSM trading strategy daily cumulative returns (9:15)

The chart shows the spread significantly increased from early 2017 to early 2018, after which it remained relatively flat until early 2020, when it presented a gradually increasing trend.

The worst performing 15 day HD period strategy had a LB period of 30 days. This strategy resulted in a -1.08% average monthly return when subtracting "Loser" portfolio returns from "Winner" portfolio returns.

The chart below presents the daily cumulative returns of quintile 1 “Winners”, quintile 5 “Losers” and the spread between the two quintiles. The spread represents the returns obtained from the (30:30) strategy across the six years tested.

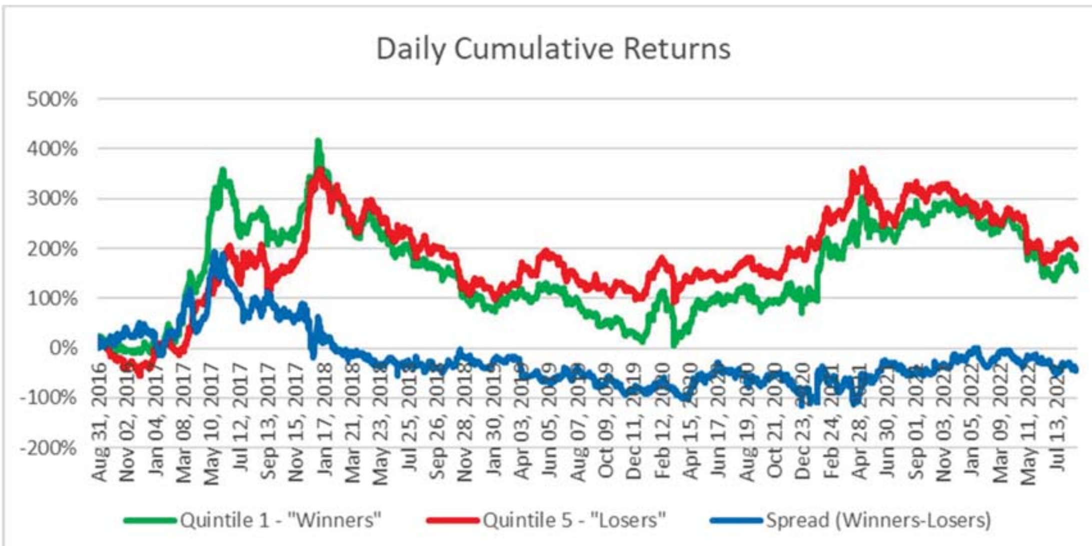

Figure 13: CSM trading strategy daily cumulative returns (30:15)

The chart shows the spread significantly increased from early 2017 to mid 2017, after which the spread returned to 0% and remained fairly flat over the tested period.

HD period of 30 days

The third test consisted of five cross-sectional momentum strategies. Each with a HD period of 30 days. The five strategies had LB periods of 3, 6, 9, 15, and 30 days.

The table below shows the average monthly returns for each strategy. The monthly returns were calculated by subtracting the "Loser" (quintile 5) returns from the "Winner" (quintile 1) returns.

Strategy	Average Monthly Returns (Winner - Loser)
(3:30)	-0.53%
(6:30)	0.03%
(9:30)	0.47%
(15:30)	-3.54%
(30:30)	-4.98%

Table 6: CSM trading strategy results holding period of 30 days

The best performing 30 day HD period strategy aligned to the best-performing 15-day HD period strategy with a LB period of 30 days. This strategy resulted in a 0.47% average monthly return when subtracting “Loser” portfolio returns from “Winner” portfolio returns.

The chart below presents the daily cumulative returns of quintile 1 “Winners”, quintile 5 “Losers” and the spread between the two quintiles. The spread represents the returns obtained from the (9:30) strategy across the six years tested.

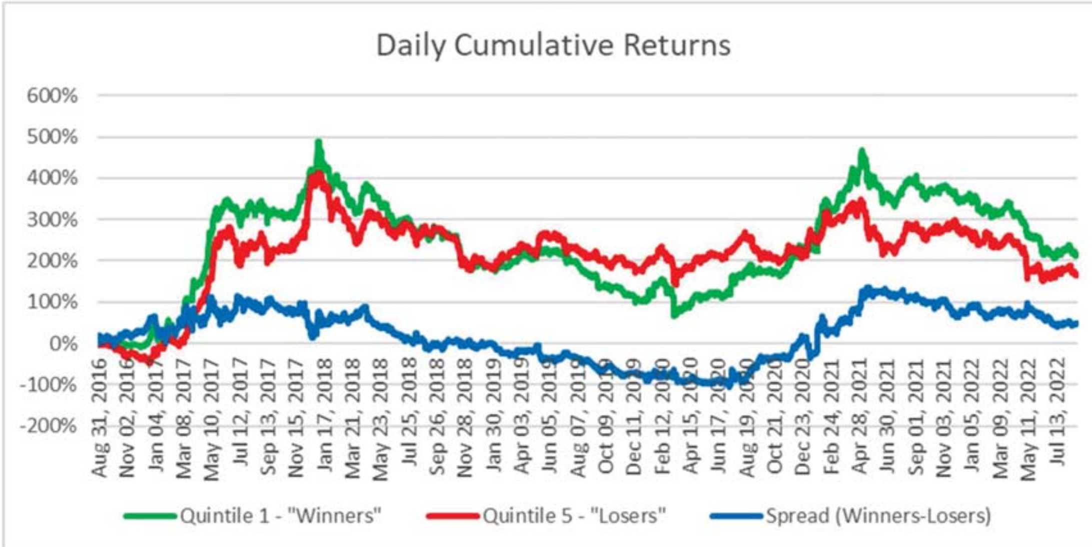

Figure 14:CSM trading strategy daily cumulative returns (9:30)

The chart presents a fairly flat spread over the period of the test. Indicating fairly similar performance of the quintiles tested.

The worst performing 30 day HD period strategy had a LB period of 30 days. This strategy resulted in a -4.98% average monthly return when subtracting "loser" portfolio returns from "winner" portfolio returns.

The chart below presents the daily cumulative returns of quintile 1 “Winners”, quintile 5 “Losers” and the spread between the two quintiles. The spread represents the returns obtained from the (30:30) strategy across the six years tested.

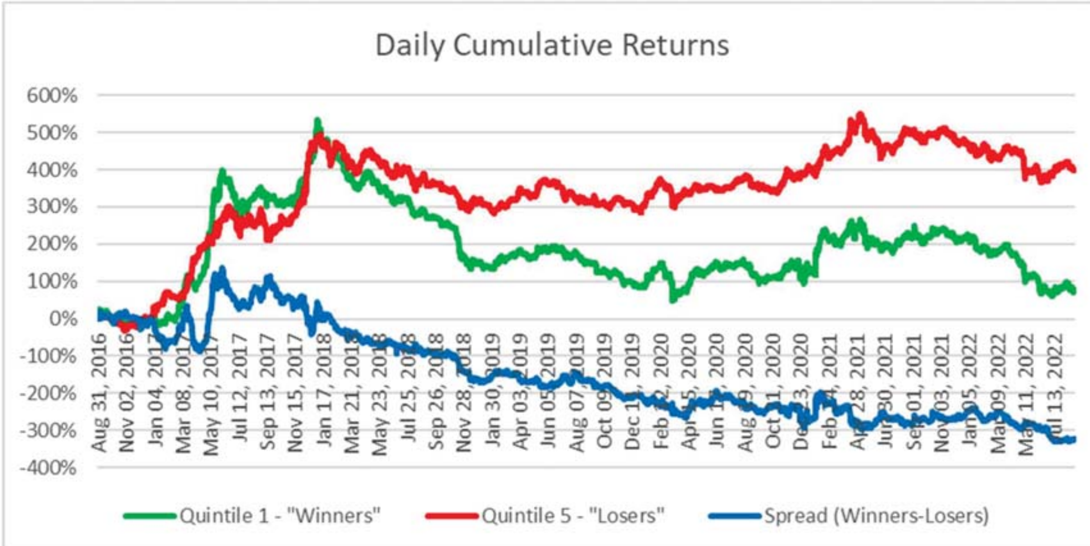

Figure 15: CSM trading strategy daily cumulative returns (30:30)

The chart shows the spread slightly increasing from early 2017 to mid-2017 after the spread reduced linearly over the tested period.

CSM strategies conclusion

After conducting the 25 CSM strategies on the 15 cryptocurrencies, a range of results was identified. The table below indicates the range of the three best and worst performing strategies. Indicating that strategies (15:6), (9:15) and (9:6) were the best performing strategies with returns of over 5% for each. However, strategies (3:3), (15:30) and (30:30) resulted in returns of less than -3% for each strategy.

Strategy	Average Monthly Returns (Winner - Loser)
(15:6)	5.86%
(9:15)	5.75%
(9:6)	5.13%
(3:3)	-3.14%
(15:30)	-3.54%
(30:30)	-4.98%

Table 7: CSM trading strategy results of the three best and worst performers

The chart below presents the average monthly returns of the "Winner" minus "Loser" portfolios for all the strategies tested across the 6 years. The chart indicates that 15 of the strategies resulted in positive returns, with the additional 10 strategies resulting in negative returns. Additionally, 5 strategies resulted in more than 4% returns, with only one strategy resulting in less than -4%.

Figure 16: CSM trading strategies average monthly returns

5.3 CSM trading strategy significance test

Question 2: Would the returns of the CSM trading strategies applied to cryptocurrencies be significantly different from zero?

- H_0: CSM trading strategy returns (Winners-Losers) = 0
- H_A: CSM trading strategy returns (Winners-Losers) ≠ 0

To test the hypothesis, an independent sample t-test was performed to identify whether the positive or negative returns obtained from the 25 strategies were significantly different from zero. The statistical outputs were presented for each HD period strategy.

Descriptive statistics for HD period of 3 days

The table below presents each strategy with a HD period of 3 days. The test was performed at a 95% confidence interval, which resulted in none of the below strategies being statistically significant from zero.

						95% Confidence Interval of the Difference		
Strategy	Momentum	n	Mean	df	Std deviation	Lower	Upper	P-Value
(3:3)	Cross-sectional momentum	71	-0.0314	70	0.258	-0.296	0.092	0.307
(6:3)	Cross-sectional momentum	71	-0.0279	70	0.267	-0.0353	0.0911	0.382
(9:3)	Cross-sectional momentum	71	0.0347	70	0.301	-0.106	0.037	0.335
(15:3)	Cross-sectional momentum	71	0.041	70	0.267	-0.104	0.022	0.203
(30:3)	Cross-sectional momentum	71	-0.022	70	0.205	-0.026	0.071	0.365

** indicates statistical significance at 5%

Descriptive statistics for a HD period of 6 days

The table below presents each strategy with a HD period of 6 days. The test was performed at a 95% confidence interval, which resulted in one of the below strategies being statistically significant from zero. The strategy which resulted in being statistically different from zero was the (15:6) strategy, with an average monthly return of 5.86%

						95% Confidence Interval of the Difference		
Strategy	Momentum	n	Mean	df	Std deviation	Lower	Upper	P-Value
(3:6)	Cross-sectional momentum	71	-0.023	70	0.285	-0.044	0.091	0.497
(6:6)	Cross-sectional momentum	71	0.045	70	0.255	-0.105	0.016	0.144
(9:6)	Cross-sectional momentum	71	0.051	70	0.289	-0.12	0.017	0.139
(15:6)	Cross-sectional momentum	71	0.059	70	0.239	-0.115	-0.002	0.043**
(30:6)	Cross-sectional momentum	71	0.005	70	0.19	-0.05	0.04	0.817

** indicates statistical significance at 5%

Descriptive statistics for a HD period of 9 days

The table below presents each strategy with a HD period of 9 days. The test was performed at a 95% confidence interval, which resulted in none of the below strategies being statistically significant from zero.

