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Momentum Strategy With Classical Assets And Cryptocurrencies

Master's Thesis

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Für Meine Liebe Oma,

Leider hast du den Tag jetzt nicht mehr erleben dürfen an dem ich mit meinem Studium fertig werde. Die Irnonie des Schicksals ist, dass ich so lange überlegt habe, wem ich diese Arbeit eigentlich widmen soll und dann bist du leider gegangen. Ich hoff du freust dich trotzdem, dass der "Dauer-Student" jetzt langsam mal fertig wird. Ich bin mir auch ganz sicher, dass du uns von dem besseren Ort, an dem du jetzt bist, zu schaust und dich mit mir freust. Lass es dir gut gehen, wenn wir uns wieder sehen bring ich dir ein Original zum Lesen mit und wir stoßen an.
Oma, wir vermissen dich sehr und werden dich nie vergessen. Danke für Alles.

Dein Donal

Contents

List of Acronyms

AMEX American Stock Exchange

HML High Minus Low

NYSE New York Stock Exchange

SMB Small Minus Big

S&P 500 Standard & Poor's 500 index

UMD Up Minus Down

U.S. United States

U.S.-$ United States Dollar

1 Introduction

Since the beginning of their existence on financial markets, private, institutional, large and small investors have been looking for the optimal investment strategy to achieve the highest possible return and to "beat the market". Strategies such as value[1] or growth[2] investing, which are used with great success by fundamental analysts like Warren Buffett, are probably among the most well-known today. On the other hand, there are the technical analysts who search for patterns and regularities in stock prices and thus are looking for the optimal investment strategy. These strategies may differ in their execution, but they have one thing in common: they clearly contradict the efficient market hypothesis, which states that prices should fully reflect all available information and are unpredictable.

Another well-known market anomaly that investors around the world use is the momentum strategy, first described and explored by Jegadeesh and Titman [1993], which is the subject of this thesis. In contrast to other strategies, the focus here is on the past performance of a security, from which a recommendation for action is made, that is relatively easy to understand and to implement: If past performance was good, the momentum strategy assumes that this will be the case for a certain time in the future and vice versa. So one should invest in such securities with good past performance and take a long position, if the performance was poor the same applies in the other directon and one should sell the relevant securities or take a short position.

Many empirical studies in the past have shown that momentum has a right to exist and that the desired excess returns can be achieved with this strategy, which is why many investors resort to it. But what has been found out about momentum in the past almost 30 years? Furthermore, a lot has changed since the introduction in 1993: The digital progress now allows data to be recorded at much finer time intervals and the financial markets have been enriched by an investment opportunity since the introduction of Bitcoin in 2009 and other cryptocurrencies thereafter. Can momentum now also be used for portfolio building on a daily basis, does this pattern also exist in the relatively new cryptocurrency market, are there any differences to classic securities and what is the risk of a momentum strategy like?

In order to shed some light on these questions, this thesis was written with the aim to show the reader the current status in the literature, examining how profitable the strategy is, when using daily data, and how high the risk of momentum strategy is like.

[1]Strategy of investing in companies whose market value is below their intrinsic value.
[2]Strategy of investing in companies originating from growth markets with high growth potential

In this thesis, stocks from the S&P500 index and the 30 largest cryptocurrencies are used. The results show very clear differences in the returns between classic securities and cryptocurrencies, which are reflected both in the yield and in the statistical properties of their distributions. The classic shares did not show any postive momentum effect over the observed period from 2018 to 2021, whereas the cryptocurrencies achieved good returns, but suffer from their high volatility in terms of risk assessment. In order to take into account the outbreak of the global COVID-19 pandemic and to assess whether the empirical results are constant over time, the period under investigation is divided into two sections: before and after the outbreak of the pandemic in march 2020. The empirical results will show that this approach makes sense, since a connection with the pandemic can be established for the momentum strategies of the S&P 500 shares as well as of cryptocurrencies. The latter seem to be a good alternative in times of economic crises on the financial markets, at least when ignoring the high volatility.

The structure of this thesis is as follows: in the remaining part of the introduction, a brief overview of the S&P 500 and the cryptocurrencies is to be provided, in the next chapter the efficient market hypothesis and the different types of momentum as an anomaly of an unpredictable market are explained. A detailed literature review in the third chapter is followed by the fourth chapter where the data and the methodology of the study are presented. The results of this study and their limitations are treated in the fifth section, while in the last chapter the results are discussed, concluded and a possible outlook for the future and further research is given.

1.1 The S&P 500 Index

The Standard & Poor's 500 Index is one of the largest stock indices in the U.S. and the world, containing 500 of the largest U.S. stocks. 400 of the shares listed in it pertain to industry, 40 are from the supply and financial sector and 20 stem from the logistics company sector. The index is revised at regular intervals, which means that stocks are eliminated and new ones are added, so there is no guarantee that the respective companies will always be included and permanently be listed.

1.2 Cryptocurrencies

With the introduction of Bitcoin in 2009, the age of cryptocurrencies began, and according to Maese et al. [2016] a cryptocurrency is *"a medium of exchange that functions like money but, unlike traditional currency, is untethered to, and independent from, national borders, central banks, sovereigns, or ats. In other words, it exists completely in the virtual world, traded on multiple global platforms".*

A key difference to classic company shares and other securities is, in accordance with Cheng et al. [2019], that cryptocurrencies are not backed by physical assets, that have a company value as their basis, or bonds, that are guaranteed by governments. Cryptocurrencies are therefore purely virtual investments and a very big variation to classic financial markets is that cryptocurrencies can be traded around the clock, 365 days a year and are not subject to the opening hours of a stock exchange or other institutions.

2 The Efficient Market & Momentum

In this section, the efficient market and random walk hypotheses are explained, and momentum, in its different forms, is introduced as an investment strategy, that contradicts them.

2.1 The Efficient Market & Random Walk Hypothesis

The *Efficient Market Hypothesis* was introduced by Fama [1970] and refers to the assumption that security prices in capital markets *"fully reflect"* all available information about it. It is divided into three different forms: *the weak, the semi-strong and the strong form*, which flow into each other as shown in Figure 1 and described below:

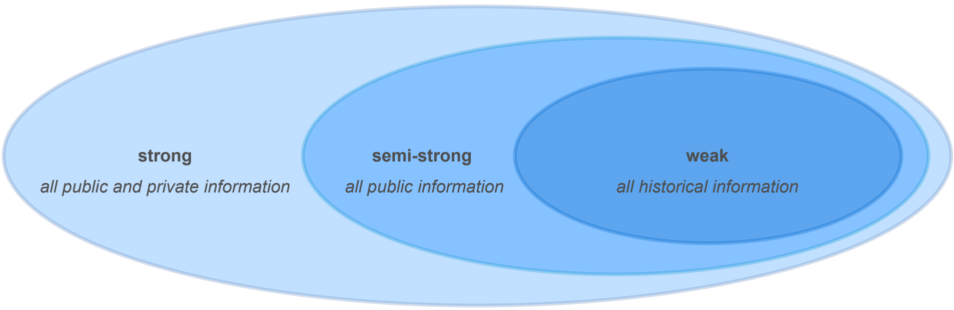


Figure 1: The three Forms of the Efficient Market Hypothesis

• <u>Weak Form:</u>
The weak form states that all historical price information, meaning good and bad news, are completely reflected by the current price of any tradable capital instrument.

• Semi-Strong Form:
The semi-strong form states that all publicly available information are completely reflected by the current price of a security. This means that, any current information like annual reports, forecasts, and any kind of earnings announcements, are inculded in additon to the weak form.

• Strong Form:
The strong form states that, in addition to information of the the weak- and semi-strong form, all private information is fully captured in a securities present price. This private information may consist of new research findings, insider information and any other type of information that may not be all publicly available.

A direct consequence of the efficienct market hypothesis is that stocks and securities prices develop as a so-called *random walk*:

$$y_t = y_{t-1} + \epsilon_t$$

where

- y_t is the price of asset y at time point t
- y_{t-1} is the price of asset y at time point $t-1$
- ϵ_t is a random shock at time point t

Ultimately, the efficient market and random walk hypotheses states that stock prices are unpredictable and today's price is yesterday's price plus a random shock, so one should not actually be able to outperform the market. However, this hypotheses hardly hold up and investors, of all colors, are always on the lookout for the most lucrative investment strategy possible. In addition to the well-known strategies such as size or value investment and many others, momentum is another market anomaly that contradicts the efficient market and random walk hypotheses and with which investors try to make profits on the financial markets.

2.2 Momentum: An Efficient Market Anomaly

Momentum is a relatively easy-to-understand investment strategy which focuses on past return patterns of tradeable assets like stocks, currencies, cryptocurrencies, commodities, and bonds. Following Jegadeesh and Titman [1993], the idea behind momentum is to buy past winners and sell past losers, by comparing stocks which exhibit good past return performance and stocks with low past performance. In a desirable scenario, the winners keep realizing better returns than the losers, so that there is a so-called momentum. In another definition, Chen et al. [2021] define momentum as a strategy to identify stocks whose past performance would persist for a period of time in the future.

However, momentum is not the same as momentum. There are essentially two different approaches in the literature on how to construct such a momentum portfolio. On the one hand, there is the so-called price momentum, which can be further divided into *cross-sectional* and *time-series momentum*, and on the other hand the so-called *earnings momentum*. The following subsection will go into more detail on the individual definitions.

2.2.1 Price Momentum

Following the definition of Jegadeesh and Titman [1993] for a cross-sectional momentum strategy, securities are ranked on their past return performance compared to their peers in the cross-section over a given formation period of time. The ranked securities are then sorted in ascending order into one of ten portfolios, with the winners in the top and the losers in the bottom. The idea of the strategy is to go long for the winners and to sell or to short the losers. The resulting zero-investment portfolio[3] is then subsequently held for a certain time period.

With regard to the time intervals for formation and holding period, however, one should keep in mind that the aforementioned study was carried out on monthly data. If one now works with daily data, for example, as in this thesis, shorter time intervals are used, but the scheme remains the same.

The difference between cross-sectional and time-series momentum according to Moskowitz et al. [2012] is that for time-series momentum one focuses purely on a security‘s own absolute past return, than on the relative reuturn of securities in the cross-section. So one takes a long position in securities with a positive past return and a short position with a negative past return. In contrast to the cross-sectional momentum, in the most extreme case this could lead to exclusively long or short positions being taken, which means that it cannot be a zero-investment strategy in some cases.

