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Time-series Momentum in the Cryptocurrency Market

M.Sc. candidate Nick Wisselink

Student ID: 483391

Supervisor: A. Emirmahmutoglu

Co-assessor: V. Spinu

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Abstract

This thesis investigates the time-series momentum anomaly in the cryptocurrency market. Time-series momentum is the anomaly that the prior returns of an asset itself can be predictive for the future returns of the asset. To investigate the existence of the anomaly in the cryptocurrency market, three different time-series trading strategies are used: the simple TSMOM strategy, the filter strategy and the percentage price oscillator. The trading signals created by the different strategies are used to create equally-weighted momentum portfolios that are rebalanced daily. The returns of the equally-weighted momentum portfolios are compared to two custom-made benchmarks and the CCI30 index. This is done to create excess returns. Significant positive excess returns are found for 85% of the long-only portfolios. However, for the long-short portfolios no significant positive returns were found. Therefore, at least to some extent, evidence is provided that the momentum anomaly does exist in the cryptocurrency market.

Contents

1. Introduction

In the aftermath of the financial crisis of 2008, Satoshi Nakamoto has published the groundwork (Nakamoto, 2008) for what became the birth of the blockchain technology and the best-known cryptocurrency of our time, the Bitcoin. Since then, the cryptocurrencies have taken the financial world by storm. New cryptocurrencies were created on an almost daily basis and the public attention regarding these assets increased. Even though most people were still struggling to understand what cryptocurrencies were, the market witnessed an abrupt development and the value of cryptocurrencies seemed to keep on rising. Not only the Bitcoin, but also the values of other cryptocurrencies exploded. Despite several warnings that cryptocurrencies might be the next bubble, more people took a position in the crypto-market than ever. Crypto-millionaires were produced overnight. However, after reaching its peak in December 2017, the cryptocurrency market declined substantially in value and has not recovered since. Still, as of the 30th of June, 2018 there are 1,567 different cryptocurrencies with a total market capitalization of over 250 billion dollar according to CoinMarketCap. The increasing attention in combination with limited previous literature does make cryptocurrencies an interesting market to investigate.

The crypto-market is on the similar stage of development as the financial markets in the beginning of the 20th century (Kosc, Sakowski & Slepaczuk, 2018). Traditionally, it is assumed that financial markets are efficient (Malkiel & Fama, 1970). The basic notion of efficient markets is that asset prices adjust to new information without delay and arbitrage opportunities, that would achieve in above-average risk-adjusted returns, do therefore not exist in the market (Malkiel, 1989; Malkiel, 2005). Despite the efficient market hypothesis (EMH) being the foundation of modern financial theory it is controversial and often disputed (Jensen, 1978). Over the last decennia, recurring return patterns are found in traditional markets. These anomalies possess evidence against the EMH. It is interesting to investigate whether anomalies known to the traditional financial markets can also be found in the young and developing crypto-market. If so, this can be seen as yet another claim against the EMH.

One market anomaly that is widely studied is the momentum effect (Dhankar & Maheswari, 2016; Kosc et al., 2018). The momentum effect can be seen as the continuation of prior returns. Something that performed well in the past will probably continue to do well in the future while assets that performed poorly in the past tend to keep on doing poorly in the future (Jegadeesh & Titman, 1993). This effect is an anomaly because it indicates that past prices can be used to predict future prices. Thereby it possesses direct evidence against even the weakest form of the EMH as it appears that technical analysis of past prices can result in excess returns. (Malkiel, 1989).

Especially in the crypto-market, a market that keeps on rising (or falling) persistently, it is interesting to investigate if there is evidence for a momentum effect. In particular because the momentum effect is most present in markets that have high volatility (Yan, 2008). Therefore, it is surprising that there is a paucity of literature applying momentum strategies on cryptocurrencies since their emergence. To the best of my knowledge only Rorhbach, Suremann and Osterrieder (2017), Kosc et al. (2018) and Yang (2018) investigated the (time-series) momentum anomaly in the cryptocurrency market with mixed conclusions. Furthermore, none of the studies made use of the more advanced method of moving average crossovers. This method can identify price momentum without really knowing the precise structure (Hong & Satchell, 2015). In order to reach consensus regarding the existence of the momentum anomaly in the cryptocurrency market the following research question is formed:

Do time-series momentum trading strategies generate economically and statistically significant positive returns in the crypto-market?

In general, the most commonly used methods to identify momentum are time-series and cross sectional. In this thesis, there has been focussed on time-series momentum trading strategies. This approach is used as it performs better when the market experiences extreme movements (Moskowitz et al., 2012). Extreme movements are common in the crypto-market. Furthermore, time-series momentum strategies are known to outperform the cross-sectional alternative (Bird, Gao & Yeung, 2017). One explanation for the outperformance is that time-series momentum portfolio holdings can vary with the state of the market. In a bullish (bearish) market, the time-series momentum strategy will assign relatively more stocks to the winner (loser) portfolios. For the cross-sectional alternative the number of assets included in the winner and loser portfolios do not vary. As a consequence, does this strategy dig too deep to find loser (winner) stocks in bullish (bearish) markets (Bird et al., 2017).

To examine the profitability of time-series momentum trading strategies, three different methods are used to create trading signals. The first method to create trading signals is the simple time-series momentum strategy based on the work of Levine and Pedersen (2016). The second method is based on the work of Fama and Blume (1966) and Baltas and Kosowski (2015) and will be referred to as the filter strategy. The last method is the percentage price oscillator and is inspired by the methodologies of among others Moskowitz et al. (2012) and Rohrbach et al. (2017). The methodologies are similar in many domains and only differ in the specific way the trading signals are generated. For every time-series momentum trading strategy both a long-short and a long-only portfolio are examined, creating in total 26 different portfolios. To find out whether there are excess returns generated by the time-series momentum trading strategies, all portfolios will be compared to two custom-made benchmarks and one publicly available benchmark, the CCI30 index. In this thesis only cryptocurrencies are included with a market capitalization of at least 0.5% and for which data was available from before 01/01/2017. This led to a data set containing eleven cryptocurrencies over the time period 28/03/2013 till 30/06/2018.

The analysis provided mixed evidence for the existence of the momentum anomaly in the crypto-market. Different results were found for the long-short and long-only portfolios. None of the long-short time-series momentum strategies significantly outperformed any of the benchmarks. In many cases did the long-short portfolios even have negative excess returns, indicating no evidence of the momentum anomaly. For the long-only time-series momentum trading strategies, results in favour of the existence of the momentum anomaly in the crypto-market have been found. All long-only trading strategies created positive excess returns over the benchmarks. These positive excess returns were found to be significant for 85% of the long-only portfolios. Therefore, at least to some extent, significant evidence is provided that the momentum anomaly exist in the crypto-market. However, these result are limited to long-only portfolios. Besides, it is shown that long-only momentum strategies significantly outperform the long-short alternative.

The remainder of this thesis is organized as follows. In the following section, section 2, the literature review will be discussed. This section will focus on the question what the momentum anomaly is and why it can be seen as an anomaly. In section 3 the data will be discussed. Section 4 focusses on the applied methodology regarding time-series momentum trading strategies and the construction of the benchmarks. Section 5 will present the returns of the different trading strategies. Finally, section 6 concludes and discusses.

2. Literature review

2.1.1 EMH

The efficient market hypothesis originated in the 1960s and can be assigned to the independent work of the two individuals Paul A. Samuelson and Eugene F. Fama. Although the latter is often seen as the founder of the hypothesis, both developed the same basic concept of market efficiency. The efficient market hypothesis states that '*security prices at any time fully reflect all available information'* and that '*a market in which prices always fully reflect available information is called efficient'* (Malkiel & Fama, 1970). The basic notion of efficient markets is that asset prices adjust to new information without delay and arbitrage opportunities, that would achieve above-average risk-adjusted return, do therefore not exist in the market. If new information develops randomly, so will the market prices (Lo, 2007; Malkiel, 2005).

Since Roberts (1967), it has been customary to distinguish three different levels of market efficiency according to their corresponding different levels of relevant information subsets. The first form of market efficiency is the weak form. The weak form of the EMH asserts that current prices fully reflect all information contained in the past price history. Thus, based on technical analysis alone an investor cannot find an investment strategy that will yield consistent abnormal profits. The second form of market efficiency is the semi-strong form of the EMH and this form asserts that current stock prices include both the historical price information and all the relevant publicly available information. Semi-strong market efficiency implies that also fundamental analysis will not yield consistent returns. The last form of market efficiency is the strong-form. The strong form asserts that all information known to anyone (both publicly and private) is fully reflected in the market price. This implies that even when an investor has private information he/she cannot exploit this privileged position to earn abnormal returns (Malkiel, 1989).

If markets are efficient, it will be impossible to predict future prices by analysing past price patterns. According to the EMH, any information resulting from such an analysis is already included in the current market price of the asset (Malkiel, 1989). Furthermore, as the arrival of new information will be random, the price changes will also be random. The EMH is therefore closely related to the random walk hypothesis. This hypothesis states that subsequent price changes will be unrelated to earlier price changes, which implies that future price changes are random and unpredictable. Since future prices in the market cannot be predicted it will be impossible for an investor to consistently earn abnormal returns and outperform the market in a systematic way (Malkiel, 2003).

2.1.2 Are markets efficient?

Although the EMH is seen as the foundation of modern financial theory, it is controversial and often disputed (Jensen, 1978). Since the beginning of this century both the theoretical foundation and the empirical evidence have been challenged (Shleifer, 2000). It is fair to say that substantial evidence does exist that poses a challenge for the EMH. Investors, such as Warren Buffet, seem to consistently beat the market and also recurring return patterns are present in the market. Lately, the dominance of the EMH became less and less self-evident.

Recurring return patters form systematic deviations away from market efficiency and are often referred to as market anomalies. The consistent profitability of exploiting market anomalies seem to poses a challenge for even the weakest form of market efficiency and reverses some of the evidence that until recently was in favour of the concept (Lo, 2007). Seeming is the right word here because any test for market efficiency does make use of an asset pricing model to account for risk. Every test for market efficiency is therefore in essence a joint hypothesis test. Rejecting the hypothesis implies either that the market is indeed inefficient or an imperfection in the model. One can never be certain which one is the case (Fama, 1970). It is important to keep in mind that a joint hypothesis problem might occur. If not, wrong conclusions might be drawn (Ackert & Deaves 2010). Nevertheless, much research has been done over the years into market efficiency, with the result that numerous market anomalies have been discovered.

Among these market anomalies, the momentum effect has attracted much of the attention (Dhankar & Maheswari, 2016). In a nutshell, the momentum effect can be seen as the continuation of prior returns. Something that performed well in the past will probably continue to do well in the future while assets that performed poorly in the past tend to keep on doing poorly in the future (Jegadeesh & Titman, 1993). Especially in the cryptocurrency market, a market that seems to keep on rising (or falling) persistently, it might be interesting to investigate the existence of the momentum effect. If positive risk-adjusted returns can be earned by using a momentum strategy, this can be seen as a claim against the weakest form of market efficiency. The next paragraph will be about cross-sectional momentum. Cross-sectional momentum chooses stocks on the basis of their *relative* performance to other stocks over some prior period (Bird, Gao & Yeung, 2017). The paragraph after that is about the recently discovered time-series momentum. Time-series momentum choose stocks on the basis of their *absolute* performance over some prior period (Bird et al., 2017).

2.2.1 Cross-Sectional Momentum

Jegadeesh and Titman (1993) were the first to discover the cross-sectional momentum (hereafter referred to as momentum) effect in their famous article "Returns to Buying Winners and Selling Losers: Implications for stock market efficiency". Their data consisted of NYSE and AMEX stocks over the sample period 1965 to 1989. They discovered that strategies b stocks that have performed well in the past and (short) sell stocks that have performed poorly in the past, generate significant positive excess returns. These positive excess returns were especially found in the first 12 months after the formation period. Jegadeesh and Titman (1993) referred to this strategy as the J-month/K-month strategy where J-month denotes the formation and K-month denotes the holding period. Their method of testing consisted of three periods. During the first period, the formation period (J), stocks were selected based on their returns over the past J months. Formation periods could range from 1 to 4 quarters. In the formation period stocks were ranked in ascending order based on the returns of the prior J months. The bottom decile would be referred to as the 'winner' portfolio and the top decile would be known as the 'loser' portfolio. The momentum strategy would go long in the winner portfolio and would go short in the loser portfolio, holding this position for K months. The holding periods also varied from 1 to 4 quarters but were overlapping. This meant that portfolio positions in any month included assets that were just bought but also assets that were bought in the past and still held today. After a position was held for K months the position would be closed. Positions were rebalanced monthly (Jegadeesh & Titman, 1993)

The authors also tested these strategies with a waiting period of a week between the formation period and the holding period. They did this to avoid the possibility of price pressure, bid ask spreads and the effects of lagged reactions. As mentioned, their momentum strategies made positive risk-adjusted excess returns. The most profitable strategy yielded a return of 1.49% monthly. This strategy was with a week of waiting between the formation period and the holding period. When a waiting week was not included between both periods the strategy yielded a monthly return of 1.31% . Both strategies were based on a formation period of 4 quarters and a holding period of 1 quarter. Since significant excess returns were found in almost all strategies, Jegadeesh and Titman (1993) concluded that market efficiency could be rejected even at the most conservative levels of significance.

Since Jegadeesh and Titman (1993) presented the groundbreaking findings in this field, the momentum anomaly has been found in countless research. The fact that the momentum anomaly remained robust over time led Fama (1998) to state that momentum remained the 'premier unexplained anomaly'. A decennia later Subrahmanyam (2008) came to the same conclusion when he mentioned that the anomaly was found and analysed extensively in subsequent literature and that there is little doubt that momentum is robust across time. Most studies on momentum were in line with the methodology introduced by Jegadeesh and Titman (1993), only then (often) applied to different stock markets. There are even plenty of studies that researched the same exchanges as Jegadeesh and Titman (1993). Among those where Moskowitz and Grinblatt (1999), Hong, Lim and Stein (2000), Lee and Swaninathan (2000), Grundy and Martin (2001), Chordia and Shivakumar (2002), Griffin, Ji and Martin (2003), Avramov, Chordia & Jostova (2007), Fama and French (2012), Asness, Moskowitz & Pedersen (2013) and finally Bird et al. (2017) who all documented significant momentum profits in the United States. However, the results differed in magnitude due to the choice of a different time period or of different characteristics of the momentum portfolio (e.g. invest in the top 33%, as opposed to the top 10%).