						95% Confidence Interval of the Difference		
Strategy	Momentum	n	Mean	df	Std deviation	Lower	Upper	P-Value
(3:9)	Cross-sectional momentum	71	-0.001	70	0.228	-0.045	0.063	0.743
(6:9)	Cross-sectional momentum	71	0.011	70	0.251	-0.070	0.048	0.713
(9:9)	Cross-sectional momentum	71	0.015	70	0.250	-0.074	0.045	0.625
(15:9)	Cross-sectional momentum	71	0.015	70	0.239	-0.071	0.042	0.603
(30:9)	Cross-sectional momentum	71	-0.008	70	0.195	-0.038	0.054	0.734

** indicates statistical significance at 5%

Descriptive statistics for a HD period of 15 days

The table below presents each strategy with a HD period of 15 days. The test was performed at a 95% confidence interval, which resulted in one of the below strategies being statistically significant from zero. The strategy which resulted in being statistically different from zero was the (9:15) strategy, with an average monthly return of 5.75%

						95% Confidence Interval of the Difference		
Strategy	Momentum	n	Mean	df	Std deviation	Lower	Upper	P-Value
(3:15)	Cross-sectional momentum	71	0.034	70	0.196	-0.080	0.012	0.148
(6:15)	Cross-sectional momentum	71	0.030	70	0.212	-0.080	0.020	0.241
(9:15)	Cross-sectional momentum	71	0.058	70	0.224	-0.111	-0.004	0.034**
(15:15)	Cross-sectional momentum	71	0.001	70	0.188	-0.045	0.044	0.968
(30:15)	Cross-sectional momentum	71	-0.011	70	0.209	-0.039	0.060	0.661

** indicates statistical significance at 5%

Descriptive statistics for a HD period of 30 days

The table below presents each strategy with a HD period of 30 days. The test was performed at a 95% confidence interval, which resulted in none of the below strategies being statistically significant from zero.

						95% Confidence Interval of the Difference		
Strategy	Momentum	n	Mean	df	Std deviation	Lower	Upper	P-Value
(3:30)	Cross-sectional momentum	71	-0.005	70	0.158	-0.032	0.043	0.773
(6:30)	Cross-sectional momentum	71	0.000	70	0.195	-0.047	0.046	0.989
(9:30)	Cross-sectional momentum	71	0.005	70	0.181	-0.048	0.038	0.825
(15:30)	Cross-sectional momentum	71	-0.035	70	0.194	-0.010	0.081	0.128
(30:30)	Cross-sectional momentum	71	-0.050	70	0.282	-0.016	0.117	0.136

** indicates statistical significance at 5%

5.4 TSM trading strategy returns

Question 4 : Would TSM trading strategies attain positive returns when applied to the sample set of cryptocurrencies?

Research question 3 aimed to identify whether trading strategies utilising the TSM model would result in positive excess returns compared to a “Buy-and-Hold” strategy. The TSM model that was utilised to attain the results identifies cryptocurrencies' historical returns over the LB period and assigns either a buy or sell indicator for the HD period. This resulted in one portfolio having several bought cryptocurrencies and the other having several sold cryptocurrencies.

25 TSM strategies were applied to the sample of 15 cryptocurrencies to identify whether positive returns could be attained. Strategies included LB periods of 3, 6, 9, 15 and 30 days with HD periods of 3, 6, 9, 15 and 30 days. The results were presented according to each HD period timeframe with multiple LB periods.

HD period of 3 days

The first test consisted of five TSM strategies. Each with a HD period of 3 days. The 5 strategies had a LB period of 3, 6, 9, 15 and 30 days.

The table below shows the average monthly returns from each strategy. The monthly returns were calculated by attaining the average of the "Buy" and "Sell" portfolios and subtracting the “Buy-and-Hold” returns. Therefore, the returns presented are excess returns over the “Buy-and-Hold” strategy.

Strategy	Average Monthly Returns
(3:3)	2.05%
(6:3)	4.27%
(9:3)	4.86%
(15:3)	7.38%
(30:3)	6.49%

Table 8: TSM trading strategy results for a holding period of 3 days

The best performing 3 day HD period strategy was the strategy that contained a 15 day LB period. This strategy resulted in a 7.38% average monthly return in excess of the "Buy-and-Hold" strategy.

The chart below presents the daily cumulative returns of the momentum strategy and the "Buy-and-Hold" strategy. The spread represents the difference in the returns of the two strategies. The spread represents the returns obtained from the (15:3) strategy across the 6 years tested.

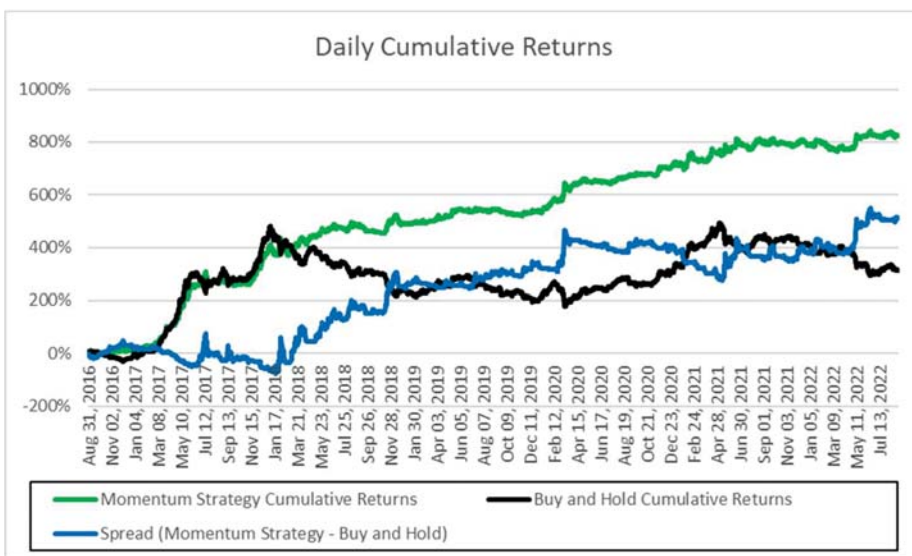

Figure 17: TSM trading strategy daily cumulative returns (15:3)

The worst performing 3 day HD period strategy was the strategy that contained a 3 day LB period. This strategy resulted in a 2.05% average monthly return in excess of the "Buy-and-Hold" strategy.

The chart below presents the daily cumulative returns of the momentum strategy and the "Buy-and-Hold" strategy. The spread represents the difference in the returns of the two strategies. The spread represents the returns obtained from the (3:3) strategy across the 6 years tested.

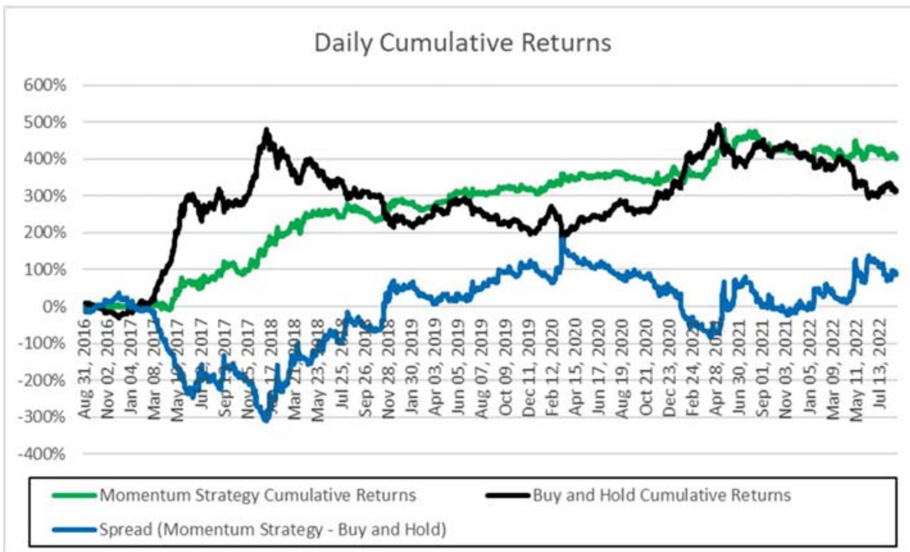

Figure 18: TSM trading strategy daily cumulative returns (3:3)

HD period of 6 days

The first test consisted of five TSM strategies. Each with a HD period of 6 days. The 5 strategies had a LB period of 3, 6, 9, 15 and 30 days.

The table below shows the average monthly returns from each strategy. The monthly returns were calculated by attaining the average of the "Buy" and "Sell" portfolios and subtracting the "Buy-and-Hold" returns. Therefore, the returns presented are excess returns over the "Buy-and-Hold" strategy.

Strategy	Average Monthly Returns
(3:6)	0.18%
(6:6)	2.13%
(9:6)	2.63%
(15:6)	5.77%
(30:6)	5.58%

Table 9: TSM trading strategy results for a holding period of 6 days

The best performing 6 day HD period strategy was the strategy that contained a 15 day LB period. This strategy resulted in a 5.77% average monthly return in excess of the "Buy-and-Hold" strategy.

The chart below presents the daily cumulative returns of the momentum strategy and the "Buy-and-Hold" strategy. The spread represents the difference in the returns of the two strategies. The spread represents the returns obtained from the (15:6) strategy across the 6 years tested.

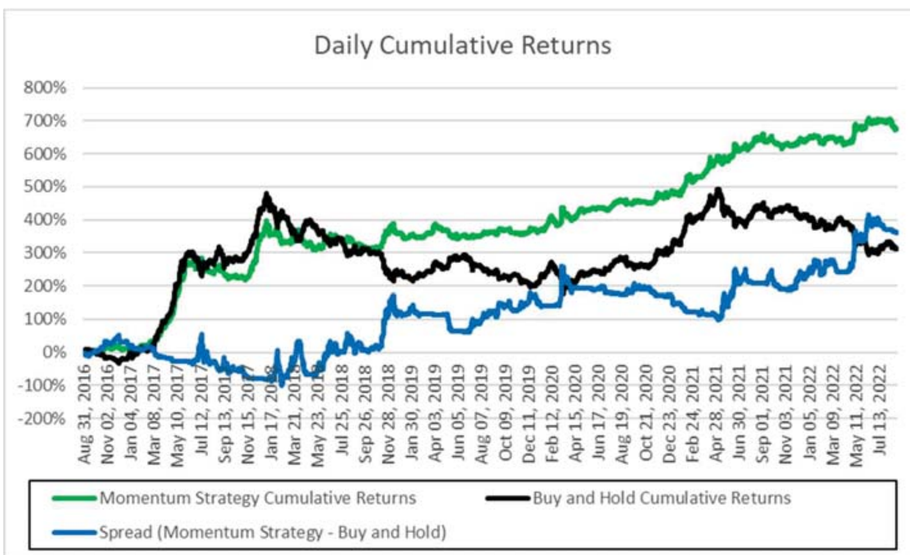

Figure 19: TSM trading strategy daily cumulative returns (15:6)

The worst performing 6 day HD period strategy was the strategy that contained a 3 day LB period. This strategy resulted in a 2.05% average monthly return in excess of the "Buy-and-Hold" strategy.

The chart below presents the daily cumulative returns of the momentum strategy and the “Buy-and-Hold” strategy. The spread represents the difference in the returns of the two strategies. The spread represents the returns obtained from the (3:6) strategy across the 6 years tested.

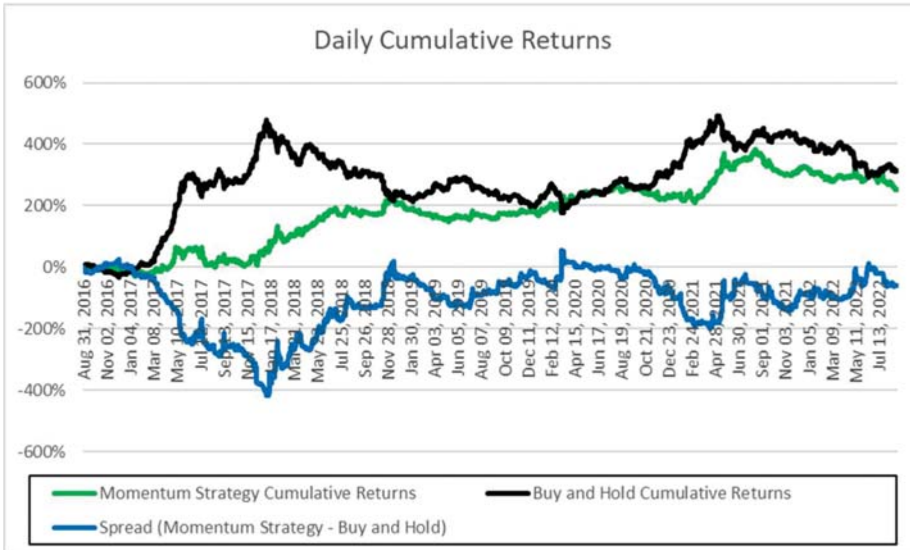

Figure 20: TSM trading strategy daily cumulative returns (3:6)

HD period of 9 days

The first test consisted of five TSM strategies. Each with a HD period of 9 days. The 5 strategies had a LB period of 3, 6, 9, 15 and 30 days.