[3]Portfolio consisting of long and short positions that has a combined net worth of zero

2.2.2 Earnings Momentum

Measures of the so-called earnings momentum try to capture the past performance of earnings news of a security. However, these variables only make sense for securities for which earnings news are also generated, such as equity shares of companies. These are rather unsuitable for cryptocurrencies, for example, since these news simply do not exist. Since these variables are not used in the course of this study, but they should nevertheless be mentioned, they are only briefly touched upon here. Chan et al. [1996] define three variables for an earnings momentum: the so-called standardized unexpected earnings (SUE), that deal with quarterly earnings per share, the cumulative abnormal stock return (ABR) which are measuring stock movements after earnings announcements and the changes in analysts' forecasts of earnings (REV6). The difference to the price momentum is that these variables are then used for the ranking according to the formation period instead of the returns.

3 Literature Review

This chapter is structured according to the following scheme: First, the most important works on momentum basics are reviewed and followed by publications that focus on explaining and finding the drivers of this stratgey. The third subsection expands the previous two chapters by certain aspects, such as how momentum performs during economic crises and other topics. As the last subsection, publications on momentum with cryptocurrenices are presented, since these are also dealt with separately in the following empirical study and are to be decoupled from the classic assets.

3.1 General Findings

Jegadeesh and Titman [1993] published the first academic paper in which they deal with a strategy to build portfolios by buying past winners and selling past losers, which enables them to generate significant positive returns over the following three to twelve months as holding periods. To show that, they rank stocks of NYSE and AMEX from 1965 to 1989 based on their past three to twelve month returns and put them in an ascending order into one of ten decile portfolios. These portfolios are then held for a following period of one to four quarters, allowing for overlapping time periods to increase the power of the results. Further the portfolios are built in two differnt ways. One way was to buy and hold the portfolios for the given time period and the other was to rebalance them monthly. Nevertheless, the findings of theses two strategies were very similar. As an example for their results, portfolios with selected stocks based on their past six month returns and then holding for another six months generate an average excess return of about 12.01% per year. Nevertheless, this effect is vanishing after about twelve months after portfolio formation, resulting in a loss of more than half of the return after 24 months in the case of the twelve months holding period portfolio. A similar behaviour is found when not looking only on the returns of stocks but also on their earnings anouncements. Past winners, for instance, generate higher returns around earnings anoncements than the losers in the first seven months after formation, but this turns around in the following thirteen months when the losers outperform the winners. Apart from showing that the momentum effect exists for up to twelve months, Jegadeesh and Titman [1993] provide a decomposition of the excess returns into different sources. To do so, they decompose a one factor model into three different sources. As the two measures related to systematic risk and an efficient market, they use the cross-sectional dispersion measured by the average size and beta of the portfolios, as well as the serial covariance of factor related returns. The empirical results for both do not indicate for them to be an explanatory source of the excess returns and futher do not support the assumption of an efficient market. As the thrid and last component the serial covariance of the model residuals, attributed to idiosyncratic risk and an inefficent market, suggest to be a source of the positive returns and a market which is not fully efficient. It turns out that stocks underreact to firm specific information and price reaction is delayed, which causes the positive returns following portfolio formation. In addition, the lead-lag effect resulting from delayed reactions to information about common factors, does not seem to be attributable to the momentum portfolio profits.

Chan et al. [1996] confirm the existance of momentum and that it lasts for at least six months. They seperate momentum into price and earnings momentum stratetgies and show that the price momentum effect is stronger and longer-lived than the earnings momentum. The earnings variables are a strong indication for the market's slow reaction to new information and circumstances, what leads to momentum in the stocks. For both possibilities, however, the returns are not completely reversed and are therefore not only driven by investor behavior. However, the effect of reversion is stronger if, for example, large positive returns are not also supported by positive earnings news as the multivariate analysis of price and earnings momentum in combination shows. More caution is generally required when it comes to earnings news, as analysts are particularly reluctant to correct their forecasts downwards or even revise them entirely. Nevertheless, a large part of the price momentum profit seems to arise around the earnings announcements, since the market then seems to be moving in the direction of the earnings news, at least for a certain time. Chan et al. [1996] and Fama and French [1996] further confirm each other and show that momentum return patterens can not be captured by factor models based on size or book-to-market ratios. Nevertheless, they find that the extreme portfolios tend to have smaller stocks.

n further work, Rouwenhorst [1998] investigates European stock markets to asses if the anomalies of momentum are due to the fact that most other researchers before have focused on substantially the same data bases of U.S. stocks and the reported patterns may therefore be unusual and U.S. specific. His findings, focusing on medium-term returns in twelve European contries, are in line with those from Jegadeesh and Titman [1993]. Constructing a portfolio out of past winners and selling the losers generates a return of approximetly 1% per month persisting for about one year. He further confirms that momentum is stronger (in the winner and the loser case) for smaller than for larger firms and additionally is not an artefact of a particular market. The European and U.S. market may both be exposed to a common factor that may drive momentum which is inconsistent with the joint hypothesis of efficiency.

Grundy and Martin [2001] argue that ranking stocks based on their past cumulative return dominates momentum strategies that rank securities on their past total return, meaning that a stock-specific return momentum strategy will lead to higher returns. The authors further show that momentum underlies some firm- or stock-specific components as well as systematic-factor related ones. They find out, that factor models may be able to explain up to 95% of the variability in returns but fail to explain the mean returns. In addition, momentum profits are not entirely explained by bearing industry risk.

Considering momentum on a global level, Griffin et al. [2005] confirm former results, but also come up with some new aspects and findings. In their study they investigate U.S. stocks as well as non-financial stocks around the globe. Focusing on the past six months performance and then holding for six months, they show that price and earnings momentum for the winners outperform the market, except for a three to five years period at the beginning of the 1990's, and for Asian and American markets, excluding the U.S., even the losers do. Combining price and earnings momentum, their results are in line with Chan et al. [1996]. A new finding by the authors is, that foreign momentum is much less correlated with momentum in the U.S. than market indices are. Hence, an international momentum investment might be a good diversification strategy, especially in the case of down markets[4]. Regarding the time series of momentum returns, three observations are pointed out. At first, regional price momentum returns seem to be less volatile than market returns but second, may be strongly autocorrelated in the case of extremely negative returns and third, these extreme negative returns then seem to occure mostly in januaries.

So far, the prementioned literature focuses on cross-sectional momentun. Moskowitz et al. [2012] bring in a new asset pricing anomaly, namely the so-called time-series momentum, where the focus lies only on an asset‘s or security‘s own past return performance. Using data of futures and forward contracts including country equity indicies, currencies, commodities and sovereign bonds, they state, that the past twelve months excess return of each instrument is a strong positive predictor for its future return for up to one year. They define two possibilities for constructing a time-series momentum strategy: one is to regress an instrument's excess return at time point t on its excess return lagged by h months or, an even easier way, on the sign (which is either positive or negative) of its past excess returns. Both strategies show a strong return continuation for the following year and weaker reversals, with the strongest directly following the momentum trend. The reported results are nearly the same for single asset or pooled panel regressions and thus are consistent among very diffenrent types of investors and instruments. When controlling by regression for other exposures (market- , bonds-, commodity market- and stock market- factors) it is shown that time-series momentum is still significant and robust across different time horizons and asset classes. The authors then construct a time-series momentum factor and conduct a regression analysis on it with similar results. The regression betas for Market, SMB or HML are not significant in explaining time-series momentum. But it turns out that it loads significantly positive on UMD of the cross-sectional momentum but is not fully explained thereby. Moskowitz et al. [2012] further suggest that their momentum approach is a hedge against extreme events as it performed well through extreme markets like in the financial crisis in 2008 due to being short in many contracts at that time when markets went from bad to worse, but suffering some losses because of the sharp trend reversal at the end of the crisis. The reported positive correlation across asset classes suggests a strong common component affecting their momentum strategies which is not present in the underlying asset classes themselves, a finding that is in line with Asness et al. [2013]. As already mentioned above, time-series and cross-sectional momentum are related but not the same. Results do indicate, there is a strong correlation structure across different asset classes,

[4] When markets close lower than the day before

but cross-sectional momentum fails to fully capture the time-series momentum which is mostly driven by the positive auto-covariance of its returns. The other way around seems to work, as time-series momentum can fully explain its cross-sectional counterpart, as the auto-covariance or the time series piece seems to be the main contributer to it.

Asness et al. [2013] are studying momentum in combination with value investing across different markets, namely the U.S., Europe and Japan, and different asset classes like stocks, equity indices, currencies, government bonds and commodity futures. As in the prementioned literature review, momentum generates positive excess returns across all markets, except for Japan, and asset classes but performes even better when combined with value, resulting in higher returns and increasing Sharpe ratios. They show that momentum and value are negatively correlated with each other in the stand-alone case suggesting that both load oppositely on some common risk factor. In fact, it turns out that momentum is not related to common macro-factors as buisness cycle, consumption and default risk but seems to be positivley related to funding liquidity risk. Hence, the latter may explain a part of its negative correlation to value. To asses the economic significance of the prementioned patterns, the authors use a so-called "Global Three-Factor Model" to explain the returns of value and momentum across markets and asset classes. As a last step they conduct time series analyses using momentum and value as a factor, to show that the momentum (and value) effect is strongly related across markets and asset classes.

A comparison between time-series and cross-sectional momentum is tackled by Goyal and Jegadeesh [2017]. To do so, the authors decompose the differences for the two types of momentum investment into three components: a risk premium, the market timing, and the asset selection. The risk premium, which is reported to be significant at all horizons of their study and increasing with longer ranking periods, is a compensation for a time-varying net long position in the market. The time-series momentum consists of such a time-varying position on in the market plus a zero-net investment, while the cross-sectional momentum stratgy is a pure zero-net investment. The market-timing component, which is especially large at the one-month horizon, stems from the profit of the time-varying investment in the equally-weigthed market for the time-series momentum. This is because the time-series momentum does not make a relative comparison, but goes long in securities that have performed well and short in those with poor performance. Accordingly, the number of long positions after an up market is greater than after a down market, which means that the share of the equally-weighted market varies. With cross-sectional momentum, on the other hand, the number of securities in the individual portfolios is always steady. This explained difference in the number of securities for the portfolios also explains the last, so-called asset selection component, which, however, is not significant, except for the biggest losers.