Outside the United States similar results have been found with regards to the momentum anomaly in stock markets. Rouwenhorst (1998), Doukas and McKnight (2005), Fama and French (2012) and Asness et al. (2013) documented significant momentum returns in European countries. Rouwenhorst (1999), Hart, Zwart and Dijk (2005) and Cakici, Fabozzi and Tan (2013) found significant positive returns in emerging countries and Fama and French (2012) found a significant effect in Asia. Chui, Wei and Titman (2000) and Griffin et al (2003) also found evidence for the momentum anomaly in Asian countries. However, this evidence was not significant. It is noteworthy that the momentum anomaly remained robust over time, countries and asset classes. Often, anomalies seem to disappear after they have been discovered.

2.2.2 Time-series momentum

Numerous studies have been conducted that showed that the relative performance of stocks to other stocks over a prior period could be used to form portfolios that earn significant momentum returns. Forming portfolios on the basis of *relative* performance is primarily *cross-sectional* in nature and can therefore be referred to as cross-sectional momentum (Moskowitz et al., (2012). Moskowitz et al. (2012) introduced time-series momentum as a different way to create momentum portfolios. They document that time-series momentum is related to, but different from cross-sectional momentum. Time-series momentum does not focus on the relative, but on the absolute performance of an asset over the prior period. To state differently, time-series momentum only focuses on each asset's *own* past returns.

Moskowitz et al. (2012) investigated time-series momentum for futures prices of commodities, cross-currency pairs, developed equity indexes and government bonds. They found significant evidence for almost all of the securities, over the last 25 years of data, that the excess returns over the past 12 months are a positive predictor for the returns over the next month. Significant positive auto-covariance is what causes this return continuation and thus significant time-series momentum effect. Over longer horizons than a year the returns will reverse. Interestingly, Moskowitz et al. (2012) found that the returns of time-series momentum tend to be the largest when the market returns experienced extreme movements. To state differently, when the market experience a large up or down movement the payoff of the time-series momentum trading strategy will be maximized.

What underlined the time-series momentum trading strategies created by Moskowitz et al. (2012) is that it focussed only on the sign of the prior returns of the asset itself. If the sign of the returns over the formation period was positive a long position was taken in the asset. If the sign over the formation period was negative a short position was taken in the asset. As seen in other momentum studies, the number of months of the formation period and holding period varied between the different strategies. Moskowitz et al. (2012) also scaled the positions to have constant ex ante volatility.

Since Moskowitz et al. (2012) discovered this alternative form of the momentum anomaly plenty of studies have been conducted in this area with mixed results. The studies that support the existence of a time-series momentum effect have had the upper hand though. Evidence of time-series momentum profits is found, among others, by Baltas and Kosowski (2012) for daily futures contracts, Antonacci (2013) for the MSCI US and EAFA indices, Hong and Satchell (2015) for 11 major international stock indices, Shi and Zhou (2017) for China and He, Li and Li (2018) showed the profitability in the US. Results that further supported the existence of the time-series momentum anomaly are documented by the long-term studies of Souza, Srichanachaichok, Wang and Yao (2016) and Hurst, Ooi and Pedersen (2017). Souza et al. (2016) documented that over the period 1927 through 2014 there was a significant profitability of time-series momentum strategies and Hurst et al. (2017) showed that since 1880 time series momentum strategies had delivered positive average returns. More evidence is provided by the study of Bird et al. (2017). They mentioned that time-series momentum strategies generate positive returns. Furthermore, they documented that a time-series momentum strategy clearly outperformed the cross-sectional alternative. Cheema, Nartea and Man (2017) elaborated on this result and showed that a time-series momentum strategy only outperformed the cross-sectional alternative if the market continued in the same state, up or down. When the market made the transition to a different state the time-series momentum strategy would underperform the cross-sectional alternative.

Not all studies supported the existence of the time-series momentum anomaly. Zakamulin (2014) stated that the performance of market timing strategies based on the time-series momentum rules are highly overstated and simply the result of data-mining and neglecting market frictions. They tested this with out-of-sample tests. Also, Kim, Tse and Wald (2016) mentioned that the returns of large time-series momentum strategies are overstated. According to them, positive returns are largely the result of volatility scaling. They found that without the scaling of volatility the time-series momentum strategies would not have generated significantly different results than a buy and hold strategy.

Sometimes the specific way in which trading signals were generated differed between the mentioned studies on time-series momentum. However, they were similar in the sense that they relied on the observation that a security's own past return could be predictive of its performance in the future. Furthermore, the methods in which trading signals were generated could broadly be assigned to either one of the following two statistical measures of price trends: *time-series momentum rules* or *moving average rules* (Pedersen, 2010). Even though the two rules are closely related, there is a subtle difference. Time-series momentum rules form a trading signal to buy (sell) when the price of an asset does move above (below) its *historical price* at a *certain historical point*. The moving average rule does create a buy (sell) signal when the price moves above (below) the *average price* over a historical period (Marshall, Nguyen & Visaltanochoti, 2014) or at the point where the short-run moving average rises above (below) the long- run moving average (Pedersen, 2010). It is empirically shown that the moving average rules tend to outperform the time-series momentum rules (Marshall et al., 2014). The outperformance in returns is the result of the fact that moving average rules create signals more frequently. The trading signal for the time-series momentum rules will only be created when there is a direction change of the moving averages, which naturally happens less frequently (Marshall et al., 2014). In depth analysis of these trading strategies can be found in the methodology section.

2.2.3 Comparison cross-sectional momentum and time-series momentum

Momentum and time-series momentum have in common that they both select securities on the basis of their past performance over some prespecified period. The main difference between both strategies is that the first approach selects securities in their portfolio on the basis of their relative performance and the latter selects securities on the basis of their absolute performance (Bird et al., 2017). Although the two approaches appear to be quite similar and at many times indeed hold the same securities in their portfolios, it is this difference that has a remarkable effect on the results of the strategies.

The first who mentioned a difference in results were Moskowitz et al. (2012) who documented that a time-series momentum strategy did outperform the cross-sectional alternative in the futures markets. This result was later supported by Bird et al. (2017). Bird et al. (2017) conducted a comprehensive study where the performance of both types of momentum were evaluated and compared in 24 major equity markets. Their results showed that with the best implementations, the time-series momentum strategy outperformed the momentum strategy in all of the markets.

According to Bird et al. (2017), the difference in returns is due to the fact that a momentum strategy always has the same number of assets included in the winner and loser portfolios. As a consequence, in a bullish (bearish) market the momentum strategy digs to deep to find loser (winner) stocks. In contrast, the number of stocks included in the winner and loser portfolio in a time-series momentum strategy do vary with the market conditions. In a bullish (bearish) market the time-series momentum strategy will assign more stocks to the winner (loser) portfolios (Bird et al., 2017). As a result of this variation in the amount of stocks included, does the time-series momentum portfolio have a higher return on average. Furthermore, as mentioned by Moskowitz et al. (2012) the benefit of a time-series momentum trading strategy is the largest when the market returns experienced extreme movements.

The crypto-market appears to experience extreme movements what indicates that varying the amount of long and short positions seems appropriate. Therefore, the time-series momentum trading strategy is chosen to investigate the anomaly in the crypto-market, as it performs best under these conditions. Another reason for choosing the time-series momentum methodology is that it outperforms the cross-sectional alternative in terms of returns.

2.3 Cryptocurrencies and (time-series) momentum

Cryptocurrencies have received far less attention with regards to the momentum and time-series momentum anomalies. Since they are a relatively new asset, it is not odd that fewer empirical studies have been carried out. What is surprising is that there is a paucity of literature applying (time-series) momentum strategies on cryptocurrencies since their emergence. To the best of my knowledge only Rorhbach et al. (2017), Kosc et al. (2018) and Yang (2018) investigated the (time-series) momentum anomaly in the cryptocurrency market.

Rorhbach et al. (2017) were the first to document the (time-series) momentum anomaly in the cryptocurrency market. Among other things, they investigated seven cryptocurrencies and found that positive returns could be earned by using a (time-series) momentum strategy over the time period 2015-2017. Furthermore, Rorhbach et al. (2017) showed that momentum strategies exhibited relatively large Sharpe-ratios. When interpreting the Sharpe ratio one has to be careful. It is of no statistical significance and it is merely a descriptive metric. In their research Rorhbach et al. (2017) did not mention whether the returns they found were statistically significant. They did mention that finding exchanges which allow short selling and that the short existence of cryptocurrencies might be problematic in implementing the strategies. Their methodology was similar to Jegadeesh and Titman (1993) in the sense that they tried to go long in the 'winner' assets and go short in the 'loser' assets. It differed in the way cryptocurrencies were assigned to either be a winner or loser. Rorhbach et al. (2017) used an algorithm presented by Baz et al. (2015) to create these trading signs. The methodology of Baz, Granger, Harvey, Roux and Rattray (2015) was based on the mixture of three crossovers of exponential moving averages (EMA) with different time horizons of past returns of the cryptocurrencies. With the use of these EMAs, trading signals were generated between -1 and 1. For the momentum strategy, one would form a cross-sectional portfolio that consisted of six cryptocurrencies. In this cross-sectional portfolio an investor would go long in the three coins with the largest trading signal and go short in the three coins with the smallest (most negative) trading signal. The position size was not affected by the value of the sign. The cross-sectional portfolio is equally weighted so every position is always equal to a sixth of the total invested arbitrary amount. For the time-series momentum portfolio the value of the sign did matter. On every rebalancing date one would invest in all the cryptocurrencies based on the value of the sign divided by the total numbers of cryptocurrencies in the portfolio. If the value of the sign is positive (negative) a long (short) position is taken in that cryptocurrency in the time-series momentum portfolio (Rorhbach et al., 2017). This meant that the amount of long/short positions could vary with the state of the market.

Kosc et al. (2018) analysed the profitability of momentum and contrarian strategies on the cryptocurrency market over the period May 2014 till October 2017 in their working paper. The contrarian effect is the tendency of trends to reverse in a very short or long time frame (Kosc et al, 2018). Kosc et al. (2018) researched the 100 largest cryptocurrencies in terms of market capitalization. The other condition for a coin to be included in their analysis was that on the rebalancing date the mean of the 14-day moving average of the daily volume of that coin was higher than 100 US dollars. The momentum portfolios were created as equally weighted investments in X% of the cryptocurrencies with the highest rate of returns over the past J days, holding them for K days. Different parameters were chosen for the size of the portfolios, the formation periods and the holding periods. The portfolios consisted of either the top 5%, 10%, 25% or 50% in terms of the rate of return. The formation period could be 1 day, 7 days or 30 days and the same timeframes were applied to the holding period.

The difference with the methodology applied by Jegadeesh and Titman (1993) is that a long only position was taken in all the momentum portfolios instead of a long-short position. The results of Kosc et al. (2018) did show that there is not enough evidence to state that an analogous momentum effect exists in the cryptocurrency market. The only benchmark that was outperformed by the momentum strategy was the buy and hold strategy of the S&P500. On the contrary, their results did show existence of a strong short-term contrarian effect (Kosc et al., 2018).

Yang (2018) found significant evidence for the momentum effect when cryptocurrencies were ranked according to the returns of the day before. When tertile portfolios were formed based on the returns of the previous day, the 'winner' portfolios outperformed the market-hedged return with a daily 0.6%. When portfolios were created based on the methodology of Jegadeesh and Titman (1993), with a formation period of one week (skipping one day), also a momentum effect was found. However, based on the past day-1 to day-2 returns prior to the formation of the portfolio, the cryptocurrencies were exhibiting a reversal effect. This is the same effect as was found by Kosc et al. (2018). Yang (2018) also found that the first-order autocorrelation of cryptocurrencies was mostly positive. Using this observation he created time-series momentum portfolios where he divided the cryptocurrencies in groups with either positive or negative returns. He found that exploiting this time-series momentum strategy yielded statistically significant returns. The dataset used by Yang (2018) dates back to March 2016 and he investigates the period till April 2018. As a maximum twelve different coins were investigated in his analysis. Yang (2018) only investigated holding periods of one day. After every day the portfolios were rebalanced.

To sum up, except for the lack of profound evidence in the cryptocurrency market, there seems to be consensus among researchers and in the literature that the momentum anomaly and the time-series momentum anomaly are still prevailing and persistent in today's markets. Not only has the (time-series) momentum anomaly been documented by numerous studies, it is also proven to remain robust over asset classes, countries and time. It is therefore not remarkable that since the discovery various authors have tried to find an explanation for its continued profitability. Consensus over the reason behind the (time-series) momentum anomaly have not been reached yet (Subrahmanyam, 2018). The studies searching for explanations can broadly be placed into two camps (Bird et al., 2017). One group that focusses on the more traditional perspective of risk-based explanations and one group that has a more behavioural-based perspective that argues that the (time-series) momentum premium is driven by non-risk factors and behavioural biases.

2.4 Risk Based Explanations.

Explanations that are based on risk take the perspective that above-average returns are the consequence of investors undertaking above-average financial risks. To state differently, the high returns that are found in (time-series) momentum investing are simply a compensation for the investors additional risk exposure. Different forms of risks can be the cause of the momentum anomaly. In finding risk-based explanations for the (time-series) momentum anomaly mixed conclusions have been reached and a discernible cause for the effect still has not been found (Dhankar & Maheswari, 2016).

Jegadeesh and Titman (1993), who were the first to document the momentum anomaly, concluded that their findings could not be explained by possible risk factors. This finding was a couple of years later supported by Fama and French (1996). Using their unconditional three-factor model (Fama & French, 1993) they tried to explain some recurring return patterns that had existed in the market. They found that their model could explain most of the market anomalies, except for the momentum anomaly. They referred to this in their study as *'the main embarrassment of the three-factor model'*.

Conrad and Kaul (1998) mentioned that cross-sectional variation in the mean returns of individual securities was the reason behind the positive momentum returns. However, these results were later contradicted by Jegadeesh and Titman (2001). Jegadeesh and Titman (2001) state that according to the study conducted by Conrad and Kaul (1998) the momentum returns in any postranking period should be the same. In their research, Jegadeesh and Titman (2001) provide evidence that the returns of the momentum strategy are actually negative starting at 13 months after portfolio formation. This clearly rejects the risk-based explanation provided by Conrad and Kaul (1998).

Johnson (2002) tried to explain the momentum anomaly using growth rates and their influence on the expected returns. If a firm has experienced a high past rate of return this indicates to the investors that the firm is more likely to grow in the future according to Johnson (2002). Since the expected growth rate is related to growth rate risk and required returns, the expected returns of the firm will change in the same direction. This does result in momentum.