The table below shows the average monthly returns from each strategy. The monthly returns were calculated by attaining the average of the "Buy" and "Sell" portfolios and subtracting the “Buy-and-Hold” returns. Therefore, the returns presented are excess returns over the “Buy-and-Hold” strategy.

Strategy	Average Monthly Returns
(3:9)	-2.15%
(6:9)	0.73%
(9:9)	3.52%
(15:9)	5.35%
(30:9)	4.44%

Table 10: TSM trading strategy results for a holding period of 9 days

The best performing 9 day HD period strategy was the strategy that contained a 15 day LB period. This strategy resulted in a 5.35% average monthly return in excess of the “Buy-and-Hold” strategy.

The chart below presents the daily cumulative returns of the momentum strategy and the “Buy-and-Hold” strategy. The spread represents the difference in the returns of the two strategies. The spread represents the returns obtained from the (15:9) strategy across the 6 years tested.

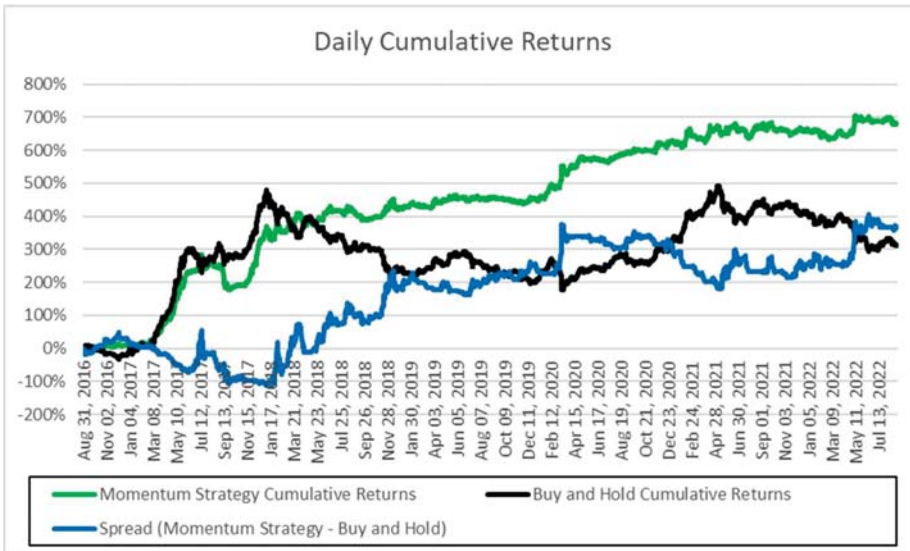

Figure 21: TSM trading strategy daily cumulative returns (15:9)

The worst-performing 9-day HD period strategy was the strategy that contained a 3-day LB period. This strategy resulted in a -2.15% average monthly return in excess of the buy-and-hold strategy.

The chart below presents the daily cumulative returns of the momentum strategy and the “Buy-and-Hold” strategy. The spread represents the difference in the returns of the two strategies. The spread represents the returns obtained from the (3:9) strategy across the 6 years tested.

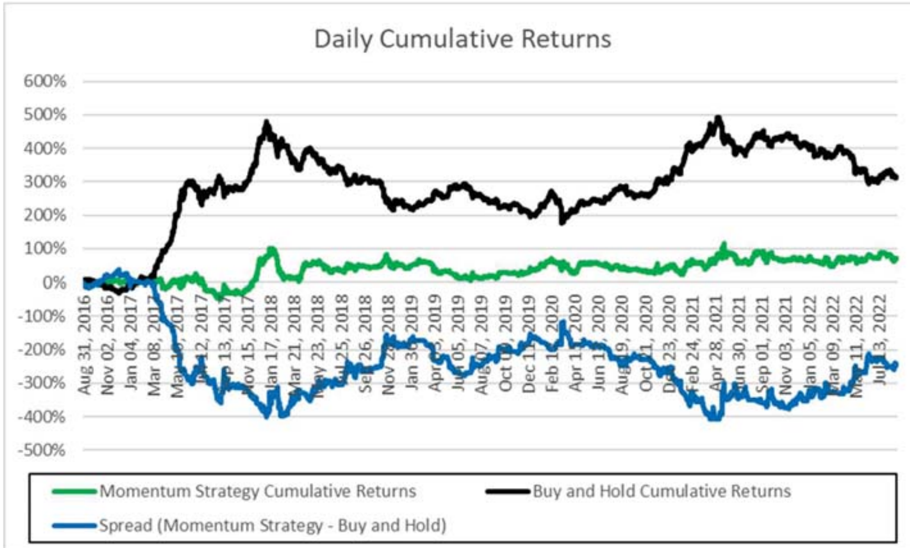

Figure 22: TSM trading strategy daily cumulative returns (3:9)

HD period of 15 days

The first test consisted of five TSM strategies. Each with a HD period of 9 days. The 5 strategies had a LB period of 3, 6, 9, 15 and 30 days.

The table below shows the average monthly returns from each strategy. The monthly returns were calculated by attaining the average of the "Buy" and "Sell" portfolios and subtracting the “Buy-and-Hold” returns. Therefore, the returns presented are excess returns over the “Buy-and-Hold” strategy.

Strategy	Average Monthly Returns
(3:15)	2.63%
(6:15)	0.58%
(9:15)	2.37%
(15:15)	1.06%
(30:15)	3.82%

Table 11: TSM trading strategy results for a holding period of 15 days

The best performing 15 day HD period strategy was the strategy that contained a 30 day LB period. This strategy resulted in a 3.82% average monthly return in excess of the “Buy-and-Hold” strategy.

The chart below presents the daily cumulative returns of the momentum strategy and the "Buy-and-Hold" strategy. The spread represents the difference in the returns of the two strategies. The spread represents the returns obtained from the (15:30) strategy across the 6 years tested.

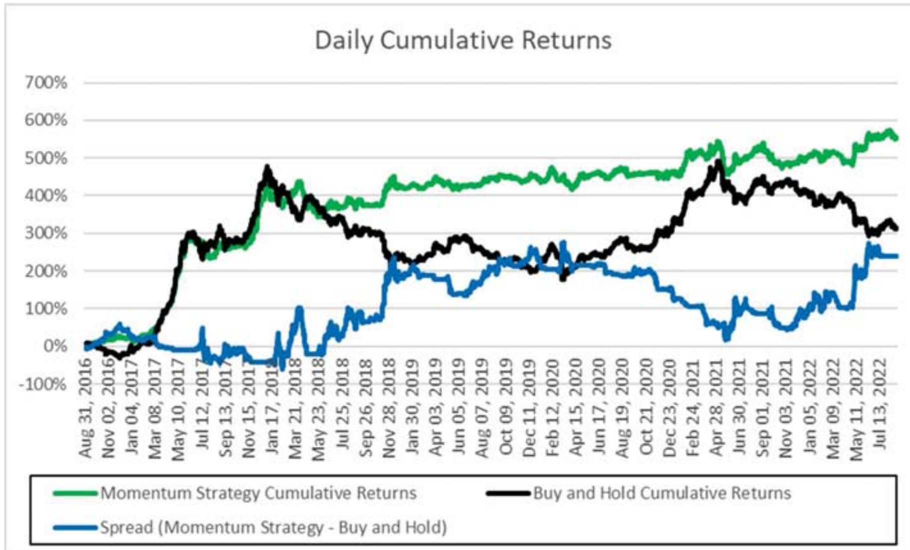

Figure 23: TSM trading strategy daily cumulative returns (30:15)

The worst performing 15 day HD period strategy was the strategy that contained a 6 day LB period. This strategy resulted in a 0.58% average monthly return in excess of the "Buy-and-Hold" strategy.

The chart below presents the daily cumulative returns of the momentum strategy and the "Buy-and-Hold" strategy. The spread represents the difference in the returns of the two strategies. The spread represents the returns obtained from the (6:15) strategy across the 6 years tested.

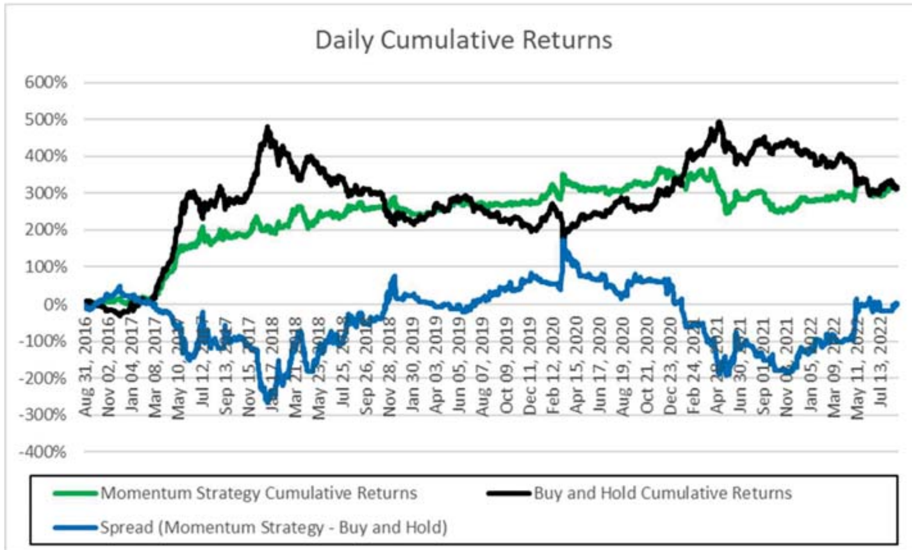

Figure 24: TSM trading strategy daily cumulative returns (6:15)

HD period of 30 days

The first test consisted of five TSM strategies. Each with a HD period of 30 days. The 5 strategies had a LB period of 3, 6, 9, 15 and 30 days.

The table below shows the average monthly returns from each strategy. The monthly returns were calculated by attaining the average of the "Buy" and "Sell" portfolios and subtracting the “Buy-and-Hold” returns. Therefore, the returns presented are excess returns over the “Buy-and-Hold” strategy.

Strategy	Average Monthly Returns
(3:30)	-1.49%
(6:30)	0.28%
(9:30)	0.00%
(15:30)	0.24%
(30:30)	1.20%

Table 12: TSM trading strategy results for a holding period of 30 days

The best performing 30 day HD period strategy was the strategy that contained a 30 day LB period. This strategy resulted in a 1.20% average monthly return in excess of the “Buy-and-Hold” strategy.

The chart below presents the daily cumulative returns of the momentum strategy and the "Buy-and-Hold" strategy. The spread represents the difference in the returns of the two strategies. The spread represents the returns obtained from the (30:30) strategy across the 6 years tested.

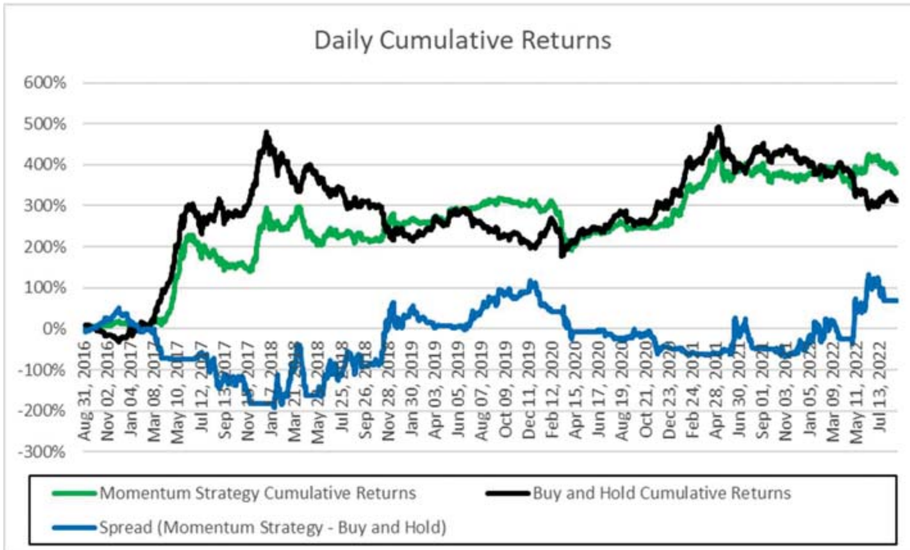

Figure 25: TSM trading strategy daily cumulative returns (30:30)

The worst performing 30 day HD period strategy was the strategy that contained a 3 day LB period. This strategy resulted in a -1.49% average monthly return in excess of the "Buy-and-Hold" strategy.