Chen et al. [2021] follow a non-parametric approach built on average ranks and signs over the formation period of daily returns to mitigate the impact of mispricing and price distortion of which parametric measures like average returns might be affected. Empirical results show that rank momentum and sign momentum outperform the price momentum by Jegadeesh and Titman [1993] on short-term holding while exhibiting no long-term return reversals. They argue that price momentum may fail to identify the real losers and winners due to over- and underreaction of investors, causing extreme oberservations which benchmarks then are applied to. Hence, their approach gives less weight to extreme observations but takes non-salient information into account, which is often neglectd by investors, leading to a better identification of winners and losers. The price momentum can further be subsumed by rank and sign momentum, but vice versa both remain robust. One last point is, that given their non-parametric properties, rank and sign momentum seem to be less sensitive to crashes when other momentum strategies performed worse.

3.2 What Drives Momentum?

Following Daniel et al. [1998] momentum patterns are driven by investors overconfidence and self-attribution. When initial private information is confirmed by public information, confidence rises and causes a continuing overreaction leading to momentum in asset prices. This is subsequently reversed when further public information slowly draws prices back to fundamentals. The difference in biased self-attribution between Western and Asian investors suggests to explain the abesence of momentum in Japan, as reported by Asness et al. [2013].

Moskowitz and Grinblatt [1999] suggest that momentum relies heavily on industries. When adjusting cross-sectional stock momentum returns for industries, they are weak and almost insignificant. On the other side, even after controlling for several other common factors like size and value, a momentum stratgey based on industries shows high returns and is more profitable. Another fact is the matter of the time horizon and the investor's position. Industry momentum seems to be mostly driven by long positions in the medium-term horizon, while individual or cross-sectional stock momentum lives from short-selling the past losers. Further, industry momentum seems to be strongest over short-term horizons and the overall effect seems to vanish after about twelve months, which is the same phenomenon for cross-sectional momentum reported by Jegadeesh and

Titman [1993]. Furthermore Moskowitz and Grinblatt [1999] point out that, in contrast to other studies, momentum strategies are not very well diversified. One reason for that is, that most of the individual stock momentum is driven by industry momentum and stocks within an industry are highly correlated, while correlation seems to be lower for stocks across industries.

Making investors the drivers of momentum Hong and Stein [1999] shed light on the strategy in a behavioral context. The difference to other work like the one of Daniel et al. [1998] is that they do not focus solely on the investors but also take the interaction of different types of agents into account. To do so, they distinguish between the so-called *news-watchers* and *momentum-traders*. The news-watchers do forecasts based on private infomation about fundamentals they receive, but do not condition on past prices to check whether they might already be incorporated in the stock price. This can trigger a jump in the stock price which is then picked-up by the momentum-traders as they use a simple forecast based on past price movements and therefore profit from past underreaction which is leading to an overreaction in the long-term. Another aspect they mention is the importance of the momentum cycle and when the traders step in. An early investment seems to be more profitable than one later in time as the effect may already vanish, when the caused overreaction is swinging back to fundamentals. This confirms early work on the persistence of the momentum effect on a finite time horizon. One key finding of Daniel et al. [1998] is that information about fundamentals seems to diffuse slowly among investors and in combinition with different agents can lead to the observed phenomenon.

Johnson [2002] is giving a rational explanation through stochastic growth-rates, which may explain all or a part of the momentum effect in tradeable securities. He states that stock prices condition on growth-rates in a highly sensitive and non-linear way, while the growth-rate-risk rises with the growth-rate itself. The link between the two is that investors expect higher future returns for stocks with higher growth-rates as they become more risky, which then leads to a momentum in the prices. To make this more clear the author shows that firms with recent positive price movements are likley to have experienced a positive growth-rate shock before. When thinking about what causes growth-rate changes, one easily ends up with its connection to major changes in business conditions and cycles which are then likely to be common within sectors or industries. Thus, the effect of growth-rates in momentum may also explain, or be linked to, the effect of industries on it, as reported by Moskowitz and Grinblatt [1999].

In contrast to that, Da et al. [2014] show that investors underreact to information that comes in smaller amounts and continuously than to information that comes in magnitude above a certain threshold, due to limited attention, what causes momentum. Information which is under a certain level of importance is processed with a delay, while rational investors are likely to take all sorts of information into account immediately. Despite the fact that continuous information seems to have a stronger short-term continuation, they do not face long-term return reversals.

Antoniou et al. [2013] shed light on the relation between price momentum and investor's sentiment in the case of the U.S. stock market. According to their findings, investors underreact more strongly when they receive new information that contradicts their actual sentiment due to cognitive dissonance. This implies that bad (good) news diffuse slowly during optimistic (pessimistic) states of investors feelings and lead momentum. Nevertheless, momentum's profits seem to be only significant during optimistic periods and hence are not significantly in pessimistic phases of the investor's sentiment. These results are robust when controlling for market returns, analyst coverage, and firm size or other measurements of investor's sentiment. The authors further show, that small investors are slow in selling losers during optimistic periods as bad news causes cognitive dissonance when they stil have optimistic beliefs, while large investors on the contrary seem to react much faster to negative information and sell losers more promptley. In addition, it is shown that long-time price reversals only occur after phases of positive sentiment as the price continuations are affected by momentum traders in optimistic periods, which subsequently are corrected towards fundamentals.

3.3 More of Momentum

Novy-Marx [2012] breaks with the general view of momentum, that securities which recently rised will tend to rise in the future and vice versa for those who had fallen. He argues that the past performance of the intermediate time horizon of twelve to seven months before portfolio formation is the main driver of momentum profits afterwards and not the more recent past. As an example, he states that a recent winner and intermediate loser will on average have lower returns than a recent loser but intermediate winner. He further found that the intermediate performance of twelve to seven months leads to better future predections and higher Sharpe ratios, not just in U.S. equity markets but further across different asset classes like industries, currencies, commodites, and others.

Asness et al. [2014] discuss ten of the most popular myths surrounding momentum and dispel them by a comparison to other strategies like value- or size-investing. Two examples for such a myth would be momentum's limitation to trading costs or that investors can catch momentum only when they go long. They conculde that momentum does not work better or worse than other strategies but suggest combining it with its peers to benefit from each strategies advantages.

The publications of Barroso and Santa-Clara [2015] and Daniel and Moskowitz [2016] deal with momentum's exposures to crashes when the strategy suffered large losses, especially in July and August 1932 and from March to May in 2009 after the subprime crisis. Barroso and Santa-Clara [2015] show that momentum's distribution suffers a fat left tail that indicating a high crash risk. They estimate its risk by realized volatility on a basis of daily returns and show that about 80% of the momentum's risk is strategy-specific, but highly predictable. Daniel and Moskowitz [2016] explain that momentum crashes occur when markets have fallen and are in panic states with high ex ante volatility and then suddenly recover with an upswing in the returns. The source of the momentum crahses is its changing portfolio beta and the past losers as main driver. Momentum is short in past losers which tend to have low down-market but high up-market betas. When markets then rebound in an upward direction the losers cause the crash as they are shorted but generate high excess returns which come from their high up-market beta. The winners are further not gaining at the same magnitude and cannot compensate for the losses from the short side of the momentum portfolio in such cases, what leads into the crash of the strategy.

3.4 Momentum & Cryptocurrcencies

Grobys and Sapkota [2019] claim to be the first to apply the momentum strategy to cryptocurrencies and come to the conclusion that there is no evidence of the existence of momentum in this relatively young financial market. Neither cross-sectional nor time-series momentum seem to generate significant positive returns, only some of the tested strategies seem to achieve negative results. The authors therefore conclude that this new digital market is more efficient than classical asset markets, which supports the effcient market hypothesis.

Kosc et al. [2019] investigate the momentum effect and its counterpart, the contrarian strategy introduced by De Bondt and Thaler [1985, 1987] which, in short, recommends investing in past losers and selling or shorting past winners. On a daily basis for about 1200 different cryptocurrencies, they report a strong contrarian effect but a lack of momentum. Besides the poor performance, they further show that momentum is underperforming other investment strategies when dealing with the relation between risk and return in terms of the information ratio.

A new approach to measure the momentum effect through fractal analysis is used by Cheng et al. [2019], who use this econophysical tool to detect correlations in non-stationary time-series in a single and multi-fractal fashion. Their results show that some of the cryptocurrencies simply follow a random walk with no identifiable momentum effect and can be seen as efficient. On the other hand, depending on different time scales, there are cryptocurrencies that show a momentum pattern. These results hold for the single and multi-fractal analysis and the authors conculde that the past price can be the significant driver for future price movements.

In contrast to some of the prementioned studies, Tzouvanas et al. [2020] report positive momentum returns up to 33% per week, implying an inefficient cryptocurrencies market in the short-term (up to 30 days) for daily data. This effect is vanishing in the directon of a more efficient market in the longer term. They further report lower correlation for cryptocurrencies' momentum with momentum for tradional assets than these asset classes experience between each other. Thus they conclude that the cryptocurrencies' momentum is disentangled from these. Based on these findings, the authors suggest monentum with cryptocurrencies as a hedge against market risks and a good diversifier.

Caporale and Plastun [2020] investigate if there is a momentum effect after abnormal returns for the three largest cryptocurrencies in daily or hourly data. One has to mention here that their momentum strategy is a bit different from the momentum strategies discussed before as they do not rank or hold the cryptocurrencies for predefined time periods but show that prices tend to move in the same diretion as the abnormal returns. This pattern can be found on the same or the following day of the occurrence of an abnormal return. Long positions in the respective cryptocurrency should be closed out according to a timing parameter which is indicating when the momentum effect is vanishing.

The effect of time-series momentum for cryptocurrencies is studied by Liu and Tsyvinski [2020] at various time-horizons from one to eight weeks. For both, cumulative and non-cumulative returns the authors find strong evidence for the existence of momentum in cryptocurrencies, as the winner outperformes the loser tercile portfolio for all time-horizons under consideration. In a next step of the study, the relation between momentum and investors attention through Google search measures is investigated. In contrast to equity momentum there is limited interaction between momentum and investors attention and they do not subsume each other. The authors further discuss the connection between cross-sectional and time-series momentum and come to the conclusion, that both strategies have different periods of profitability and are thus not the same phenomenon.

In conclusion, it can be said that in almost 30 years of research on the topic of momentum, quite a bit has happened. There are several different methods to rank and sort assets. Two main approaches are cross-sectional and time series momentum. Momentum does not seem to be bound to any country borders and is also applicable to different types of assets and as probably with every strategy there are also bad times in which the performance is poor. Also, the various drivers of the strategy have not been ignored, be it the investors themselves, how they deal with information, or the underlying industries from which, for example, the companies originate. And last but not least, it has been shown that momentum with the rather new market of cryptocurrencies is worth investigating.

