Cryptocurrency momentum strategy

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Abstract

In this paper I examine 25 momentum strategies in the cryptocurrency market, all containing a total of 17 cryptocurrencies. Although most of them are found to generate excess returns, non of them are highly significant. Three of the strategies are used to compare to other financial instruments in the cryptocurrency market. I find they all fail in an attempt to outperform Tether and investing in Bitcoin. Therefore is concluded that momentum strategies do not generate excess returns.

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1 Introduction

Unprecedented is the effortlessness with which one can start investing nowadays. Dozens of exchange apps are bombarding the general public with advertisements, promoting their extraordinarily low if not complete lack of transaction costs. Where only a decade ago trading was limited to a group of screaming man on Wall Street and it's kinds, anybody can start in just a few clicks in this day and age. This accessibility to trading provides the opportunity for new products and markets to come out and grow. On top of that, the COVID-19 crisis inspired masses of people to start investing. Everybody had time on their hands, realised their money was stood still, heard the success stories of others and wanted to get a piece of the pie. One of the markets profiting most from this rise in investors is the cryptocurrency market. With it's promise of uncommonly high returns, many people are lured into investing in some way or form in cryptocurrency. Just a mere few years ago a Bitcoin was something hardly anyone knew about. Today, the total market cap of all cryptocurrencies combined is well over a trillion US dollars, with the all time high nearing three trillion dollars. However, maybe even more so than for its high gains, the cryptocurrency market is likewise very well known for its high volatility, providing an extra challenge when investing.

Both consumer and institutional investors are constantly trying to find new ways to better predict future prices in order to grow profits. Historically, the most looked at risk factors when determining the price of a stock were standard factors like inflation and employment rate. Fama and French (1992) published their groundbreaking three factor model, forming the way investors would look at stock pricing for the next decades. But the search for new determinants has kept on going. One of the factors that has seen an increase in attention in more recent times is momentum. First introduced into the stock market by Jegadeesh and Titman (1993), many research has already been conducted to see if strategies based off of momentum provide excess returns, in varying types of markets. However, in the relatively new market of cryptocurrencies, a lot of research is yet to be done. That is why the main purpose of this research is to find if momentum strategies provide excess returns in the market of cryptocurrencies.

In this work, I find that momentum strategies do not provide excess return. When comparing the returns to those of Tether, the worlds largest stablecoin, they are all concluded to not have outperformed it in this sample. The same is found when comparing the returns to those of simply investing in Bitcoin, the cryptocurrency with the highest market capitalisation. I also find that there is no difference between including or excluding Bitcoin into your portfolio's. It follows that momentum strategies do not provide excess returns when looking at the cryptocurrency market.

The remaining structure of the paper is as follows. Section 2 will present an overview on related literature regarding momentum in the stock market, momentum in other markets and momentum in cryptocurrency. Section 3 will tell about the data used and which restrictions were put up. In section 4 the methodology will be discussed, while in section 5 the corresponding results will be reported. Section 6 gives a conclusion and discusses some limitations of the research as well as providing recommendations for further research.

2 Related literature

Originally defined by Jegadeesh and Titman (1993), a momentum strategy in the stock market is defined as a strategy buying stocks that have performed propitious in recent times whilst selling stocks that have performed poorly during that period, in hopes to generate excess returns. The idea is that the past winners keep on winning, whilst the past losers keep on losing. They state that the found profits cannot be declared due to their systematic risk or due to a delayed reaction to the common factors. Jegadeesh and Titman (2001) looked at other possible explanations for the excess returns found when making use of a momentum strategy. Apart from finding that the excess returns from their 1993 paper were again found later on the 90's, indicating that there had been no datasnooping, they looked at then recent behavioral models that stated that momentum profits are caused by a delayed overreaction and that these profits would eventually be reverted. Their evidence provides support for these models, although they say this should be tempered with caution.

Even though great amounts of research has been done investigating momentum strategies, there still is not a single widely accepted explanation for their returns. However, it has been proven that momentum has a stronger effect on some firms than others. Hong et al. (2000) found that momentum is larger among smaller firms, whilst Avramov et al. (2007) found it to be larger amidst companies that have a lower credit rating. Sagi and Seasholes (2007) found momentum to be larger among firms with high revenue growth volatility and Eisdorfer (2008) found it's returns to largely be concentrated in companies with a relatively high chance of going bankrupt. So even though there is still not a single commonly accepted explanation for momentum returns, there are differences in strength to be observed.

Moreover, momentum strategies are found to have longer periods of negative results, so called momentum crashes. As pointed out by Daniel and Moskowitz (2016), momentum crashes are persistent strings of negative results occurring when the market is in a state of panic and has increased volatility. These crashes are somewhat predictable, so should always be looked at carefully.

Apart from in the stock market, others have also been researched, for example the bond market. Gebhardt et al. (2005) found momentum strategies to not work with investment-grade bonds. Asness et al. (2013) found similar results when looking at bonds on a country level. On the other hand, Jostova et al. (2013) found momentum strategies to yield positive returns for non-investment grade bonds and that these returns are even higher when looking at bonds issued by private firms.

In the commodities market the high momentum strategies returns are shown to be associated with market states with low levels of inventory, suggesting higher risk, as found by Gorton et al. (2013). Other research in the commodities market done by Bianchi et al. (2016) found both the 52-week high and 52-week low momentum strategies to be profitable in the commodities futures market. These profits are largely explained by the anchoring behaviour of investors around the 52-week high and low prices. Miffre and Rallis (2007) similarly found profitable momentum strategies in this market, generating an average of 9.38% per annum.

Another market already researched is the foreign exchange market, so the trade in currencies. In 2012, Menkhoff et al. (2012) found an excess return of up to 10% per year when making use of momentum strategies in the foreign exchange market. These returns could not be explained by the traditional risk factors, only partially be explained by transaction costs and show consistent behaviour with overreaction from investors. However, they found there to be effective limits to arbitrage withholding investors from being able to exploit these returns. Further research done by Okunev and White (2003) found that, after having researched a total of eight currencies from 1980 till 2000, an investor going long at the end of each month in the currency with the best last-month performance whilst going short in the currency with the worst last-month performance, would yield an average return of 6% per annum. They conclude that the profitability of momentum strategies holds in the foreign exchange market.

