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Price momentum in the cryptocurrency markets

Bachelor Thesis Financial Economics

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Abstract

This thesis examines the existence of cross-sectional price momentum in the cryptocurrency markets. Cryptocurrencies are a very new type of asset class, of which only little data is available and to which little research has been done so far. The main research question of this thesis is: '*Do price momentum strategies exist in the cryptocurrency markets?'* By making use of a large data set that explicitly takes into account a potential survivorship bias, multiple momentum strategies are tested. The results show positive and significant returns for the short term momentum strategies. The results of the medium term strategies are not significant. The risk-adjusted average returns (alphas) of the strategies are calculated based on different benchmarks. The alphas of the short term momentum strategies are also positive and significant, the alphas for the medium term strategies are again not significant. This shows that there is price momentum in the cryptocurrency markets on the short term, but not on the medium term.

Key words: Cryptocurrencies; Cross-sectional momentum; Factor investing; Momentum; Bitcoin; Blockchain

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I. Introduction

The revolutionary blockchain technology and its capabilities have increasingly come under the attention of the mainstream media and of an increasing amount of people over the past few years. The technology has a lot of (potential) application possibilities and has undergone a true hype. Cryptocurrencies are one of these applications of blockchain technology that have had an explosive growth and increase in attention over the past few years, with Bitcoin being the most well-known cryptocurrency and probably even the most well-known blockchain application of all. In fact, the technology created a whole new asset class, existing for only a few years. This asset class rapidly developed itself to the point where it is now, with numerous easily accessible exchanges and the possibility of trading hundreds of different cryptocurrencies. It is still a very new and unexplored asset class and future development of the blockchain technology and the cryptocurrency markets will have to show how this new asset class will eventually be used in practice.

Factor investing, and more specifically the momentum factor, are thoroughly researched topics in the investment world since the groundbreaking work of Fama and French (1992). There is plenty of literature and research on factor investing and the momentum factor to traditional asset classes. The momentum factor has indicated to be profitable across a wide variety of asset classes. For example, Jegadeesh and Titman (1993) were the first to study momentum strategies in the US stock market, Rouwenhorst (1998) studied momentum strategies in stock markets in an international context and Menkhoff, Sarno and Schmeling (2012) investigated momentum strategies in the foreign exchange markets.

But it is this new asset class of cryptocurrencies that is interesting to take as subject of a study to momentum strategies. Only little financial research to cryptocurrencies is available. Next to this, most of the research that has been done is based on a very small amount of data. For example, Hubrich (2017) conducted research on factor investing and momentum in the cryptocurrency world but he seems to fail to take into account a survivorship bias in the data that he uses. Bianchi (2018) investigates the aggregate relationship between cryptocurrencies and standard asset classes, but his data sample consists of only one and a half year of data. Bringing together the well-known price momentum strategies and the new world of cryptocurrencies is highly interesting. Empirically testing whether these momentum strategies also exist in a newly arisen asset class can shed new light on the reasons for the existence of the momentum factor in general. Next to this, it can give potential profitable trading strategies in the cryptocurrency market, which will be even more valuable in case this market continues to develop in the future. Consequently, the former has led to the following research question for this thesis: *'Do price momentum strategies exist in the cryptocurrency markets?'*

The contribution of this thesis to the literature is threefold. First, this thesis connects the well-established topic of momentum strategies with the emerging world of and studies to cryptocurrencies. Second, by using a large dataset that entails almost all data on cryptocurrencies this thesis goes beyond earlier research on cryptocurrency momentum. Third, this thesis explicitly takes into account a potential survivorship bias problem.

The remainder of this thesis is organized as follows. Section II explains what price momentum is and gives an overview of the existing research to momentum strategies in traditional asset classes as well as to momentum strategies in cryptocurrencies. Section III extensively describes the sample and the data that is used in order to conduct the research. Section IV describes the methodology that is used. Section V presents the results. Section VI discusses the results and compares them to earlier research. Section VII provides the conclusions and limitations of this thesis.

II. Relevant literature

Price momentum in general

Factor investing is a widely discussed and profoundly researched topic in the investment world. For example, Ang, Goetzmann and Scheafer (2009) wrote an extensive report about active asset management and factor investing to the Norwegian Ministry of Finance. A factor can be described as a certain characteristic relating to a group of securities that is important in explaining the returns and the risk of that group of securities. Factor investing is the process of investing that aims to yield returns through exposure to these certain factors. The current most well-known factors are value, low size, low volatility, high yield, quality and momentum. The momentum factor has shown to be profitable across a wide variety of asset classes, which will be discussed later in this section. Since cryptocurrencies are a very new kind of investment class, it is highly relevant to investigate whether momentum strategies are also present in the cryptocurrency markets. Testing whether such a well-established factor is also present in this new asset class may provide new information about the factor in general. The former being the reason to focus on the momentum factor in this thesis. The momentum factor reflects future excess returns to stocks (or other assets) with stronger past performance. There are two types of momentum: cross-sectional momentum and time series momentum, both of which will be explained in more detail later on. The cross-sectional momentum factor can be described as a trading strategy that yields excess returns by buying assets with a strong past performance (winners) and selling assets with a bad past performance (losers), relative to each other. The theory underlying the momentum factor, or the reason for its existence, is still matter of discussion. There is no unifiable theory that is able to explain the momentum factor. Most of the theories that try to explain momentum are behavioral explanations. These theories state that (irrational) investors either under- or overreact to information that reaches the markets, which both can lead to the presence of a momentum effect. A few common criticisms of momentum strategies are the phenomenon of data mining and the risk of sudden reversals that these strategies bear (Bender, Briand, Melas, & Subramanian, 2013).

Momentum research to traditional asset classes

Jegadeesh and Titman (1993) were among the first to study momentum or relative strength strategies. They examine the existence of momentum strategies over 3- to 12 month horizons in the US stock market in the period 1965-1989. They show that certain of these strategies generate significant positive returns. They consider strategies that select stocks based on their returns over the past 1, 2, 3 or 4 quarters (look-back period) and they also consider a holding period of 1, 2, 3 or 4 quarters, referring to these strategies as a J-month/K-month strategy. This way they test a total of 16 strategies. At the beginning of each month they rank all the stocks based on their returns over the past J months. Based on this ranking they create ten decile portfolios and the strategy buys the winning portfolio and (short)sells the losing portfolio, holding the position for K months. Next to this, they examine a second set of 16 strategies, where one week is skipped in between the formation of the portfolio and the holding period. The reason to skip this one week is to avoid some of the bid-ask spread and price pressure. The examined trading strategies that buy past winners and sell past losers generate significant excess returns. The strategy that they examined in most detail is the strategy that selects stocks based on their past 6-month performance and holds these stocks for 6 months and does not skip a week between the formation and holding period. The average monthly return of this strategy was 0.95%, an average excess return of 12.01% per year.