The chart below presents the daily cumulative returns of the momentum strategy and the "Buy-and-Hold" strategy. The spread represents the difference in the returns of the two strategies. The spread represents the returns obtained from the (3:30) strategy across the 6 years tested.

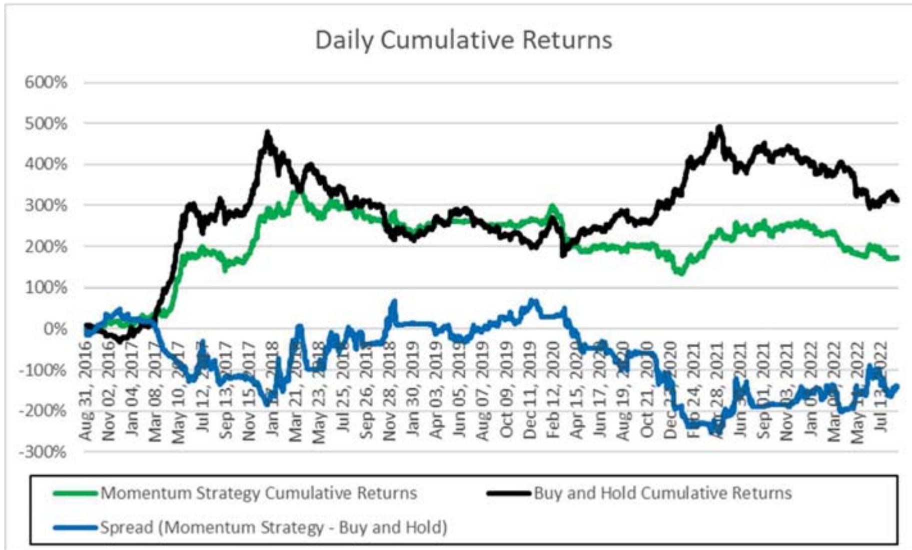

Figure 26: TSM trading strategy daily cumulative returns (3:30)

TSM trading strategies conclusion

After conducting the 25 TSM strategies on the 15 cryptocurrencies, a range of results were identified. The table below indicates the range of the three best and worst performing strategies. Indicating that strategies (15:3), (30:3) and (15:6) were the best performing strategies with excess returns of over 5% for each. However, strategies (3:30) and (3:9) resulted in excess losses of more than 1.49% and 2.15%, respectively.

Strategy	Average Monthly Returns
(15:3)	7.38%
(30:3)	6.49%
(15:6)	5.77%
(9:30)	0.00%
(3:30)	-1.49%
(3:9)	-2.15%

Table 13: TSM trading strategy results of the three best and worst performers

The chart below presents the average monthly excess returns for all the strategies tested across the 6 years. The chart indicates that 22 strategies resulted in positive returns, with the additional 3 strategies resulting in negative returns. Additionally, the range of positive excess returns for the 22 strategies was larger than for the 3 strategies that resulted in losses.

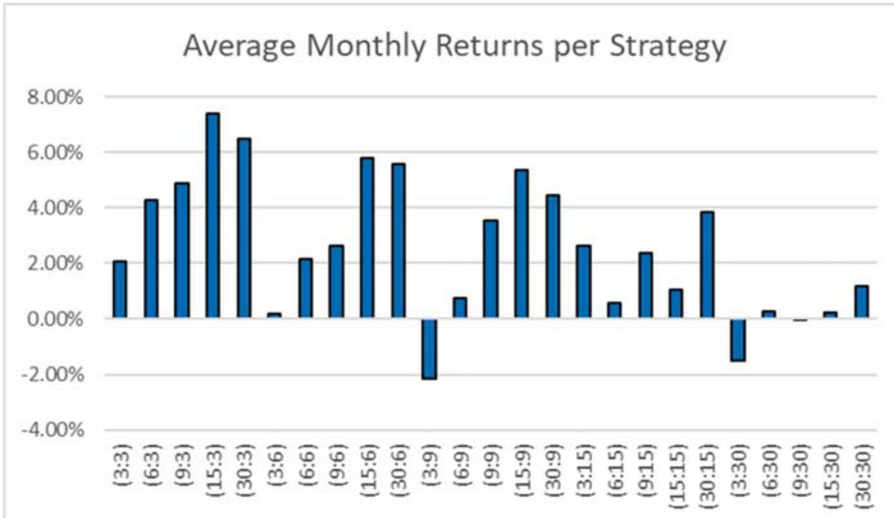

Figure 27: TSM trading strategies average monthly returns

5.5 TSM trading strategy significance test

Question 4: Would the returns of the TSM trading strategies applied to cryptocurrencies be significantly different from zero?

- H_0: TSM trading strategy returns = 0
- H_A: TSM trading strategy returns ≠ 0

To tests hypothesis 2, an independent sample t-test was performed to identify whether the positive or negative returns obtained from the 25 strategies were significantly different from zero. The statistical outputs are presented for each HD period strategy.

Descriptive statistics for a HD period of 3 days

The table below presents each strategy with a HD period of three days. The tests were performed at a 95% confidence interval, which resulted in none of the below strategies being statistically significant from zero.

						95% Confidence Interval of the Difference		
Strategy	Momentum	n	Mean	df	Std deviation	Lower	Upper	P-Value
(3:3)	Time-series momentum	71	0.021	70	0.365	-0.107	0.066	0.636
(6:3)	Time-series momentum	71	0.043	70	0.350	-0.125	0.040	0.307
(9:3)	Time-series momentum	71	0.049	70	0.340	-0.129	0.032	0.233
(15:3)	Time-series momentum	71	0.074	70	0.335	-0.153	0.006	0.068
(30:3)	Time-series momentum	71	0.065	70	0.313	-0.139	0.009	0.085

** indicates statistical significance at 5%

Descriptive statistics for a HD period of 6 days

The table below presents each strategy with a HD period of six days. The tests were performed at a 95% confidence interval, which resulted in none of the below strategies being statistically significant from zero.

						95% Confidence Interval of the Difference		
Strategy	Momentum	n	Mean	df	Std deviation	Lower	Upper	P-Value
(3:6)	Time-series momentum	71	0.002	70	0.378	-0.091	0.088	0.967
(6:6)	Time-series momentum	71	0.021	70	0.353	-0.105	0.062	0.612
(9:6)	Time-series momentum	71	0.026	70	0.344	-0.108	0.055	0.522
(15:6)	Time-series momentum	71	0.058	70	0.331	-0.136	0.021	0.146
(30:6)	Time-series momentum	71	0.056	70	0.330	-0.134	0.022	0.159

** indicates statistical significance at 5%

Descriptive statistics for a HD period of 9 days

The table below presents each strategy with a HD period of nine days. The tests were performed at a 95% confidence interval, which resulted in none of the below strategies being statistically significant from zero.

						95% Confidence Interval of the Difference		
Strategy	Momentum	n	Mean	df	Std deviation	Lower	Upper	P-Value
(3:9)	Time-series momentum	71	-0.021	70	0.344	-0.060	0.103	0.600
(6:9)	Time-series momentum	71	0.007	70	0.338	-0.087	0.073	0.855
(9:9)	Time-series momentum	71	0.035	70	0.325	-0.112	0.042	0.365
(15:9)	Time-series momentum	71	0.053	70	0.335	-0.133	0.026	0.183
(30:9)	Time-series momentum	71	0.044	70	0.315	-0.119	0.030	0.239

** indicates statistical significance at 5%

Descriptive statistics for a HD period of 15 days

The table below presents each strategy with a HD period of fifteen days. The tests were performed at a 95% confidence interval, which resulted in none of the below strategies being statistically significant from zero.

						95% Confidence Interval of the Difference		
Strategy	Momentum	n	Mean	df	Std deviation	Lower	Upper	P-Value
(3:15)	Time-series momentum	71	0.026	70	0.363	-0.112	0.060	0.544
(6:15)	Time-series momentum	71	0.006	70	0.372	-0.094	0.082	0.897
(9:15)	Time-series momentum	71	0.024	70	0.330	-0.102	0.055	0.548
(15:15)	Time-series momentum	71	0.011	70	0.359	-0.096	0.074	0.804
(30:15)	Time-series momentum	71	0.038	70	0.345	-0.120	0.043	0.354

** indicates statistical significance at 5%

Descriptive statistics for a HD period of 30 days

The table below presents each strategy with a HD period of thirty days. The tests were performed at a 95% confidence interval, which resulted in none of the below strategies being statistically significant from zero.

						95% Confidence Interval of the Difference		
Strategy	Momentum	n	Mean	df	Std deviation	Lower	Upper	P-Value
(3:30)	Time-series momentum	71	-0.015	70	0.346	-0.067	0.097	0.717
(6:30)	Time-series momentum	71	0.003	70	0.350	-0.086	0.080	0.946
(9:30)	Time-series momentum	71	0.000	70	0.318	-0.075	0.075	1.000
(15:30)	Time-series momentum	71	0.002	70	0.316	-0.077	0.072	0.949
(30:30)	Time-series momentum	71	0.012	70	0.353	-0.095	0.071	0.776

** indicates statistical significance at 5%

5.6 TSM trading strategy returns – individual

Question 5: Would any of the returns of the TSM trading strategies applied to individual cryptocurrencies (above the overall average of the group) be significantly different from zero?

- H_0: TSM trading strategy individual returns = 0
- H_A: TSM trading strategy individual returns ≠ 0

Research question 5 aimed to identify which individual cryptocurrency would result in the highest excess returns when utilising the TSM model and whether they would result in significant returns.

25 TSM strategies were applied to the sample of 15 cryptocurrencies to identify which cryptocurrency attained the highest excess monthly returns. Strategies included LB periods of 3, 6, 9, 15 and 30 days with HD periods of 3, 6, 9, 15 and 30 days.

The result of the 25 TSM trading strategies tested over 2016 to 2022 in question 3 resulted in an overall average excess monthly return of 2.56% across all the strategies. The individual cryptocurrencies which outperformed the overall average of 2.56% were Stellar (3.15%), Syscoin (3.54%), DigiByte (3.89%), Lisk (4.23%), NEM (7.2%) and Siacoin (7.39%).

TSM trading strategies – Stellar

The table below indicates the range of the 5 best and worst performing strategies. Indicating that strategies (15:3), (9:3) and (15:6) were the best performing strategies with excess returns of over 8% for each. Strategies (6:30), (15:30) and (3:9) resulted in excess losses of more than 1%.

Strategy	Stellar
(15:3)	10.32%
(9:3)	9.60%
(15:6)	8.63%
(15:9)	7.97%
(6:3)	6.93%
(30:9)	-0.45%
(3:30)	-0.80%
(6:30)	-1.08%
(15:30)	-2.29%
(3:9)	-5.46%

Table 14: TSM trading strategy results for Stellar

The chart below presents each strategy with its. The chart also indicates that a majority of the strategies resulted in positive returns.