For momentum strategies to provide excess returns, either the market has to be inefficient or momentum has to be a proxy for other factors, like systematic risk, as stated by Jegadeesh and Titman (2001). Zhang et al. (2018) found that for nine cryptocurrencies, including Bitcoin, all markets are inefficient. Urquhart (2016) found the same when researching only Bitcoin. Interestingly, when Nadarajah and Chu (2017) revisit Urquhart's paper they conclude that Bitcoin does satisfy the efficient market hypothesis. The same two-way conflict can be seen when looking at the profitability of momentum strategies in cryptocurrencies. Contrary to Hou et al. (2020) and Asness et al. (2013), Grobys and Sapkota (2019) found there to be no evidence for cross-sectional momentum in cryptocurrencies. It is clear more research is needed on momentum in cryptocurrencies. This paper adds to that by taking more recent data into consideration, whilst also looking at smaller intervals.

3 Data

The data sample for this paper contains the daily price off 17 cryptocurrencies for the period from December 13^{th} 2017 all the way through to April 30^{th} 2022. In total, the sample contains exactly 1600 trading days. The time frame was chosen because December 13^{th} 2017 was the first day data for all 17 cryptocurrencies was available. All data was downloaded from Yahoo! Finance. The data was provided to Yahoo! Finance by CoinMarketCap.com.

For a cryptocurrency to be eligible multiple restrictions were set up. Firstly, it had to have data available on Yahoo! Finance for the above mentioned period. Secondly, all coins with a market cap outside the top 75 of all cryptocurrencies, according to CoinMarketCap.com on May 1^{st} 2022, were removed. Thirdly, the coin could not be a stablecoin. An example of such coin is Tether. One single Tether coin should always be worth one dollar as in theory every Tether coin is backed by an actual dollar. When owning a Tether coin, you always have the right to exchange it for an actual dollar. If the price of Tether drops below one dollar, there is an arbitrage opportunity which will see the demand increase until Tether is back at one dollar. Because all stable coins are very nonvolatile and all potential gains are quickly arbitraged away, there is very little momentum to perceive, making them unsuited for this research. In the end a total 17 cryptocurrencies that passed all restrictions were left. Table 1 shows which ones they are and gives some descriptive statistics for each of them. Clearly, there is a wide variety of cryptocurrencies in the sample. Prices range from less than \$0.01 for Dogecoin all the way through to \$68,789.63 for Bitcoin. The same wide variance can be seen in the market capitalisations on the right side of the table.

Table 1: **Descriptive statistics for cryptocurrencies in sample.**

Coin		Descriptive					
Name	Short	Open	Close	High	Low	MC Open	MC Close
Binance Coin	BNB	$2.69	$377.77	$690.93	$2.57	$275.07M	$64.18B
Bitcoin	BTC	$17,500.00	$37,714.88	$68,789.63	$3,191.30	$277.13B	$734.59B
Cardano	ADA	$0.13	$0.76	$3.09	$0.02	$3.48B	$26.68B
Chainlink	Link	$0.23	$11.00	$52.88	$0.16	$91.66M	$5.28B
Dash	DASH	$925.02	$85.08	$1,642.22	$34.91	$6.87B	$965.02M
Decentraland	MANA	$0.09	$1.43	$5.90	$0.01	$279.36M	$2.63B
Dogecoin	DOGE	$0.00	$0.13	$0.74	$0.00	$388.75M	$17.62B
Eos	EOS	$5.32	$2.02	$22.89	$1.46	$4.53B	$2.08B
Ethereum	ETH	$644.91	$2,730.19	$4,891.71	$82.83	$67.04B	$339.51B
Ethereum Classic	ETC	$30.29	$25.92	$176.16	$3.30	$2.98B	$3.48B
Filecoin	FIL	$11.47	$14.33	$237.24	$1.83	$0.00M	$2.82B
Litecoin	LTC	$315.36	$96.17	$412.96	$22.82	$15.17B	$7.04B
Maker	MKR	$622.42	$1,452.42	$6,339.02	$177.23	$0.00M	$1.42B
Monero	XMR	$307.43	$214.66	$517.32	$27.70	$4.73B	$3.85B
Ripple	XRP	$0.37	$0.59	$3.84	$0.12	$29.29B	$28.24B
Stellar	XLM	$0.15	$0.17	$0.94	$0.03	$2.79B	$4.41B
Tron	TRX	$0.01	$0.06	$0.30	$0.01	$1.61B	$6.38B

Notes: The table shows descriptive statistics for each of the cryptocurrencies in the sample of this research. The two leftmost columns show the full name and the abbreviation for each of the coins. Open shows the price at the beginning of December 13^{th} 2017. Close shows the price at the end of April 30^{th} 2022. High shows the highest value of the coin during this period, low shows the lowest value. MC Close and MC Open show the total market capitalisation for each coin on December 13^{th} 2017 and April 30^{th} respectively. M stands for million, B stands for billion.

4 Methodology

The methodology section is split into two parts. Firstly will be explained how the portfolios are constructed and how their returns are calculated. Afterwards will be explained how the returns are compared to other strategies in the market. As cryptocurrencies stand for a decentralized finance systems, there should be no transaction costs. Therefore transaction costs are omitted in this statistical analysis.