4 Data & Methodology

This section will describe how the data for the empirical analysis of this thesis are drawn and how the empirical analysis is conducted. It starts with an overview of the data and is followed by the applied methodology.

4.1 Data

The data for the following empirical analyses are collected from *yahoo!Finance* over the time period from 01.01.2018 until 31.12.2021 on a daily basis. Stocks were selected if they were listed in the S&P500 index by april 2022 and data were availabale over the prementioned time period. Stocks with first collectable data afterwards were excluded. All togehter, 489 stocks are included on the basis of their share price in U.S.-$. The cryptocurrencies are selected as the top 30 with respect to market capitalization, which is in line with Grobys and Sapkota [2019] and Tzouvanas et al. [2020], by april 2022 and availability of data over the same time period with their respective exchange rate price in U.S.-$. Hence, cryptocurrencies with first data available after january 2018 are left out and the next biggest in terms of market capitalization is included. One thing to mention here is, that the timely observations for stocks and cryptocurrencies differ. Cryptocurrencies can be traded all the time, as already mentioned, no matter of weekends or public holidays, so data are available for each calendar day in the time period under investigation leading to a total of 1,461 observations for each cryptocurrency. For the stocks, data were only available for trading days when markets are open resulting in a total of 1,007 observations for each single stock. The data for the risk-free rate was downloaded from *Kenneth French's* website. To have a quick overview how the orginally collected data look like, the follwoing table will show the first tree days of Agilent Technologies, Inc. as an example.

Table 1: Agilent Technologies, Inc. (A)

First three days of originally collected stock data of Agilent Technologies, Inc. (A)

	A.Open	A.High	A.Low	A.Close	A.Volume	A.Adjusted
2018-01-02	67.42	67.89	67.34	67.60	1,047,800	65.42069
2018-01-03	67.62	69.49	67.60	69.32	1,698,900	67.08526
2018-01-04	69.54	69.82	68.78	68.80	2,230,700	66.58202

For the further analyses only the adjusted prices, which are close prices adjusted for splitsm dividend and capital gain distributions, of each stock and cryptocurrency are kept.

4.2 Momentum Portfolio Construction

The way of constructing the portfolios for the price momentum approach of this study is following the manner of Jegadeesh and Titman [1993] where stocks are ranked based on their past return performance over a formation period of j time points and then held for a holding period of k time points.

The past performance in terms of the return of an asset is defined as:

$$Formation\_Return_{i,t-j:t} = \frac{Price_{i,t} - Price_{i,t-j}}{Price_{i,t-j}} \tag{1}$$

where

- $Price_{i,t}$ is the price of asset i at time point t
- $Price_{i,t-j}$ is the price of asset i at time point $t-j$ and j refers to the formation period

After calcualting the past performance over a given formation period of j days, the assets are ranked within the cross-section based on their formation returns and either sorted in the equally weigthed winner or loser portfolio if they belong to the top or bottom share at a certain point in time t. As is usual in the literature, a certain period of time between the end of the formation and beginning of the holding period, in the case of this study one day, is skipped. These so constructed portfolios are then held for a holding period of k days.

The return for the holding period of an asset is calaculted as:

$$Holding\_Return_{i,t:t+k} = \frac{Price_{i,t+k} - Price_{i,t}}{Price_{i,t}} \tag{2}$$

where

- $Price_{i,t+k}$ is the price of asset i at time point $t + k$ and k refers to the holding period
- $Price_{i,t}$ is the price of asset i at time point t when the portfolio was constructed

The return of the equally weighted portfolio is constructed as:

$$Portfolio\_Return_{j,k} = \sum_{i=1}^{n} w_i * Holding\_Return_{i,t:t+k} \tag{3}$$

where

- n is the number of assets
- $w_i = \frac{1}{n}$ is the weight of asset i
- $Holding\_Return_{i,t:t+k}$ is the return over the holding period of asset i

It should be mentioned at this point that the actual returns are used, since these are portfolio additive.

And finally, the momentum return is build as:

$$Momentum\_Return_{j,k} = Portfolio\_Return_{j,k,winners} - Portfolio\_Return_{j,k,losers} \tag{4}$$

where

- j is the formation period
- k is the holding period

- $Portfolio\_Return_{j,k,winners}$ is the portfolio return of asstets assigned to the winners portfolio
- $Portfolio\_Return_{j,k,losers}$ is the portfolio return of asstets assigned to the losers portfolio

The whole process of the momentum strategy is illustrated again in Figure 2:
First of all, the returns on an investment are evaluated over a certain formation period and then ranked within the cross section. The assets are then sorted into the winner or loser portfolio. After skipping some points in time, these portfolios are then held for a certain period and the resulting returns are calculated. In the last step, the yield of the loser portfolio is subtracted from that of the winner portfolio and the momentum yield is determined.

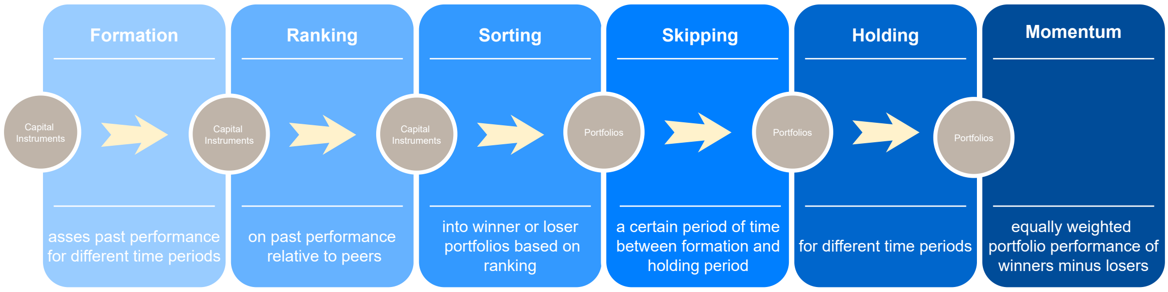


Figure 2: The Process of the Momentum Strategy

4.3 The Sharpe Ratio

The *Sharpe ratio* was first introduced by Sharpe [1966] and is one of today's most famous performance metrics for the risk-adjusted return on an investment. The revised ex-post Sharpe ratio by Sharpe [1994] in a slightly modified form to reflect the data on a daily basis is used to assess the risk-adjusted returns of momentum strategies in this study. This ratio is used to measure the historical average return per unit of historical variability or risk of the return and is defined as:

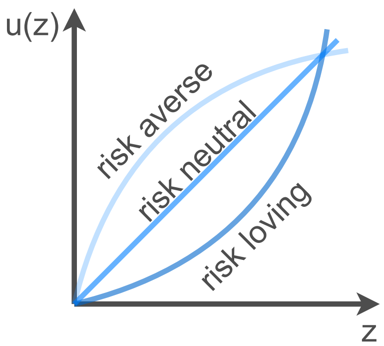
$$S = \frac{(\overline{R} - \overline{R_f})}{\sqrt{Var(R_i - R_f)}} \times scale \tag{5}$$

where

- $\overline{R}$ is the mean return of a portfolio

- $\overline{R_f}$ is the mean risk-free rate f
- R_i is the return of portfolio i
- R_f is the risk-free rate f
- *scale* is a scaling factor to annualize the returns and the risk-free rate

Hence, with the Sharpe ratio, investments can not only be compared to a risk-free investment based on their excess return, but also the relationship between the excess return and volatility can be taken into account, whereby this happens independently of the market index. It is therefore possible that, when comparing two investments with different returns this can be made in different markets. Further, the investment with the lower return but lower volatility may achiev a higher Sharpe ratio than the investment with the higher return and is therefore preferable. A positive Sharpe ratio with a value $>$ 1 means that an excess return was achieved compared to the risk-free investment, which exceeds the risk of the investment itself. For values between $]0;1[$ the excess return is below the respective volatility and with values < 0, on the other hand, the return on the risk-free investment was not even exceeded. In order to be able to interpret the Sharpe ratio and derive a recommendation for action, one must also know the risk preference of the investor. This can be divided into three different types, as shown in Figure 3 with the corresponding Bernoulli utility functions and an explanation below:



Risk attitude	Characteristics of u()	Sharpe ratio preference
Risk-averse	concave	higher
Risk-neutral	linear	equal
Risk-loving	convex	lower

Figure 3: The three different Types of Risk Attitude

• Risk-averse:
Risk-averse investors have concave utility functions with decreasing marginal utility of risk and, when comparing two investments, prefer the one with the higher Sharpe ratio.

- Risk-neutral:

Risk-neutral investors have linear utility functions with constant marginal utility of risk. The Sharpe ratio is irrelevant for these types, since they will always prefer the investment with the higher expected value.

- Risk-loving:

Risk-loving investors have convex utility functions with increasing marginal utility of risk. When comparing two investments, those will always choose the one with the lower Sharpe ratio.

5 Empirical Results

This section will present some descreptive aspects of momentum portfolio returns and their sharp ratios, which are build on a daily basis from January 2018 until December 2021 with a formation period between one and thirty days and a subsequent holding period between one and thirty days. For the shares, the 50 best and worst, for the cryptocurrencies the ten best and worst, are sorted into the respective winner or loser portfolio, from which the momentum return is then calculated. Overall, this leads to a total of 900 different momentum strategies for each day for the stocks and cryptocurrencies. As already mentioned, three time periods are considered and analyzed; a full period covering the entire period of the study as well as a period before and after the outbreak of the COVID-19 pandemic in March 2020. To keep things simple, the empirical results for the best and the worst strategy of each type of security, in terms of their mean returns, will be shown and discussed in the following and for certain aspects all strategies will be taken into account for the analyses. The two-sided t-tests always refer to a significance level of $\alpha = 0.05$ and when interpreting the Sharpe ratios, a risk-averse investor should be assumed who would therefore like to achieve the highest possible Sharpe ratio. One important thing to point out is, that due to the prementioned timely observation differences in the data the dates depending on formation and holding period differ between stocks and cryptocurrencies. Hence, for the cryptocurrencies the formation and holding period refers to actual calendar days, whereas it refers to trading days, in example when markets are open, for the stocks.

With regard to the construction of the portfolios, it should be mentioned that these can overlap in time, as shown in Figure 4.