Griffin et al. (2003) investigated if macroeconomic risk could explain the momentum anomaly. Using two different models, they found that macroeconomic risk could not be seen as a risk-based explanation for momentum. Furthermore, they found that after 1 to 5 years the returns of a momentum strategy reversed. Again a result that was inconsistent with existing risk-based explanations. Their results were supported by Cooper, Gutierrez and Hameed (2004) who documented that macroeconomic factors could not be used to explain the momentum anomaly.

Pastor and Stambaugh (2003) provided some evidence in favour of a risk-based explanation. They showed that the liquidity risk factor could explain a substantial part of the momentum profits. Sadka (2006) reached similar conclusions and showed that there is a relation between momentum and liquidity risk. According to them, the higher returns of a momentum strategy are the result of an investor bearing liquidity risk. A momentum investor is especially prone to liquidity risk since a momentum portfolio is rebalanced relatively much. As a consequence the momentum investor would not like the market liquidity to decline since the costs for him/her to rebalance his portfolio would rise accordingly.

Dittmar, Kaul and Lei (2007) investigated whether the cross-sectional variation in expected risk and returns could be the reason for the momentum profits. As mentioned, this was also researched by Conrad and Kaul (1998) and Jegadeesh and Titman (2001). Dittmar et al. (2007) did find that the momentum returns were entirely driven by cross-sectional differences in expected risk and returns. Nonetheless, they do mention that this pattern could be the result of behavioural biases. Bulkley and Nawosah (2009) also find that momentum profits simply reflect cross-sectional variation of expected stock returns. However, they state that they did not use a theoretical measure for expected returns.

Also recently, researchers have tried to find risk-based explanations for the prevalence of the momentum anomaly. Among them was Dobrynskaya (2014), who tried to explain the anomaly by separating the total market risk into an upside and downside factor. She showed that the momentum anomaly is hedged against the upside risk but is fully exposed to the downside risk. This asymmetric risk profile is the reason for the positive momentum profits. Ruenzi and Weigert (2018) also showed that crash-risk exposure can be seen as a possible risk-based explanation for the momentum anomaly. They documented that crash-risk exposure does at least explain a part of the returns that are made using a momentum strategy. However, in their study they mentioned that a behavioural-based explanation could not be excluded.

2.5 Behavioural based explanations.

Shortly after the discovery of the momentum anomaly, Fama (1998) and Barberis and Thaler (2003) already concluded that the anomaly could only be explained from a behavioural perspective. Also Jegadeesh and Titman (2005) mentioned that the momentum anomaly could not be explained by risk. The lack of an accepted and straightforward risk-based explanation for the momentum profits has led researchers to further analyse the persistence of the anomaly from a different perspective. In their search to find an explanation they stumbled upon behavioural finance. Behavioural finance is a relatively new approach that focusses on investors not always being fully rational because they ‘suffer’ from certain behavioural biases and heuristics in making decisions and forming beliefs. The irrational behaviour of investors might result in substantial mispricings in the market with asset prices deviating away from their fundamental value (Dhankar & Maheswari, 2016). Due to limits to arbitrage the mispricing could continue to exist (Barberis & Thaler, 2003). Most of the behavioural models trying to explain the momentum anomaly can be classified as either in the domain of underreaction or overreaction. Although it seems that the two models contradict each other, they in fact reinforce each other. Momentum can also be explained by the disposition effect.

One prominent attempt proposed a theory of initial overreaction to explain momentum profits is documented by Daniel, Hirshleifer and Subrahmanyam (1998). They tried to form this theory on the basis of two well-known psychological biases, namely investor overconfidence and the self-attribution bias. Overconfidence is the bias that causes people to overestimate their own knowledge. The self-attribution bias is the tendency of people to attribute success to their own talents and failures to bad luck or others (Daniel et al., 1998).

According to Daniel et al. (1998) will overconfident investors overestimate the precision of their private information and underestimate public information. So, when positive private information arrives people tend to put too much weight on this information and as a result the price of an asset will be pushed above the fundamental value. This causes the initial overreaction. Due to the self-attribution bias the investors overconfidence increases even more after public information arrives that does confirm his beliefs. Public news that does not confirm his beliefs will be disregarded because of this bias. To state differently, the investor does not update his beliefs rationally since the arrival of ‘bad’ news will simply be disregarded. As a consequence of this (again) increased overconfidence the overreaction is strengthened causing the momentum effect. Over the long run a reversal effect will take place (Daniel et al., 1998; Dhankar & Maheswari, 2016).

More evidence for the overreaction hypothesis is given by Delong, Shleifer, Summers and Waldmann (1990). They propose an intuitive explanation for the momentum effect. They state that positive feedback traders cause momentum. If a stock increases (decreases) in value, positive feedback traders will start buying (selling) it in the subsequent period. Furthermore, if there are positive feedback traders present in the market it might be rational for speculators to exploit the mispricing instead of trying to correct it. If a rational speculator thinks that feedback/noise traders will worsen the mispricing tomorrow he/she should invest today in the direction of the mispricing. The study of DeLong et al. (1990) indicates that rational speculators could worsen the mispricing instead of correcting it. The market participants together create a momentum effect pushing assets above/below fundamental values.

The model by Barberis, Schleifer and Vishny (1998) argues that both an underreaction and overreaction create the momentum anomaly. In their model two different psychological biases are mentioned to explain the momentum anomaly. The first bias is conservatism which causes underreaction. The conservatism bias refers to the tendency of people to revise their belief insufficiently when new evidence is presented. Barberis et al. (1998) document that as a result of this bias, people don't update their beliefs sufficiently when positive news about a stock is presented. As a consequence, the stock price rises too little. Since the price of a stock will be below its fundamental value, this will result in higher average returns in the subsequent period, that in turn generates momentum. The other heuristic that Barberis et al. (1998) mentions is representativeness. The representativeness heuristic is *"the tendency of experimental subjects to view events as typical or representative of some specific class and to ignore the laws of probability in the process"* (Barberis et al., 1998). Due to this heuristic, investors might mistakenly think that the consistent flow of positive past earnings is representative for the future. They thereby overestimate the growth opportunities and overreact by pushing the price above the fundamental values which generates excessive momentum. Over the long run this will result in a reversal because earnings are not as high as expected (Barberis et al. (1998).

The last model about underreaction and overreaction is proposed by Hong and Stein (1999). Their model is composed of two groups of traders. According to them, every market consists of newswatchers and momentum traders. Newswatchers trade only on the basis of private information and momentum traders trade purely on the basis of historical prices. Prices are initially driven by newswatchers. When new information arrives, this only spreads gradually among the newswatchers what, in turn, causes the underreaction. Momentum traders who observe this underreaction try to exploit it, thereby creating an overreaction resulting in excessive momentum. In the long run prices will reverse to fundamental values (Hong and Stein, 1999).

The momentum anomaly can also be explained by the disposition effect. The disposition effect is the tendency of investors to hold on to losing stocks for too long and to sell winning stocks too soon (Shefrin & Statman, 1985). A study of Grinblatt and Han (2002) showed the relationship between the disposition effect and the momentum anomaly. After the announcement of good news the price does not immediately rise to its new fundamental value because people have the tendency to sell the winning stock too soon. The opposite is the case when bad news is announced. The price will not immediately fall to its new fundamental value because people have the tendency to hold on to a losing stock for too long. In both cases this causes an underreaction in the stock price and a gap will arise between the fundamental value and the market price. This gap will be exploited by rational investors. If they discover that the stock is undervalued (overvalued) they start buying (selling) the stock and thereby creating an upward (downward) momentum effect (Dhankar & Maheswari, 2016). Grinblatt and Han (2005) and Frazzini (2006) provide convincing evidence that the disposition effect has effect on the momentum premium.

To conclude, the momentum anomaly remained robust over time, countries, markets and different methodologies. Consequently, there are many risk-based and behavioural explanations for the momentum anomaly in the financial markets. Currently, neither rational explanations nor the behavioural explanations have succeeded to explain the anomaly undoubtedly. Probably, both explanations contribute to the anomaly and the truth is somewhere in the middle. (Dhankar & Maheswari, 2016). It is beyond the scope of this thesis to identify the source of momentum but further research is necessary to identify the driver(s) behind the momentum anomaly. The purpose of this thesis is to reach consensus regarding the existence of the momentum anomaly in the crypto-market. So far, the results for the crypto-market have been mixed and there is no profound evidence for or against the existence of the momentum anomaly in the market.

3. Data

The empirical cryptocurrency data used in this thesis is collected through the API of the database CoinMarketCap. CoinMarketCap is one of the most influential providers of data on cryptocurrencies. Their database list and ranks all cryptocurrencies based on their market capitalisation and provides information about the price, volume and circulating supply on a daily basis. Prices are calculated by weighting an exchange's volume of a cryptocurrency over the last 24 hours, relative to the overall volume of that cryptocurrency over the last 24 hours and multiplying this weight by the price of that coin on the exchange. To state it differently, CoinMarketCap calculates the price of a cryptocurrency by taking the volume weighted average of all the prices quoted on the different markets. To diminish the influence of fake/bot traders, only exchanges with fees are being included in their calculation. As of June 30th 2018, CoinMarketCap provides the data of 1,567 different cryptocurrencies with a total market capitalisation of $256,160,431,002. The market capitalisation of a cryptocurrency is calculated by multiplying the circulating supply and the price of that coin.

For cryptocurrencies to be included in my analysis at least 18 months of historical price data needs to be available and the market capitalisation must exceed 0.5% of the total market capitalisation as of June 30th 2018. The chosen timespan is due to the considerable formation periods that some trading strategies have. The condition on market capitalisation is selected to ensure the liquidity of a cryptocurrency. This led to a total data set of 11 cryptocurrencies over a time span of 269 weeks starting at 28th April 2013. The 28th of April was the first date that CoinMarketCap provided data on cryptocurrencies. The data that will be collected for each included cryptocurrency is the daily closing price and daily market capitalization. The included cryptocurrencies can be found in table 1. The data is used to create the trading strategies as well as some of the benchmarks. More on this can be found in the methodology section. An in depth analysis of blockchain technology and cryptocurrency mining would be beyond the scope of this thesis and more in the domain of technology. Furthermore, it does not contribute in answering the research question.

Table 1

Overview of potential cryptocurrencies for analysis

NAME	ABBREVIATION	MCT	DATA AVAILABLE	INCLUDED
BITCOIN	**BTC**	**1.06405E+11**	**28-4-2013**	**x**
ETHEREUM	**ETH**	**43789500000**	**7-8-2015**	**x**
RIPPLE	**XRP**	**17829400000**	**4-8-2013**	**x**
BITCOINCASH	BCH	12340700000	23-7-2017	
EOS	EOS	6936720000	1-7-2017	
LITECOIN	**LTC**	**4515210000**	**28-4-2013**	**x**
STELLAR	**XLM**	**3506610000**	**5-8-2014**	**x**
CARDANO	ADA	3267740000	1-10-2017	
TETHER	**USDT**	**2715290000**	**25-2-2015**	**x**
IOTA	MIOTA	2681710000	13-6-2017	
TROM	TRX	2451030000	13-9-2017	
MONERO	**XMR**	**2050040000**	**21-5-2014**	**x**
NEO	**NEO**	**1930510000**	**9-9-2016**	**x**
DASH	**DASH**	**1913510000**	**14-2-2014**	**x**
ETHEREUM CLASSIC	**ETC**	**1572500000**	**24-7-2016**	**x**
VECHAIN	VEN	1423110000	22-8-2017	
NEM	**XEM**	**1370680000**	**1-4-2015**	**x**

Note. Cryptocurrencies are selected on two criteria: market capitalization of at least 0.5% on 30/06/2018 and data available since 01/01/2017. Included cryptocurrencies are highlighted in bold.

Descriptive statistics of the included cryptocurrencies can be found in table 2. Although the definition of some (statistical) variables speak for themselves, there are some variables that demand an explanation. In depth analysis on the calculation and interpretation of these variables can be found in the methodology section.

In calculating the Sharpe-ratio the risk-free rate is used. As a proxy for the risk-free interest rate, the daily 3-month US dollar London Interbank Offered Rate (LIBOR) is used. In financial studies the LIBOR curve is one of the most widely accepted proxies for the short-term risk-free rate (Brooks & Yan, 1999). However, data for the LIBOR curve is limited to weekdays. In order to use the LIBOR curve in this thesis a small adjustment is made because cryptocurrencies are traded on every day of the week. The LIBOR rate that will be used in the weekend on both Saturday and Sunday is the LIBOR rate of the preceding

Friday. Daily 3-month USD LIBOR rates are collected from www.theice.com. More information on the calculation and definition of the Sharpe-ratio can be found in the methodology section.

In this thesis several benchmarks are used to measure the performance of the different time-series momentum strategies. One of the benchmarks is the Crypto Currencies Index (CCI30). As the name implies the CCI30 index is constituted of the top 30 cryptocurrencies in terms of market capitalization. The weight of each cryptocurrency in the benchmark is equal to the square root of its smoothed (using the EMA) market capitalization. The index is refreshed every quarter and once a month the constituents in the index are rebalanced. In this thesis, daily closing values of the CCI30 index are used. Data for the CCI30 is available on their website. However, data for the CCI30 index is not available before 2015. Therefore, when using the CCI30 index to measure performance, the strategies will be evaluated over the same time frame as data is available for the CCI30 index.

Table 2
Descriptive statistics of the included cryptocurrencies

NAME	Arithmetic Average (%)	Geometric Average (%)	Standard Deviation	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Sharp ratio
BITCOIN	0.30	0.20	0.0448776	-23.37	42.97	12.82	0.507	1.29
ETHEREUM	0.80	0.48	0.0768811	-72.80	51.03	15.77	0.240	1.97
RIPPLE	0.58	0.24	0.0082552	-46.01	179.37	99.54	6.12	1.22
LITECOIN	0.40	0.16	0.0758815	-40.19	129.19	67.89	4.84	1.01
STELLAR	0.68	0.31	0.0941455	-30.68	106.07	35.61	3.84	1.38
TETHER	0.01	-0.02	0.0242067	-49.88	64.95	575.38	8.70	0.08
MONERO	0.60	0.29	0.0805545	-31.49	79.43	14.20	1.62	1.41
NEO	1.26	0.61	0.1237259	-40.70	122.81	25.80	3.00	1.94
DASH	0.80	0.41	0.1051413	-37.35	256.29	231.94	10.47	1.44
ETHEREUMCLASSIC	0.99	0.40	0.1466046	-37.26	323.31	332.83	15.20	1.28
NEM	1.01	0.55	0.105652	-30.33	170.63	64.80	4.84	1.81
AVERAGE	0.68	0.33	0.080538718	-40.00	1.39	134.24	5.40	1.35

Note. The table shows summary statistics for the raw returns of the cryptocurrencies. The arithmetic average, the geometric average, the standard deviation, the minimum, the maximum, the kurtosis, the skewness and the Sharpe-ratio for every cryptocurrency are shown. In depth analysis of the calculation and interpretation of any of the variables can be found in the methodology section.