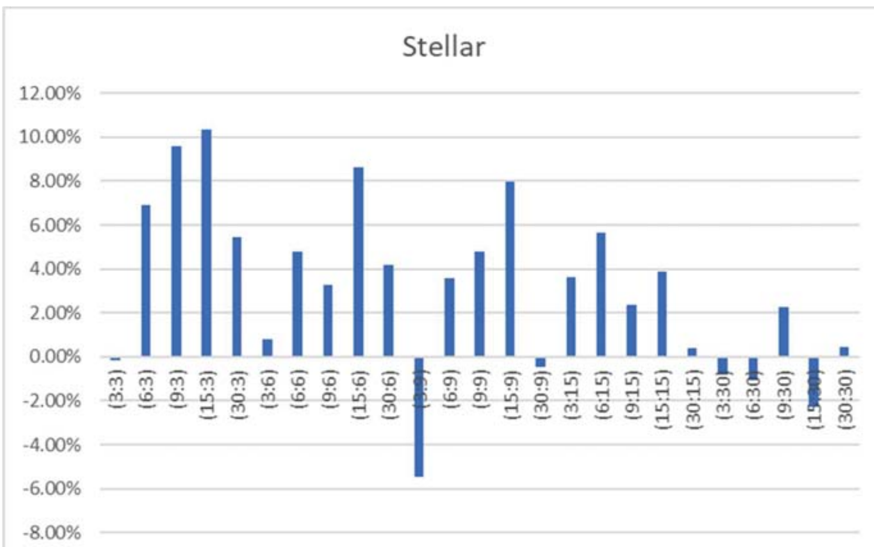

Figure 28: TSM strategies average monthly returns - Stellar

TSM trading strategies – Syscoin

The table below indicates the range of the 5 best and worst performing strategies. Indicating that strategies (30:9), (30:6) and (15:9) were the best performing strategies with excess returns of over 10% for each. Strategies (6:3), (6:9) and (3:9) resulted in excess losses of more than 6%.

Strategy	Syscoin
(30:9)	12.20%
(30:6)	10.56%
(15:9)	10.49%
(30:3)	9.95%
(3:15)	9.12%
(3:3)	-1.91%
(3:6)	-4.17%
(6:3)	-6.42%
(6:9)	-10.12%
(3:9)	-11.01%

Table 15: TSM trading strategy results for Syscoin

The chart below presents each strategy with its returns. The chart also indicates that most of the strategies resulted in positive returns except for the two, which resulted in large losses of over 10%.

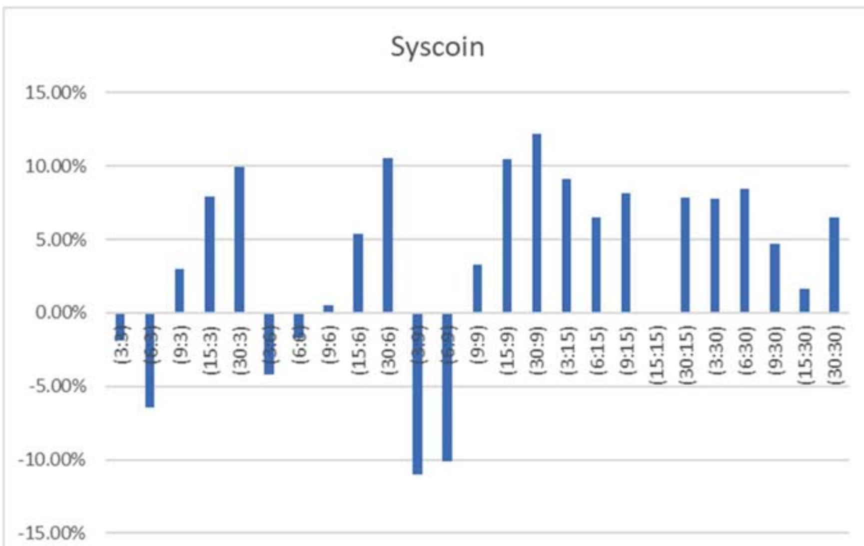

Figure 29: TSM strategies average monthly returns - Syscoin

TSM trading strategies – DigiByte

The table below indicates the range of the 5 best and worst performing strategies. Indicating that strategies (15:6), (15:9) and (3:6) were the best performing strategies with excess returns of over 8% for each. Strategies (9:30), (3:15) and (6:30) resulted in excess losses of more than 4%.

Strategy	DigiByte
(15:6)	10.45%
(15:9)	9.25%
(3:6)	8.36%
(9:6)	8.17%
(6:3)	7.79%
(3:3)	1.30%
(3:30)	-3.16%
(9:30)	-4.11%
(3:15)	-4.66%
(6:30)	-7.49%

Table 16: TSM trading strategy results for DigiByte

The chart below presents each strategy with its returns. The chart also indicates that most strategies resulted in positive returns except for the longer-term strategies, which resulted in negative returns.

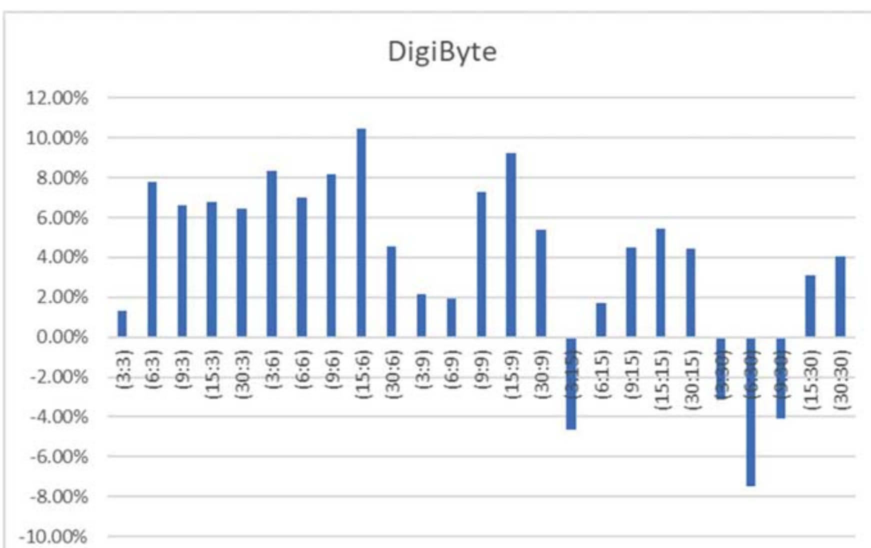

Figure 30: TSM strategies average monthly returns - DigiByte

TSM trading strategies – Lisk

The table below indicates the range of the 5 best and worst performing strategies. Indicating that strategies (15:3), (15:6) and (9:3) were the best performing strategies with excess returns of over 8% for each. Strategies (6:30), (30:30) and (3:30) resulted in excess losses of more than 0%.

Strategy	Lisk
(15:3)	12.11%
(15:6)	9.54%
(9:3)	8.12%
(30:3)	7.71%
(6:3)	6.89%
(3:9)	1.72%
(6:6)	1.52%
(6:30)	-0.47%
(30:30)	-1.89%
(3:30)	-3.79%

Table 17: TSM trading strategy results for Lisk

The chart below presents each strategy with its returns. The chart also indicates that a majority of the strategies resulted in positive returns except for 3 of the longer term strategies, which resulted in negative returns.

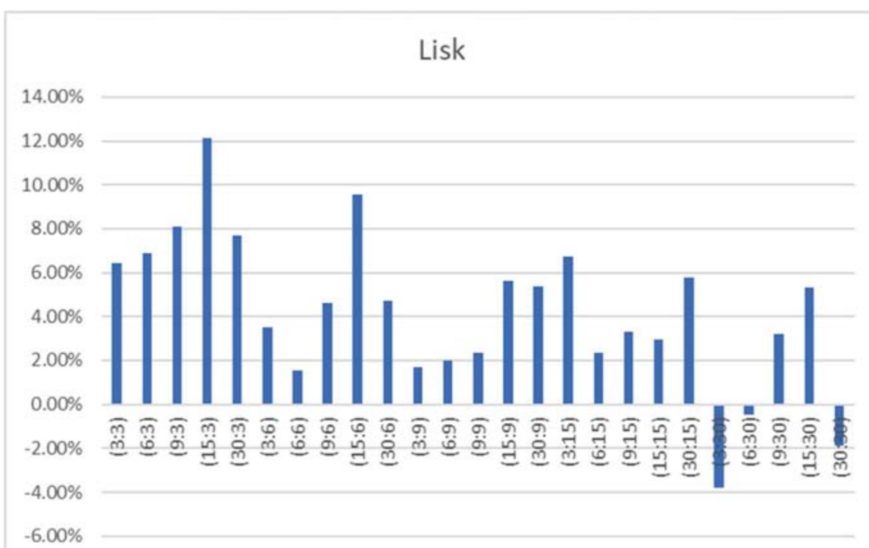

Figure 31: TSM strategies average monthly returns - Lisk

TSM trading strategies – NEM

The table below indicates the range of the 5 best and worst performing strategies. Indicating that strategies (15:3), (30:3) and (15:30) were the best performing strategies with excess returns of over 11% for each. With only one strategy that resulted in losses of larger than 2%.

Strategy	NEM
(15:3)	14.16%
(30:3)	13.27%
(15:30)	11.25%
(6:3)	11.00%
(30:6)	10.70%
(3:15)	4.86%
(9:30)	4.26%
(3:3)	2.33%
(3:9)	-0.73%
(3:30)	-2.18%

Table 18: TSM trading strategy results for NEM

The chart below presents each strategy with its returns. The chart also indicates that a majority of the strategies resulted in positive returns except for 2, which resulted in negative returns.

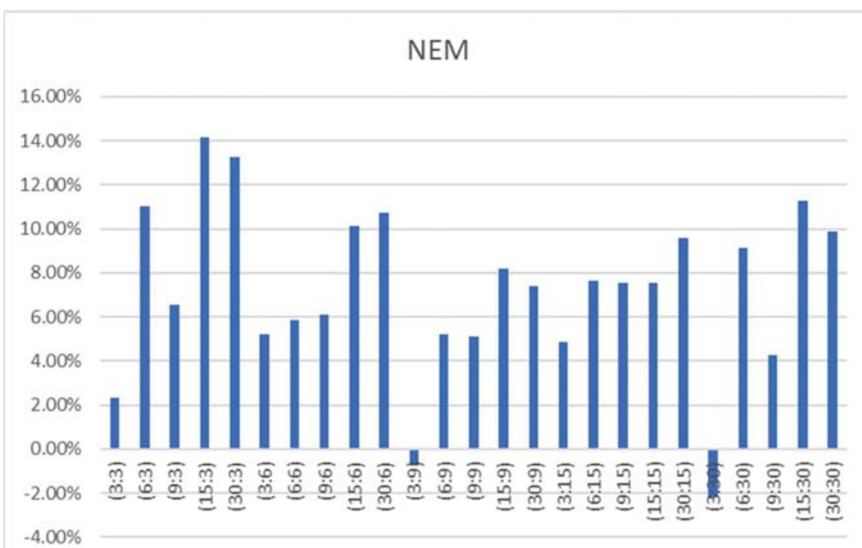

Figure 32: TSM strategies average monthly returns - NEM

TSM trading strategies – Siacoin

The table below indicates the range of the 5 best and worst performing strategies. Indicating that strategies (30:6), (30:3) and (30:9) were the best performing strategies with excess returns of over 12% for each. With only one strategy that resulted in losses of larger that 2%.

Strategy	Siacoin
(30:6)	16.18%
(30:3)	15.02%
(30:9)	12.85%
(9:6)	11.50%
(9:3)	10.98%
(9:30)	3.69%
(15:15)	3.01%
(3:30)	2.10%
(3:6)	-1.30%
(3:9)	-2.09%

Table 19: TSM trading strategy results for Siacoin

The chart below presents each strategy with its returns. The chart also indicates that a majority of the strategies resulted in positive returns except for 2, which resulted in negative returns.

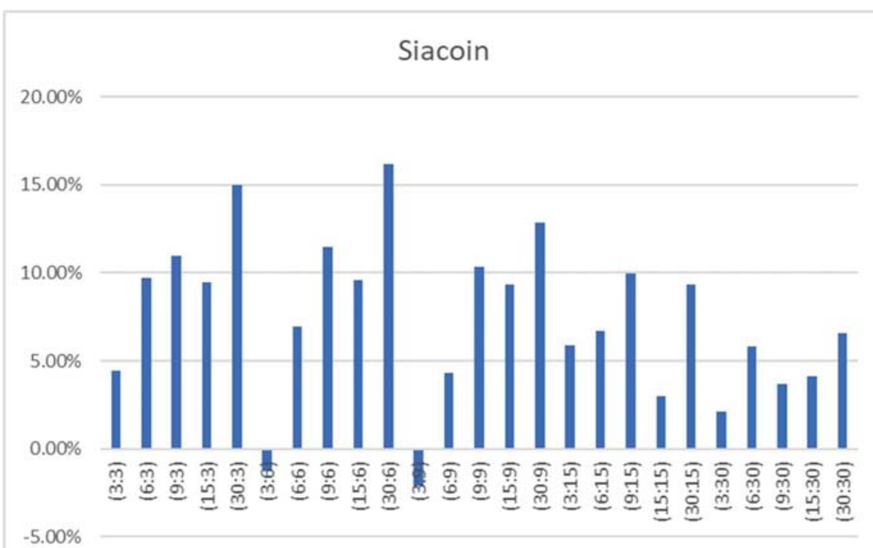

Figure 33: TSM strategies average monthly returns - Siacoin

Question 5 significance test

To test hypothesis 3, a one-sample t-test was performed. The test identified whether the average excess positive returns obtained from the 25 strategies were significantly different from zero.