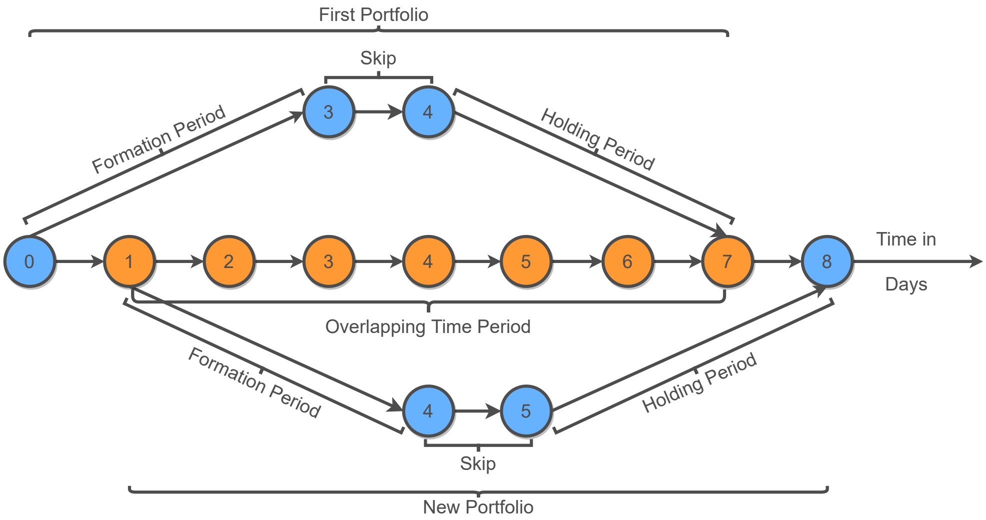


Figure 4: Overlapping Momentum Portfolios

This has the advantage, that the construction of a new momentum cycle does not have to wait until the previous one has expired and more data points are available for the analysis. Moreover, this procedure is common in the literature and the results are not affected by the overlapping of portfolios as shown by Jegadeesh and Titman [1993].

When looking at various plots, please note that the scales are not always identical, which is due to the data.

5.1 Descriptive Analysis of Momentum Returns

5.1.1 Full Period (01/2018 - 12/2021)

Looking at the summary statistics reported in Table 2 and beginning with the mometum strategies of the stocks over the full time period of the study, it turns out that a formation period of five days and subsequent holding period of eleven days has the best performance with a mean return of 0.051% per day, which is not statistically different from zero with a t-Statistic of 0.36. On the opposite, a formation period of 28 days and a following holding period of 30 days has the worst outcome with a daily mean return of -1.398% and a t-Statistic of -5.59, which would result in a loss of about 27.96% per month (if one takes 20 days as a month which is justified with the available data). This strongly negative result is comparable to the momentum crash of 1933 as described by Daniel and Moskowitz [2016], when the momentum portfolio lost 28.90% in one month. So far, the positive momentum strategy reported by Jegadeesh and Titman [1993] and others, in the case of the full period of this study, is not confirmed. A first explanation for the weak or negative returns could be the COVID-19 pandemic, which broke out at the beginning of 2020 and markets were in a crisis during that time period.

The mean returns for the cryptocurrencies range between 2.589% with a t-Statistic of 6.04 for a formation of ten days and a subsequent holding period of 22 days and 0.043% for a formation period of one day and then holding the portfolios for two days. However, with a t-statistic of 0.40, the latter return is not significantly different from zero. What strikes now, is that the cryptocurrencies seem to have consistently generated positive, or at least no negative returns, with 846 out of 900 strategies being statistically significantly different from zero which is in sharp contrast to some of the reviewed literature. Overall, for the stocks, only 25 out of 900 strategies have a positive return, with none of them being statistically significant. Of the remaining 875 negative-return strategies, 574 are significantly non-zero.

Table 2: Summary Statistics of Momentum Returns (01/2018 - 12/2021)

This table shows the summary statistics for the best and worst momentum strategy for S&P500 stocks and cryptocurrencies with the highest market capitalization for the full time period from January 2018 until December 2021.

	Stocks		Cryptocurrencies	
	best	worst	best	worst
Formation / Holding	5 / 11	28 / 30	10 / 22	1 / 2
Mean (%)	0.051	-1.398	2.589	0.043
Volatility (%)	4.48	7.70	16.21	4.07
t-Statistic	0.36	-5.59	6.04	0.40
Skewness	0.72	-1.68	0.33	-1.06
Kurtosis	8.51	10.70	5.76	24.79
Periods N=	990	948	1,428	1,457

In terms of volatility, there are also clear differences between stocks and cryptocurrencies, as the latter seem to be significantly more volatile. The best cryptocurrency strategy has a volatility of 16.21%, while the best stock strategy comes in at 4.48%, which is very close to the 4.07% of the worst cryptocurrency strategy. In comparison, the volatility of the worst momentum strategy of stocks is 7.70%, but significantly higher than that of cryptocurrencies.

Looking at Figure 5 and look at the time series plot of the return of the stocks' best momentum strategy, one can see that it fluctuates around zero with quite stable ups and downs. Only in the fourth quarter of 2018, there is an extreme upswing of almost

10%. The year 2019, on the other hand, is already significantly more volatile, which is noticeable in the form of several strong upward and downward fluctuations from the middle of the year onwards, which level off somewhat towards the end of the year. But what really catches the eye is the start of the COVID-19 pandemic at the end of the first quarter in 2020. Here one can observe extreme swings upwards of almost 30% and downwards of almost 25%. Barroso and Santa-Clara [2015] and Daniel and Moskowitz [2016] report that momentum performs poorly when markets are stressed and particularly volatile, which is clearly the case here. As already indicated, this could well be the reason for momentum's comparatively poor performance. Towards the middle of the year, this flattens out again, but becomes much more extreme again towards the end of the year. This is another indication of the influence of the pandemic, which was much more relaxed in the middle of the year and became more tense again at the end of 2020, which was also reflected in the political measures. Volatility did only decrease and become more stable again from the middle of 2021.

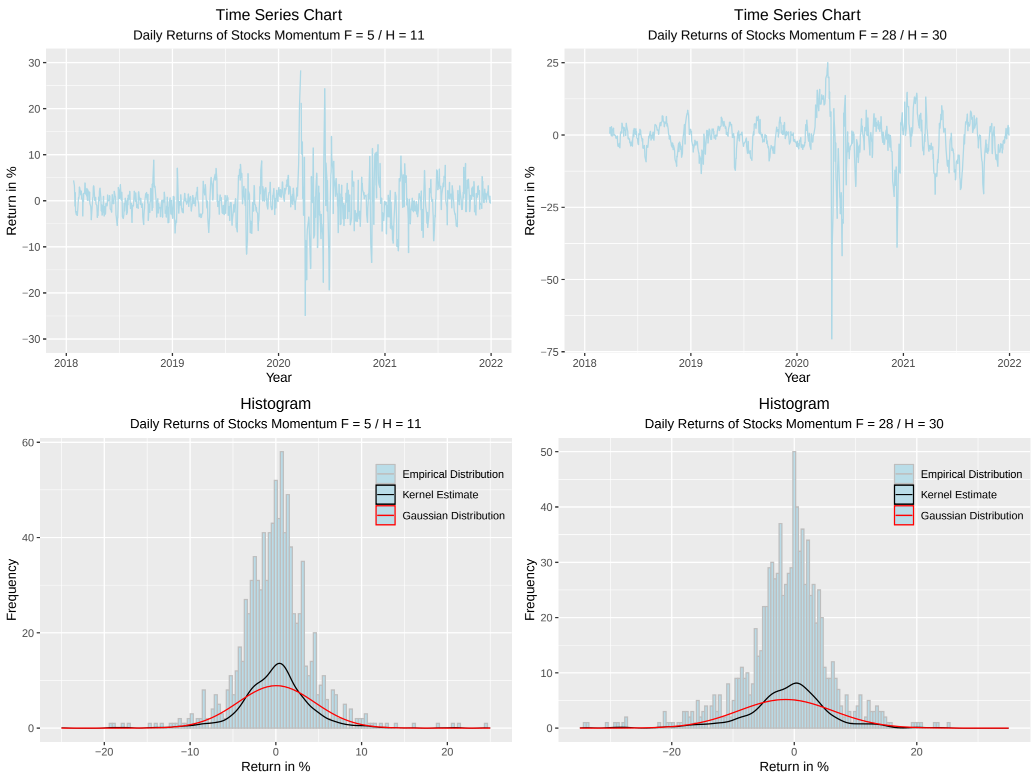


Figure 5: Time Series Plots and Histograms of Stocks Momentum Returns (01/2018 -12/2021)

This figure shows the time series plot and corresponding histogram of the returns of the S&P 500 stocks for the best, on the left, and worst momentum strategy, on the right, over the full time period from January 2018 until December 2021.

For the worst of the equity momentum strategies, it can be seen, in the upper right plot of 5, that the return also fluctuates around zero without a trend, but is more volatile. The standard deviation here is 7.70% compared to 4.48% for the best strategy, which can be seen from the stronger up and down swings around zero with the years 2018 and 2019 being quite similar. But what immediately catches the eye is the global pandemic from the first quarter of 2020 again. At the beginning, the yield rises sharply, only to drop to almost -75% over the course of the year. Here the fluctuations are somewhat less extreme from the middle of the year. Towards the end of the year, extreme downward fluctuations can be observed again, whereas the year 2021 begins with strongly positive returns. The further course is a lot more volatile overall than the years 2018 and 2019, with the negative deviations clearly predominating.