Rouwenhorst (1998) examines price momentum strategies in an international context. Just like Jegadeesh and Titman (1993), he focuses only on medium term return patterns (3- to 12-month horizon). Rouwenhorst uses a sample of 2190 stocks from 12 European countries in the period 1978-1995. He uses the same methods as Jegadeesh and Titman (1993) to construct the momentum portfolios. The main conclusion of this paper is that an internationally diversified portfolio that buys past winners and sells past losers earns about 1% per month. This conclusion holds for all the 12 markets used in the sample. Furthermore, Rouwenhorst concludes that his findings about international momentum strategies are very similar to the results of Jegadeesh and Titman (1993) regarding momentum strategies in the United States and that those results are not simply due to luck.

Menkhoff, Sarno and Schmeling (2012) investigate momentum strategies in the foreign exchange market. They mention that there are some important differences between foreign exchange markets and stock markets, including the absence of short-selling constraints, the higher liquidity, large traded volumes, low transaction costs and the high population of professional investors in the foreign exchange markets. The data used in their research covers the sample period from January 1976 to January 2010 and consists of a total of 48 countries. The momentum portfolios are constructed at the end of each month, where six portfolios are formed based on the lagged returns of the previous 1, 3, 6, 9 or 12 months and these portfolios are held for the same number of months. The portfolios are long in the winner currencies and short in the loser currencies. Their results show that currency momentum strategies generate high abnormal excess returns of about 6 - 10% per year for the shorter holding period of one month and that the returns decrease for longer holding periods. Nevertheless, momentum strategies with longer holding periods also yield significant excess returns. Next to this, they find that momentum profits are mostly due to minor currencies that have relatively high transaction costs and bear higher country risks. Furthermore, they conclude that the currency momentum profits are highly time varying.

Raza, Marshall and Visaltanachoti (2014) investigate whether momentum strategies exist in weekly foreign exchange returns, rather than on a medium term horizon like Menkhoff et al. (2012). They use weekly and monthly data of a total of 63 currencies of emerging and developed markets in the period November 1997 to July 2013 to examine momentum strategies based on a 1-4 week look-back (J) and holding period (K). For each look-back period, 1, 2, 3 or 4 weeks, they construct a winner (long) and a loser (short) portfolio based on the 20% best and worst performing currencies of the considered look-back period and they hold this portfolio for 1, 2, 3 or 4 weeks as well. This yields a total of 16 strategies to examine. Their methodology is basically the same as used by Jegadeesh and Titman (1993), with the difference being, as said, that they use weekly returns rather than monthly returns. This way of investigating momentum strategies on a weekly basis is of particular interest for research to momentum strategies for cryptocurrencies, that will be discussed later in this section. Their results show strong evidence of short term momentum in foreign exchange markets. All of the 16 strategies generate positive abnormal returns, which range from 1.84% (1,1 strategy) to 8.60% (4,4 strategy) per year. The returns are lowest for strategies that have a 1 week look-back period and highest for strategies with a 3 to 4 week look-back period. Increasing the look-back period increases the momentum returns.

All of the above mentioned papers investigated the so-called cross-sectional momentum strategies. Moskowitz, Ooi and Pedersen (2012) came up with a different momentum strategy, called time series momentum. This is related to, but not the same as cross-sectional momentum. Both momentum strategies select stocks (or other assets) based on their past performance. The difference between the two types of momentum strategies is that cross-sectional momentum selects securities based on their *relative* performance, whereas time series momentum selects securities based on their *own* or absolute past performance. Moskowitz et al. (2012) examine futures prices of 24 different commodities, 12 cross-currency pairs, 9 equity indexes and 13 developed government bonds. Their sample period is from January 1965 to December 2009. The time series momentum trading strategies that they examine are constructed based on a varying number of months for the look-back period as well as for the holding period. For every security that they examine, they calculate whether its excess return based on the look-back period is positive or negative. If the securities' excess return is positive, they take a long position and if the securities' excess return is negative, they take a short position in the security. Their results show that a diversified portfolio of time series momentum strategies yields significant abnormal excess returns across all the asset classes that they consider. They notice that cross-sectional momentum and time series momentum are significantly related (though still different) and that the driving force behind both of the strategies is the auto-covariance of returns.

Goyal and Jegadeesh (2015) examine the differences between time series momentum strategies and cross-sectional momentum strategies in further detail. They find some significant differences in returns between the two strategies. Their analysis of these differences suggest that time series strategies partly exist of a net-zero long/short strategy (as with a cross-sectional strategy) and partly exists of a time-varying long position in the market index. The returns of a time series momentum strategy that are generated by this investment in a market portfolio are due to the additional risk that this bears and to market timing.

Momentum research to cryptocurrencies

Hubrich (2017) is among the first to study cryptocurrency returns. More specifically, he conducted research on factor investing in the cryptocurrency world. He investigated the momentum, value and carry factor. He considers both single factor and multi factor portfolios and concludes that multi factor portfolios perform better. Furthermore, he looks at both the cross-sectional and longitudinal (time series) dimension of the factors. An important factor of this paper to mention, is the data that is used. Hubrich uses data of 11 cryptocurrencies of which data is available per September 2017, of these 11 currencies only a few have more than 4 years of data available. This way of data selecting does not seem to take into account a potential survivorship bias problem. It selects currencies that by definition have survived the entire sample period (the selection takes place at the end of the sample period), while not taking into account the risk that cryptocurrencies may stop to exist somewhere during the sample period. This is known as a 'survivalship bias', since it only considers the securities that have survived the sample period. Not taking into account a survivalship bias may lead to spurious results (Brown, Goetzmann and Ross, 1995). However, he does take the different sample length of individual cryptocurrencies into account to avoid a hindsight benefit by allowing portfolios to grow overtime. He only starts building the portfolios once at least four currencies are available for investment. Another important factor of this paper to mention is the fact that only 10% of the portfolios are invested and that the remaining 90% is held in cash. Hubrich argues that because of the extremely high volatility of cryptocurrencies it is better to construct portfolios based on a look-back period and holding period of one week. He makes the following comparison to argue for this choice: "As an illustration, we can think of typical asset classes as large mammals like lions or horses, with slow metabolism and low heart rates. By contrast, cryptocurrencies are mice and chipmunks – their hearts beat faster, and their metabolism is much quicker." He views the weekly rhythm for the "fast metabolism" cryptocurrency market as the rough equivalent of monthly analysis in traditional asset classes. Since cryptocurrency markets continue during weekends and holidays, one week entails seven days. Next to this, cryptocurrency trading continues for 24 hours a day, so one trading day on the cryptocurrency markets is three times longer than a trading day on the traditional equity markets. Although most of the momentum research to traditional asset classes is based on monthly returns, using weekly data to construct portfolios and test for momentum strategies is in line with Raza et al. (2014) examining short term momentum strategies in foreign exchange markets as mentioned in the previous section. Next to this, Hubrich mentions that cryptocurrencies cannot yet be sold short at scale, but that it nevertheless is still relevant to include both long and short portfolios. This seems plausible, since short selling will become more available once cryptocurrency markets will continue to develop. The main conclusion of Hubrich's paper is that the momentum factor has the most favorable individual performance, with the time series momentum generating an average annualized return of 6.3% and cross-sectional momentum generating an average annualized return of 5.6%. Hubrich reports a Sharpe ratio of 0.91 for the cross-sectional momentum strategy and a Sharpe ratio of 0.77 for the time series momentum strategy. However, since only 10% of the portfolios is invested, these results seem misleading. With a fully invested portfolio, the time series momentum would have generated an average annualized return of 63% and for the cross-sectional momentum this would have been 56%.