The table below presents each coin with an average excess return above the average attained in question 3. The tests were performed at a 95% confidence interval, which resulted in all of the below coins being statistically significant from zero.

				95% Confidence Interval of the Difference		
Coin	t-stat	df	Mean Difference	Lower	Upper	One-sided P
Stellar	4.048	24	3.15%	1.54%	4.75%	<0,001**
Syscoin	2.73	24	3.54%	0.86%	6.21%	0.006**
DigiByte	4.221	24	3.89%	1.99%	5.80%	<0,001**
Lisk	6.017	24	4.23%	2.78%	5.68%	<0,001**
NEM	9.301	24	7.20%	5.60%	8.80%	<0,001**
Siacoin	8.149	24	7.39%	5.52%	9.26%	<0,001**

** indicates statistical significance at 2.5% (one-sided)

6. Discussion of Results

The results presented for each research question in the previous chapter will be discussed below. The study found that both CSM and TSM strategies produced overall average positive returns when applied to portfolios and individual cryptocurrencies. The positive returns obtained from the CSM and TSM strategies, when applied to portfolios, were not significant and supported the findings of Bariviera (2017), Grobys and Sapkota (2019) and Nadarajah and Chu (2017). However, some of the cryptocurrencies that produced positive returns from the TSM strategies produced significant returns.

6.1 CSM trading strategy returns

Question 1: Would CSM trading strategies attain positive returns when applied to the sample set of cryptocurrencies?

The outcomes of the 25 CSM trading strategies tested from 2016 to 2022 resulted in an overall average excess monthly return of 0.72%. The number of strategies producing positive average monthly excess returns outperformed the number of strategies that produced negative average monthly excess returns. 15 strategies resulted in positive average monthly returns, with only 10 strategies resulting in negative average monthly returns.

The table below provides an overview of each CSM strategy and its excess monthly returns with a colour coding representing positive (green) and negative (red) returns. Additionally, an average is provided for each LB period with a combination of HD periods as well as each HD period with a combination of its LB periods.

Strategy		Holding Period (Days) 3	6	9	15	30	Average
Look-back Period (Days)	3	-3.14%	-2.31%	-0.89%	3.39%	-0.53%	-0.70%
	6	-2.79%	4.47%	1.10%	2.97%	0.03%	1.16%
	9	3.47%	5.13%	1.45%	5.75%	0.47%	3.25%
	15	4.07%	5.86%	1.48%	0.09%	-3.54%	1.59%
	30	-2.22%	0.52%	-0.79%	-1.08%	-4.98%	-1.71%
Average		-0.12%	2.74%	0.47%	2.23%	-1.71%	

Table 20: CSM trading strategies average monthly returns

The table above presents that all CSM strategies with a combination of LB and HD periods of 6, 9 and 15 (9 strategies) resulted in positive average monthly returns. In addition, the table showed that all CSM strategies with a combination of LB and HD periods of 3 and 30 (16 strategies) resulted in negative average monthly returns.

All strategies with a combination of LB and HD periods of 6, 9 and 15 resulted in positive returns. The worst performing strategy within the 6, 9 and 15 combination set was the (15:15) strategy, with monthly average returns of 0.09%. Even though the return for the (15:15) strategy was low, it still resulted in a positive return. The optimal strategy within the 6, 9 and 15 combination set was the (15:6) strategy with monthly average returns of 5.86%. Additionally, an overall average monthly return of 3.14% would be obtained if only the 6, 9 and 15 combination sets were implemented.

The longer-term strategy (30:30) resulted in a negative average monthly return of -4.98% from 2016 to 2022. The negative returns correspond to the results obtained by Grobys and Sapkota (2019) with their (30:30) strategy. Grobys and Sapkota (2019) found that using a (30:30) strategy would, over a period of 4 years (2014-2018), result in an average monthly return of -6.28%. The (30:30) strategy also resulted in the worst performing combination with a linearly decreasing cumulative spread of winner minus losers returns from 2017 to 2022.

The results produce insights into the trends that the cryptocurrency market follows. Indicating that the 6, 9 and 15 day trends tend to continue over the following 6, 9 and 15 days. Whereas the 30-day trend tends to reverse over the following 30 days.

The chart below provides a graphical overview of the average monthly returns per strategy. The chart presents that there is a pattern of positive returns across the combination of the 6, 9 and 15 LB and HD period strategies. Showing a reversal pattern of returns across the longer dated strategies.

Figure 34: CSM strategies average monthly returns

In conclusion, the 25 CSM trading strategies applied over the six years of data tested resulted in overall positive returns. The tests also indicate that strategies with combination of LB and HD periods of 6, 9 and 15 resulted in higher average returns than those with combinations of LB and HD periods of 3 and 30.

Additional interesting findings not related to the research question.

The best performing strategies with average monthly returns of over 5% were (15:6) (5.86%), (9:15) (5.75%) and (9:6) (5.13%). The chart below presents the three strategies cumulative daily returns (Winner – Loser) over the period tested.

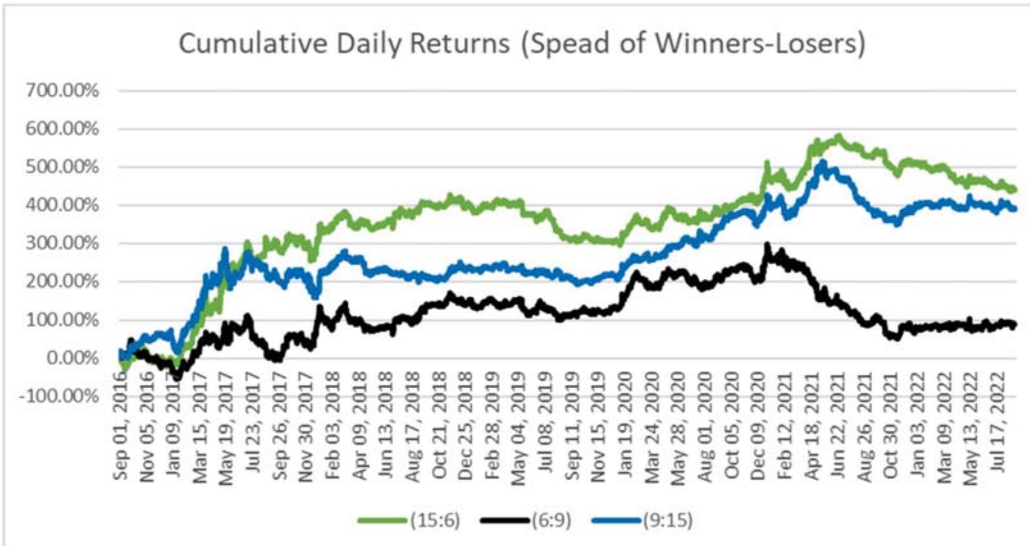

Figure 35: CSM cumulative daily returns

The cumulative daily returns presented in the graph follow an upward trend from 2016 to 2020. Whereafter the general trend reverses and continues downwards. In the tests performed by Bariviera (2017) on the inefficiency of bitcoin, he concluded that bitcoin had a regime shift after 2014. Indicating that bitcoin was inefficient before 2014 and efficient after 2014. The change in the direction of the trend indicates that the momentum trading strategies are not as profitable from 2021 onwards as they were in prior years. An indication of a possible regime shift is noted in 2021 and could result in CSM trading strategies that prove negative returns when applied to the current market.

6.2 CSM trading strategy significance test

Question 2: Would the returns of the CSM trading strategies applied to cryptocurrencies be significantly different from zero?

- H_0: CSM trading strategy returns (Winners-Losers) = 0
- H_A: CSM trading strategy returns (Winners-Losers) ≠ 0

The overall finding for the hypothesis led to the acceptance of the null hypothesis and the conclusion that, even though CSM momentum trading strategies produce a positive return on average, they do not provide significant returns.

The 25 strategies that were tested resulted in only two CSM strategies with significant returns. These strategies were the (15:6) (5.86%) and the (9:15) (5.75%) strategies. Additionally, the 23 remaining strategies resulted in returns which were not significantly different from zero.

The results obtained in the study align with the findings of Grobys and Sapkota (2019). In addition, the study aligns to Bariviera (2017), Brauneis and Mestel (2018) and Nadarajah and Chu (2017), who concluded that the cryptocurrency market is efficient (accepting EMH) and that momentum trading strategies would not result in significant returns.

The study concludes and adds to the growing body of literature that CSM trading strategies do not provide significant returns in the cryptocurrency markets (accepting EMH).

6.3 TSM trading strategy returns

Question 3: Would TSM trading strategies attain positive returns when applied to the sample set of cryptocurrencies?

The 25 TSM trading strategies tested from 2016 to 2022 resulted in an overall average excess monthly return of 2.56% across all the strategies. The number of strategies that outperformed the buy-and-hold strategy outweighed the strategies that did not outperform the buy-and-hold strategy. 22 of the 25 TSM strategies produced positive average monthly returns, with only 3 strategies resulting in negative returns.

The below table provides an overview of each TSM strategy and its excess monthly returns. The table presents a colour gradient of each return, with higher returns in green and lower returns in red. Additionally, an average is provided for each LB period with a combination of HD periods as well as each HD period with a combination of LB periods.

Strategy		Holding Period (Days)					
		3	6	9	15	30	Average
Look-back Period (Days)	3	2.05%	0.18%	-2.15%	2.63%	-1.49%	0.24%
	6	4.27%	2.13%	0.73%	0.58%	0.28%	1.60%
	9	4.86%	2.63%	3.52%	2.37%	0.00%	2.67%
	15	7.38%	5.77%	5.35%	1.06%	0.24%	3.96%
	30	6.49%	5.58%	4.44%	3.82%	1.20%	4.30%
Average		5.01%	3.26%	2.38%	2.09%	0.05%	

Table 21: TSM trading strategies average monthly returns

According to the table above, average returns tend to increase as HD period days are reduced. While average returns tend to rise as LB period days are reduced. The table also identifies that all the averages for each LB period, with its combination of HD periods, resulted in positive average monthly returns. In addition, only strategies (3:9), (3:30) and (9:3) resulted in negative returns.

The best performing TSM strategies have a combination of longer LB periods and shorter HD periods. TSM strategies with HD periods of 3 and 6 days resulted in the highest average returns across the five HD period strategies. The average monthly returns for the 3-day HD period strategy across all the LB periods was 5.01%, with the average monthly returns for the 6-day HD period across all the LB periods return being 3.26%. In addition, TSM strategies with LB periods of 15 and 30 days resulted in the highest average returns across the five LB period strategies. The average monthly returns for the 15-day LB across all the HD periods was 3.96%, with the average monthly returns for the 30-day LB across all the HD periods being 4.30%.

The chart below provides a graphical overview of the average monthly returns per TSM strategy as presented in table X. It provides insights into the magnitude of the returns attained from the TSM trading strategies.