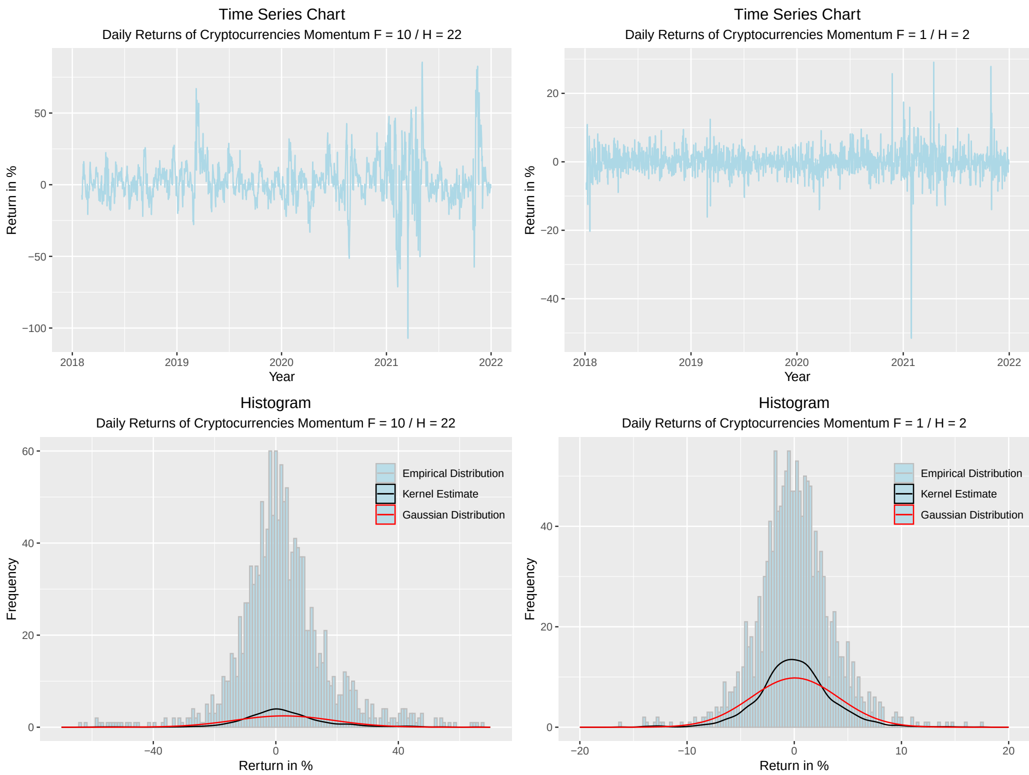


Figure 6: Time Series Plots and Histograms of Cryptocurrencies Momentum Returns (01/2018 -12/2021)

This figure shows the time series plot and corresponding histogram of the returns of cryptocurrencies with the highest market capitalization for the best, on the left, and worst momentum strategy, on the right, over the full time period from January 2018 until December 2021.

The time series plot from Figure 6 for the best cryptocurrency strategy shows the higher volatility compared to the stocks' momentum returns that was already described in Table

2. As with stocks, returns fluctuate around zero without any discernible trend. At the end of the first quarter of 2019, extreme returns of well over 50% can be seen. Another key difference to the observed returns on shares is that the start of the COVID-19 pandemic does not seem to trigger any extreme fluctuations in the returns on cryptocurrencies. From the middle of 2020, the volatility increases again with fluctuations between plus and minus 50%. By the end of 2021, the time series will then become even more volatile with losses of over 100% and subsequent gains of over 75%. From the second quarter of 2021 onwards, the phase with the lowest volatility over the period under review begins before it then increases significantly again towards the end of the year.

When comparing the worst cryptocurrency strategy with the other three return plots, one will first notice that this time series is apparently the most stable one with the least strong fluctuations. Only at the beginning of 2018 and in the first quarter of 2019 volatility increases somewhat. As with the other cryptocurrency strategy, no influence of the COVID-19 pandemic on the return can be seen here either, with the most volatile phase beginning at the end of 2020, but much later than for stocks, which posted losses of over 50% at the beginning of 2021, but this quickly settles back down to the level of 2018/2019. Whether the pandemic will have an impact with a time delay is rather questionable. Between the 3rd and 4th quarter of 2021, there are even stronger upward fluctuations. Overall, however, the losses are lower here than with the worst stocks and best cryptocurrency strategy.

Next, some aspects of the distributions of returns will be discussed. As can be seen in Figures 5 and 6 and in Table 2, the distributions for both stocks' and cryptocurrencies' momentum returns are not normally distributed with positive kurtosis indicating heavy tails as described by Barroso and Santa-Clara [2015]. The cryptocurrencies take on the more extreme values here: the best strategy with a kurtosis of 5.76 is still closest to the normal distribution, which means that the heavy tails are the least pronounced. This result is somewhat surprising as the strategy has the highest volatility, which is often associated with heavy tails. The worst cryptocurrency strategy has the highest kurtosis at 24.76. The stocks' returns show a kurtosis of 8.51 for the best and 10.70 for the worst strategy, which, as already mentioned, also speaks against the normal distribution and is an indication of heavy tails. The best stock and cryptocurrency strategies have a skewness of 0.72 and 0.33, which speaks for slightly right-skewed distributions. Overall, the best cryptocurrency strategy is the most similar to the normal distribution. The two worst strategies have a skewness of -1.68 for stocks and -1.06 for cryptocurrencies and are therefore both left-skewed. This is also a little surprising, since the stock strategy has a clearly negative return and the cryptocurrencies have a positive one, although the latter is not significantly different from zero, it is at least not negative.

As the last aspect of this subsection, Figure 7 depicts the mean returns of the different combinations of formation and holding periods for the stocks on the left and the cryptocurrencies on the right for all 900 strategies of each. It will now be discussed how the structural differences between the two are in relation to the formation and holding period.

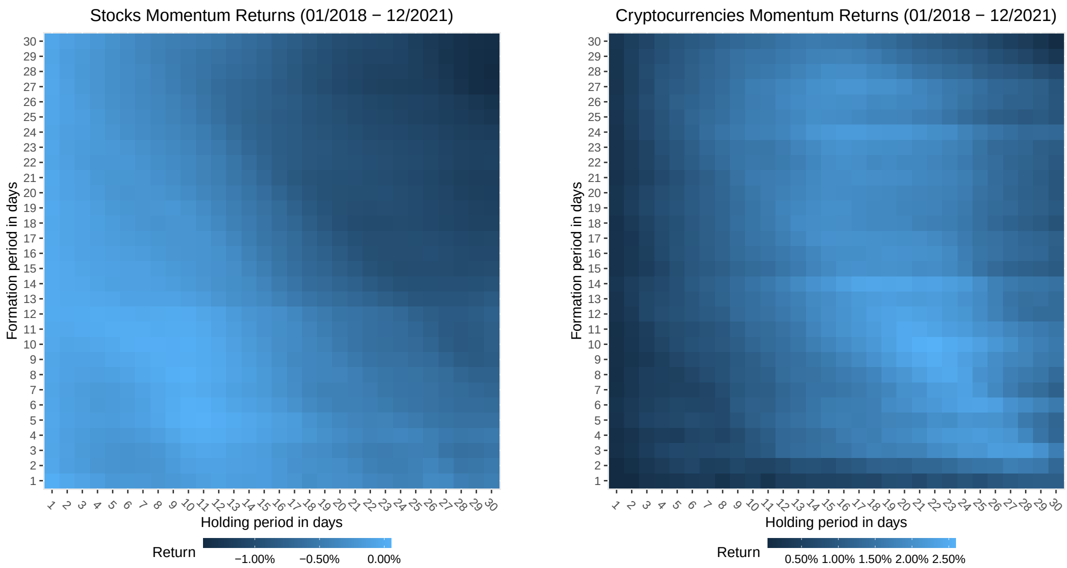


Figure 7: Heat Plots of the Mean Returns (01/2018 - 12/2021)

This figure shows the mean returns of the different combinations of formation and holding period for the S&P500 stocks on the right and cryptocurrencies with the highest market capitalization on the left for the full time period from January 2018 until December 2021. The lighter the color of the individual boxes, the higher is the respective mean return for the given combination.

At a first glance, one can easily see that there are differences in the mean returns between the stocks and cryptocurrencies regarding their respective formation and holding periods. This can not just be stated in terms of the magnitude of the mean returns, which range as already mentioned from 0.051% to −1.398% for the stocks and from 2.589% to 0.043% for the cryptocurrencies, but also in the composition of formation and holding period. A somewhat diagonal structure is noticeable in the stock returns and the following picture emerges for the formation period, which increases from bottom to top: With a longer formation period, the mean returns are apparently higher for a shorter than for longer holding periods. The mean returns appear to have been particularly poor for a formation period of between 27 and 30 days combined with a holding period of 27 to 30 days, as indicated by the dark spot in the upper right corner of the chart. However, one should keep in mind that the momentum returns were zero at best and as mentioned above a positive return in the case of stocks over the full time period is not proven. The aforementioned diagonal structure now arises from the fact that as the formation period becomes shorter, the holding period from which the returns appear to deteriorate becomes longer. Additionally, for shorter formation periods, up to twelve days, this effect appears to be less strong.

If onw now looks at the average returns for the cryptocurrencies, one will notice clear differences to the stocks. Irrespective of the formation period, short holding periods of up to around four days tend to result in poorer returns, which then increase between ten to 15 days. A key difference to stocks is that the formation period does not seem to have that much of an impact on the combination with the holding period at all, and the diagonal structure described above is not present here either. The highest returns appear to be achieved in the 16 to 24 day range, after which returns fall again. In the range of formation periods between three to ten days, holding periods of up to 28 days achieve quite high returns. Overall, however, one can see that regardless of the formation period, a holding period that is too long does not make sense and the momentum effect, also described by Jegadeesh and Titman [1993] and others, disappears again

5.1.2 Pre-COVID Period (01/2018 - 02/2020)

Starting with the time before the pandemic, Table 3 holds the summary statistics for the stocks and cryptocurrencies. For the shares, the result is that the best strategy, with a formation and holding period of three days, achieves an average return of 0.073% per day, which, however, as for the full period with a t-Statistic of 1.26, is not significantly different from zero. The worst strategy, with a formation of 20 days and a subsequent holding period of 26 days, achieves a loss of 1.072% per day, which according to the t-Statistic of -6.24 is clearly significant. Of the 900 strategies tested, 20 are positive, none of which are significant. This contrasts with 701 out of 880 with a significantly negative return. Compared to the full period, the mean returns in the best and worst case are slightly better here, but the number of strategies with non-negative returns has actually decreased. Overall, this picture is a bit surprising, as one would have expected momentum to perform significantly better in the pre-COVID period. At least for the stocks of the S&P500, as in the previous subsection, the strategy does not appear to be successful in the observed period.

For the cryptocurrenices, there is a range of 2.436% for the best strategy with a formation of six days and a holding period of 21 days, and −1.846% for the worst one with a similar formation and holding period of 30 days. Both values are significantly different from zero, with t-Statistics of 6.13 and -3.39.

Table 3: Summary Statistics of Momentum Returns (01/2018 - 02/2020)

This table shows the summary statistics for the best and worst momentum strategy for S&P500 stocks and cryptocurrencies with the highest market capitalization for the pre-COVID period from January 2018 until February 2020.