Bianchi (2018) investigates the aggregate relationship between cryptocurrencies and standard asset classes and tries to find the driving factors behind market activity on the short and medium term. However, he does not investigate the existence of momentum effects in cryptocurrencies. The main data sample that he uses consists of 1251 cryptocurrencies that are quoted from April 2016 to September 2017. He filters this sample based on market capitalization and average weekly traded volume to obtain his final data sample. He eliminates those currencies that have a market capitalization that is below the top 5th percentile at the end of the sample and those currencies that have an average traded volume below the sample median. This yields a final sample of 14 cryptocurrencies. To investigate the relationship between cryptocurrencies and traditional asset classes, Bianchi uses proxies for the equity, bond, real estate, energy, gold, options and foreign exchange markets to test for these relationships. He finds that only the returns on commodities as energy and gold have some systematic correlations with cryptocurrencies. Furthermore, Bianchi investigates the relationship between volatility and volume for cryptocurrencies and traditional asset classes. He finds that risk in cryptocurrencies does not correlate with risk in other asset classes and that volume does not cause volatility. Or in other words, that market activity does not significantly drives volatility. Next to this, Bianchi investigates causal relationships between realized returns and traded volumes. His results suggest that trading activity in cryptocurrency markets is primarily driven by past performance of cryptocurrencies rather than by macroeconomic factors.

Rohrbach, Suremann and Osterrieder (2017) study momentum trading strategies for global currency markets and for cryptocurrencies. They study both time series momentum as well as cross-sectional momentum for cryptocurrencies. The sample period however, consists of only 18 months and includes 7 cryptocurrencies. Their results show an annualized return of 42.02% for the time series portfolio and an annualized return of 56.94% for the cross-sectional portfolio. The reported Sharpe ratios are 1.48 and 1.68, respectively. Hence, they conclude that there is a lot of momentum in cryptocurrencies and that cross-sectional momentum portfolios seem to be better working for cryptocurrencies. This is contrary to the findings of Hubrich (2017), who concludes that time-series momentum strategies generate higher returns for cryptocurrencies. At first sight it may seem that the results of Rohrbach et al. (2017) are much higher than the initially mentioned results of Hubrich (2017) (42.02% vs. 6.3% for time series momentum and 56.94% vs. 5.6% for cross-sectional momentum). But as mentioned earlier above, the results of Hubrich are based on portfolios that are invested for only 10%. When accounting for this, the results of Rohrbach et al. (2017) and Hubrich (2017) are actually quite close (42.02% vs. 63% for time series momentum and 56.94% vs. 56% for cross-sectional momentum).

Kakushadze (2018) creates a model to test for different factors in daily cryptocurrency returns. He considers four factors: a size factor (based on market cap), an intraday volatility factor, a volume factor and a momentum factor. The momentum factor, the most interesting factor for this thesis, is defined as the previous day's open-to-close return. The results show that the momentum factor (based on the one day prior returns) is by far the best predicting factor. The momentum factor shows mixed results when considering look-back periods of more than one day. However, these results are based on regression t-statistics, in his paper Kakushadze does not give any percentage returns. The regression coefficients of the momentum factor are negative, which indicates that there is a mean-reversion effect in the daily momentum returns. The most interesting part of the paper of Kakushadze (2018), however, is the data that he uses. He selects all cryptocurrencies that have downloadable and complete data as of August 19, 2018 and goes back one year plus 21 days for an out-of-sample period. This gives him a total of 362 cryptocurrencies. This way of data selecting, just as in Hubrich (2017), does not seem to take into account a possible survivorship bias. This data selection method, again, can lead to spurious results.

III. Data

The data that is used in this thesis is weekly data. The data sample period that is used covers the period from the first week of January 2014 until the start of May 2018. This means that the sample consists of 226 weeks of data, with week 1 being the first week of January 2014 and week 226 being the last week of April 2018. This is almost 4.5 years of data. This is a fairly long sample period compared to the earlier research of Bianchi (2018), who uses a sample period from April 2016 to September 2017 and Rohrbach et al (2017) who uses a period of 18 months. The sample period used in this thesis entails almost all available data on cryptocurrencies. Cryptocurrencies exist for only a short period of time. The only data left out of the sample period is the data that is available for 2013, with April 28 being the first available data point. The reason for letting out 2013 is that there are too little cryptocurrencies available in the market, which does not fit with the trading strategies to be tested in this thesis. All data is retrieved from the website coinmarketcap.com. This is one of the most used sources for cryptocurrency (price) information. It uses price information of multiple worldwide exchanges to quote a weighted average price for all the cryptocurrencies available in the market.

The weekly data gives an overview of the complete market situation for each week. The historical weekly rankings based on market capitalization are available, as well as the total market capitalization, the price, the total circulating supply, the 24 hour volume, the 1- and 24 hour performance and the 7 day performance for each cryptocurrency in the market for every particular week.

Over the past years the cryptocurrency market has developed significantly, with Bitcoin being by far the most dominant currency in the market. For example, the total market capitalization, the 24 hour market volume and the total amount of cryptocurrencies available in the market have increased with large numbers. The total cryptocurrency market cap increased from 11,956 million dollar to 434,787 million dollar since the start of 2014. These developments are shown below in figure 1 and 2, respectively. Next to this, a numerical yearly overview since the start on 28 April 2013 of the total market capitalization and the total amount of cryptocurrencies, together with the market dominance of Bitcoin is shown in table 1. Furthermore, to construct the dataset, I looked at the market situation for every individual week. I selected the cryptocurrencies in the top 5th percentile based on market capitalization ranking per week. With this way of looking at the weekly varying market situations, a potential survivorship bias problem is explicitly taken into account. Because of the fact that the total amount of cryptocurrencies is still small at the beginning of the sample, I decided to set the minimum amount of currencies to select per week to twenty. This way the weekly amount of selected currencies increases gradually during the sample period and gives a meaningful and not a too small or big amount of weekly selected currencies to test different momentum strategies. So, if the top 5th percentile did not yield a total amount of 20 currencies for a specific week, I selected the top 20 currencies based on market capitalization for that week. Starting from week 35 (August 31, 2014), the total amount of cryptocurrencies in the market was sufficient to yield a total of at least 20 currencies per week based on the top 5th percentile criterium. As opposed to taking a fixed market cap as the weekly selection criterium, taking the top 5th percentile yields a more diversified and equally distributed sample. Next to this, determining which fixed market capitalization to use as a criterium is very arbitrary.

Logically, as the total amount of currencies increased during the sample period (see figure 2), the amount of weekly selected currencies increased as well during the sample period. The largest amount of weekly selected currencies is 78, for weeks 226 (April 29, 2018), 222 (April 22, 2018) and 221 (March 25, 2018). The highest, lowest and median market capitalization for the currencies selected in week 1 are \$10,543,005,152 (Bitcoin), \$3,840,618 (Anoncoin) and \$18,130,469 (Megacoin), respectively. For week 226, the final week of the sample period, these numbers are \$159,921,919,639 (Bitcoin), \$269,063,490 (Cortex) and \$696,976,539 (Stratis). This, again, shows the huge development of the cryptocurrency markets over the sample period. In total, a number of 242 different cryptocurrencies come across in the sample period.