4.1 Calculating returns

A total of 25 distinct momentum strategies will be examined in this paper. While most research of momentum strategies concentrates on monthly data, here the focus lies on daily data. The nature of the underlying asset is the cause of this difference in focus. Cryptocurrency trade happens 24/7, whereas for example stock trading happens only eight hours per day, five days per week, meaning that one week of cryptocurrency trading consists of more trading hours than a month of stock trading. This aspect of continuous trading makes research on momentum in cryptocurrencies suitable to focus on shorter time frames. There are five different possible formation periods, $f = 1$, 3, 7, 14 or 28 days. The same goes for the holding period, with $h = 1$, 3, 7, 14 or 28 days. For each of the 25 strategies a high minus low portfolio will be created. The formulas to determine which coins would be selected and their respective returns are as follows.

$$R_{f,t} = \frac{1}{f}\sum_{j=1}^{f} r_{t-j}$$

$$R_{h,t} = \sum\left(\frac{p_{i,t}-p_{i,t-h}}{p_{i,t-h}} - 1\right) * \frac{\frac{1}{\sigma_i}}{\frac{1}{\sigma_i}+\frac{1}{\sigma_j}+\frac{1}{\sigma_k}+\frac{1}{\sigma_l}}$$

When forming the portfolios the average returns over the past f days are used. From here four cryptocurrencies are chosen, depending on what type of portfolio it is. The high momentum portfolio chooses the four highest average returns over the past f days for example. The portfolio returns are calculated using the sum of all four returns over the past h days multiplied by the weight of each cryptocurrency in the portfolio. The weight is volatility based and calculated by dividing the inverse of the rolling standard deviation over the past 28 days of a coin by the sum of all inverse rolling standard deviations of the coins in the portfolio. Making use of the inverses ensures the biggest part of the portfolio is to be invested in the coins with the least amount of volatility, in an attempt to reduce the risk the returns have in a market very well known for its risk.

As mentioned, this part looks at the high minus low portfolio for each of the 25 momentum strategies. Each day, for each combination of f and h, the cryptocurrencies are divided into four groups all containing four cryptocurrencies, from low to high momentum. The cryptocurrency with the most medium momentum, so the cryptocurrency with the 9^{th} highest average return over the past f days, will be ignored. A high minus low portfolio for a MOM(f,h) means buying the high portfolio momentum cryptocurrencies, whilst selling the low momentum portfolio cryptocurrencies over the past f days, and holding the position for the next h days. The returns of a high minnus low momentum strategy are calculated by subtracting low portfolio returns from the high momentum portfolio.

For each strategy a stop-loss and a stop-profit is set up, both at 25%. A stop-loss is set to limit the downside risk of an investment. A stop-profit is put into place to reduce the exposure of the results to extreme gains some coins had during the sample. These kind of extremely high spikes would have a great deal of influence on the results, making them less reliable when looking at other cases. For each of the strategies an OLS regression will be run with Newey-West standard errors. For these regressions the lags are set at seven, as the data is daily and trading happens seven days a week in the cryptocurrency market. This type of standard errors are used because, although they are usually quiet high, they deal better with heteroskedasticity and autocorrelation.

4.2 Comparing returns

4.2.1 Risk free rate

The return made on cryptocurrencies is made in US dollars. That is why for the risk free rate the paper looks at the 10 year US Treasury Bonds, which had an average of 1.88% during the sample. Excess returns and Sharpe ratios will be calculated making use of this percentage. With these Sharpe ratios it can be determined how risky each strategy is, and how the risks compare.

4.2.2 Tether

When all returns are calculated, the paper will select the top three strategies to dive into deeper. This makes it more comprehensible when comparing the results to other strategies and financial products. With these three strategies comparisons will be made to multiple different products. First of all they will be compared to the interest earned on Tether. Tether is chosen because it is by far the largest stablecoin when looking at total market capitalisation, which should make it the least risky cryptocurrency to invest in. YouHodler.com promises up to 12.8% interest per year on your Tether. Being the highest interest rate anyone offers, it makes it the most interesting to compare momentum strategies to. Since Tether has a stable value and when investing you are always obliged to get at least the same amount of Tethers back, this type of investment is relatively low risk.

The actual comparison will be done in the following manner. All portfolios, so the low momentum, medium low momentum, medium high momentum, high momentum and high minus low momentum for the three selected strategies are compared to the interest YouHodler.com promises. This is done by simply subtracting the promised 12.8% from the return of each of the portfolios. Just like with the returns of all the strategies, an OLS regression with Newey-West standard errors will be run on all portfolios to see if they are significantly different from zero. The lag is again set at seven.

4.2.3 Bitcoin

Next the returns of the top three momentum strategies will be compared to the return of simply buying and holding Bitcoin. As stated previously, Bitcoin is the largest cryptocurrency. During this sample, the market capitalisation of Bitcoin was equivalent to somewhere between 32.44% and 71.89% of the combined market capitalisations of all cryptocurrencies. When any asset takes up at the very least one third of the total market, it is bound to have some effect on the other assets in that market. For the comparison the same is done like when comparing the results to the return on Tether. The returns of Bitcoin are subtracted from the returns from each of the portfolios for each strategy, and for each of the strategies an OLS regression is run with Newey-West standard errors. The lag is again set at seven.

As stated previously it is not hard to imagine that value changes of Bitcoin have an effect on the values of other cryptocurrencies. To test this, the same three strategies will be looked at, but now they cannot include Bitcoin. So instead of the 17 cryptocurrencies the portfolios could choose from first, now they can only choose from 16 cryptocurrencies, meaning that all cryptocurrencies are constantly used. The returns will be recalculated for each portfolio from each strategy. Of course the correlation between the portfolios, both including as excluding Bitcoin, will be calculated and compared.

5 Results

5.1 Returns

The excess returns, so the returns minus the risk free rate, of the 25 strategies with different holding and formation periods, ranging from 1 to 28 days, can be seen in table 2. Alongside the returns the t-statistics from an OLS-regression with Newey-West standard errors are shown for each strategy in this table. Each column represent a different formation period, being either 1, 3, 7, 14 or 28 days. Each row represents it's own holding period, with the same options like with the formation period. For the sake of readability when discussing strategies they will mostly be referred to as a MOM(*f*,*h*) strategy, with *f* representing the formation period and *h* the holding period.