	Stocks		Cryptocurrencies	
	best	worst	best	worst
Formation / Holding	3 / 3	20 / 26	6 / 21	30 / 30
Mean (%)	0.073	-1.072	2.436	-1.846
Volatility (%)	1.34	3.38	10.97	14.71
t-Statistic	1.26	-6.24	6.13	-3.39
Skewness	-0.04	-0.21	1.14	-0.52
Kurtosis	3.81	2.90	6.99	5.78
Periods N=	536	496	762	729

Overall, 830 out of 900 cryptocurrency strategies have a positive return, of which 655 are also statistically significant. 70 have a negative average return, 13 of which are also significant. Interestingly, the cryptocurrencies now show a clearer difference to the full period than one would actually expect. For one thing, momentum, albeit in only 13 instances, also generates significantly negative mean returns, which was not the case in the previous chapter over the full period. On the other hand, the number of positive strategies has dropped statistically significantly. Based on the previous section, one would have expected that the returns would remain the same or better in the time before the pandemic as markets were not in crisis.

One may notice big differences when looking at volatility, both in terms of the time period and the type of investment. Compared to the full period of the study, the volatility of the momentum strategies of the stocks has decreased significantly to 1.34% for the best and 3.38% for the worst strategy, which is also what one would expect when looking again at the Figure 5 with the time series plots of the returns. Thus, COVID-19 appears to be having a significant negative impact for the volatility, as yields are less volatile until the outbreak as shown here. The cryptocurrencies, on the other hand, seem to be more volatile than the stocks for the pre-COVID subperiod as well. The values of 10.97% for the best and 14.71% for the worst strategy, which are now well above the full period, are also significantly higher than for stocks' returns and the poorest strategy is now clearly more volatile than the best.

The plots of the returns of the stocks' momentum strategies shown in Figure 8 show a similar picture, the best strategy fluctuates relatively stably around zero without a recognizable trend while the worst has more pronounced up and down swings. As already known from Table 3, the worst strategy is a bit more volatile, which can also be seen in the plot. For the best strategy, there are phases with greater and less pronounced volatility. Extreme fluctuations, as in Figure 5, cannot be seen for the time before COVID, which is to be expected. The worst strategy, on the other hand, has a much higher volatility, which is nonetheless still lower than for the full period.

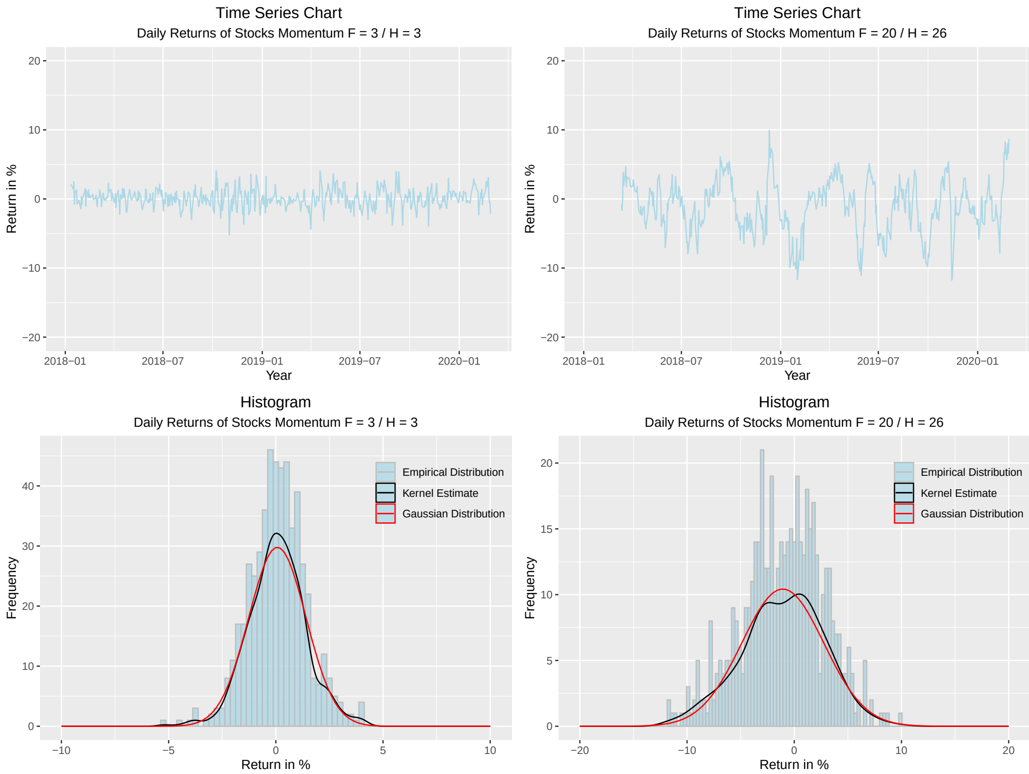


Figure 8: Time Series Plots and Histograms of Stocks Momentum Returns (01/2018 - 02/2020)

This figure shows the time series plot and corresponding histogram of the returns of the S&P 500 stocks for the best, on the left, and worst momentum strategy, on the right, for the pre-COVID period from January 2018 until February 2020.

For the yields of cryptocurrencies, shown in Figure 9, a similar picture emerges as for the full period. The best strategy fluctuates around zero and one can see the higher volatility compared to stocks. From the second quarter of 2019 onwards, there are extreme upward swings with returns of over 60%. At the beginning of 2020, the cryptocurrencies are again more volatile, with extreme upward swings which are then followed by extreme downward swings. The worst strategy, on the other hand, now fluctuates more in the pre-COVID period and is more volatile. There are always phases with recognizable upward and downward trends. Here, too, the second quarter of 2019 is more volatile than for stocks, with returns exceeding -75% to the extreme. At the beginning of 2020, a slight downward trend can be seen again.

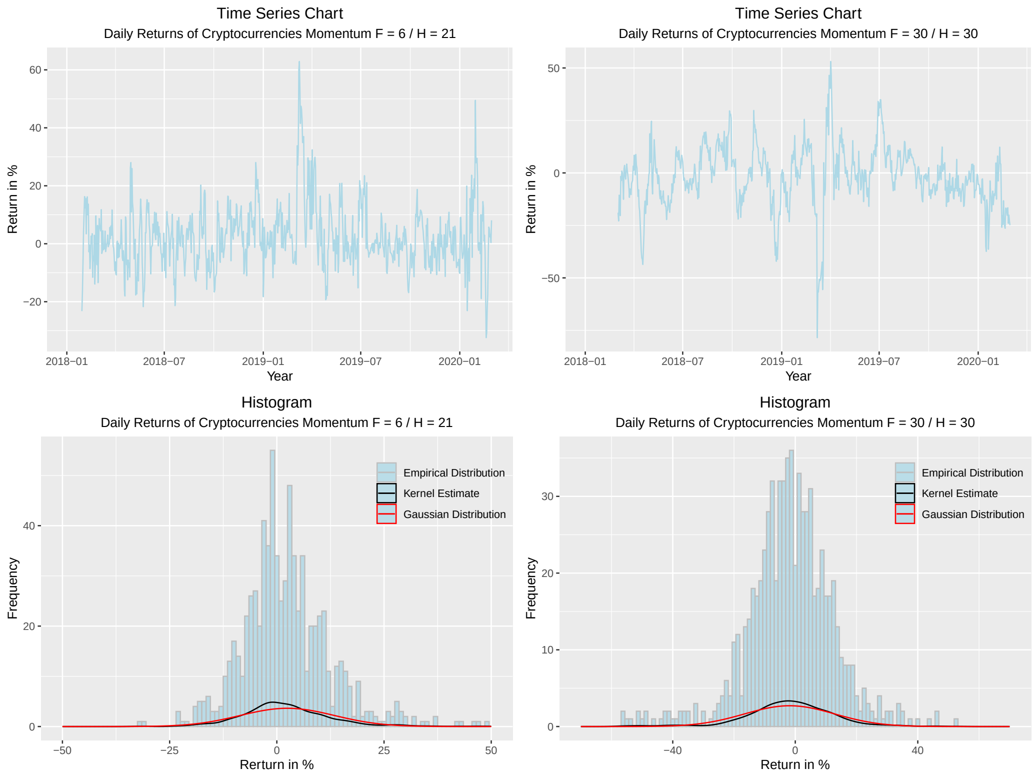


Figure 9: Time Series Plots and Histograms of Cryptocurrencies Momentum Returns (01/2018 -02/2020)

This figure shows the time series plot and corresponding histogram of the returns of cryptocurrencies with the highest market capitalization for the best, on the left, and worst momentum strategy, on the right, for the pre-COVID period from January 2018 until February 2020.

For the distributions of the returns, there are also some differences between the two periods considered, as well as between the stocks and the cryptocurrencies if one compares Figures 8 and 9 and the summary statistics in Table 3. The best and worst stock momentum strategies are now both slightly left-skewed with values of -0.04 and -0.21 and a kurtosis of 3.81 and 2.90, but approximately normally distributed without heavy tails. This is somewhat surprising, given that the worst-performing strategy had, on average, a negative return, as discussed above. Hence, for the latter one would expect a more pronounced kurtosis compared to the full period. For the cryptocurrencies, the results show that the best strategy, with a value of 1.14, is now more skewed to the right than it was for the full period, and the kurtosis has also increased to a value of 6.99. For the worst strategy, however, the skewness has dropped to -0.52 and the kurtosis to 5.78. Unlike the shares, however, the cryptocurrencies are clearly not normally distributed with heavy tails, which was already the case for the full period.

In the last part of this sub-section, the returns of the different combinations of formation and holding period, which are shown in Figure 10, are discussed. Starting with the stocks, a first look at the chart immediately shows that the diagonal structure described in the previous subsection is retained. Thus, even in the period before the outbreak of the pandemic, longer holding periods still lead to higher returns in the case of a shorter formation than in the case of longer formation periods. Further contrasts are, on the one hand, that the longest formation and holding period no longer result in the worst returns; in this time window under consideration, these are in the range of 8 to 21 days for the formation and from around 16 days for the holding period. On the other hand, the combination of very short formation and holding periods achieve the best returns. However, it is important to remember here that the returns are zero at best, as they are for the full span of the study.