Figure 1:
Total cryptocurrency market capitalization development Jan '14 - May '18 (retrieved from coinmarketcap.com).

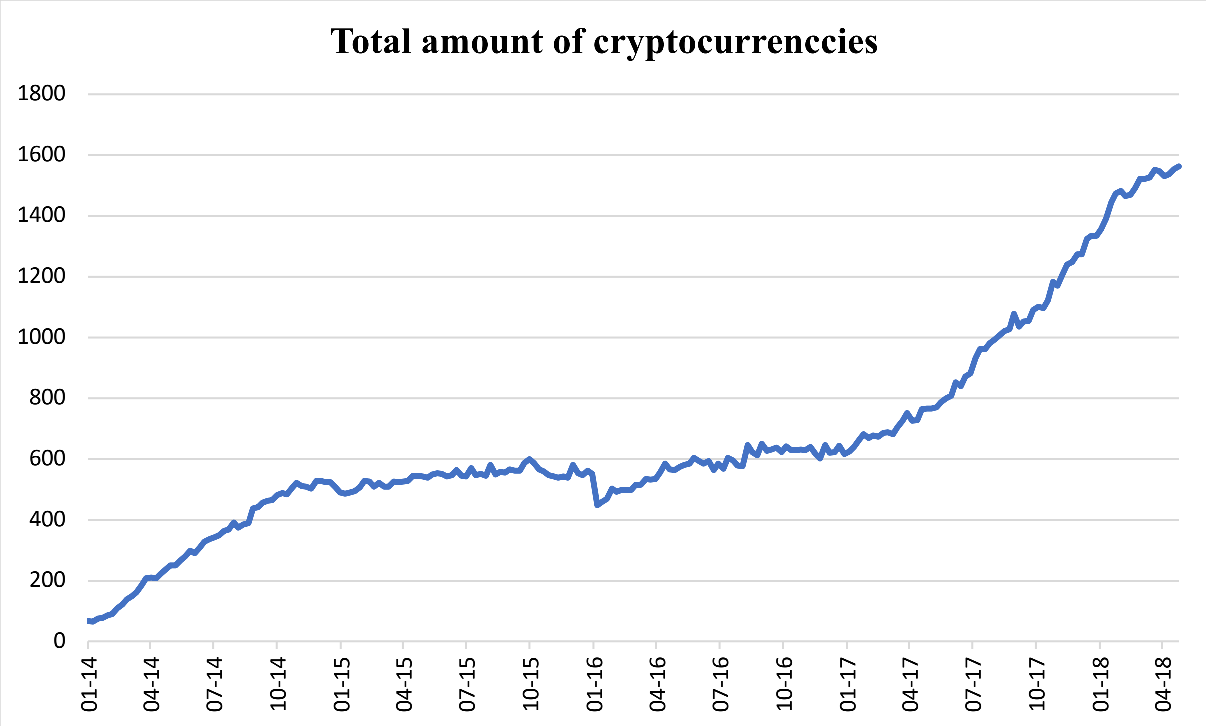

Figure 2:
Development of the total amount of cryptocurrencies available on the market during the sample period (number of currencies on the Y-axis, date on the X-axis).

Table 1*:*
Numerical yearly cryptocurrency market development overview.

Year:	Total market cap (in millions):	Bitcoin dominance:	Amount of cryptocurrencies:
(28-4) 2013	$1,596	94.2%	7
2014	$11,956	88.18%	67
2015	$4,843	79.62%	491
2016	$7,093	91.48%	551
2017	$17,700	87.47%	617
(29-5) 2018	$434,787	36.78%	1563

IV. Methodology

The methodology used in this thesis is based on that of Jegadeesh and Titman (1993) and that of Raza et al. (2014). Multiple short term and medium term strategies are considered to examine the existence of cross-sectional momentum strategies in the cryptocurrency markets. The strategies have look-back periods of 1, 2, 4, 8, 12, 26 or 52 weeks (J), while keeping the holding period (K) constant to one week. This way, a total number of seven different strategies are considered. The holding period is kept constant to one week because of the fact that the cryptocurrency markets do not exist for so long. Hence, as mentioned earlier in this thesis, the amount of data on cryptocurrencies is limited. Although 4.5 years of data is a fairly long period for research to cryptocurrencies, it is still very little compared to research on traditional asset classes where they also consider multiple holding periods. By keeping the holding period constant to one week the total number of observations stays sufficiently large.

The momentum portfolios are constructed by weekly ranking all the cryptocurrencies based on their performance of the past J weeks. For every look-back period, 1, 2, 4, 8, 12, 26 or 52 weeks, a winner and a loser portfolio are constructed. Just like the methodology of Raza et al. (2014), the winner portfolio is based on the 20% best performing cryptocurrencies of the considered look-back period and the loser portfolio is based on the 20% worst performing cryptocurrencies of the considered look-back period. The strategies go long in the winner portfolio and short in the loser portfolio, to create a zero cost strategy, and hold the portfolios for one week. In formula, the portfolio construction looks as follows:

$$R_{pt} = \sum_{i=1}^{I} W_{i,t-J} \, R_{it} \qquad (1)$$

$$W_{i,t-J} = \frac{1}{N_{t-J}} \qquad (2)$$

Where R_{pt} is the portfolio return of the considered momentum strategy and R_{it} are the returns of the individual selected cryptocurrencies. N_{t-J} is the number of cryptocurrencies selected based on the 20% best or worst performing cryptocurrencies of the considered look-back period.

Although cryptocurrencies cannot yet be sold short at scale, it is nevertheless still relevant in light of future developments to include both long and short portfolios. Also, whether the strategies can be exploited in practice is a different question than whether a pattern exists in the returns of cryptocurrencies. Next to the limitation of short selling cryptocurrencies, the practical implementation for example also depends on transaction costs.

After the results are gathered, the next step is to calculate and analyze the risk-adjusted average returns (alphas) of the considered cross-sectional momentum strategies. I will first briefly explain Jensen's alpha, i.e. alpha in the context of the Capital Asset Pricing Model (CAPM). Simply stated in words, Jensen's alpha is a measure of portfolio performance. It denotes the return of a portfolio, or any security, in excess of the (theoretical) expected rate of return of that portfolio based on the CAPM. The formula of the CAPM is as follows:

$$E(R_j) = R_f + \beta_j\left[E(R_m) - R_f\right] \qquad (3)$$

Where $E(R_j)$ is the expected return of a portfolio (or any other security), R_f is the risk free (interest) rate, β_j is the measure of systematic risk of the portfolio and $E(R_m)$ is the expected rate of return of the "market portfolio". This formula implies that the expected return of a portfolio is the risk free rate plus a risk premium that is equal to the product of the systematic risk of the portfolio and the market risk premium ($E(R_m) - R_f$). The expected returns of the CAPM take account of the relative riskiness of a portfolio and are said to be 'risk adjusted'. To return to Jensen's alpha, Jensen's alpha is the difference between the realized return (R_{jt}) on a portfolio and the expected return of the portfolio based on the CAPM. In formula, Jensen's alpha looks as follows:

$$\alpha_j = R_{jt} - [R_{ft} + \beta_j(R_{mt} - R_{ft})] \quad (4)$$

If the alpha of a portfolio (α_j) is positive and significant, it means that the portfolio is earning excess returns, performs structurally better than the expected returns based on the CAPM and that the portfolio returns compensate for the level of risk that it bears (Jensen, 1968).