Table 2: **Returns of different momentum strategies**

		Formation period				
		1	3	7	14	28
Holding period	1	-15.39%	-61.53%	65.99%	29.12%	96.61%
		[-0.59]	[-2.25**]	[1.27]	[0.69]	[1.73*]
	3	71.49%	42.86%	134.52%	131.35%	350.86%
		[0.84]	[0.43]	[1.02]	[0.96]	[1.59]
	7	386.29%	4.08%	213.85%	707.52%	907.95%
		[1.83*]	[0.04]	[0.83]	[1.31]	[1.33]
	14	363.66%	48.86%	1,106.34%	3,903.24%	1,256.92%
		[1.49]	[0.27]	[1.27]	[1.63*]	[1.10]
	28	224.53%	418.45%	648.39%	554.73%	89.56%
		[0.98]	[0.94]	[0.86]	[0.70]	[0.21]

Notes: This table shows the excess returns of different momentum strategies. Each row represents it's own holding period, each column represents it's own formation period. Within each row there are two lines. The top ones represent the excess returns made, to bottom ones within the brackets represent the t-value of OLS regression with Newey-West standard errors run on each strategies. The stars next to these numbers represent the significance. * means that it is signifcant at 10%, ** at 5% and *** at 1%.

It appears that strategies with a formation and a holding period of one day provides an annualized average excess return of about -15.39% per year. When taking the same formation period, but looking at longer holding periods, the returns seem to rise. For example, a MOM(1,14) strategy provides 363.66% annualized average excess returns per year. However, when looking at an even longer holding period of 28 days the returns somewhat deteriorate. The same phenomenon can be seen when looking at other formation periods. A MOM(7,1) strategy provides 65.99% excess returns, where as a MOM(7,14) strategy provides a lot more, 1,106.34% to be exact. But again, a strategy with an even longer holding period provides less returns, with MOM(7,28) providing

648.39% excess returns per year. A similar trend is observed when looking at a formation period of 14 or 28 days.

Something else that stands out when looking at the results is that the excess returns seems to rise with longer formation periods, especially when comparing the results of strategies with 7, 14 or 28 days formation periods to those with 1 or 3 days of formation period. When looking at a holding period of three days, the MOM(1,3) and MOM(3,3) strategies both get less excess returns than 72% per year, whilst the longer formation periods of MOM (7,3), MOM(14,3) and MOM(28,3) provide 134.52%, 131.35% and 350.86% in annualized average excess returns respectively. When looking at a holding period of 14 days the same is observable, with the returns of strategies MOM(7,14), MOM(14,14) and MOM(28,14) being at least three times as big as those from the MOM(1,14) and MOM(3,14) strategies. Only when looking at strategies with a holding period of 28 days the rise in returns seems to be absent. The MOM(28,28) strategy is outperformed by all other MOM(f,28) strategies. Even though the MOM(7,28) and MOM(14,28) still provide the highest two returns, the difference with the MOM(1,28) and MOM(3,28) is smaller than with other holding periods. This may indicate that the predictable power of the past dies off when holding position for too long whilst looking back at a relatively long period, which would make it useless to look back even further, meaning the most important periods are researched, therefore adding to the power of the paper.

Even though some good excess returns are found, not many of them are that significantly different from zero. Only the MOM(3,1) strategy provide returns significant at 5%, all be it negative. Three more strategies provide returns significant at 10%, with that being the MOM(28,1), MOM(1,7) and MOM(14,14) strategies. Even the high returns of the MOM(28,14) strategies are not significant. This is because of the extremely high standard errors. The standard error of the MOM(28,14) strategy is 973.25% when annualized, making it hard for any return to be significant. This high standard error can partially be declared because of the standard errors used, since Newey-West standard errors are known to be high, but also are a consequence of the high volatility associated with the cryptocurremcy market. The lack of significance in the returns makes it clear that not any random momentum strategy would provide excess returns, even though most returns found are positive.

The returns in table 2 show that despite the stop-profit limitation at 25% some pretty good returns would have been made making use of a momentum strategy in the cryptocurrency market. Shamefully though, these returns nearly all are insignificant. This means that it cannot be concluded that any momentum strategy would provide the investors with high excess returns, making it so that momentum strategies in the cryptocurrency market are very risky strategies to apply. They may provide high returns, but because of the volatility these returns are far from guaranteed. Table 9 in the appendix shows the returns of equally weighted portfolios, but these paint the same picture so will not be discussed further.

Table 3: **Sharpe ratios of different momentum strategies**

		Formation period				
		1	3	7	14	28
Holding period	1	-0.01	-0.06	0.03	0.02	0.04
	3	0.02	0.02	0.04	0.04	0.06
	7	0.05	0.00	0.04	0.04	0.06
	14	0.04	0.01	0.06	0.08	0.06
	28	0.02	0.03	0.04	0.04	0.01

Notes: This table shows the Sharpe ratios of each of the 25 momentum strategies. Each row has its own holding period, each column its own formation period. The results are calculated by subtracting the risk free return from the momentum returns, and dividing that by the volatility of the momentum returns.

To confirm that momentum strategies are risky, the Sharpe ratios of all 25 momentum strategies are calculated and compared. The Sharpe ratios shown in table 3, maxing out at 0.08, are all very low. This complies with the assumption that the cryptocurrency market is a market known for its volatility. Besides, it confirms that investing in cryptocurrency is very risky, especially when looking at the shorter formation periods. The Sharpe ratios of the strategies with a formation period of 14 and 28 days are a fraction higher, but remain very low. According to these ratios the relatively least risky strategy to implement would be the MOM(14,14) strategy, but be aware that the high returns shown in table 2 are still very far from guaranteed.

These extremely low Sharpe ratios should be interpreted as a reason to shy away from using momentum strategies in the cryptocurrency market. With all values being around the zero mark, it indicates that when taking risk into account momentum strategies hardly outperform the risk free asset of US Treasury bonds. The risk that surround investing with this strategy does not at all make it attractive to use them, as the same returns can be expected when investing in the risk free asset. Investing in cryptocurrencies making use of momentum strategies exposes an investors to unnecessarily high amounts of risk making the high returns found worthless.