4. Methodology

The methodology is documented in four different sections. The first section is about the performance metrics that help to get a deeper understanding of the performance of the portfolios and the benchmarks. The second section does mention how the benchmarks are constructed. The third section documents how the trading strategies are formed and how trading signals are created. The last section is about the evaluation of the strategies.

4.1 Performance Metrics

In order to get a deeper understanding of the performance of the portfolio, the following measures have been employed:

Return calculation

The returns of the cryptocurrencies are calculated using daily closing values. Two approaches are common in economics when calculating returns. These methods are the *simple net return* and *continuously compounded return* (log return). In this thesis the simple net return, R_t, is chosen to calculate the daily returns. The formula is defined as

$$R_t = \frac{P_t}{P_{t-1}} - 1 \tag{1.1}$$

where P_t is the price of the cryptocurrency at time t and P_{t-1} is the price of the cryptocurrency at time t-1. Although log returns are often used by academicians, they do have one disadvantage compared to simple net returns. Using simple net returns, the return of a portfolio can be calculated using the weighted average of the simple returns of the assets themselves. Log returns do not share this convenient property. This is because the sum of logs is not the same as the log of a sum (Campbell, Lo & MacKinlay, 1997). Since creating portfolios and comparing the performance of portfolios is a central theme in this thesis, simple net returns are chosen to calculate the returns.

Arithmetic and Geometric average

In this thesis the arithmetic and geometric average will be mentioned for every cryptocurrency, benchmark portfolio and trading strategy. The formula for the arithmetic average, AA, is the sum of all the terms divided by the count of that sequence. The following is the mathematical formula:

$$AA = \frac{1}{N}\sum_{i=1}^{N} a_i \tag{1.2}$$

where *N* is the number of terms in the sequence and a is the value of each individual item in the list of numbers being averaged.

The geometric average, GA, is calculated by taking the product of a sequence and raising it to the inverse of the count of that sequence. The formula is defined as

$$GA = \sqrt[N]{(a_1) * (a_2) * \dots (a_n)} \quad (1.3)$$

where *N* is the number of terms in the sequence and a is the value of each individual item in the list of numbers being averaged.

When considering investment returns, the geometric average is of more use than the arithmetic average. The geometric mean does namely take into account that compounding occurs from period to period. Using arithmetic averages, the investment returns will always be overstated unless there is no volatility in the market. Since there seems to be a lot of volatility in the cryptocurrency market, the geometric average will more accurately reflect the returns.

Skewness and Kurtosis

Skewness and kurtosis are traditional descriptive statistics for the normality of distributions. Skewness characterizes the degree of asymmetry of a distribution around the mean. A symmetric distribution has per definition a skewness of 0. A positive (negative) number indicates that the distribution is positively (negatively) skewed. Positively (negatively) skewed distributions have a long right (left) tail which indicates a greater change of extremely positive (negative) outcomes (Ho & Yu, 2015). In the case of a positively (negatively) skewed distribution the mean lies above (below) the median.

Kurtosis is a measure of the asymmetry of the tails. A normal distribution has a kurtosis of 3 and is referred to as a mesokurtic distribution. Sometimes, the kurtosis is standardized by subtracting three. In this thesis the kurtosis will not be standardized. If a distribution has a kurtosis above three it is leptokurtic. A leptokurtic distribution indicates that the distribution is heavy-tailed. This means that there is a greater risk of extreme outcomes. If the kurtosis is below three, the distribution is platykurtic. Naturally, this indicates that the distribution is light-tailed and that there is a smaller risk of extreme outcomes (Westfall, 2014).

Since the descriptive statistics of the raw data showed signs that the data might be non-normally distributed, a Jarque-Bera test will be conducted. The Jarque-Bera test uses values of skewness and kurtosis to test if the data comes from a normal distribution (Jarque-Bera, 1980). The Jarque-Bera test is used with two adjustments for sample size by Agostino, Belanger and Agostino (1990) and Roston (1991).

Sharpe Ratio

In 1966, William F. Sharpe, introduced a measure for performance to which he proposed the term reward-to-variability ratio. Since then, it became known as the Sharpe ratio and is it one of the most used methods for calculating risk-adjusted returns. The Sharpe ratio shows the excess return per unit of risk. It is calculated by subtracting the risk-free rate from the average return of the asset/portfolio and dividing that number by the standard deviation of the asset/portfolio. The formula for the Sharpe ratio is defined as

$$SR = \frac{R_p - R_f}{\sigma_p} \tag{1.4}$$

where R_p is the average return of the asset/portfolio, R_f is the risk-free rate and σ_p is the standard deviation of the asset/portfolio (Sharpe, 1994) It is important to note that the Sharpe ratio is of no statistical significance and merely a descriptive metric. It can be used to compare the performance of different assets and portfolios. Investors have a preference for the investments with the highest Sharpe ratios since these investment have the best performance in risk-adjusted terms.

Information Ratio

In 1973, the information ratio (originally referred to as the appraisal ratio) was developed by Treynor and Black (1973). The information ratio is similar to the Sharpe ratio in the sense that it uses excess returns to calculate risk-adjusted returns. The difference is the way in which these excess returns are calculated. Where the Sharpe ratio subtracts the risk-free rate from the average returns of the portfolio, the information ratio does subtract the benchmark returns from the average returns of the portfolio. Thereafter, these excess returns are divided by the standard deviation of the excess returns. The denominator of the information ratio is often referred to as the tracking error. The information ratio shows the outperformance of a portfolio over the benchmark portfolio. The higher the value of the information ratio, the higher the outperformance in risk-adjusted returns. The formula of the information ratio, IR, is defined as

$$IR = \frac{R_p - R_b}{\sigma_{ER}} \tag{1.5}$$

where R_p is the average return of the portfolio, R_b is the average return of the benchmark and σ_{ER} is the standard deviation of the excess return (Treynor & Black, 1973; Goodwin, 1998). In this thesis the information ratio will be used to compare the trading strategies to the different benchmarks. The way benchmarks are constructed will be elaborated upon in the next section.

4.2 Benchmark Construction

Three different benchmarks will be used to evaluate the performance of the trading strategies. Two of them will be custom-made and one of them will be the CCI30 benchmark. The benchmarks differ in length and the method in which cryptocurrencies are weighted and allocated to the benchmarks. The CCI30 benchmark is explained upon in the data chapter. In this chapter the custom-made benchmarks will be discussed.

Equally weighted benchmark portfolio

The equally weighted benchmark portfolio is created as an equally-weighted investment in all the included cryptocurrencies available at the time. Together with the value-weighted benchmark, it is one of the most used methods to weight and compute portfolio returns (Crawford, Hansen & Price, 2011). This method assigns an equal weight to any cryptocurrency in the benchmark portfolio, no matter what their size is. Since the number of cryptocurrencies will increase over time, the cryptocurrencies constituting the equally weighted benchmark portfolio will increase as well. If data is available for N different cryptocurrencies, then the benchmark portfolio will also include N cryptocurrencies, each currency weighted at $\frac{1}{N}$. The benchmark portfolio will be rebalanced daily. Since the benchmark portfolio is equally weighted, the daily returns can be calculated by taking the simple average of the daily returns of the cryptocurrencies constituting the portfolio at that time. In mathematical terms, the daily returns at time *t* of the equally weighted benchmark portfolio (*D.EW*) can be defined by a formula similar to formula 1.2

$$D.EW_t = \frac{1}{N}\sum_{i=1}^{N} r_{i,t} \tag{1.6}$$

where *N* indicates the number of cryptocurrencies in the portfolio at time *t* and r_i is the return of the *i-th* cryptocurrency measured at time *t*. The equally weighted benchmark is available from the 28th of April 2013.

Market capitalization weighted benchmark portfolio

The market capitalization weighted benchmark (also referred to in literature as the value weighted benchmark) is a benchmark where the components are weighted according to their share of the total market capitalization. As mentioned, it is one of the most used methods to compute portfolio returns (Crawford et al., 2011). As in the prior benchmark portfolio, the number of cryptocurrencies constituting the market-cap weighted benchmark portfolio will increase over time. If data is available for N cryptocurrencies, the market-cap weighted benchmark portfolio will also include N cryptocurrencies, each cryptocurrency being weighted by their percentage share of the total market capitalization of the included cryptocurrencies. The daily portfolio returns are calculated by multiplying the weight of each cryptocurrency with their respective returns and taking the sum of these. The formula for the daily returns at time *t* of the market-cap weighted benchmark portfolio (*D.MW*) is defined as

$$D.MW_t = \sum_{i=1}^{N} \left(w_{i,t} * r_{i,t}\right) \tag{1.7}$$

where *N* refers to the number of included cryptocurrencies in the portfolio at time *t*, *w* refers to the percentage (weight) of the *i-th* cryptocurrency inside the portfolio at time *t* and *r* refers to the return of the *i-th* cryptocurrency at time *t*. The market-cap weighted benchmark will be available from the 28th of April 2013. It is important to note that due to the dominance of the Bitcoin in the cryptocurrency market, the market-cap weighted benchmark is largely driven by the returns of the Bitcoin. As of 30-06-2018 the Bitcoin constitutes over 50% of the total market capitalization in the cryptocurrency market. Descriptive statistics of the custom-made benchmarks and the CCI30 benchmark can be find in Appendix A1.

4.3 Trading strategies

Since it has been found that time-series momentum strategies seems to outperform their cross-sectional alternative (Bird et al., 2017) and besides that the time-series momentum trading strategy performs better if the market experiences extreme movements (Moskowitz et al., 2012) in this thesis is chosen to use the time-series momentum methodology to investigate the anomaly in the cryptocurrency market. The construction of the time-series momentum trading strategies closely follows recent literature on time-series momentum.

This section will first focus on the differences between the trading strategies in generating the trading signals. Afterwards the similarities between the trading strategies in forming portfolios and calculating returns will be discussed. One similarity that is important to know in advance is that for every trading strategy a long-short as well as a long-only portfolio is constructed. The same methodology is used to generate trading signals for both portfolios. The difference is that where a long-short portfolio does take long and short positions in the cryptocurrencies, the long-only portfolio does only take the long position. To exemplify this difference consider the following scenario. The generated trading signals at the time indicate that a long-position should be taken in seven cryptocurrencies and a short positon in four. In that case, the long-short investor will initiate eleven positions (seven long, four short) and the long-only investor will initiate only seven position (seven long and no short positions). Since, long-only investors do not take short positions, this will result in not taking any positions on certain days in their portfolio. Long-short investors do take a position (either long or short) in every available cryptocurrency on a daily basis. The reason that long-only strategies will also be tested in this thesis is because it might be difficult to find exchanges willing to short-sell cryptocurrencies (Rohrbach et al., 2017).

Three different methods are used to construct the time-series momentum trading portfolios. The first method is based on the work of Levine and Pedersen (2016). The second method is based on a combination of the studies by Baltas and Kosowki (2015) and Fama and Blume (1966). The last method is based on a combination of various methodologies including, among others, Moskowitz et al. (2012)

and Rohrback et al. (2017). The trading strategies decrease in simplicity and become more technical. The first two trading strategies are based on time-series momentum rules. The last is in the area of the moving-average rules. Despite this difference, the methodologies are actually quite similar. The main difference between the methods is the way the specific trading signals are generated. Besides, in creating the trading signals no transaction costs are considered. Whether this is a realistic assumption or not will be elaborated upon in the discussion section.

Simple TSMOM strategy

The first method that creates trading signals is in the domain of time-series momentum and is the simplest of all the momentum strategies examined in this thesis. It is based on the methodology of Levine and Pedersen (2016). Levine and Pedersen (2016) applied a simple approach to capture the price trends. They referred to this strategy as the simple TSMOM strategy (TSMOM referred to time-series momentum). As with all time-series momentum strategies it will create trading signals based on an assets own past returns over a certain formation period. In their paper, Levine and Pedersen (2016) considered formation periods of respectively 1-month, 3-months and 12-months. Their TSMOM strategy creates a signal to go long when the price of an asset has been moving up and creates a signal to go short (take no position) when the price has been moving down over some time period, say *d*. Based on their methodology, the formula to go long and go short (take no position) is defined as follows

$$signal_t^{tsmom(d)} = \begin{cases} 1, & P_t - P_{t-d} \geq 0 \\ -1 \; or \; . \, , & P_t - P_{t-d} < 0 \end{cases} \tag{1.8}$$

where *d* indicates the formation period in days, P_t refers to the price today and P_{t-d} indicates the price *d* days ago. The signal to go long has a value equal to 1 for both portfolios. The signal to go short has a value equal to -1 for the long-short portfolio. The signal to take no position is equal to a dot for the long-only portfolio. These signals are created daily for every included cryptocurrency. The way these trading signals are used to construct portfolios will be mentioned in the next section.

No studies of promising time frames for the formation periods of momentum strategies and cryptocurrencies have been conducted yet. In this thesis is chosen to use shorter formation periods than is common for the momentum strategies. This has been done for two different reasons. Since the cryptocurrency market is relatively new, the available data is limited and a lot of data will be lost when the common formation periods are used. Furthermore, since the cryptocurrency market is relatively volatile, shorter formation periods are used to better time the market. For the simple TSMOM strategy three formation periods will be used of one day (referred to as the TSMOM1 strategy), seven days (referred to as the TSMOM7 strategy) and thirty-one days (referred to as the TSMOM31 strategy).

Therefore portfolios of the simple TSMOM strategy are available from respectively 29-04-2013, 05-05-2013 and 29-05-2013. Descriptive statistics of the raw returns and the number of positions taken by the different simple TSMOM strategies can be found in the Appendix A.2

Filter TSMOM strategy

The filter TSMOM strategy is inspired by the findings of Baltas and Kosowski (2015) and based on the methodology of Fama and Blume (1966). Baltas and Kosowski (2015) showed that trading only on statistically significant price trends can benefit the performance of the time-series momentum strategy. In this thesis, the filter-rule of Fama and Blume (1966) is used to examine whether a cryptocurrency changed enough in value. This strategy falls in the domain of time-series momentum and will be referred to as the *FILTER strategy.*

Although the FILTER strategy seems to be quite similar to the simple TSMOM strategy, there is an important difference. Only significant price changes will be used in the FILTER strategy to trade upon. The *x* percent filter rule is defined by Fama and Blume (1966) and best summarized by the following quote: *"If the daily closing price of a particular security moves up at least x per cent, buy and hold the security until its price moves down at least x per cent from a subsequent high, at which time simultaneously sell and go short. The short position is maintained until the daily closing price rises at least x per cent above a subsequent low at which time one covers and buys"* (Fama & Blume, 1966). Nothing does happen when the price change is less than x per cent. *X* refers to any chosen percentage.