The alpha of a portfolio can also be calculated based on other benchmarks than the CAPM, for example the three-factor model of Fama and French (1992). In order to calculate the risk adjusted average returns of the cryptocurrency momentum strategies and to investigate whether these strategies have positive alphas, I use two different factors. The returns of Bitcoin (BTC) and the Equity Market Returns (EMR) are used to test whether the momentum strategies have positive alphas. Multiple regressions are performed with the results of the long-short portfolios of the different momentum strategies as the dependent variable and the returns of Bitcoin and EMR as the independent variables to compute the alphas. Bitcoin is used because of its dominance in the cryptocurrency markets. Since the cryptocurrency markets constituted for almost 90% of Bitcoin the past four years (see table 1 in section III) it is a good benchmark to use for the calculation of the alpha and to check whether the results of the momentum strategies are (largely) caused by just one cryptocurrency or not. EMR is used as a second benchmark and to check whether the results of the traditional equity markets may (partly) explain the results of the momentum strategies. The weekly results of the S&P 500 are used as a proxy for the EMR. The weekly returns of the S&P 500 are retrieved from finance.yahoo.com. The returns of the long-short portfolios of the momentum strategies (R_{pt}) are the dependent variable and the returns of Bitcoin or EMR (or both) are used as independent variables. This way, a total of three regressions are performed per momentum strategy (21 in total). The regressions are as follows:

$$R_{pt} = \alpha_{p,BTC} + \beta_{p,BTC} * R_{BTC,t} + \in_{pt,BTC} \quad (5)$$

$$R_{pt} = \alpha_{p,EMR} + \beta_{p,EMR} * R_{EMR,t} + \in_{pt,EMR} \quad (6)$$

$$R_{pt} = \alpha_{p,MF} + \beta_{p,BTC} * R_{BTC,t} + \beta_{p,EMR} * R_{EMR,t} + \in_{pt,MF} \quad (7)$$

Where R_{pt} denotes the return at time t of the long-short portfolios of one of the seven different momentum strategies; $\alpha_{p,BTC}$, $\alpha_{p,EMR}$ and $\alpha_{p,MF}$ are the the alphas of the considered strategy based on the different benchmarks, $\beta_{p,BTC}$ is the measure of risk arising from exposure to the Bitcoin returns factor, $\beta_{p,EMR}$ is the measure of risk arising from exposure to the EMR factor, $R_{BTC,t}$ denotes the return of Bitcoin at time t, $R_{EMR,t}$ denotes the EMR at time t; $\in_{pt,BTC}$, $\in_{pt,EMR}$ and $\in_{pt,MF}$ are the error terms of the considered momentum strategy at time t for the different benchmarks.

The null hypothesis is that the alphas of the momentum strategies are zero: H_0: $\alpha_p = 0$. This hypothesis is tested against the alternative hypothesis that the momentum strategies have an alpha that is different from zero: H_1: $\alpha_p \neq 0$. If the alpha of a momentum portfolio (α_p) is positive and significant, it means that the portfolio is earning excess returns and that the momentum portfolio returns compensate for the level of risk that it bears. Or in other words, the results of the momentum strategies are not simply caused by movements in the greater market (the returns of Bitcoin or EMR). If the alpha is negative, the momentum strategies earn too little for the risks that they are exposed to.

Next to looking at the alphas of the momentum portfolios based on different (market) benchmarks, I also consider risk-adjusted returns based on volatility by looking at the Sharpe ratios of the momentum portfolios. Just like Lustig, Roussanov and Verdelhan (2011) and Raza et al. (2014), I annualize the weekly average returns by multiplying by 52. In order to obtain the annualized volatility of the momentum portfolios I multiply the weekly standard deviations by $\sqrt{52}$. I calculate the Sharpe ratio as the ratio of the annualized average return to the annualized volatility.

V. Results

In this section the results of the seven different momentum strategies will be shown. The results show that the short term momentum strategies generate statistically significant positive returns. These are the (1,1), (2,1) and (4,1) strategy. The strategies generate average weekly returns of 3.61%, 4.00% and 2.84%, with volatilities of 17.90%, 20.27% and 18.11% per week, respectively. This comes down to average annualized returns of 187.7%, 208.0% and 147.7%, leading to annualized Sharpe ratios of 1.45, 1.42 and 1.13, respectively. These results are significant at a 5% significance level. The other, medium term, strategies all show positive average weekly returns, though lower than the before mentioned short term strategies. These are the (8,1), (12,1), (26,1) and (52,1) strategies. Although the medium term strategies show positive weekly returns, none of these results are significant. Only the results of the (12,1) strategy, with an average weekly return of 1.68%, are statistically significant at a 10% significance level, but not at a 5% significance level. These results together indicate that there is short term cross-sectional price momentum in the cryptocurrency markets, but that there is no cross-sectional momentum in the cryptocurrency markets on the medium term. Table 2 contains an overview of the results of the long-short (zero cost) portfolios of all the seven different momentum strategies. An overview of the results of the long-only and short-only portfolios of all the different strategies is given in appendix 1.

Table 2:
Overview of the results of the long-short portfolios of the different momentum strategies.

	Momentum strategy:						
	(1,1):	(2,1):	(4,1):	(8,1):	(12,1):	(26,1):	(52,1):
Observations	225	224	222	218	214	200	174
Average weekly return	3.61%	4.00%	2.84%	1.11%	1.68%	0.23%	0.94%
St. dev.	17.90%	20.27%	18.11%	16.25%	15.07%	11.79%	12.85%
T-statistic	3.03	2.95	2.34	1.04	1.63	0.28	0.96
P-value	0.0014	0.0018	0.0101	0.1500	0.0524	0.3895	0.1688
Sharpe ratio	1.45	1.42	1.13	0.49	0.80	0.14	0.53

The cumulative excess returns of the long-short portfolios of the three significant short term momentum strategies, together with the cumulative returns of Bitcoin are shown in figure 3. As can be seen in this figure, the cumulative excess returns of the three short term momentum strategies decrease in the first months of the sample, before increasing significantly from May 2014 to March 2016. After the first quarter of 2016 a sharp decrease in the excess returns of the three momentum strategies can be seen. Starting from July 2016, the cumulative excess returns of the momentum strategies start to gradually increase again. In July 2017, the cumulative returns of both the (1,1) and the (2,1) strategy explosively increase. An investment of 1 USD invested at the beginning of the sample would have grown to USD 95.88, 135.44 and 19.45 at the end of the sample on a cumulative basis for the (1,1), (2,1) and (4,1) strategies, respectively. An investment of 1 USD at the beginning of the sample solely in Bitcoin would have resulted in USD 12.99 only.