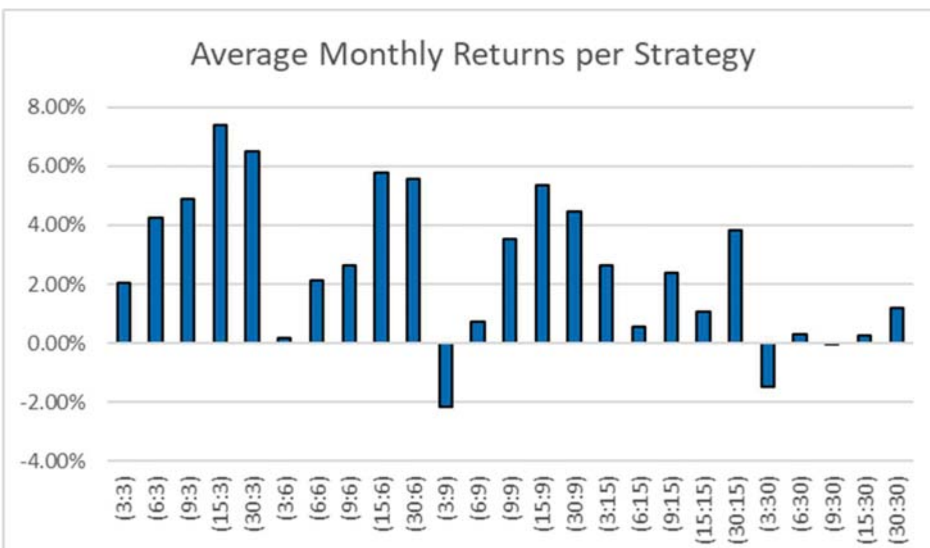

Figure 36: TSM strategies average monthly returns

In conclusion, the 25 TSM trading strategies applied over the six years of data tested resulted in overall positive returns. The tests performed also indicated that strategies with lower HD periods and longer LB periods performed better than TSM strategies with higher HD periods and lower LB periods.

6.4 TSM trading strategy significance test

Question 4: Would the returns of the TSM trading strategies applied to cryptocurrencies be significantly different from zero?

- H_0: TSM trading strategy returns = 0
- H_A: TSM trading strategy returns ≠ 0

The overall finding for the hypothesis led to the acceptance of the null hypothesis and the conclusion that, even though TSM momentum trading strategies produce a positive return on average, they do not provide significant returns. Additionally, none of the 25 TSM trading strategies tested produced significant returns.

The results obtained in the study align with the findings of Grobys and Sapkota (2019). In addition, the study aligns with Bariviera (2017), Brauneis and Mestel (2018) and Nadarajah and Chu (2017), who concluded that the cryptocurrency market is efficient (accepting EMH) and that momentum trading strategies would not result in significant returns. However, the results contradict the findings of Liu and Tsyvinski (2021) and Shen et al. (2021), who used TSM trading strategies to conclude that cryptocurrencies show significant returns.

The study concludes and adds to the growing literature that TSM trading strategies do not provide significant returns in the cryptocurrency markets (accepting EMH).

6.5 TSM trading strategy returns - individual

Question 5: Would any of the returns of the TSM trading strategies applied to individual cryptocurrencies (above the overall average of the group) be significantly different from zero?

- H_0: TSM trading strategy individual returns = 0
- H_A: TSM trading strategy individual returns ≠ 0

The results of the 25 TSM trading strategies resulted in most of the cryptocurrencies having positive excess monthly returns, with only 2 cryptocurrencies having overall negative returns. The two cryptocurrencies that produced overall negative returns were Bitcoin, with a return of -1.36% and Monero, with a return of -1.85%. The remaining 22 cryptocurrencies had returns ranging from 0.92% to 7.39%.

The table below shows each cryptocurrency's average return across the 25 TSM trading strategies applied. Additional information on price and market capitalisation is also provided as of the 31st of August 2022. As with the results in in question 3, the overall average excess monthly return was 2.56%.

Cryptocurrency name	Overall average TSM strategy return	Price (USD)	Market capitilisation (USD)
Bitcoin	-1.36%	19 796.8100	378 850 670 474
Ethereum	0.92%	1 523.8400	186 176 738 543
XRP	2.49%	0.3269	16 227 920 584
Dogecoin	1.91%	0.0615	8 162 617 342
Etherium Classic	1.68%	32.4200	4 429 050 490
Litecoin	0.92%	53.8600	3 827 402 072
Stellar	3.15%	0.1043	2 636 240 558
Monero	-1.85%	149.0300	2 707 590 835
Dash	2.50%	44.6200	485 978 352
Decred	1.80%	28.3800	406 129 611
NEM	7.20%	0.0441	396 875 656
Siacoin	7.39%	0.0040	209 424 692
DigiByte	3.89%	0.0105	164 528 249
Lisk	4.23%	1.0600	136 024 438
Syscoin	3.54%	0.1345	88 601 414
Overall average	2.56%	1 442.05	40 327 052 887

Table 22: Individual cryptocurrencies TSM strategies average monthly returns

The chart below provides an overview of the overall average monthly returns per cryptocurrency. Providing a view of each cryptocurrency performed relative to the average returns. The particular cryptocurrencies which outperformed the overall average are Stellar (3.15%), Syscoin (3.54%), DigiByte (3.89%), Lisk (4.23%), NEM (7.2%) and Siacoin (7.39%).

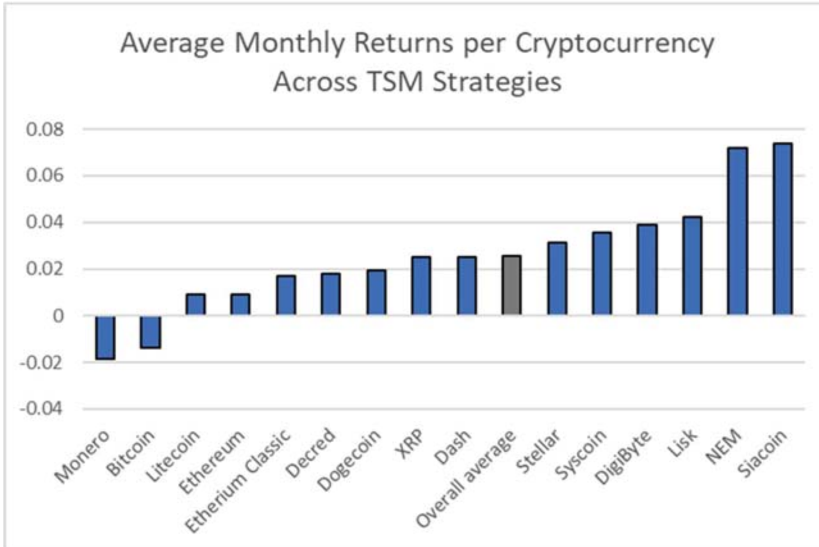

Figure 37: Individual cryptocurrencies TSM strategies average monthly returns

The findings of the hypothesis testing performed on the six individual cryptocurrencies led to rejecting the null hypothesis and concluding that each cryptocurrency that was tested produced a significant return.

The study's results align with the findings of Zhang et al. (2018), who conclude that the cryptocurrency market is inefficient. Additionally, the results obtained contradict Grobys and Sapkota (2019), who conclude that TSM strategies do not result in significant returns.

It has been noted that the tests performed by Zhang et al. (2018) were done on individual cryptocurrencies, as with the test in this question, whereas the tests that were performed by Grobys and Sapkota (2019) were performed on a group/portfolio basis.

The study therefore concludes and adds to the growing body of literature that TSM trading strategies could provide significant returns in the cryptocurrency markets when applied to the correct instruments (rejecting EMH).

7. Conclusion

7.1 Research findings

The study's objective was to identify whether momentum trading strategies could be used to attain significant returns within the cryptocurrency market. The study applied two momentum trading methodologies on a sample of 15 cryptocurrencies from 1 September 2016 to 31 August 2022.

The 25 CSM trading strategies that we applied to the sample of cryptocurrencies were found to produce an overall positive average monthly return. The overall average monthly return amounted to 0.72%. From the 25 CSM trading strategies, only 2 individual strategies resulted in significant returns. The two strategies that resulted in significant returns were the (15:6) strategy, with monthly average returns of 5.86% and the (9:15) strategy, with monthly average returns of 5.75%. Even though the study concluded that the CSM strategies produced positive returns, it also concluded that the returns were not significant. The results align with the CSM trading strategies study by Grobys and Sapkota (2019). Additionally, the results produced in the report support the findings of the studies done by Bariviera (2017), Brauneis and Mestel (2018) and Nadarajah and Chu (2017), who found that the bitcoin and cryptocurrency market is efficient (accepting EMH).

The 25 TSM trading strategies that we applied to the sample of cryptocurrencies were also found to produce an overall positive average monthly return. The overall average monthly return was higher than that of the CSM trading strategy and amounted to 2.56%. As with the CSM trading strategies, the TSM trading strategies did not produce significant returns. The results align with the TSM trading strategies study by Grobys and Sapkota (2019). However, the study contradicts the results produced by Liu and Tsyvinski (2021) who concluded that TSM strategies over the short term (1 to 5 weeks) produce significant returns.

Surprising results were produced when the 25 TSM trading strategies were applied to the 6 individual cryptocurrencies. When the TSM methods were used separately on each of the six cryptocurrencies, they produced significant returns. This is supported by Zhang et al. (2018), who tested the efficiency of the cryptocurrency market on individual cryptocurrencies instead of using a group/portfolio of cryptocurrencies together. The test indicated that there are a number of individual cryptocurrencies that do provide significant returns when appropriately selected.

7.2 Business implications

The Financial Times (2021) and Forbes (2021) both noted the entry of institutional investors into the cryptocurrency market. This highlighted the need to understand the price predicting capabilities of momentum trading strategies on cryptocurrencies.

The study found that momentum trading strategies could be used as a tool to gain positive returns even though the returns were not significant. The results also found that TSM trading strategies could potentially produce higher returns than CSM trading strategies which would be insightful to investors.

Additionally, TSM momentum strategies could also be used by investors to assist them in identifying individual cryptocurrencies which produce significant returns. Providing the, with insights into cryptocurrencies in which they should invest in. These methods align with Dragomirescu-Gaina et al.'s (2021) observations of investors that use a number of estimations and price predictions before investing.

7.3 Theoretical implications

Research on the use of momentum trading strategies on cryptocurrencies has shown conflicting outcomes. Schilling and Uhlig (2019) claim that bitcoin prices are unpredictable. This idea is supported by the study done by Grobys and Sapkota (2019), who discovered that there is no momentum in the cryptocurrency market. However, Liu and Tsyvinski (2021) and Zhang et al. (2018) offer contradictory proof that momentum does exist in the short-term cryptocurrency market.

The study provides additional evidence to the contradicting body of literature. The results conclude that momentum trading strategies do not produce significant returns when applied on a portfolio basis. These findings support the conclusions of Bariviera (2017), Brauneis and Mestel (2018), Grobys and Sapkota (2019), Nadarajah and Chu (2017) and Schilling and Uhlig (2019). Additionally, the study finds that TSM trading strategies applied to individual cryptocurrencies could result in identifying individual cryptocurrencies which produce significant returns. The findings align with the results produced by Zhang et al. (2018) when testing individual cryptocurrencies.

7.4 Suggestions for future research

There is multiple future research suggestion which could build on this study. The research presented in this study provided insights into the performance of momentum trading strategies on cryptocurrencies. It has been noted that specific time periods produced better results than others. Further research into identifying the reasons for this phenomenon would expand the understanding of the patterns and behavioural characteristics of the cryptocurrency market. This would also expand into the research performed by Bariviera (2017), who identified a regime shift in the price predictability of the bitcoin market during 2014.

The study found that TSM trading strategies generally outperformed CSM trading strategies. Further research into the relationship between the two strategies and whether they perform significantly differently would give insights into which method performs the best. Testing each method's risk and return metrics could also provide insights into which method provides the highest risk-adjusted returns.

Further research into cryptocurrencies' risk factors and price drivers could also provide additional insight. Understanding the driving factors of cryptocurrencies' prices could provide insights into the predictability of their future returns.

7.5 Limitations

Multiple limitations were noted when testing the momentum strategies on the 15 cryptocurrencies. These limitations were discussed below.

The sample only consisted of the 15 highest-ranked cryptocurrencies (by market capitalisation) with at least 6 years of pricing data. Restricting the research sample to the 15 cryptocurrencies could have misrepresented the full population of at least 21 000. However, Grobys and Sapkota (2019) ran their momentum strategies on a sample of 143 and the top 30 (by market capitalisation) cryptocurrencies to find that the results were comparable when testing both samples.

The model built by the researcher only used the closing prices as inputs. By only using the closing prices, intraday volatility was ignored. Additionally, the closing prices do not provide insights into the bid/offer spread at the time of recording the closing price. The results could be overstated by ignoring the bid/offer spread, as slippage is not accounted for in the model outputs.