Similar, to the methodology of Fama and Blume (1966), different filters will be used in this thesis. The different filters used are a 0.5%, 1%, 1.5%, 2%, 2.5%, 5%, 10% and 20% change in the opposite direction from the previous reference point. On a daily basis, the trading strategy will assign a value of 1 to a cryptocurrency when a long position should be taken that day and a value of -1 (or a dot) when a short (no) position should be taken in the cryptocurrency on that day. The initiated position (either long, short, or none) in a cryptocurrency will be maintained until a different trading signal arrives for that cryptocurrency. In that case the filter TSMOM investor covers and invests in the opposite direction. Therefore, the formation period of every cryptocurrency can differ between the trading strategies. Only a change in position is initiated when the price change is at least *x* per cent. The strategy is rebalanced every day to keep it equally-weighted, though. All trading strategies start with a long position in the cryptocurrencies. This is maintained until a change of at least *x* per cent occurs. The filter TSMOM strategies are available for all the filters as of the 29th of April, 2013. The raw returns and the number of positions taken by the different filter TSMOM strategies can be found in appendix A.3. The filter TSMOM strategies will be referred to as the *FILTER x %* strategy (e.g. the filter strategy using a 5% filter will be indicated as the FILTER5% strategy).

Price Percentage Oscillator

The last strategy to create trading signals is in the domain of moving average crossovers (MACROSS). MACROSS strategies are popular because they can identify price momentum without really knowing the precise structure (Hong & Satchell, 2015). The idea behind trading on moving averages crossovers is simple. When recent prices are above (below) where prices were used to be, the MACROSS investor should buy (sell) because the asset is in an upward (downward) trend. This is calculated using two moving averages of prices with different time horizons. The first moving average is referred to as the 'fast' moving average and puts more weight on the recent prices. The other moving average is referred to as the 'slow' moving average and puts more weight on the past prices. If the 'fast' moving average is above (below) the 'long' moving average the MACROSS investor should buy (sell) (Levine & Pedersen, 2016).

Two of the most calculated moving averages are the simple moving average (SMA) and the exponential moving average (EMA) (Hansun, 2013). The SMA is equally weighted and is calculated by adding up all the values of the time horizon and then divide by the number of added values. All values receive the same weight. This is different for the EMA. As the name implies, the averages are exponentially weighted instead of equally weighted. The EMA puts more weight on the more recent values in the time horizon. The EMA is more common in practice (Hansun, 2013) and therefore used in this thesis to calculate the fast and slow moving averages. The formula to calculate the EMAs is inspired by the studies of Rosillo, Fuente and Brugos (2013) and Osterrieder et al. (2017). The formula is defined as follows:

$$EMA_t = \begin{cases} SMA_n, & t = 0 \\ \alpha \cdot P_t + (1-\alpha) \cdot EMA_{t-1}, & t > 0 \end{cases} \tag{1.9}$$

where $\alpha = \frac{2}{n+1}$ is the exponential smoothing ratio, *n* refers to the number of periods for the EMA, P_t is the price of an asset at time *t* and EMA_{t-1} is the EMA of the prior period. To calculate the EMA at time *t,* the EMA of the prior period (*t-1*) is needed. However, for the initial EMA there is no prior EMA available yet. Therefore, for the initial *n*-day EMA the *n*-day SMA is used.

In this thesis a well-known version of a MACROSS strategy is used to generate trading signals. The strategy used in this thesis is a normalised version of the famous technical MACD (moving average convergence divergence) indicator, first mentioned by Appel in the 1970s (Zhou and Zhu, 2013). Since the discovery, many studies have shown that this strategy generated significant returns. Also recently, the profitability of the MACD strategy is still documented in research (Ling and Ruzita, 2017; Amunga, 2017). The idea is that when market trends are improving, the averages in the short run will rise above the long-run averages (Appel, 2005). The normal version of the MACD strategy can be calculated by subtracting the slow EMA from the fast EMA. The slow EMA is calculated over 26 days and the fast EMA is calculated over 12 days. These time periods are the most commonly used for long and short-period EMAs (Murphy, 1999; Rosillo et al. 2013). The equation of the MACD is shown in formula 1.10:

$$MACD = EMA_{12} - EMA_{26} \tag{1.10}$$

As mentioned, in this thesis a normalised version of the MACD indicator is used, called the price percentage oscillator (PPO). This is done by dividing the MACD with the long EMA. The formula for the PPO is defined as follows:

$$PPO = \frac{EMA_{12} - EMA_{26}}{EMA_{26}} \tag{1.11}$$

Using the PPO instead of the MACD has the advantage that the trading signals are more comparable between the assets. However, the generated trading signals are the same for the normal and normalised version of the trading strategy in practice. In order to create signs using the PPO strategy, two different methods will be used in this thesis. The first method is inspired by the methodology of Chong and Ng (2008). In their study a signal to go long is generated when the PPO crosses the zero line from below. To state differently, when the PPO becomes positive. Naturally, a signal to go short (or take no position) is generated when the PPO crosses the zero line from above. (that is when the PPO becomes negative). The signal to go long has a value equal to 1. The signal to go short (or take no position) has a value of a -1 (a dot). The signs will be created daily for every cryptocurrency. This method will be referred to as the PPO (12,26,0) strategy.

The other method used to generate trading signals with the PPO is inspired by the methodology of Rosillo et al. (2013) and Chong, Ng and Liew (2014). Although it is quite similar to the methodology of Chong and Ng (2008), a different line is used to generate the trading signals. A signal line is created by taking the 9-day EMA of the PPO. A buy signal is generated when the PPO crosses the signal line from below and a sell signal is created when the PPO crosses the signal line from above. As with all the trading strategies, the trade signal to go long has a value equal to 1 and the signal to go short (take no position) has a value equal to -1 (a dot). The signs will be created daily for every cryptocurrency. This method will be referred to as the PPO (12,26,9) strategy. The raw returns and the number of positions taken by the different PPO strategies can be found in the appendix A.4.

Similarities trading strategies

This section will focus on the similarities between the trading strategies after the trading signals have been generated. For all trading strategies, an equally-weighted portfolio of cryptocurrencies is created on the basis of the generated trading signals for the individual cryptocurrencies. Equally-weighted momentum strategies are often implemented in literature (Yao, 2012). As mentioned, the trading signals for the individual cryptocurrencies are generated daily and take a value of either 1 or -1 for the long-short portfolio and a value of either 1 or a dot for the long-only strategies. Similar to the methodology of Moskowitz et al. (2012), a long position is taken in a cryptocurrency if the trading signal is positive and a short (no) position is taken if the trading signal is negative (a dot).

Due to the volatile and rapidly changing cryptocurrency market, it is chosen to held all positions for one day and rebalance the portfolio daily. Daily rebalancing is inspired by the methodology of Levine and Pedersen (2016) and Yang (2018). Every day, prior positions will be closed and new positions will be initiated for the portfolio. Furthermore, rebalancing the portfolio daily keeps the portfolio equally-weighted. On every rebalancing date, every included cryptocurrency will be assigned a weight of $\frac{1}{N}$ and take a position according to the sign of the generated trading signal. In this formula, *N* refers to the total numbers of cryptocurrencies included in the portfolio. Furthermore, the amount of long and short (no) positions in the portfolio do not have to be the same and can vary with the state of the market. It is possible that at any time the number of long positions are above/below or equal to the number of short (no) positions in the portfolio.

The method used to calculate the returns of the momentum strategies is inspired by Rohrbach et al. (2017) and is common in studies on time-series momentum. The method does apply to both the long-short and long-only portfolio. As a first step, time-series momentum returns for the individual cryptocurrencies will be calculated by multiplying the daily arithmetic returns of the cryptocurrencies with the trading signal lagged by one day. This trading signal is either a 1 or -1 for the long-short momentum strategies and a 1 or . for the long-only momentum strategies. Naturally, this indicates that for the long-only momentum strategy not always a position is taken in a cryptocurrency. The formula for the time-series momentum returns of a cryptocurrency *i* at time *t* can be defined as follows

$$R.Cr_{i,t} = signal_i(t_{-1}) * R_{i,t} \tag{1.12}$$

where *signal* refers to the generated trading signal at time *t-1* and $R_{t,I}$ is the return of the *i-th* cryptocurrency at time *t*. As mentioned, the signal can take a value of a 1, -1 or a dot.

Since all the time-series momentum portfolios are equally-weighted, their returns can be calculated by taking the simple average of the daily time-series momentum returns for the cryptocurrencies constituting the portfolio at that time. The number of cryptocurrencies constituting the long-short portfolio is always equal to the number of cryptocurrencies that data is available for at that time. This is different for the long-only momentum strategies. For the long-only portfolios, the number of cryptocurrencies constituting the portfolio at any time, is dependent on the number of cryptocurrencies that a long position is taken in at that time. A formula similar to 1.6 can be defined to calculate the daily time-series momentum returns, $R.Mom_t$, for the both the long-short and long-only portfolios at time t

$$R.Mom_t = \frac{1}{N}\sum_{i=1}^{N} R.Cr_{i,t} \tag{1.13}$$

where N indicates the number of cryptocurrencies constituting the portfolio at time t and $R.Cr_{i,t}$ is the time-series momentum return of the *i-th* cryptocurrency measured at time t.

4.4 Evaluation of strategies

For evaluating the trading strategies only excess returns are used. These are the returns in excess of the three benchmark returns. Excess returns are calculated on a daily basis by subtracting the returns of the benchmark from the returns generated by the trading strategy. Since markets are assumed to be efficient, the excess returns are expected to be zero (Malkiel, 2005). Showing that returns from a momentum strategy are significantly different from zero does provide evidence for the existence of the momentum anomaly. This is based on the methodology of Moskowitz et al. (2012). To test whether momentum returns are statistically significant different from zero, the student t-test is conducted. One assumption of the student t-test is that the underlying distribution needs to be normal. However, even when the underlying distribution is non normal, the t-test has proven to be quite robust when sample sizes are fairly large and tests are two-tailed (Sawilowsky & Blair, 1992). This finding is supported by Ghasemi and Zahediasl (2012). Ghasemi and Zahediasl (2012) document that a parametric tests should cause no major problems when the sample size is larger than 40 observations. Furthermore, if the data sample consists of hundreds of observations, the distribution of data can even be ignored (Altman & Bland, 1995; Ghasemi & Zahediasl, 2012). Therefore the student t-test will be used to examine if the results are significant.

In order to evaluate the performance of the different strategies, three different hypotheses are tested. These hypotheses are based on the previous literature and will be used to provide an answer to the main research question of this paper. The hypotheses were based on the empirical finding that the momentum anomaly remained robust over time, countries and asset classes. In many markets momentum strategies, and time-series momentum strategies in particular, are still able to generate excess returns. Since there is a lack of profound literature for the crypto-market the following hypotheses are tested:

H1: Long-short Time-Series Momentum trading strategies generate economically and statistically significant excess returns in the crypto-market

H2: Long-only Time-Series Momentum trading strategies generate economically and statistically significant excess returns in the crypto-market

H3: Long-only strategies generate significantly higher (excess) returns than long-short strategies in the crypto-market.

5. Results

5.1 Returns of the Long-Short Momentum Strategies

In this section the raw returns and the excess returns of the long-short trading strategies are presented. At the end of this section a general conclusion, regarding the long-short momentum strategies and the hypotheses is presented. In total 13 long-short trading strategies are examined per benchmark. Excess returns are created by comparing the returns of the trading strategies to the returns of the different benchmark strategies. The excess returns will be compared to the benchmarks separately. The excess returns and the p-values of the long-short time-series momentum trading strategies are presented in table 3. In this table the variation in returns is depicted by the variation in colours. The highest excess return of all tested strategies (both long-short and long-only) was 66.47 basis points (66.47 basis points is 0.6647%) per day and is defined as green. The lowest excess return of all tested strategies was -33.70 basis points and is defined as red. In between the colours vary. This method of displaying results is inspired by the work of Stoffel (2017). All (excess) returns are calculated before transaction costs. Other performance metrics are presented in the appendix A.6.

Raw returns

All the forms of long-short time-series momentum strategies generated positive raw returns. The results of the long-short trading strategies can be found in appendix A.2, A.3, A.4, A.5 and A.6. The simple TSMOM strategies had on average a raw return of 45.82 basis points per day and a geometric average of 35.47 basis points per day. The FILTER strategies had on average a lower raw returns with a raw return of 31.93 basis points per day and a daily geometric average of 21.38 basis points. In terms of raw returns the PPO strategies performed the best with an average daily raw return of 47.26 basis points and a geometric average of 37.64 basis points per day.

The different forms of long-short strategies created on average a raw return of 37.50 basis points per day. The geometric average of the long-short strategies were 27.13 basis points per day. Besides, the Sharpe-ratio of all the long-short strategies is on average 1.55, which is higher as the average Sharpe-ratio (1.348) of the included cryptocurrencies. In terms of raw returns and Sharpe-ratios two strategies were the most profitable. They reached almost identical results. The most profitable long-short strategy in terms of raw returns was the TSMOM7 strategy with an average daily raw return of 53.55

basis points, a geometric average of 43.27 basis points and a Sharp-ratio of 2.212. The highest Sharpe-ratio was achieved by the PPO (12,26,0) strategy and was 2.216, which is higher than the Sharp-ratio of any of the individual cryptocurrencies examined. The daily raw return of the PPO (12,26,0) strategy was 52.78 basis points and the geometric average was 42.91 basis points. Even the average raw return and the Sharpe-ratio of the worst performing strategy (the FILTER2% strategy) are relatively high. The average raw return of this strategy was 26.28 basis points per day and the Sharpe-ratio was 1.0621. Similar results are unlikely to be found in other asset classes considering that the average Sharpe-ratio of the famous Warren Buffets' Berkshire Hathway is a 'merely' 0.76. Berkshire Hathaway's Sharpe-ratio is already nearly double that of the overall stock market (Frazzini, Kabiller & Pedersen, 2013).

What is noteworthy about all the long-short trading strategies is that both the kurtosis and skewness are above the values for a normal distribution. The values show that the distributions are positively skewed and leptokurtic. This means respectively that there is a long right tail and that the distributions are heavy-tailed, indicating that there is a greater chance of extreme (positive) outcomes. This finding is supported by the minimum and maximum daily returns of the long-short strategies ranging between respectively -38% and 256.29%. That the data for the long-short strategies is not normally distributed was also found by the Jacque-Bera test at the 1% significance level.