From this point on wards the focus of the research lies on just three momentum strategies. The strategies that will be dived into deeper are the MOM(1,28), MOM(1,14) and MOM(14,14) strategies. These strategies were chosen because they all can be linked to each other. The MOM(1,28)

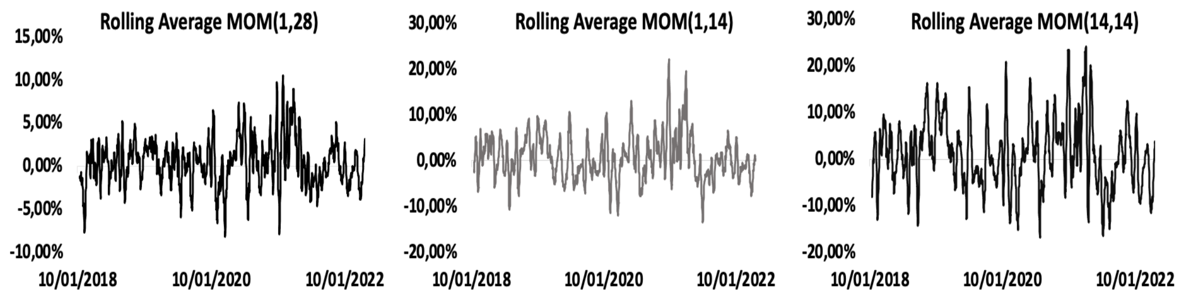

Figure 1: Rolling average returns over time.

and MOM(1,14) strategy have the same formation period, whilst the MOM(1,14) and MOM(14,14) strategies have the same holding period. Researching these three strategies provides the opportunity to compare different returns with the same formation period or holding period, but also to compare what happens when both are different. Figure 1 show the 14-day rolling average returns of the three strategies during the sample. The leftmost line shows the MOM(1,28) returns, the middle one the MOM(1,14) returns and the right one the MOM(14,14) returns.

It is clear to see that the rolling average returns of each of the three strategies are not constant at all and vary a lot over time. The returns for a MOM(1,28) strategy are relatively seen the least inconsistent returns, ranging from about -8% through to 10%. The shorter holding period of a MOM(1,14) strategy makes the returns even less consistent, having higher peaks at nearly 20% but also lower lows at about -13%. And when taking the same 14 day holding period, but having a longer formation period also of 14 days the returns vary even more. The returns of a MOM(14,14) range from about -18% all the way up to nearly 25%.

The results in figure 1 do comply with what is to be expected when looking at a volatile asset like cryptocurrency. Holding an asset for a longer period of time lowers the variety of average returns because the extremely high or low spikes are evened out better over a longer period of time. That is why the MOM(1,28) returns vary less than the MOM(1,14). That the returns of a MOM(14,14) strategy fluctuate more than those of a MOM(1,14) might be a bit more striking at first glance, but can be explained through the high and low spikes some cryptocurrencies experience. Look for example at an extremely high spike of one of the cryptocurrencies. With a MOM(1,14) strategy the spike has a huge effect for just one single day. The return for that particular day might be a bit abnormal, but the 14 day rolling average shown in figure 1 is impacted relatively little. With a MOM(14,14) this one high spike will at some point have an effect on all of the 14 returns in the rolling average, therefore making all of the returns abnormal, therefore varying more.

5.2 Tether

In this part of the paper the three selected momentum strategies will be compared to the returns made on Tether as promised by YouHodler.com which stands at 12.8% per year. Table 4 shows the annualized average excess returns of each of the portfolios for all three momentum strategies, including the high minus low portfolios.

Table 4: **Returns compared to Tether**

	Low	2	3	High	High-Low
MOM(1,28)	1,020.36%	2,651.44%	12,650.26%	9,699.11%	-81.57%
	[0.55]	[0.77]	[1.11]	[1.05]	[-1.40]
MOM(1,14)	2,944.96%	1,567.12%	5,140.39%	15,197.74%	11.39%
	[1.01]	[0.83]	[1.16]	[1.46]	[0.10]
MOM(14,14)	747.91%	1,836.18%	3,781.32%	37,721.70%	869.89%
	[0.61]	[0.87]	[1.07]	[1.67*]	[1.00]

Notes: The returns for each of the different portfolios of the three researched momentum strategies, subtracted by the 12.8% returns promised on Tether. Each column represents its own portfolio, each row its own strategy. The numbers in between brackets show the t-statistics of OLS regression with Newey-West standard errors. * means they are significant at 10%, ** at 5% and *** at 1%.

The results put some interesting things to light. Apart from the high minus low portfolio for the mom(1,28) strategy all portfolios provide excess returns for the MOM(1,28), MOM(1,14) and MOM(14,14) strategies. Especially the MOM(14,14) strategy portfolios provide some extreme annualized average excess returns. The low momentum portfolio provides 747.91%, the medium low portfolio more than doubles that with 1,836.36%. The medium high portfolio return is again more than twice as high as the medium low one with 3,781.32% excess return, and the high momentum portfolio excess return are even nearly ten times higher at 37,721.70%. When looking at the MOM(1,28) and MOM(1,14) strategies the differences between the portfolios are a little less extreme but still very much prominent. For the MOM(1,28) strategy the return for the high momentum portfolio is around nine times as big as the low momentum portfolio, for the MOM(1,14) strategy around five times bigger. On the contrary of all the positive returns found for the individual portfolios, the high minus low portfolios paint a different picture. The high minus low portfolio for the MOM(1,28) gets outperformed by Tether and the high minus low momentum for the MOM(1,14) strategy only just about beats it. The MOM(14,14) strategies still flourishes however, providing 869.89% excess return per year.

Even though nearly all of the excess returns found when comparing momentum to Tether are positive, it cannot be concluded that momentum outperforms it. That is because virtually none of the results are significant. Only the high momentum portfolio for the MOM(14,14) strategy provides returns significant at just 10%. All other returns are far from significant, making it impossible to say they outperformed Tether. It might come as a surprise that momentum strategies cannot be concluded to outperform the returns of 12.8% on Tether seeing as the market has seen a meteoric rise in size and liquidity during the sample, but it can probably be elucidated through the high volatility. Where as YouHodler.com promises a relatively safe and little fluctuating return of 12.8%, which itself is not a bad return, the returns of momentum strategies differ quite a bit over time, making investing using such a strategy way riskier, as also can be seen by the low Sharpe ratios. This high risk and fluctuation compared to the stable return on YouHodler.com makes it very hard to outperform the 12.8%, which apparently is something these three momentum strategies are not capable of doing.