Survivorship bias was introduced as the sample only consists of cryptocurrencies which are currently being traded in the market. However, the research expands on the range of cryptocurrencies as most of the studies reviewed for the research have been performed on bitcoin only (Bariviera, 2017; Nadarajah & Chu, 2017; Urquhart, 2016).

The static date range selected for the study could provide unatonable results in the future. Bariviera (2017) found that bitcoin returns were predictable in the years before 2014 and were unpredictable after.

Lastly, returns presented by the study exclude any taxes that form part of trading profits and losses. Taxes would reduce the volatility of the returns by reducing their magnitude. The reduction of returns could result in cryptocurrencies that produced significant returns misrepresented.

Reference List

Abarbanell, J. S., & Bushee, B. J. (1998). Abnormal returns to a fundamental analysis strategy. *Accounting Review*, *73*(1), 19–45. https://doi.org/10.2139/ssrn.40740

Analytics Insight. (2022, 29th January). CRYPTOCURRENCY LATEST NEWS. https://www.analyticsinsight.net. https://www.analyticsinsight.net/top-10-biggest-cryptocurrency-asset-gainers-in-january-2022/

Baltussen, G., Da, Z., Lammers, S., & Martens, M. (2021). Hedging demand and market intraday momentum. *Journal of Financial Economics*, *142*(1), 377–403. https://doi.org/10.1016/j.jfineco.2021.04.029

Bariviera, A. F. (2017). The inefficiency of Bitcoin revisited: A dynamic approach. *Economics Letters*, *161*(2017), 1–4. https://doi.org/10.1016/j.econlet.2017.09.013

Bianchi, D. (2020). Cryptocurrencies as an asset class? An empirical assessment. *Journal of Alternative Investments*, *23*(2), 162–179. https://doi.org/10.3905/JAI.2020.1.105

Bogomolov, T. (2013). Pairs trading based on statistical variability of the spread process. *Quantitative Finance*, *13*(9), 1411–1430. https://doi.org/10.1080/14697688.2012.748934

Brauneis, A., & Mestel, R. (2018). Price discovery of cryptocurrencies: Bitcoin and beyond. *Economics Letters*, *165*, 58–61. https://doi.org/10.1016/j.econlet.2018.02.001

Brown, A., Reade, J. J., & Vaughan Williams, L. (2019). When are prediction market prices most informative? *International Journal of Forecasting*, *35*(1), 420–428. https://doi.org/10.1016/j.ijforecast.2018.05.005

Chevalier, C., & Darolles, S. (2019). Trends everywhere? The case of hedge fund styles. *Journal of Asset Management*, *20*(6), 442–468. https://doi.org/10.1057/s41260-019-00141-5

Chu, J., Chan, S., Nadarajah, S., & Osterrieder, J. (2017). GARCH modelling of cryptocurrencies. *Journal of Risk and Financial Management*, *10*(4), 17. https://doi.org/10.3390/jrfm10040017

Chu, J., Chan, S., & Zhang, Y. (2020). High frequency momentum trading with cryptocurrencies. *Research in International Business and Finance*, *52*(July 2019), 101176. https://doi.org/10.1016/j.ribaf.2019.101176

Ciaian, P., Rajcaniova, M., & Kancs, d'Artis. (2018). Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets. *Journal of*

International Financial Markets, Institutions and Money, *52*, 173–195. https://doi.org/10.1016/j.intfin.2017.11.001

Coinmarketcap. (n.d.). Methodology. CoinMarketCap. Retrieved October 31, 2022, from https://coinmarketcap.com/methodology/

Cong, L. W., Li, Y., & Wang, N. (2021). Tokenomics: dynamic adoption and valuation. *Review of Financial Studies*, *34*(3), 1105–1155. https://doi.org/10.1093/rfs/hhaa089

Dragomirescu-Gaina, C., Philippas, D., & Tsionas, M. G. (2021). Trading off accuracy for speed: Hedge funds' decision-making under uncertainty. *International Review of Financial Analysis*, *75*(July 2020), 101728. https://doi.org/10.1016/j.irfa.2021.101728

Dyhrberg, A. H. (2016). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters*, *16*, 139–144. https://doi.org/10.1016/j.frl.2015.10.025

Eriksen, J. N. (2019). Cross-sectional return dispersion and currency momentum. *Journal of Empirical Finance*, *53*(July), 91–108. https://doi.org/10.1016/j.jempfin.2019.07.002

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

Fama, E. F. (1991). Efficient capital markets : II. *The Journal of Finance*, *46*(5), 1575–1617. https://www.jstor.org/stable/2328565

Fama, E. F., & French, K. R. (2008). Dissecting anomalies. *Journal of Finance*, *63*(4), 1653–1678. https://doi.org/10.1111/j.1540-6261.2008.01371.x

Financial Times. (2021, 15th June). Hedge funds expect to hold 7% of assets in crypto within five years. https://www.ft.com/content/4f8044bf-8f0f-46b4-9fb7-6d0eba723017

Forbes. (2021, 12th August). Institutional Money Is Pouring Into The Crypto Market And Its Only Going To Grow. https://www.forbes.com/sites/lawrencewintermeyer/2021/08/12/institutional-money-is-pouring-into-the-crypto-market-and-its-only-going-to-grow/?sh=2043792a1459

Gehrig, T., & Menkhoff, L. (2004). The use of flow analysis in foreign exchange: Exploratory evidence. *Journal of International Money and Finance*, *23*(4), 573–594. https://doi.org/10.1016/j.jimonfin.2003.12.006

Gerritsen, D. F., Bouri, E., Ramezanifar, E., & Roubaud, D. (2020). The profitability of technical trading rules in the Bitcoin market. *Finance*

Research Letters, *34*(July 2019), 101263. https://doi.org/10.1016/j.frl.2019.08.011

Grinblatt, M., Jostova, G., Petrasek, L., & Philipov, A. (2020). Style and skill: Hedge funds, mutual funds, and momentum. *Management Science*, *66*(12), 5505–5531. https://doi.org/10.1287/mnsc.2019.3433

Grobys, K., & Sapkota, N. (2019). Cryptocurrencies and momentum. *Economics Letters*, *180*, 6–10. https://doi.org/10.1016/j.econlet.2019.03.028

Hairudin, A., Sifat, I. M., Mohamad, A., & Yusof, Y. (2020). Cryptocurrencies: A survey on acceptance, governance and market dynamics. *International Journal of Finance and Economics*, *December*, 1–27. https://doi.org/10.1002/ijfe.2392

Hilkevics, S., & Hilkevica, G. (2018). The information system for us stock market: Fundamental and technical analysis. *Journal of Systemics, Cybernetics and Informatics, Proceedings*, *3*(3), 6–12.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, *48*(1), 65–91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Köhler, T., Landis, R. S., & Cortina, J. M. (2017). Establishing methodological rigor in quantitative management learning and education research: The role of design, statistical methods, and reporting standards. *Academy of Management Learning and Education*, *16*(2), 173–192. https://doi.org/10.5465/amle.2017.0079

Köseoglu, M. A., Altin, M., Chan, E., & Aladag, O. F. (2020). What are the key success factors for strategy formulation and implementation? Perspectives of managers in the hotel industry. *International Journal of Hospitality Management*, *89*(May), 102574. https://doi.org/10.1016/j.ijhm.2020.102574

Kurka, J. (2019). Do cryptocurrencies and traditional asset classes influence each other? *Finance Research Letters*, *31*(July 2018), 38–46. https://doi.org/10.1016/j.frl.2019.04.018

Levine, A., & Pedersen, L. H. (2016). Which trend is your friend? *Financial Analysts Journal*, *72*(3), 51–66. https://doi.org/10.2469/faj.v72.n3.3

Lisa, A. (2021, 30th June). 7 of the biggest bitcoin crashes in history. Yahoo Finance - Stock Market Live, Quotes, Business & Finance News. https://finance.yahoo.com/news/7-biggest-bitcoin-crashes-history-180038282.html

Liu, J., & Serletis, A. (2019). Volatility in the cryptocurrency market. *Open*

Economies Review, *30*(4), 779–811. https://doi.org/10.1007/s11079-019-09547-5

Liu, W. (2019). Portfolio diversification across cryptocurrencies. *Finance Research Letters*, *29*(May 2018), 200–205. https://doi.org/10.1016/j.frl.2018.07.010

Liu, Y., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *Review of Financial Studies*, *34*(6), 2689–2727. https://doi.org/10.1093/rfs/hhaa113

Lo, S., & Wang, J. . C. (2014). Bitcoin as money? motivation. *Current Policy Perspectivesves*, *14*, 1–28.

Maciel, L. (2021). Cryptocurrencies value-at-risk and expected shortfall: Do regime-switching volatility models improve forecasting? *International Journal of Finance and Economics*, *26*(3), 4840–4855. https://doi.org/10.1002/ijfe.2043

Malkiel, B. G. (2003, November). The efficient market hypothesis and its critics (Summary). CFA Institute. https://www.cfainstitute.org/en/research/cfa-digest/2003/11/the-efficient-market-hypothesis-and-its-critics-digest-summary

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, *104*(2), 228–250. https://doi.org/10.1016/j.jfineco.2011.11.003

Nadarajah, S., & Chu, J. (2017). On the inefficiency of Bitcoin. *Economics Letters*, *150*(August 2010), 6–9. https://doi.org/10.1016/j.econlet.2016.10.033

Nakamoto, S. (2008). *Bitcoin: a peer-to-peer electronic cash system*.

Peng, Y., Albuquerque, P. H. M., Camboim de Sá, J. M., Padula, A. J. A., & Montenegro, M. R. (2018). The best of two worlds: Forecasting high frequency volatility for cryptocurrencies and traditional currencies with Support Vector Regression. *Expert Systems with Applications*, *97*, 177–192. https://doi.org/10.1016/j.eswa.2017.12.004

Psaradellis, I., Laws, J., Pantelous, A. A., & Sermpinis, G. (2021). Technical analysis, spread trading, and data snooping control. *International Journal of Forecasting*. https://doi.org/10.1016/j.ijforecast.2021.10.002

Saunders, M. N., & Lewis, P. (2018). Doing research in business and management: An essential guide to planning your project (2nd ed., p. 112). Pearson Higher Ed.

Schilling, L., & Uhlig, H. (2019). Some simple bitcoin economics. *Journal of*

Monetary Economics, *106*, 16–26. https://doi.org/10.1016/j.jmoneco.2019.07.002

Schmid, O., & Wirth, P. (2021). Optimal allocation to time-series and cross-sectional momentum. *Journal of Portfolio Management*, *47*(4), 160–179. https://doi.org/10.3905/JPM.2021.1.213

Shen, D., Urquhart, A., & Wang, P. (2021). Bitcoin intraday time series momentum. *Financial Review*, 319–344. https://doi.org/10.1111/fire.12290

Sifat, I. (2021). On cryptocurrencies as an independent asset class: Long-horizon and COVID-19 pandemic era decoupling from global sentiments. *Finance Research Letters*, *43*(December 2020), 102013. https://doi.org/10.1016/j.frl.2021.102013

Sloan, R. G. (2019). Fundamental analysis redux. *Accounting Review*, *94*(2), 363–377. https://doi.org/10.2308/accr-10652

Statista. (2021, 29th September). Bitcoin price history 2013-2021. https://www.statista.com/statistics/326707/bitcoin-price-index/

Trimborn, S., & Härdle, W. K. (2018). CRIX an Index for cryptocurrencies. *Journal of Empirical Finance*, *49*(May 2017), 107–122. https://doi.org/10.1016/j.jempfin.2018.08.004

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters*, *148*, 80–82. https://doi.org/10.1016/j.econlet.2016.09.019

Vincent, K., Hsu, Y. C., & Lin, H. W. (2021). Investment styles and the multiple testing of cross-sectional stock return predictability. *Journal of Financial Markets*, *56*, 100598. https://doi.org/10.1016/j.finmar.2020.100598

Yermack, D. (2013). Is Bitcoin a Real Currency? In *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2361599

Zhang, W., Wang, P., Li, X., & Shen, D. (2018). The inefficiency of cryptocurrency and its cross-correlation with Dow Jones Industrial Average. *Physica A: Statistical Mechanics and Its Applications*, *510*(92), 658–670. https://doi.org/10.1016/j.physa.2018.07.032