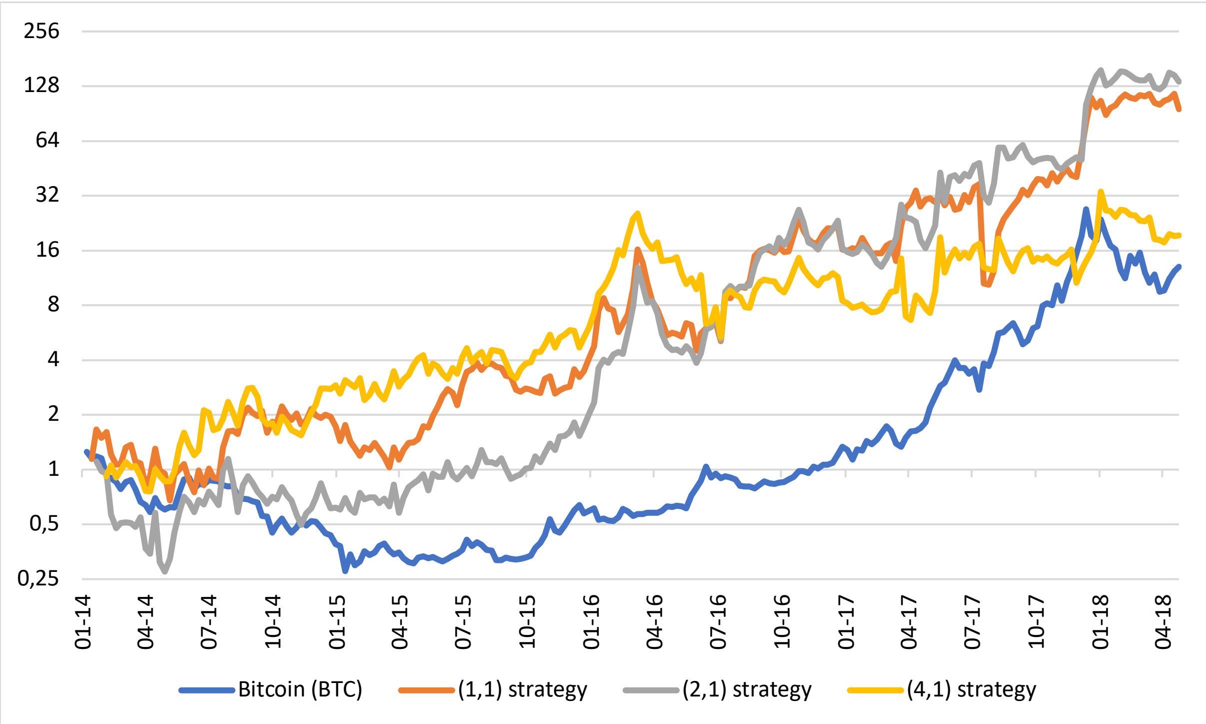

Figure 3:
This figure shows the cumulative excess returns of the long-short portfolios of the three significant short term momentum strategies, together with the cumulative returns of Bitcoin (BTC) during the sample period.

After the returns and the volatilities of the long-short portfolios were known, multiple regressions were performed to calculate the risk-adjusted average returns (alphas) of the portfolios. For every regression, the results of the long-short portfolios of one of the momentum strategies are used as the dependent variable, while the returns of Bitcoin or EMR (or both) are used as the independent variables. As mentioned in the methodology section above, the weekly results of the S&P 500 were used as a proxy for the EMR. The portfolios to calculate the alphas of first, are the significant long-short portfolios of the short term momentum strategies. The results of the regressions show that the alphas of these three significant short term strategies, (1,1), (2,1) and (4,1), are positive and significant. The risk-adjusted average returns, calculated based on the regression with the returns of Bitcoin as the only independent variable, show just a little decrease compared to the non-adjusted returns. Only for the (2,1) strategy, which is the only strategy that shows a significant $\beta_{p,BTC}$ coefficient (0.29), the alpha decreases with almost 0.5% to 3.51% per week. For the other two significant short term strategies the $\beta_{p,BTC}$ coefficient is not significant and the risk-adjusted return decreases with only 0.05% for the (1,1) strategy and 0.22% for the (4,1) strategy compared to the non-adjusted returns. These results imply that the portfolios generate returns that compensate for the risk exposure to Bitcoin and that the returns of the portfolios cannot be simply explained by movements in the returns of Bitcoin. Only the returns of the (2,1) strategy can be partly explained by the returns of Bitcoin.

The risk-adjusted average returns, calculated based on the regression with the EMR as the only independent variable, are also positive and significant for the three significant short term momentum strategies. The results show little to no difference compared to the non-adjusted returns. For all three of the strategies, the $\beta_{p,EMR}$ coefficient is not significant. This means that, based on EMR as the benchmark, the momentum portfolios generate excess returns and that the returns cannot be explained by movements in EMR.

Calculating the alphas of the three significant short term momentum portfolios based on a multifactor regression, with both EMR and the returns of Bitcoin as independent variables, does not, or barely, change the above mentioned results. The alphas of all the three strategies are positive and significant and the alphas of the portfolios based on the multifactor regression are almost identical to the ones based on the single factor regressions. This also accounts for the $\beta_{p,BTC}$ and $\beta_{p,EMR}$ coefficients. Only the $\beta_{p,BTC}$ in the (2,1) strategy is significant, all other coefficients are not. This implies that the three significant short term momentum strategies generate excess returns based on the multifactor benchmark and that these returns cannot be explained by movements in the greater market, i.e. returns of Bitcoin and EMR.

The above mentioned results lead to the conclusion that the null hypothesis (H_0: $\alpha_p = 0$) can be rejected for the three short term momentum strategies. Based on all the three different benchmarks used to calculate the alphas, the alphas of the three short term momentum strategies are positive and significant.

The same regressions were performed with the results of the four other long-short portfolios of the medium term momentum strategies. As being said, the results of these portfolios are not significant. The alphas of these portfolios, calculated based on both the single factor regressions as well as on the multifactor regression, are not significant. This means that the null hypothesis ($H_0: \alpha_p = 0$) cannot be rejected for the four medium term momentum strategies. For the regression with the returns of Bitcoin as the only independent variable, the $\beta_{p,BTC}$ coefficients are significant and vary from 0.18 for the (12,1) strategy to 0.30 for the (52,1) strategy. None of the EMR coefficients are significant.

An overview of the regression results and the alphas of the long-short portfolios for all the different strategies is shown in table 3.

Table 3:

Overview of the regression results. The numbers in parentheses are the corresponding t-statistics. The table reports the risk-adjusted average returns (alphas) of the momentum portfolios, calculated based on regressions with the returns of the long-short portfolios of the momentum strategies as the dependent variable and the returns of Bitcoin (BTC returns) and EMR as the independent variables, as well as the beta coefficients and the R-squared of the regressions. The second column shows the non-adjusted average returns (see table 2) of the momentum strategies to quickly compare the results.