5.3 Bitcoin

5.3.1 Correlation

Referring to the methodology, the total market cap of Bitcoin has been by far the largest market cap of all cryptocurrencies in this paper, with the market cap taking up anywhere between 32% and 71% of the total market cap of all cryptocurrencies combined. Therefore it is not uncanny to think the price fluctuation of Bitcoin have some effect on the price fluctuation of other cryptocurrencies. Table 5 shows the correlation between the returns of the different portfolios for the different momentum strategies. Each momentum strategy's correlation is calculated relative to its own Bitcoin return. For instance, the correlation for MOM(1,28) is calculated relative to the Bitcoin return over the past 28 days.

In the table it is clear to see that the low, medium low, medium high and high portfolios are largely correlated to their corresponding Bitcoin returns. The coefficients are all between 0.70 and 0.77, making it safe to say there is a connection between them and their respective Bitcoin returns. This can partially be explained by the fact that Bitcoin itself can be in any of these portfolios, which would clearly enlarge the correlation. Moreover, it is clear to see that the low and high momentum portfolios for each strategy are respectively less correlated than the medium low and medium high portfolios, possibly suggesting that Bitcoin is more likely to perform very well or very bad, rather than slightly good or bad. The most interesting part of the results in table 5 is that it shows the correlation between the high minus low portfolios for each strategy and their particular Bitcoin

Table 5: **Correlation momentum and Bitcoin.**

	Low	2	3	High	High-Low
$\rho(MOM(1,28), BTC_{28})$	0.704	0.732	0.734	0.711	-0.001
$\rho(MOM(1,14), BTC_{14})$	0.723	0.760	0.767	0.732	0.000
$\rho(MOM(14,14), BTC_{14})$	0.712	0.748	0.752	0.709	0.020

Notes: Correlation between the different portfolios from the MOM(1,28), MOM(1,14), MOM(14,14) strategies. The fifth column represents the correlation between the respective high minus low portfolios and Bitcoin. For all momentum strategies the correlation is calculated relative to their respective Bitcoin returns. So for MOM(1,28) the Bitcoin return over the past 28 days is used for example.

returns to be all rather small, not much different from zero. With these kind of portfolios being the most frequently used ones when making use of a momentum strategy, it can be concluded that the returns of momentum strategies are basically uncorrelated to the Bitcoin returns, whatever the formation or holding period.

5.3.2 Returns

Next the returns of the momentum strategies and their respective Bitcoin returns are compared. Table 6 shows the annualized average excess returns, so the annualized average of the daily returns for each portfolio minus the relevant return of that day, for each of the covered momentum strategies. The numbers in brackets show the t-statistics for an OLS regression with Newey-West standard error.

Table 6: **Returns compared to Bitcoin, including Bitcoin itself.**

	Low	2	3	High	H-L
MOM(1,28)	-98.17%	-95.43%	-78.26%	-83.37%	-99.57%
	[-1.53]	[-1.25]	[-0.62]	[-0.70]	[-1.90*]
MOM(1,14)	-77.69%	-87.89%	-61.33%	14.55%	-99.22%
	[-0.71]	[-1.06]	[-0.49]	[0.06]	[-1.48]
MOM(14,14)	-93.90%	-85.90%	-71.47%	186.68%	-91.60%
	[-1.21]	[-0.94]	[-0.61]	[0.44]	[-0.69]

Notes: Column one through 4 show the annualized excess average returns of each of the portfolios for the MOM(28,3), MOM(14,7) and MOM(14,14) strategies when compared to the Bitcoin return. Column 5 shows the returns for the high minus low portfolios. The numbers in between brackets show the t-statistics of OLS regression with Newey-West standard errors. * means they are significant at 10%, ** at 5% and *** at 1%.

The results show nearly all of the low, medium low, medium high and high minus low momentum portfolios to have negative excess returns, indicating they were outperformed by Bitcoin in this sample. With the negative excess returns going all the way down to -99.97% per year, the returns missed out on by not investing in Bitcoin can be found to be quiet big. Most of these negative returns are insignificant though. Apart form the high minus low momentum portfolio for the MOM(1,28) strategy all returns are insignificant. And the one that is significant is only so at a significant level of 10%. Only two portfolios outperform Bitcoin. The high momentum portfolio for the MOM(1,14) and MOM(14,14) strategies provide 14.55% and 186.68% excess return per year respectively. But again, non of these returns are significant. Hence in cannot be concluded that the momentum portfolios outperformed the Bitcoin returns in the sample.

That momentum strategies fail in an attempt to outperform Bitcoin may have multiple explanations, one of which is the pure size of Bitcoin. With Bitcoin being undoubtedly the biggest cryptocurrency it becomes a relatively safer cryptocurrency to invest in. Most retail investors that start investing into cryptocurrency will likely start with either Bitcoin or Ethereum, as these two are by far the most well known cryptocurrencies there are, pushing the prices higher and maintaining it at a relatively higher level. The size also makes it so that investors sell other cryptocurrencies and invest in Bitcoin when things are going downhill, as the fast amounts of money circulating around Bitcoin make it seemingly too big to completely crash. The flee into Bitcoin when times are bad limits the downfall Bitcoin makes when others are completely crashing. This can also be seen when looking how the closing prices compares to the all time high prices of the cryptocurrencies found in table 1. Whereas most coins such as Dogecoin, Ripple, Stellar or Tron had a closing price of less than 20% of their all time high, for Bitcoin that was still over 54%. Because of this aspect of Bitcoin, investors invested in it are hit less hard than those invested into smaller coins via a momentum strategy when things take a turn for the worse, exposing a potential explanation as to why momentum strategies fail to outperform simply investing in Bitcoin.