Equally-Weighted Benchmark

In comparison to the equally-weighted benchmark, none of the long-short trading strategies generated positive excess returns on average. Results are presented in table 3. The average of all the excess returns of the long-short strategies was -23.02 basis points per day. For 6 of the 13 long-short trading strategies these negative excess returns were significant. For the TSMOM1, the FILTER1% and the FILTER2.5% strategies the negative excess returns were significantly different from zero at the 10% significance level. For the FILTER1.5%, the FILTER2.0% and the FILTER20% the negative returns were different from zero at the 5% significance level. For the other strategies the negative excess returns were not significant. Since all the long-short trading strategies generated negative excess returns, also all the information ratios had negative signs. The average information ratio for the long-short strategies is -0.03495. The least unprofitable strategy compared to the equally-weighted benchmark was the TSMOM7 strategy, yielding an average negative excess return of 7.57 basis points per day, an information ratio of -0.011 and a sharp-ratio of 2.212. The least profitable strategy in terms of the excess returns was the FILTER2% strategy with an average daily negative excess return of 33.70 basis points, an information ratio of -0.048 and a sharp-ratio of 1.0621. The strategy with the lowest information ratio is the FILTER20% strategy with an information ratio of -0.06272, an average daily negative excess return of 29 basis points and a sharp-ratio of 1.291.

Market Capitalization Benchmark

In comparison to the market-capitalization benchmark, all the simple TSMOM strategies and the PPO strategies generated positive excess returns. However, only half of the excess returns of the FILTER strategies were positive. Therefore, nine of the thirteen long-short strategies generated positive excess returns on average. Results are presented in table 3. The average of all the daily excess returns of the long-short strategies was 5.51 basis points and the average information ratio was 0.009. However, for none of the long-short strategies the excess returns were also significantly different from zero. The best performing strategy in terms of excess returns was the TSMOM7 strategy with a positive daily excess return of 20.77 basis points and an information ratio of 0.032. The best performing strategy in terms of the information ratio was the PPO (12,26,0) strategy with an information ratio of 0.034 and an average excess return of 20.14 basis points. The worst performing strategy was again the FILTER2% strategy with negative excess returns of 5.4 basis points daily and an information ratio of -0.008.

CCI30 Benchmark

No data for the CCI30 benchmark was available prior to 2015. Therefore, the long-short time-series momentum trading strategies were compared to the CCI30 index benchmark over the same time-frame as data was available for the CCI30 benchmark. Results are presented in table 3. The total numbers of trading days examined and positions initiated can be found in appendix. In comparison to the CCI30 benchmark, only three of the long-short strategies generated positive excess daily returns. Those were the PPO (12,26,0) strategy and two of the simple TSMOM strategies. The generated positive excess returns were not significantly different from zero. Negative daily excess returns were found for the remainder of the strategies. However, only the negative excess return for the FILTER20% strategy was also significantly different from zero at the 5% level. The information ratio of the FILTER20% was also the worst of all the long-short strategies being -0.0593. The average of the all the information ratios was -0.0211. The best performing long-short strategy in comparison to the CCI30 benchmark was the PPO (12, 26, 0) strategy with daily excess returns of 11.26 basis points, an information ratio of 0.0216 and a Sharpe-ratio of 2.216. The average of the excess returns of all the long-short strategies in comparison to the CCI30 benchmark was -10.98 basis points.

To conclude, there seems to be evidence to at least partially reject the first hypotheses that *'long-short time-series momentum trading strategies generate economically and statistically significant returns'.* A total of 13 long-short trading strategies are compared to three different benchmarks creating in total 39 different average excess returns. Out of these 39 different excess returns, only 12 were positive and none of these positive excess returns were significantly different from zero. Furthermore, 27 of the excess returns had the opposite sign making it negative excess returns. Since out of these 27 excess returns only seven were significantly different from zero at differing levels of significance it is not possible to fully reject the first hypothesis. However, there seems to be at least some evidence that long-short time-series momentum strategies are more likely to generate negative than positive excess returns.

Tabel 3

Excess returns in basis points per day of the long-short strategies over the benchmark.

	EQUALLY WEIGHTED	MARKET CAPITALIZATION	CCI 30 BENCHMARK
TSMOM STRATEGY			
TSMOM1	-28.05	0.246	-24.36
	(0.0812)*	(0.9874)	(0.1257)
TSMOM7	-7.567	20.77	10.36
	(0.6286)	(0.1659)	(0.5139)
TSMOM31	-9.895	19.46	6.234
	(0.4654)	(0.1422)	(0.6638)
FILTER STRATEGY			
FILTER0.5%	-23.35	4.945	-17.98
	(0.1480)	(0.7524)	(0.2639)
FILTER1%	-28.07	0.219	-20.4
	(0.0821)*	(0.9888)	(0.2078)
FILTER1.5%	-32.26	-3.968	-22.78
	(0.0494)**	(0.8003)	(0.1581)
FILTER2.0%	-33.7	-5.408	-20.53
	(0.0382)**	(0.7279)	(0.1992)
FILTER2.5%	-30.67	-2.38	-19.1
	(0.0564)*	(0.8774)	(0.2227)
FILTER5%	-23.6	4.69	-10.62
	(0.1458)	(0.7638)	(0.4800)
FILTER10%	-23.72	4.571	-11.96
	(0.1091)	(0.7519)	(0.3932)
FILTER20%	-29	-0.708	-20.1
	(0.0065)***	(0.9506)	(0.0341)**
PPO STRATEGY			
PPO(12,26,0)	-8.947	20.14	11.26
	(0.5234)	(0.1400)	(0.4401)
PPO(12,26,9)	-20.38	9.058	-2.759
	(0.2282)	(0.5690)	(0.8674)
AVERAGE	-23.02	5.511	-10.98

Note: Daily excess returns in basis points per long-short strategy. Excess returns are obtained by comparing the raw returns of the long-short strategies to the returns of the benchmark portfolios. P-values are obtained using a t-test to find out whether the excess returns are significantly different from zero. P-values are included between brackets. The variation in returns is depicted by the variation in colours. Colours vary between the highest excess return of 66.47 basis points per day (defined as green) and the lowest excess return of -33.70 per day (defined as red). Significant values are indicated by the asterisks (* = p < 0.1, ** = p < 0.05, *** = p < 0.01)

5.2 Returns of the Long-Only Momentum Strategies

In this section the raw returns and the excess returns of the long-only time-series momentum trading portfolios are presented. At the end of this section, a general conclusion regarding the long-only momentum strategies and the hypotheses is presented. Long-only trading signals are generated using the same methodology as the long-short strategies. Long-only strategies differ because the long-only investor never takes a short position in their portfolio. Since only long positions are initiated in this strategy, the amount of initiated positions taken in the portfolio might vary across time. The number of initiated positons by every trading strategy can be found in appendix A.7. In total 13 long-only trading strategies are examined per benchmark. Excess returns are created by comparing the returns of the trading strategies to the returns of the different benchmark strategies. The excess returns will be compared to the benchmarks separately. The excess returns and the p-values of the long-only time-series momentum trading strategies are presented in table 4. In this table the variation in returns is depicted by the variation in colours. The highest excess return of all tested strategies (both long-short and long-only) was 66.47 basis points per day and is defined as green. The lowest excess return of all tested strategies was -33.70 basis points and is defined as red. In between the colours vary. This method of displaying results is inspired by the work of Stoffel (2017). All (excess) returns are calculated before transaction costs. Other returns and performance metrics are presented in the appendix.

Raw Returns

All the forms of long-only time-series momentum trading strategies generated positive raw returns. The results of the long-only trading strategies can be found in appendix A.2, A.3, A.4, A.5 and A.7. The raw return of all the forms of long-only strategies was on average 84.79 basis points per day and the geometric average was on average 64.36 basis points per day. The averages of the long-only portfolios are roughly twice as high as the averages of the long-short portfolios. Similar outperformance is found when comparing the different forms of time-series momentum trading strategies separately. The long-only simple TSMOM strategy had on average a daily raw return of 85.65 basis points and a daily geometric average of 66.98 basis points. The raw returns for the FILTER strategies were slightly lower with an average raw return of 83.17 basis points per day and a geometric average of 61.12 basis points per day. The best performance was achieved by the long-only PPO strategies with an average daily return of 90.02 basis points and geometric average of 73.4 basis points. All of the separate long-only trading strategies outperformed their long-short alternative.

The individual trading strategy that achieved the highest raw return was the long-only FILTER0.5% strategy. This strategy had a raw return of 100.1 basis points per day and a geometric average of 74.48 basis points. The corresponding Sharpe-ratio is 2.162. However, due to the high standard deviation this Sharpe-ratio is below the average of the long-only strategies. The average Sharpe-ratio of all the long-only strategies is 2.206. The highest Sharpe-ratio is achieved by the long-only PPO (12,26,9) strategy. The Sharpe-ratio was a remarkable 2.936 with a raw return of 89.29 basis points per day and a geometric average of 73.75 basis points. The worst performing long-only strategy was the FILTER20% strategy. This strategy had a raw return of 61.64 basis points per day and a geometric average of 48.63 basis points. Still, it outperformed the best performing long-short strategy in terms of both the raw returns as geometric average.

The skewness and kurtosis for the long-only strategies are above the values for a normal distribution. For 12 out of the 13 long-only trading strategies the skewness is also higher than the long-short alternative. Similar results are found for the kurtosis that is higher for the long-only strategies in 10 out of the 13 trading strategies. This shows that the long-only trading strategies are relatively positively skewed and leptokurtic. This does indicate the there is a greater chance of (positive) extreme outcomes for the long-only momentum strategies as their long-short alternative.

Equally-weighted benchmark

In comparison to the equally-weighted benchmark, all of the long-only trading strategies generated positive excess returns. Results are presented in table 4. For nine of the long-only trading strategies the excess returns were also significantly different from zero. At the 10% significance level, the FILTER2% strategy had significant positive excess returns. The positive excess returns of the TSMOM1, TSMOM31, FILTER0.5%, FILTER1%, FILTER1.5% and PPO (12,26,9) strategies were significant at the 5% level and the TSMOM7 and PPO (12,26,0) were significant at the 1% confidence level. On average, all the long-only trading strategies generated a positive excess return of 22.92 basis points per day. The average information ratio of the long-only was 0.469, which is significantly higher than the average information ratio of the long-short portfolios. The most profitable long-only strategy in terms of excess returns was the FILTER0.5%, with an excess return of 37.89 basis points and an information ratio of 0.0621. In terms of the information ratio did the PPO (12,26,9) strategy perform best, having an information ratio of 0.0873. The excess return of this long-only strategy was 31.91 basis points per day. The worst performing strategy was the FILTER20% with an information ratio of 0.0003 and a daily excess return of 0.006 basis points.

Market Capitalization Benchmark

In comparison to the market-capitalization benchmark, all of the long-only strategies generated excess returns that were positive and significantly different from zero. Results are presented in table 4. For 11 of the 13 trading strategies the excess returns were significant at the 1% level. For the other two strategies, the FILTER 5% and FILTER10%, the positive excess returns were significantly different from zero at the 5% confidence level. The average excess return of the long-short trading strategies over the market-capitalization benchmark was 51.18 basis points per day and the average information ratio was 0.0811. The long-only strategy with the highest excess returns was the FILTER0.5% strategy with an excess return of 66.47 basis points per day and a corresponding information ratio of 0.0824. The highest information ratio was achieved by the PPO (12,26,0) strategy. The information ratio of this strategy was 0.1223 and the excess returns were 60.08 basis points per day. The worst performing strategies were the FILTER10% and FILTER20% long-only strategies. These trading strategies had an excess return of respectively 37.44 basis points and 29.42 basis point per day. The corresponding information ratios were respectively 0.0521 and 0.0693.

CCI30 Benchmark

The total numbers of trading days examined and positions initiated by the long-only time-series momentum trading strategies can be found in the appendix. Results are presented in table 4. In comparison to the CCI30 benchmark, all of the trading strategies generated positive excess daily returns. The positive excess returns were significantly different from zero for all the trading strategies except for the FILTER2.5% and FILTER5% strategies. At the 1% confidence level the excess returns of the PPO strategies and two of the simple TSMOM strategies were significant. The excess returns of the long-only TSMOM1 and FILTER0.5% strategy were significant at the 5% level and the excess returns of the long-only FILTER1%, FILTER1,5%, FILTER2%, FILTER10% and FILTER20% were significant at the 10% level. For all forms of long-only trading strategies was the excess return over the CCI30 benchmark on average 25.43 basis points per day and the average information ratio was 0.0670. The best performing strategy was the PPO (12,26,0) strategy with an excess return of 37.16 basis points and an information ratio of 0.1126. The worst performing strategy was the FILTER5% strategy with excess returns of 13.46 basis points and an information ratio of 0.0383.

To conclude, there is enough evidence to state that '*long-only time-series momentum trading strategies generate economically and statistically significant returns'.* For the long-only strategies a total of 13 trading strategies were compared to three different benchmarks creating in total 39 different average excess returns. The signs of these excess returns were all positive. Out of these 39 different average excess returns, 33 were also significantly different from zero at differing levels of significance. Therefore, the second hypothesis that *long-only time-series momentum trading strategies generate economically and statistically significant returns'* cannot be rejected. There seems to be enough evidence to document that long-only time-series momentum strategies are more likely to generate significant positive excess returns.

Furthermore, there seems to be evidence that '*long-only strategies generate significantly higher (excess) returns than long-short strategies'.* Using a student t-test it is found that both the (excess) returns and the information ratios are significantly higher for the long-only portfolios than for the long-short portfolios at the 1% level (p-value 0.000)(Appendix A.8). Therefore the last hypotheses cannot be rejected, since long-only strategies performed significantly better than long-short strategies.