		BTC returns			EMR			Multifactor			
Momentum Strategy:	Average return	$\alpha_{p,BTC}$	$\beta_{p,BTC}$	R^2	$\alpha_{p,EMR}$	$\beta_{p,EMR}$	R^2	$\alpha_{p,MF}$	$\beta_{p,BTC}$	$\beta_{p,EMR}$	R^2
(1,1):	3.61%	3.56%	0.035	0.001	3.67%	-0.266	0.001	3.60%	0.036	-0.273	0.001
	(3.03)	(2.94)	(0.32)		(3.04)	(-0.37)		(2.96)	(0.33)	(-0.38)	
(2,1):	4.00%	3.51%	0.290	0.025	4.07%	-0.482	0.002	3.60%	0.292	-0.543	0.028
	(2.95)	(2.59)	(2.41)		(2.99)	(-0.60)		(2.64)	(2.43)	(-0.68)	
(4,1):	2.84%	2.62%	0.132	0.007	2.28%	0.101	0.000	2.61%	0.132	0.079	0.007
	(2.34)	(2.13)	(1.21)		(2.30)	(0.14)		(2.10)	(1.21)	(0.11)	
(8,1):	1.11%	0.76%	0.207	0.020	1.24%	-0.532	0.003	0.86%	0.210	-0.586	0.024
	(1.04)	(0.68)	(2.12)		(1.12)	(-0.81)		(0.77)	(2.15)	(-0.90)	
(12,1):	1.68%	1.33%	0.181	0.018	1.60%	0.413	0.002	1.27%	0.179	0.362	0.020
	(1.63)	(1.28)	(1.98)		(1.55)	(0.68)		(1.21)	(1.95)	(0.60)	
(26,1):	0.23%	-0.17%	0.202	0.037	0.17%	0.413	0.004	-0.22%	0.199	0.350	0.040
	(0.28)	(-0.20)	(2.76)		(0.20)	(0.85)		(-0.26)	(2.72)	(0.73)	
(52,1):	0.94%	0.15%	0.300	0.073	0.93%	0.060	0.000	0.16%	0.300	-0.018	0.073
	(0.96)	(0.16)	(3.68)		(0.94)	(0.10)		(0.16)	(3.67)	(-0.03)	

VI. Discussion

In this section I will discuss the results presented in the previous section and compare them to the results of the earlier in this thesis mentioned research to cryptocurrency returns. I will only discuss the results of the significant strategies. The significant strategies are the (1,1), (2,1) and (4,1) strategy, generating average annualized returns of 187.7%, 208.0% and 147.7%, respectively. It is fair to say that this are extremely high returns, but in light of the extreme development of the cryptocurrency markets during the sample period these results do not have to come as a huge surprise. For example, the total cryptocurrency market cap has increased over 3500% during the sample period (see figure 1 and table 1 in section III). A side note to this market cap increase, however, is that the market cap also includes Initial Coin Offerings (ICO's).

Comparison of the results

Hubrich (2018) comes to an average annualized return of 6.3% for time series momentum and to an average annualized return of 5.6% for cross-sectional momentum. The reported Sharpe ratios are 0.77 and 0.91, respectively. As mentioned in section II these results are based on portfolios that invest only 10% and hold the other 90% in cash. With fully invested portfolios, the average annualized return would be 63% for time series momentum and 56% for cross-sectional momentum. For this discussion, only the result of the cross-sectional momentum is relevant, since this thesis only investigated the existence of cross-sectional momentum. As can be seen, the difference between annualized returns found in this thesis and that of Hubrich (2017) are very high. In case of the (2,1) strategy, the returns are well over ten times as high compared to the result found by Hubrich. The Sharpe ratio of the (2,1) strategy is 1.42, whereas Hubrich reports a Sharpe ratio of 0.91 for cross-sectional momentum. I think the reason for this big difference in the results can be found in the sample period and the data that is used. In this thesis I used nearly all available data on cryptocurrencies in a period of almost 4.5 years in which a total of 242 different cryptocurrencies come across, whereas Hubrich (2018) only uses data of 11 different cryptocurrencies of which only a few have more than 4 years of data. Next to this, the data selection process of Hubrich does not seem to take into account a survivalship bias. However, it seems that by using a survivorship bias free data sample, like in this thesis, the returns of momentum strategies will be higher. Not having a survivalship bias free sample lowers the results. A possible explanation for this could be that with the momentum factor, the bad performing cryptocurrencies (and potential dropouts in the sample) have a positive effect on the momentum returns, because these currencies are sold short. This is different with, for example, the low volatility factor, where the dropout currencies have a negative effect on the factor returns. If this is not taken into account with the low volatility factor, the results seem higher than they actually are. The results of Hubrich could possibly be more in line with the findings in this thesis when a survivalship bias was taken into account. By making use of a much bigger and completer dataset, I believe that the results are more accurate and more in line with the development of the total cryptocurrency market. This can explain the huge difference in obtained results.

Rohrbach et al. (2017) found an average annualized return of 42.02% for time series momentum and an average annualized return of 56.94% for cross-sectional momentum. The reported Sharpe ratios are 1.48 and 1.68, respectively. A major drawback to these results once again is the sample period and the data that is used to obtain the results. The results are very similar to the ones found by Hubrich (2017). The difference between the results of Rohrbach et al. (2017) and the results of this thesis is also very big. Again, I believe this big difference is due to the data and sample period that is used. Rohrbach et al. (2017) use a sample period of 1.5 years and the data sample consists of only seven different cryptocurrencies. Again, I believe that by making use of a much bigger and completer dataset like in this thesis, the results are more accurate and in line with the development of the total cryptocurrency market.

Just like Hubrich (2017), Kakushadze (2018) uses a very small data set in which he does not seem to take into account a possible survivorship bias. As opposed to the results in this thesis, based on a much larger and carefully selected data set, the results of Kakushadze may potentially be spurious.

Break-even analysis of transaction costs

As mentioned earlier in section IV, the practical implementation of the tested momentum strategies depends on multiple factors. These factors include the possibility of short selling cryptocurrencies, which is not yet possible at scale and thus obstructs the practical implementation of the momentum strategies. The practical implementation also depends on the transaction costs accompanied by trading cryptocurrencies. Because of the fact that transaction costs can vary heavily depending on the traded cryptocurrency or the exchange that is used to trade the cryptocurrency, there is no reliable view of the true trading costs for cryptocurrencies. Hence, these transaction costs are not taken into account in this thesis. Since there is no reliable view of the true transaction costs that come with trading cryptocurrencies, I calculate the amount of transaction costs that would result in the strategies' returns to be break-even.

For this break-even analysis I use the annualized return of the (4,1) strategy, since this is the least performing significant short term momentum strategy. The (4,1) strategy generates an average annualized return of 147.7%. In the first year of implementing this strategy there are 48 weeks in which to buy and sell cryptocurrencies (52 weeks minus a four week look-back period). In each of these 48 weeks the current long portfolio has to be sold and a new long portfolio has to be bought, this means two transactions per week for the long portfolio. Only for the first week there is just one transaction instead of two, since there is nothing to be sold yet. So, a total of 95 transactions per year for the long portfolio. This is also the case for the short portfolio of the strategy. This means that the (4,1) strategy requires a total of 190 transactions in the first year. After the first year the (4,1) strategy requires 208 transactions per year based on the same calculation method. The break-even transaction cost is then calculated by dividing the average annualized return of the strategy by the total amount of required transactions. To calculate the break-even transaction cost, I use the higher amount of 208 required transactions per year instead of the 190 transactions in the first year in order not to overestimate the break-even point. The break-even transaction cost of the (4,1) strategy is than 0.71%. Since the (4,1) strategy is the least performing significant short term momentum strategy, the other two short term momentum strategies are still profitable at a transaction cost level of 0.71%.