The results in table 5 and 6 all compared momentum strategies that could include Bitcoin to Bitcoin itself. Table 5 shows the individual portfolios for each momentum strategy to rather be correlated with the returns of Bitcoin, therefore making it interesting to see what would happen if Bitcoin was taken out of the momentum strategy. So, after removing Bitcoin, only 16 cryptocurrencies remained available for the momentum portfolios. Table 7 shows their excess returns in comparison to the returns made on Bitcoin.

Most results in table 7 correspond to those from table 6. The low and medium low momentum portfolios hardly changes for each of the strategies since removing Bitcoin, potentially meaning that

Table 7: **Returns compared to Bitcoin, excluding Bitcoin itself.**

	Low	2	3	High	H-L
MOM(1,28)	-98.60%	-97.32%	-87.93%	-94.39%	-99.99%
	[-1.57]	[-1.35]	[-0.79]	[-1.04]	[-2.07**]
MOM(1,14)	-76.33%	-88.85%	-71.02%	-51.05%	-99.70%
	[-0.65]	[-1.03]	[-0.58]	[-0.32]	[-1.75*]
MOM(14,14)	-92.63%	-87.78%	-74.79%	146.39%	-99.87%
	[-1.10]	[-0.97]	[-0.62]	[0.36]	[-0.80]

Notes: Column one through four show the annualized excess average returns of each of the portfolios for the MOM(1,28), MOM(1,14) and MOM(14,14) strategies when compared to the Bitcoin return. Column 5 shows the returns for the high minus low portfolios. This time Bitcoin itself could not be selected when forming the portfolios. The number in between brackets show the t-statistics of OLS regression with Newey-West standard errors. * means they are significant at 10%, ** at 5% and *** at 1%.

Bitcoin would rarely be in the lower momentum portfolios. When looking at the medium high and high momentum portfolios the differences between table 6 and 5 are much larger, especially for the high momentum portfolios. In table 6 the momentum portfolio for a MOM(1,14) strategies provides a decent return of nearly 15% per year. When excluding Bitcoin from the portfolio the returns drop all the way to over -51%. This could indicate that Bitcoin was one of the major driving forces behind the high returns made in the high momentum portfolios. But again, just as in table 6, the returns in table 7 are basically all insignificant. Therefore the only conclusion that can be drawn remains the one that momentum strategies did not outperform Bitcoin in the sample.

The results strengthen the possible explanations given after table 6. The fact that higher momentum portfolios are negatively hit harder by removing Bitcoin than lower momentum portfolios could indicate that Bitcoin is hit less when the markets turn red in comparison to the other 16 cryptocurrencies in the sample. The explanations given for this after table 6 therefore still stand.

Since the excess returns found are very similar, it is interesting to check whether or not the correlation acts in a comparable way now that Bitcoin can no longer be used for the momentum strategies. Table 8 shows the results of these correlation calculations.

Just like table 7 showed similar returns to those from table 6, table 8 shows similar returns to those from table 5. Even though all correlations might be a tiny bit lower than those in table 5, they remain high. This indicates that most correlation found in table 5 does not come from the fact that Bitcoin could be in either of those portfolios, but from the fact that price fluctuations of Bitcoin are strongly correlated to those of other cryptocurrencies. However, since the most frequently used high minus low portfolios' correlation remains very low, the conclusion remains that the returns of

Table 8: **Correlation momentum and Bitcoin, excluding Bitcoin in momentum.**

	Low	2	3	High	H-L
$\rho(MOM(1,28), BTC_{28})$	0.689	0.705	0.708	0.687	-0.015
$\rho(MOM(1,14), BTC_{14})$	0.708	0.741	0.736	0.708	-0.009
$\rho(MOM(14,14), BTC_{14})$	0.705	0.735	0.728	0.690	-0.015

Notes: Correlation between the different portfolios from the MOM(1,28), MOM(1,14), MOM(14,14) strategies. The fifth column represents the correlation between the respective high minus low portfolios and Bitcoin. For all momentum strategies the correlation is calculated relative to their respective Bitcoin returns. So for MOM(1,28) the Bitcoin return over the past 28 days is used for example.

momentum strategies are not correlated to the returns of Bitcoin.

The lack of correlation means that there is no large common component between Bitcoin and momentum strategies in the cryptocurrencies market. Momentum strategies handle different information than Bitcoin, which could mean that some information has an effect on others coins, but not on Bitcoin. Knowing this and researching it could lead to a better understanding of how the Bitcoin price works in general.

6 Conclusion & Discussion

6.1 Conclusion

The main purpose of the research was to find if excess returns are provided by momentum strategies in the cryptocurrency market and compare these to other financial instruments. Taking everything into consideration, it is concluded that momentum strategies do not provide excess returns when compared to the US treasury bond. Each of the 25 strategies researched at the start might have found positive excess returns, up to thousands of percents per year, but non of them were very significantly positive. When the boundaries of 25% profit or loss would be dropped, it would be likely to see the returns rise even higher. The boundaries set to the returns are not all bad though. They reduce the risk of the strategies, which is something very much needed in the cryptocurrency world. When looking at the Sharpe ratios, they are all extremely low, confirming the assumption that investing in cryptocurrency is risky and that the returns are exceptionally volatile.

It can however not be concluded that momentum strategies outperformed the other two instruments it was compared too, Tether and investing in Bitcoin. Even though all returns found when comparing momentum to Tether were positive and quiet high, non of them were significant. And when comparing to the returns of Bitcoin, each of the three mainly examined portfolios produced mostly negative returns. But again, basically non of them were found to be significant, making it impossible to conclude that momentum was outperformed by Bitcoin.

Making use of momentum strategies in the cryptocurrency market during the sample would have provided the investor with some excess returns, but it cannot be said to be the best strategy for the cryptocurrency market. Against the relatively low threshold of 1.88% per year from the US treasury bonds momentum strategies it failed in generating any significant returns. And when taking the risk into account, this not so great image of momentum strategies only gets worse. The paper corroborates with the findings of Grobys and Sapkota (2019) and makes it unattractive to invest into cryptocurrency making use of momentum strategies. Cryptocurrencies might remain an utopia of easy high returns for most, but any institutional investor should think twice before applying momentum strategies in the market.