	EQUALLY WEIGHTED	MARKET CAPITALIZATION	CCI 30 BENCHMARK
TSMOM STRATEGY			
TSMOM1	32.51	59.93	24.69
	(0.0233)**	(0.0017)***	(0.0309)**
TSMOM7	21.8	47.67	33.6
	(0.0065)***	(0.000)***	(0.0012)***
TSMOM31	21.15	48.12	31.33
	(0.0100)**	(0.000)***	(0.0005)***
FILTER STRATEGY			
FILTER0.5%	37.89	66.47	29.8
	(0.0104)**	(0.0007)***	(0.0137)**
FILTER1%	32.93	60.75	22.27
	(0.0250)**	(0.0018)***	(0.0620)*
FILTER1.5%	31.55	59.76	23.59
	(0.0315)**	(0.0019)***	(0.0593)*
FILTER2.0%	24.6	52.52	24.29
	(0.0872)*	(0.0050)***	(0.0547)*
FILTER2.5%	22.34	48.69	19.74
	(0.1176)	(0.0099)***	(0.1013)
FILTER5%	13.58	43.29	13.46
	(0.3128)	(0.0146)**	(0.1737)
FILTER10%	7.267	37.44	15.44
	(0.5624)	(0.0268)**	(0.0977)*
FILTER20%	0.063	29.42	15.58
	(0.9904)	(0.0027)***	(0.0781)*
PPO STRATEGY			
PPO(12,26,0)	31.91	60.08	37.16
	(0.0004)***	(0.0000)***	(0.0001)***
PPO(12,26,9)	20.37	51.15	39.64
	(0.0276)**	(0.0000)***	(0.0011)***
AVERAGE	22.92	51.18	25.43

Tabel 4

Excess returns in basis points per day of the long-only strategies over the benchmark.

Note: *Daily excess returns in basis points per long-only strategy. Excess returns are obtained by comparing the raw returns of the long-only strategies to the returns of the benchmark portfolios. P-values are obtained using a t-test to find out whether the excess returns are significantly different from zero. P-values are included between brackets. The variation in returns is depicted by the variation in colours. Colours vary between the highest excess return of 66.47 basis points per day (defined as green) and the lowest excess return of -33.70 per day (defined as red).* Significant values are indicated by the asterisks (* = p < 0.1, ** = p < 0.05, *** = p < 0.01)

6. Discussion and Conclusion

Momentum is one of the oldest anomalies in the market. It can be seen as the continuation of prior returns. Something that performed well in the past will probably continue to do well in the future while assets that performed poorly in the past tend to continue doing poorly in the future (Jegadeesh & Titman, 1993). Despite the fact that a lot of research showed that it remained robust over time, countries and asset classes, there is a paucity of literature regarding the momentum anomaly in the cryptocurrency market. In this paper will be researched whether time-series momentum trading strategies generate statistically and economically significant excess returns in the young and developing cryptocurrency market. If significant positive excess returns are found this can be seen as a claim against the EMH.

Three different forms of time-series momentum trading strategies were used to generate trading signals for the eleven included cryptocurrencies over the time period 28/04/2013 till 30/06/2018. The different trading strategies increased in complexity and were respectively the simple TSMOM strategy, the filter TSMOM strategy and the price percentage oscillator. Three different parameters were used for the simple TSMOM strategy, eight for the filter TSMOM strategy and two for the price percentage oscillator. Besides, for every time-series momentum trading strategy both a long-short and long-only portfolio were examined, creating in total 26 different portfolios. The portfolio returns of all trading strategies were compared to the returns of the benchmarks, of which two were custom made and one was the publicly available CCI30 index benchmark, to create excess returns. If positive excess returns are found using the trading strategies this does provide evidence for the existence of the momentum anomaly.

The analysis provided mixed evidence for the existence of the momentum anomaly in the crypto-market. This is because different results were found for the long-short and long-only time-series momentum trading strategies. None of the long-short time-series momentum portfolios generated positive excess returns and for almost 70% of the long-short portfolios the excess returns were negative. The negative excess returns were significant for seven of the long-short trading strategies. Although it is not possible to fully reject the first hypotheses, at least some evidence is provided that long-short time-series momentum strategies are more likely to generate negative than positive excess returns. This contradicts previous literature on momentum that showed that the momentum effect is robust among asset classes and time. A possible explanation is the generally upward trend that has been prevailing in the crypto-market for a considerable amount of time. Taking short-positions in a market as volatile and bullish as the crypto-market can potentially result in losses, as a decrease in value of a cryptocurrency one day is potentially followed by already an increase in the cryptocurrency the other day. This contradicts the result of Yan (2008) and Moskowitz et al. (2012) who documented that returns of momentum strategies are actually largest when the market experience extreme movements or volatility.

For the long-only time-series momentum trading strategies, results in favour of the existence of the momentum anomaly in the cryptocurrency market have been found. All long-only trading strategies created positive excess returns over all the benchmarks. The positive excess returns were found to be significant for 85% of the long-only portfolios. This result does resemble the results on momentum that has been documented in previous literature. Besides, the long-only time-series momentum strategy significantly outperformed the long-short alternative. This indicates that the observed momentum in long positions is stronger than the observed momentum in short positions. Again, a potential explanation could be the prevailing upward trend in the crypto-market.

When interpreting the results, it is important to note that a backtest is performed to evaluate the performance of the trading strategies. This might have an influence on the results since market conditions were extremely positive and volatile during the analysed period. The backtest might also create a selection bias since only the cryptocurrencies that have survived the preselection are included in the analysis. Cryptocurrencies that do not meet the criteria are excluded. This could impact the results of the trading strategies. However, the selection effect is mitigated by the fact that two of the benchmarks are composed of the same set of cryptocurrencies and mostly excess returns are used in the analysis. Additionally, no transaction costs or bid-ask spreads were considered in the analysis. Therefore, the return calculations will overestimate the actual returns. Neglecting transaction costs has been done deliberately. Transaction costs differ significantly between exchanges and do vary with the amount of capital an investor wishes to invest. By mentioning the raw returns/excess returns before transaction costs, the investor can choose whether the costs he/she faces are low enough to profit from the momentum trading strategy. Another limitation is that it is assumed that all cryptocurrencies can be shorted without a problem. As mentioned by Rohrbach et al. (2017), finding exchanges which allow short selling might be problematic.

As the available research on (time-series) momentum in the young and developing crypto-market is limited, a lot of research can still be done in this field. As a starting point, it is important to create a prevalent and accepted asset pricing model that describes the relationship between risk and return for cryptocurrencies. If, as Kosc et al. (2018) mentioned, cryptocurrencies are at the verge of becoming a new financial asset, it is important to have an asset pricing model that can help to explain the source of their returns. If an accepted asset pricing model is constructed, this will help to define excess returns what will be beneficial for all studies investigating market efficiency and anomalies in the crypto-market. Furthermore, having one accepted asset pricing model to account for risk does make the results of separate studies easier to compare.

Another interesting direction for future research lies in the area of providing explanations for the momentum anomaly. As mentioned, neither rational explanations nor the behavioural explanations have succeeded to explain the anomaly undoubtedly. Given the differences in both regulation and the spreading of information between the crypto-market and traditional financial markets, rational and behavioural explanations can be tested in a different way in the crypto-market. By proving or ruling out possible explanations for the momentum anomaly more consensus might be reached in this field.

In conclusion, since mixed results have been found in this study it is difficult to make a claim about the existence of the momentum anomaly and the efficiency of the crypto-market. At least to some extent, significant evidence is provided that excess returns can be made using time-series momentum strategies. However, these returns are limited to long-only portfolios. Since there is still a lack of research regarding the momentum anomaly and the cryptocurrency market, a lot of research can still be done in this field. As the cryptocurrency market is still in the early stages it is interesting to see how it will develop in the years to come and whether market anomalies prevailing in the traditional markets will also be found in the crypto-market. If so, this can be seen as yet another claim against the traditional EMH.

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8. Appendix

Appendix A.1

Table A.1

Descriptive statistics of the benchmarks

Benchmarks	Arithmetic average in basis points	Geometric average in basis points	Standard Deviation	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Sharp – Ratio	N =	Starting Date
Equally Weighted	60.17	46.28	0.053	-25.29	64.87	27.98	2.28	2.11	1889	28/04/2013
MarketCapitalization	32.06	22.37	0.044	-24.14	43.83	13.57	0.39	1.38	1889	28/04/2013
CCI30 Index	40.20	31.48	0.042	-23.23	19.52	7.42	-0.35	1.83	1276	01/01/2015
AVERAGE	44.15	33.38	0.047	-24.21	42.74	16.32	0.78	1.77		

Note. The table shows summary statistics for the raw returns of the benchmarks. The arithmetic average, the geometric average, the standard deviation, the minimum, the maximum, the kurtosis, the skewness and the Sharpe-ratio for every cryptocurrency are shown.

Appendix A.2

Table A.2.1

Descriptive statistics of the raw returns of long-short simple TSMOM trading strategies.

Trading Strategy	Arithmetic Average in basis points	Geometric Average in basis points	Standard Deviation	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Sharp-ratio	Positions initiated (N)
TSMOM 1	31.94	20.98	0.047	-38.0	63.28	32.84	1.67	1.28	1888
TSMOM 7	53.55	43.27	0.046	-38.0	60.0	30.81	1.64	2.21	1882
TSMOM 31	51.97	42.15	0.045	-32.37	60.0	33.56	2.15	2.18	1858
AVERAGE	45.82	35.47	0.0463	-36.12	60.87	32.40	1.82	1.89	

Note. The table shows summary statistics for the raw returns of the long-short simple TSMOM trading strategies. The daily arithmetic average, the daily geometric average, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness, Sharpe-ratio and the number of initiated positions for every simple TSMOM trading strategy are shown.

Table A.2.2

Descriptive statistics of the raw returns of long-only simple TSMOM trading strategies.

Trading Strategy	Arithmetic Average in basis points	Geometric Average in basis points	Standard Deviation	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Sharp-ratio	Positions initiated (N)
TSMOM 1	95.26	70.85	0.087	-22.0	256.29	441.204	15.72	2.10	1753
TSMOM 7	80.19	65.27	0.056	-22.0	59.67	17.31	1.79	2.72	1713
TSMOM 31	81.50	64.82	0.60	-25.44	59.67	20.92	2.04	2.60	1673
AVERAGE	85.65	66.98	0.67	-23.13	125.21	159.81	6.52	2.47	

Note. The table shows summary statistics for the raw returns of the long-only simple TSMOM trading strategies. The daily arithmetic average, the daily geometric average, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness, Sharpe-ratio and the number of initiated positions for every simple TSMOM trading strategy are shown. As mentioned, the long-only investor does only take long positions.

Appendix A.3

Table A.3.1
Descriptive statistics of the raw returns of long-short FILTER strategies.

Trading Strategy	Arithmetic Average in basis points	Geometric Average in basis points	Standard Deviation	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Sharp-ratio	Positions initiated (N)
FILTER 0.5%	36.64	25.80	0.047	-38.0	63.28	33.42	1.67	1.47	1888
FILTER 1%	31.91	21.10	0.047	-38.0	63.28	33.57	1.65	1.28	1888
FILTER 1.5%	27.72	16.90	0.047	-38.0	63.28	34.36	1.48	1.12	1888
FILTER 2.0%	26.28	15.57	0.047	-38.0	63.28	35.05	1.57	1.06	1888
FILTER 2.5%	29.31	18.86	0.046	-38.0	63.28	35.74	1.64	1.20	1888
FILTER 5.0%	36.38	25.54	0.047	-38.0	63.28	35.44	1.49	1.47	1888
FILTER 10%	36.26	26.07	0.046	-38.0	63.28	45.65	2.52	1.49	1888
FILTER 20%	30.98	21.20	0.045	-38.0	63,91	48.77	2.90	1.29	1888
AVERAGE	31.94	21.38	0.047	-38.0	63.36	37.75	1.87	1.30	

Note. The table shows summary statistics for the raw returns of the long-short FILTER trading strategies. The daily arithmetic average, the daily geometric average, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness, Sharpe-ratio and the number of initiated positions for every FILTER trading strategy are shown.

Table A.3.2

Descriptive statistics of the raw returns of long-only FILTER strategies.

Trading Strategy	Arithmetic Average in basis points	Geometric Average in basis points	Standard Deviation	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Sharp-ratio	Positions initiated (N)
FILTER 0.5%	100.1	74.48	0.088	-22.47	256.29	418.24	15.17	2.16	1708
FILTER 1%	95.68	70.85	0.087	-21.68	256.29	435.18	15.61	2.09	1718
FILTER 1.5%	94.03	69.19	0.087	-21.68	256.29	439.83	15.54	2.06	1718
FILTER 2.0%	85.43	61.70	0.085	-28.28	256.29	467.32	16.16	1.91	1752
FILTER 2.5%	80.53	55.79	0.086	-35.29	256.29	454.23	15.69	1.78	1715
FILTER 5.0%	78.51	59.62	0.081	-28.28	256.29	564.78	18.27	1.85	1772
FILTER 10%	69.42	48.72	0.081	-28.28	256.29	562.31	18.34	1.63	1810
FILTER 20%	61.64	48.63	0.057	-23.36	86.03	60.39	4.36	2.04	1875
AVERAGE	83.17	61.12	0.0816	-26.16	235.00	425.29	14.89	1.94	

Note. The table shows summary statistics for the raw returns of the long-only FILTER trading strategies. The daily arithmetic average, the daily geometric average, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness, Sharpe-ratio and the number of initiated positions for every FILTER trading strategy are shown. As mentioned, the long-only investor does only take long positions.

Appendix A.4

Table A.4.1

Descriptive statistics of the raw returns of the long-short PPO strategies.

Trading Strategy	Arithmetic Average in basis points	Geometric Average in basis points	Standard Deviation	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Sharp-ratio	Positions initiated (N)
PPO (12,26,0)	52.78	42.91	0.045	-31.79	59.67	31.40	1.87	2.22	1864
PPO (12,26,9)	41.74	32.36	0.043	-38.00	48.76	21.68	0.66	1.82	1856
AVERAGE	47.26	37.64	0.044	-34.90	54.21	26.54	1.26	2.02	

Note. The table shows summary statistics for the raw returns of the long-short PPO trading strategies. The daily arithmetic average, the daily geometric average, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness, Sharpe-ratio and the number of initiated positions for every PPO trading strategy are shown.

Table A.4.2

Descriptive statistics of the raw returns of the long-only PPO strategies.

Trading Strategy	Arithmetic Average in basis points	Geometric Average in basis points	Standard Deviation	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Sharp-ratio	Positions initiated (N)
PPO (12,26,0)	90.76	73.05	0.062	-25.29	59.67	22.17	2.37	2.79	1666
PPO (12,26,9)	89.29	73.75	0.058	-23.46	54.55	18.82	2.29	2.93	1638
AVERAGE	90.02	73.40	0.060	-24.37	57.11	20.50	2.33	2.87	

Note. The table shows summary statistics for the raw returns of the long-only PPO trading strategies. The daily arithmetic average, the daily geometric average, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness, Sharpe-ratio and the number of initiated positions for every PPO trading strategy are shown. As mentioned, the long-only investor does only take long positions.