Coinbase is one of the largest cryptocurrency exchanges and they also have a trading platform for more experienced traders, called Coinbase Pro. Although it is one of the largest cryptocurrency exchanges, only five different cryptocurrencies can be traded on this exchange. These are Bitcoin (BTC), Bitcoin Cash (BCH), Ethereum (ETH), Litecoin (LTC) and Ethereum Classic (ETH). Since some of the largest cryptocurrencies can be traded on the Coinbase Pro trading platform, I use their trading fees as a gross indication of the transaction costs for cryptocurrencies in general and compare this to the break-even transaction cost of 0.71% of the (4,1) strategy. Coinbase Pro uses a maker-taker model to determine the transaction fees. The transaction fee for a taker order is 0.30% (Coinbase, 2018). It is clear that at this point in time the Coinbase Pro transaction fee of 0.30% is not a reliable view of the true transaction costs for a trading strategy that buys and sells many different cryptocurrencies that cannot be all bought at just one exchange. However, if the 0.30% transaction fee would be an indication of the overall future transaction costs, this would be below the break-even transaction cost of 0.71% of the (4,1) strategy. This means that the (4,1) strategy, and the two other short term momentum strategies, would be profitable with trading costs taken into account.

VII. Conclusion

Summary and conclusion to research question

There is a vast amount of research on factor investing and price momentum in traditional asset classes. Research has shown that the momentum factor is profitable across a wide variety of asset classes. Cryptocurrencies are a very new type of asset class and little research has been done to cryptocurrencies. In this thesis I try to combine the well-established topic of price momentum with the new world of cryptocurrencies by answering the following research question: "*Do price momentum strategies exist in the cryptocurrency markets?*".

The little research that has been done to cryptocurrencies is mostly based on a very short sample period and a small dataset. In this thesis I make use of a dataset that entails almost all available data on cryptocurrencies to answer the above mentioned research question. I examine whether cross-sectional momentum strategies exist in the cryptocurrency markets by testing a total of seven different short term and medium term momentum strategies. The results show that the three short term momentum strategies, the (1,1), (2,1) and (4,1) strategy, all generate significant positive returns. The strategies generate average weekly returns of 3.61%, 4.00% and 2.84%, respectively. This comes down to average annualized returns of 187.7%, 208.0% and 147.7%, respectively. The risk-adjusted average returns (alphas) of the strategies are calculated based on regressions with the returns of the momentum strategies as the dependent variable and the returns of Bitcoin or the Equity Market Returns (EMR) (or both) as the independent variables. The returns of the S&P 500 are used as a proxy for the EMR. The alphas of the three short term strategies are positive and significant for all the used benchmarks. The alphas of the (1,1), (2,1) and (4,1) strategies are 3.56%, 3.51% and 2.62%, respectively, based on the returns of Bitcoin as the benchmark. Based on EMR as the benchmark, the alphas of the strategies are 3.67%, 4.07% and 2.28%, respectively. The multifactor regressions show that the alphas of the strategies are 3.60%, 3.60% and 2.61%, respectively. The null hypothesis that the alphas of the momentum strategies are zero (H_0: $\alpha_p = 0$) can be rejected for the three short term strategies. This means that the momentum portfolios generate returns that compensate for the exposed risk of the benchmarks that are used. The returns cannot be simply explained by movements in the returns of Bitcoin or EMR.

The four other, medium term, strategies all show positive returns, but none of the results of these four medium term strategies are significant. The regression results show that the alphas of these strategies are not significantly different from zero. This means that the null hypothesis (H_0: $\alpha_p = 0$) cannot be rejected for the four medium term momentum strategies. Thus, the conclusion to the research question is as follows. Price momentum strategies do exist in the cryptocurrency markets on a short term, but not on a medium term.

The obtained results are very high, in absolute numbers as well as compared to other research on momentum strategies in cryptocurrencies. Explanation for these extremely high numbers can be found in the extreme development of the cryptocurrency markets during the used sample period. The big differences in results compared to other research can be explained by the fact that all of the other research is based on very small data sets and short sample periods that are not in line with actual development of the overall market.

Limitations and suggestions for future research

There are a couple of limitations in this thesis that have to be taken in mind. The first thing to mention is that, although this thesis uses a large dataset compared to other research, 4.5 years of data is still very little, especially compared to research to traditional asset classes where the sample periods can be decades.

The second limitation is the amount of strategies that have been tested in this thesis. The holding period is kept constant to one week, whereas a lot more momentum strategies could be tested if the holding period varies, just like the look-back period. This is also due to the little amount of available data. However, it is recommended to include a varying holding period into future research.

The next limitation to mention is the practical implementation of the tested strategies, which depends on multiple factors. The cross-sectional momentum strategies consist of going long a winner portfolio and going short a loser portfolio. As mentioned earlier in this thesis, short-selling cryptocurrencies is not (yet) possible for a lot of cryptocurrencies. This means that at this point in time, the strategies probably cannot be used in practice. However, it is still relevant to include short portfolios in light of future developments.

The last limitation to mention is the fact that trading costs are not taken into account in this thesis. Trading takes costs with it, this is also the case for trading cryptocurrencies. However, these trading costs can vary heavily depending on the exchange that is used to buy or sell a cryptocurrency, which makes it very difficult to get a reliable view of the true trading costs. These trading costs for trading cryptocurrencies are not taken into account in this thesis. However, I did perform a break-even analysis for transaction costs to calculate at what level of transaction costs the least performing short term momentum strategy would no longer be profitable. Taking these costs into account will lower the returns generated by the momentum strategies. I suggest to take trading costs into account in future research once more is known about it.

Next to this, a good addition to future research would be to include time series momentum. Due to the scope of this thesis and the available time, this thesis includes only cross-sectional momentum. Including time series momentum would give a more complete view of the momentum factor in cryptocurrencies.

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Appendix 1

Appendix 1:
Overview of the results of the long-only and short-only portfolios of the seven different momentum strategies.

	(1,1):		(2,1):		(4,1):		(8,1):		(12,1):		(26,1):		(52,1):	
	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
Average weekly return	3.74%	0.12%	4.59%	0.60%	4.19%	1.34%	3.00%	1.86%	3.51%	1.83%	2.42%	2.19%	3.10%	2.17%
St. dev.	21.86%	16.47%	24.16%	14.58%	21.14%	15.05%	18.40%	13.50%	17.20%	11.97%	14.45%	10.12%	14.54%	8.89%
T-statistic	2.566	0.114	2.845	0.618	2.950	1.328	2.409	2.034	2.988	2.243	2.371	3.057	2.815	3.218
P-value	0.006	0.455	0.002	0.269	0.002	0.093	0.008	0.022	0.002	0.013	0.009	0.001	0003	0.000