6.2 Extension

Further research into the topic of excess returns generated by momentum strategies in the cryptocurrency market should focus on three things in particular. Firstly it should try to find daily data for market capitalization per cryptocurrency. This would allow portfolios to be value weighted, which is more frequently used than the now used volatility weighting. The second focus point of further research should be trying to incorporate more relatively smaller cryptocurrencies. Now the data only contains coin well within the top 75 market capitalisation coins there are, potentially making them all a little less volatile than the smaller coins. It might be the case that higher returns can be made when taking some smaller market capitalisation coins into the equation. The third aspect that further research should focus on is taking a smaller time frame, but having more frequent data points. So instead of have over 4 years of daily data, focus on maybe 1 or 2 years of hourly or even minutely data. Recommending a shorter time frame might sound weird at first but there is a reason. During the researched period, especially at the beginning, the the cryptocurrency market itself was still very up and coming. And it is not weird to expect up and coming markets to behave different from more traditional markets like the stock market. Now that the cryptocurrency market is a bit more settled and better known to the general public, the findings in this paper might not comply with the current time anymore. Hence it would be interesting if a follow-up paper focuses only on more recent data.

Then there are two problems one might find when reading this paper. The first one being that the whole cryptocurrency market is said to have exponentially grown during the sample. So much so that is raises the question if the returns found by momentum strategies are momentum exclusive, or whether nearly all strategies would have provided excess returns. With the total market capitalisation rising from around $500 billion to nearly $3 trillion, it is to be expected that investing in general, no matter what strategy, would generate some great profits. The second problem one might find is regarding the stop-loss and stop-profit boundaries. These boundaries are now based on the end-of-the-day results. For example, if the returns of a trade was -30%, it is set to -25%. However, if during the day a position would go down to -30%, but before the end of the day it would go back up to -20%, it reports the -20% as a results. Because intraday data is missing, it does not know when during the day a return drops below -25% before going back up, therefore falsely not reporting the lower limit of -25% as a return. The same goes for returns on the upper boundary of +25%. One could say that since the problem occurs at both ends of the spectrum they even out, but follow-up research should still take a good look at this.

7 Appendix

Table 9: **Returns of different momentum strategies**

		Formation period				
		1	3	7	14	28
Holding period	1	19.55%	12.50%	10.33%	19.21%	95.22%
		[0.45]	[0.29]	[0.25]	[0.46]	[1.74*]
	3	5.89%	33.51%	24.91%	134.34%	362.15%
		[0.08]	[0.33]	[0.25]	[0.92]	[1.54]
	7	176.44%	-8.99%	32.13%	644.13%	660.36%
		[1.10]	[-0.08	[0.19]	[1.21]	[1.12]
	14	146.96%	73.50%	523.51%	4689.22%	1222.24%
		[0.82]	[0.36]	[0.91]	[1.64]	[1.04]
	28	64.74%	100.55%	352.21%	90.27%	-22.26%
		[0.39]	[0.38]	[0.63]	[0.23]	[-0.08]

Notes: This table shows the excess returns of different momentum strategies, based on equal weights. Each row represents it's own holding period, each column represents it's own formation period. Within each row there are two lines. The top ones represent the excess returns made, to bottom ones within the brackets represent the t-value of OLS regression with Newey-West standard errors run on each strategies. The stars next to these numbers represent the significance. * means that it is signifcant at 10%, ** at 5% and *** at 1%.

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Stata command code

Note that all momentum portfolios and their excess returns were created in Excel.

clear all

import excel "/Users/pieterbakker/Desktop/Thesis Bachelor.xlsx (1)", sheet("With") firstrow

drop all before 2-2-18, as not all portfolios were active before then

drop if MOM_2828_HL>=.

set timeseries for newey west test

tsset Date

newey test excess returns

newey EX_11, lag(7)

newey EX_31, lag(7)

newey EX_71, lag(7)

newey EX_141, lag(7)

newey EX_281, lag(7)

newey EX_13, lag(7)

newey EX_33, lag(7)

newey EX_73, lag(7)

newey EX_143, lag(7)

newey EX_283, lag(7)

newey EX_17, lag(7)

newey EX_37, lag(7)

newey EX_77, lag(7)

newey EX_147, lag(7)

newey EX_287, lag(7)

newey EX_114, lag(7)

newey EX_314, lag(7)

newey EX_714, lag(7)

newey EX_1414, lag(7)

newey EX_2814, lag(7)

newey EX_128, lag(7)

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newey EX_2828, lag(7)
*newey west test tether*
newey E128_L, lag(7)
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newey E114_L, lag(7)
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newey BE1414_HL, lag(7)
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*calculate correlation*
corr BTC_HR28 P128_L P128_ML P128_MH P128_H P128_HL
corr BTC_HR14 P147_L P114_ML P114_MH P114_H P114_HL
corr BTC_HR14 P1414_L P1414_ML P1414_MH P1414_H P1414_HL
*part without bitcoin*
clear all
*import second tab from file*
import excel "/Users/pieterbakker/Desktop/Thesis Bachelor (1).xlsx", sheet("Without") firstrow
*drop all before 2-2-18, as not all portfolios were active before then
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*set timeseries for newey west test*
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newey BE1414_HL, lag(7)
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corr BTC_HR14 P114_L P114_ML P114_MH p114_H P114_HL
corr BTC_HR14 P1414_L P1414_ML P1414_MH P1414_H P1414_HL
```

appendix

clear all

import file import excel "/Users/pieterbakker/Desktop/Thesis Bachelor.xlsx", sheet("With") firstrow

drop all before 2-2-18, as not all portfolio's were active before then drop if MOM_2828_HL¿=.

set timeseries for newey west test tsset Date

newey test excess returns

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newey EX_31, lag(7)

newey EX_71, lag(7)

newey EX_141, lag(7)

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newey EX_13, lag(7)

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newey EX_2828, lag(7)