Appendix A.5

Table A.5.1

Descriptive statistics of the raw returns of all the long-short strategies combined

Trading Strategy	Arithmetic Average in basis points	Geometric Average in basis points	Standard Deviation	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Sharp-ratio
Long-Only	37.50	27.63	0.046	-37.09	61.38	34.79	1.76	1.55

Note. The table shows summary statistics for all the long-short strategies combined. The daily arithmetic average, the daily geometric average, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness, Sharpe-ratio for a combination of all the long-short strategies are shown.

Table A.5.2

Descriptive statistics of the raw returns of all the long-only strategies combined

Trading Strategy	Arithmetic Average in basis points	Geometric Average in basis points	Standard Deviation	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Sharp-ratio
Long-Only	84.79	64.36	0.075	-25.19	182.30	301.75	11.03	2.21

Note. The table shows summary statistics for all the long-only strategies combined. The daily arithmetic average, the daily geometric average, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness, Sharpe-ratio for a combination of all the long-only strategies are shown.

Appendix A.6

Table A.6.1

Descriptive statistics of the long-short excess returns over the Equally-Weighted Benchmark

Trading Strategy	Excess Returns in basis points	Standard Deviation	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Information-Ratio
TSMOM 1	-28.05 (0.0812)*	0.070	-86.06	50.57	35.03	-1.84	-0.04
TSMOM 7	-7.57 (0.6286)	0.068	-76.0	50.57	27.57	-1.61	-0.011
TSMOM 31	-9.90 (0.4654)	0.058	-65.93	41.90	25.19	-1.44	-0.017
FILTER 0.5%	-23.35 (0.1480)	0.070	-86.06	50.57	34.78	-1.77	-0.033
FILTER 1%	-28.07 (0.0821)*	0.070	-86.06	50.57	34.74	-1.76	-0.04
FILTER 1.5%	-32.26 (0.0494)**	0.071	-86.06	50.57	34.73	-1.94	-0.045
FILTER 2.0%	-33.70 (0.0382)**	0.071	-86.06	50.57	35.88	-2.0	-0.048
FILTER 2.5%	-30.67 (0.0564)*	0.070	-86.06	50.57	35.85	-2.07	-0.044
FILTER 5.0%	-23.60 (0.1458)	0.070	-90.69	50.57	39.76	-2.25	-0.033
FILTER 10%	-23.72 (10.91)	0.064	-76.0	50.57	34.07	-1.74	-0.037
FILTER 20%	-29.0 (0.0065) ***	0.046	-76.0	50.57	81.91	-3.04	-0.063
PPO (12,26,0)	-8.95 (0.5234)	0.060	-65.93	41.90	24.41	-1.53	-0.015
PPO (12,26,9)	-20.38 (0.2282)	0.073	-86.06	50.57	31.68	-1.76	-0.028
AVERAGE	-23.02	0.066	-81.0	49.24	36.58	-1.90	-0.035

Note. The table shows summary statistics for the excess returns of the long-short trading strategies over the equally-weighted benchmark. The average excess returns in basis points, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness and the information-ratio are shown. P-values are included between brackets. Significant values are indicated by the asterisks (* = p < 0.1, ** = p < 0.05, *** = p < 0.01)

Table A.6.2

Descriptive statistics of the long-short excess returns over the Market Capitalization Benchmark

Trading Strategy	Excess Returns in basis points	Standard Deviation	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Information-Ratio
TSMOM 1	0.246 (0.9874)	0.068	-71.17	61.68	26.24	-0.246	0.0004
TSMOM 7	20.77 (0.1659)	0.065	-71.17	49.43	18.94	-0.406	0.032
TSMOM 31	19.46 (0.1422)	0.057	-38.02	38.84	12.13	0.127	0.034
FILTER 0.5%	4.95 (0.7524)	0.068	-71.17	61.68	26.07	-0.246	0.007
FILTER 1%	0.219 (0.9888)	0.068	-71.17	61.68	26.32	-0.224	0.0003
FILTER 1.5%	-3.97 (0.8003)	0.068	-71.17	61.68	26.26	-0.26	-0.006
FILTER 2.0%	-5.40 (0.7279)	0.068	-71.17	61.68	26.81	-0.243	-0.008
FILTER 2.5%	-2.38 (0.8774)	0.067	-71.17	61.68	26.75	-0.292	-0.004
FILTER 5.0%	4.69 (0.7638)	0.068	-74.86	61.68	29.18	-0.458	0.007
FILTER 10%	4.57 (0.7519)	0.063	-71.17	61.68	27.23	-0.043	0.007
FILTER 20%	-0.708 (0.9506)	0.05	-71.17	62.32	51.6	0.3209	-0.001
PPO (12,26,0)	20.14 (0.1400)	0.059	-38.71	39.46	13.18	-0.056	0.034
PPO (12,26,9)	9.06 (0.5690)	0.069	-71.17	49.43	22.64	-0.619	0.013
AVERAGE	5.51	0.064	-66.41	56.38	25.64	-0.203	0.009

Note. The table shows summary statistics for the excess returns of the long-short trading strategies over market-capitalization benchmark. The average excess returns in basis points, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness and the information-ratio are shown. P-values are included between brackets. Significant values are indicated by the asterisks (* = p < 0.1, ** = p < 0.05, *** = p < 0.01)

Table A.6.3

Descriptive statistics of the long-short excess returns over the CCI30 Index Benchmark

Trading Strategy	Excess Returns in basis points	Standard Deviation	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Information-Ratio
TSMOM 1	-24.36 (0.1257)	0.057	-32.51	46.34	14.53	0.243	-0.043
TSMOM 7	10.36 (0.5139)	0.057	-35.62	46.34	15.22	0.402	0.018
TSMOM 31	6.23 (0.6638)	0.051	-32.21	35.78	13.15	-0.04	0.012
FILTER 0.5%	-17.98 (0.2639)	0.057	-34.84	46.34	14.96	0.34	-0.031
FILTER 1%	-20.40 (0.2078)	0.058	-34.84	46.34	14.87	0.385	-0.035
FILTER 1.5%	-22.78 (0.1581)	0.058	-34.84	46.34	15.13	0.43	-0.04
FILTER 2.0%	-20.53 (0.1992)	0.057	-34.88	46.34	15.15	0.55	-0.036
FILTER 2.5%	-19.10 (0.2227)	0.056	-34.88	39.92	14.28	0.53	-0.034
FILTER 5.0%	-10.62 (0.4800)	0.054	-34.88	35.83	14/24	0.33	-0.02
FILTER 10%	-11.96 (0.3932)	0.05	-34.88	38.31	16.09	-0.03	-0.024
FILTER 20%	-20.10 (0.0341)**	0.034	-26.99	18.93	13.5	-1.07	-0.059
PPO (12,26,0)	11.26 (0.4401)	0.052	-34.84	35.78	13.41	-0.09	0.022
PPO (12,26,9)	-2.76 (0.8674)	0.059	-35.62	46.34	13.91	0.451	-0.005
AVERAGE	-10.98	0.054	-33.99	40.69	14.50	0.188	-0.021

Note. The table shows summary statistics for the excess returns of the long-short trading strategies over the CCI 30 index benchmark. The average excess returns in basis points, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness and the information-ratio are shown. P-values are included between brackets. Significant values are indicated by the asterisks (* = p < 0.1, ** = p < 0.05, *** = p < 0.01)

Appendix A.7

Table A.7.1

Descriptive statistics of the long-only excess returns over the Equally-Weighted Benchmark.

Trading Strategy	Excess Returns in basis points	Standard Deviaton	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Information-Ratio	(N)
TSMOM 1	32.51 (0.0233)**	0.06	-38.16	191.42	596.4	18.95	0.054	1753
TSMOM 7	21.80 (0.065)***	0.033	-37.07	22.35	21.27	-0.40	0.066	1713
TSMOM 31	21.15 (0.0100)**	0.034	-32.97	52.41	55.13	2.54	0.063	1673
FILTER 0.5%	37.89 (0.0104)**	0.061	-34.82	191.42	568.11	18.41	0.062	1708
FILTER 1%	32.93 (0.0250)**	0.061	-34.82	191.42	573.40	18.48	0.054	1718
FILTER 1.5%	31.55 (0.0315)**	0.061	-34.71	191.42	576.27	18.39	0.052	1718
FILTER 2.0%	24.60 (0.872)*	0.06	-34.71	191.42	589.32	18.69	0.041	1752
FILTER 2.5%	22.34 (0.1176)	0.059	-34.71	191.42	643.11	19.84	0.038	1715
FILTER 5.0%	13.58 (0.3128)	0.047	-34.44	191.42	738.70	21.66	0.024	1772
FILTER 10%	7.27 (0.5624)	0.053	-32.04	191.42	917.10	25.25	0.014	1810
FILTER 20%	0.06 (0.9904)	0.023	-32.74	26.36	53.57	0.165	0.0002	1875
PPO (12,26,0)	31.91 (0.0004)***	0.037	-33.00	52.41	47.82	2.678	0.087	1666
PPO (12.26,9)	20.37 (0.0276)**	0.037	-35.28	42.77	32.49	0.925	0.054	1638
AVERAGE	22.92	0.049	-34.58	132.90	416.36	12.74	0.047	

Note. The table shows summary statistics for the excess returns of the long-only trading strategies over the equally-weighted benchmark. The average excess returns in basis points, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness, the information-ratio and number of initiated positions (N) are shown. P-values are included between brackets. Significant values are indicated by the asterisks (* = p < 0.1, ** = p < 0.05, *** = p < 0.01)

Table A.7.2

Descriptive statistics of the long-only excess returns over the Market-Capitalization Benchmark

Trading Strategy	Excess Returns in basis points	Standard Deviaton	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Information-Ratio	(N)
TSMOM 1	59.93 (0.0017)***	0.080	-20.29	254.59	592.39	19.41	0.075	1753
TSMOM 7	47.67 (0.000)***	0.045	-20.29	31.39	11.62	1.59	0.105	1713
TSMOM 31	48.12 (0.000)***	0.046	-19.94	67.52	37.54	3.32	0.104	1673
FILTER 0.5%	66.47 (0.0007)***	0.081	-19.03	254.69	582.82	19.26	0.082	1708
FILTER 1%	60.75 (0.0018)***	0.081	-19.94	254.69	583.78	19.24	0.075	1718
FILTER 1.5%	59.76 (0.0019)***	0.079	-19.94	254.69	612.48	19.69	0.075	1718
FILTER 2.0%	52.52 (0.0050)***	0.078	-28.35	254.69	640.45	20.23	0.067	1752
FILTER 2.5%	48.69 (0.0099)***	0.078	-28.35	254.69	657.61	20.59	0.062	1715
FILTER 5.0%	43.29 (0.0146)**	0.075	-28.35	254.69	766.34	22.77	0.058	1772
FILTER 10%	37.44 (0.0268)**	0.072	-28.35	254.69	867.64	24.72	0.052	1810
FILTER 20%	29.42 (0.0027)***	0.042	-20.94	84.26	101.84	6.29	0.069	1875
PPO (12,26,0)	60.08 (0.000)***	0.049	-19.94	67.52	3.63	3.63	0.122	1666
PPO (12.26,9)	51.15 (0.000)***	0.048	-18.88	45.98	2.75	2.75	0.107	1638
AVERAGE	51.18	0.066	-22.51	179.55	14.11	14.11	0.081	

Note. The table shows summary statistics for the excess returns of the long-only trading strategies over the market-capitalization benchmark. The average excess returns in basis points, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness, the information-ratio and number of initiated positions (N) are shown. P-values are included between brackets. Significant values are indicated by the asterisks (* = p < 0.1, ** = p < 0.05, *** = p < 0.01)

Table A.7.3

Descriptive statistics of the long-only excess returns over the CCI30 Index Benchmark

Trading Strategy	Excess Returns in basis points	Standard Deviaton	Minimum (%)	Maximum (%)	Kurtosis	Skewness	Information-Ratio	(N)
TSMOM 1	24.69 (0.0309)**	0.040	-19.52	35.15	16.27	1.76	0.061	1255
TSMOM 7	33.60 (0.0012)***	0.037	-19.52	22.06	11.22	1.03	0.092	1241
TSMOM 31	31.33 (0.0005)***	0.032	-15.82	24.13	10.89	0.999	0.099	1233
FILTER 0.5%	29.80 (0.0137)**	0.042	-19.42	29.78	12.85	1.72	0.070	1230
FILTER 1%	22.27 (0.0620)*	0.042	-19.42	30.24	12.90	1.54	0.053	1235
FILTER 1.5%	23.59 (0.0593)*	0.044	-19.42	42.71	19.80	2.18	0.054	1236
FILTER 2.0%	24.29 (0.0547)*	0.045	-17.48	57.95	35.14	3.11	0.054	1259
FILTER 2.5%	19.74 (0.1013)	0.042	-17.48	46.27	21.57	2.27	0.047	1223
FILTER 5.0%	13.46 (0.1737)	0.035	-17.48	24.65	10.46	0.96	0.038	1261
FILTER 10%	15.44 (0.0977)*	0.033	-18.77	39.57	12.63	0.80	0.046	1272
FILTER 20%	15.58 (0.0781)*	0.032	-17.93	37.94	28.28	2.50	0.049	1276
PPO (12,26,0)	37.16 (0.0001)***	0.033	-15.22	29.17	15.28	1.53	0.113	1225
PPO (12.26,9)	39.64 (0.0011)***	0.042	-14.97	42.71	27.81	2.98	0.095	1196
AVERAGE	25.43	0.038	-17.88	34.79	18.08	1.80	0.067	

Note. The table shows summary statistics for the excess returns of the long-only trading strategies over the CCI30 index benchmark. The average excess returns in basis points, the daily standard deviation, the minimum, the maximum, the kurtosis, the skewness, the information-ratio and number of initiated positions (N) are shown. P-values are included between brackets. Significant values are indicated by the asterisks (* = p < 0.1, ** = p < 0.05, *** = p < 0.01)

Table A.8
Results of comparing the long-short strategies and long-only strategies

		Long-Short Strategy		Long-Only Strategy		
	N =	Mean in basis points	Standard Deviation	Mean in basis points	Standard Deviation	P-value
Raw Return	13	37.50	0.0009	84.79	0.0011	(0.0000)***
Excess Return EW	13	-23.02	0.0009	22.92	0.0011	(0.0000)***
Excess Return MC	13	5.51	0.0009	51.18	0.0010	(0.0000)***
Excess Return CCI	13	-10.98	0.0012	25.43	0.0008	(0.0000)***
	N =	Mean	Standard Deviation	Mean	Standard Deviation	
Information - Ratio	39	-0.016	0.026	0.065	0.027	(0.0000)***