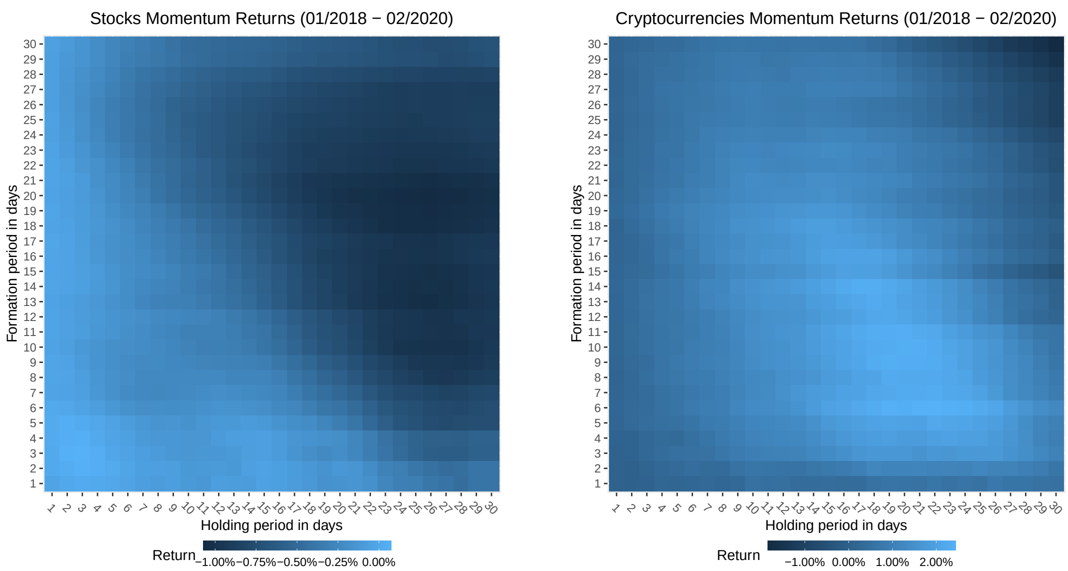


Figure 10: Heat Plots of the Mean Returns (01/2018 - 02/2020)

This figure shows the mean returns of the different combinations of formation and holding period for the S&P500 stocks on the right and cryptocurrencies with the highest market capitalization on the left for pre-COVID period from January 2018 until February 2020. The lighter the color of the individual boxes, the higher is the respective mean return for the given combination.

In the case of cryptocurrencies, this shorter period under observation also shows that, as in the case of the full time period, the diagonal structure of the shares cannot be seen and, however, the formation period is less important than the holding period. Holding periods that are too short sometimes achieve negative returns, or at least not the highest returns. The highest returns are achieved within a formation period of six to eleven days and a subsequent holding period of around 17 to 24 days. However, as in the previous chapter, the positive effect disappears again and yields decrease again with a longer holding period of 21 days or more, in the case of the formation longer than 16 days, and holding periods of 25 days or more for the shorter formation periods. This supports the hypothesis that the momentum effect is not permanent and disappears over time.

5.1.3 COVID Period (03/2020 - 12/2021)

In the last section, the results of the momentum strategies for the period from the beginning of the COVID-19 pandemic are discussed, the corresponding summary statistics are shown in Table 4. The best strategy for the shares, which results from the formation and holding period of one day, has a positive average yield of 0.075%, which is not significant with a t-statistic of 0.82. Nevertheless, this result is surprising, as this is the best value for all periods examined and at this time there is clearly an economic crisis mood. For the worst combination of a formation and a subsequent holding period of both 29 days, there is a negative average return of -2.788%, which is the worst of all periods and provides a significant result with the available t-statistic of -6.71. In summary, only one out of 900 combinations of stock momentum is positive, but as already mentioned not statistically significant. On the negative side, only 299 of the remaining 899 strategies are statistically significant. This result is surprising as one would have expected the number of negative mean returns to be more in line with the previous two periods, but not decreasing. It is therefore questionable whether the period of economic crisis, after all, the time interval since the beginning of the pandemic has delivered the significantly worse result, is responsible for the bad performance. The poor performance of momentum during economic crisis described by Daniel and Moskowitz [2016] can now on the one hand be confirmed because it shows the worst result of all sub-periods, and on the other hand be rejected because there are significantly less negative returns. If one looks at the worst returns of the stocks over all three sub-periods, one will notice that these always occur with a combination of a long to very long formation period and a very long holding period. This leads to the conclusion that the momentum effect, as with Jegadeesh and Titman [1993] and Chan et al. [1996], disappears again over time and reverses. Ultimately, it could be a combination of both, if the holding period is too long while the economic situation is tense, the momentum strategy for equity investments does not seem to be successful. On the other hand, there is only one non-negative result for the period after die beginning of the COVID-19 pandemic, so one would expect at least some better results for the shorter holding and formation periods which is not the case. So in the case of this subperiod, the economic crisis seems to be the main driver of stocks' momentums' bad performance.

Table 4: Summary Statistics of Momentum Returns (03/2020 - 12/2021)

This table shows the summary statistics for the best and worst momentum strategy for S&P500 stocks and cryptocurrencies with the highest market capitalization for the COVID period from March 2020 until December 2021.

	Stocks		Cryptocurrencies	
	best	worst	best	worst
Formation / Holding	1 / 1	29 / 29	24 / 30	1 / 11
Mean (%)	0.075	-2.788	4.867	0.022
Volatility (%)	1.97	8.36	23.37	12.46
t-Statistic	0.82	-6.71	5.17	0.05
Skewness	-0.44	-1.08	0.10	-0.27
Kurtosis	7.16	2.26	3.42	6.95
Periods N=	461	405	616	658

For the cryptocurrencies, on the other hand, as for the full period, the returns are zero in the worst case. The best strategy delivers an average return of 4.867% per day with a formation of 24 and a holding period of 30 days. This value is statistically significant with a t-statistic of 5.17 and the best value for all periods under consideration. The worst strategy, which is not significant with a t-statistic of 0.05, consists of a formation of one day and a subsequent holding period of eleven days and delivers 0.022%. Overall, out of 900 strategies tested, 771 are statistically significant with a positive mean return. One can therefore assume that momentum investing with cryptocurrencies is a good alternative, at least in times of economic crises. This could be due to the fact that the cryptocurrencies are not economic companies and, unlike classic currencies, are simply not influenced by macroeconomic factors. Another aspect that has already been raised several times is that the formation period does not seem to have as great an impact as the holding period. The best strategies have quite long holding periods compared to the stocks, with rather short ones. For the worst strategies, the pattern is not as clear, but a fromation period of just one day does not seem to be all that successful. Yesterday's winners seem to be tomorrow's losers as well, which is also reflected in the often mentioned higher volatility and could explain the bad performance with a ranking based on one day.

With regard to the volatility, one can clearly see the influence of the pandemic on the stocks, the standard deviation of 1.97% for the best and 8.36% for the worst strategy are the respective peak value for the periods under consideration. In the period before the start of the pandemic, however, both values are at their lowest. For the cryptocurrencies, the picture is again not quite that clear, although the best strategy has the highest of all values at 23.37% in this phase, the worst strategy has 12.46%, but is below the value of the time before the start of the pandemic.

The plots of returns shown in Figure 11 and Figure 12 will not be discussed in detail as this has already been done in great detail in the previous two sections. However, they show the clear differences between stocks and cryptocurrencies, especially with respect to the volatility.

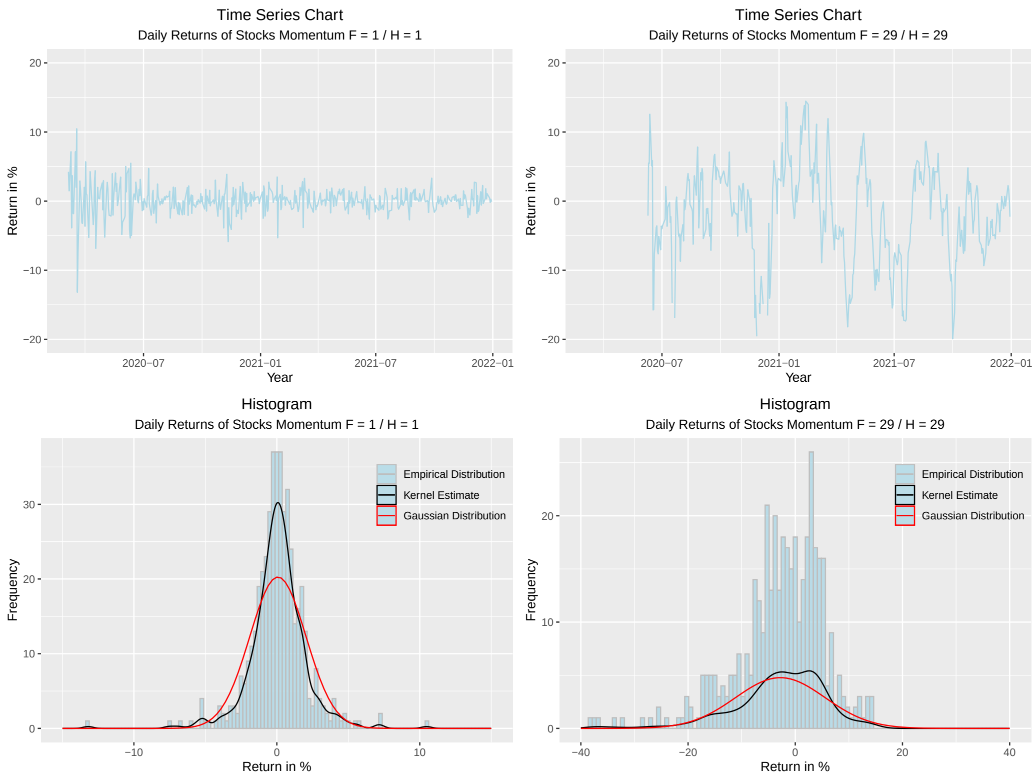


Figure 11: Time Series Plots and Histograms of Stocks Momentum Returns (03/2020 -12/2021)

This figure shows the time series plot and corresponding histogram of the returns of the S&P 500 stocks for the best, on the left, and worst momentum strategy, on the right, for the COVID period from March 2020 until December 2021.

For the distributions of returns, also shown in Figures 11 and 12 as well as inTable 4, it turns out that the returns of the stocks' momentum are clearly not normally distributed with heavy tails, similarly to the full time span. The best strategy has a kurtosis of 7.16

and skewness of -0.44 and the worst has a kurtosis of 2.26 and skewness of -1.08. In any case, the crisis period during the pandemic seems to have a influence on the distribution of returns.

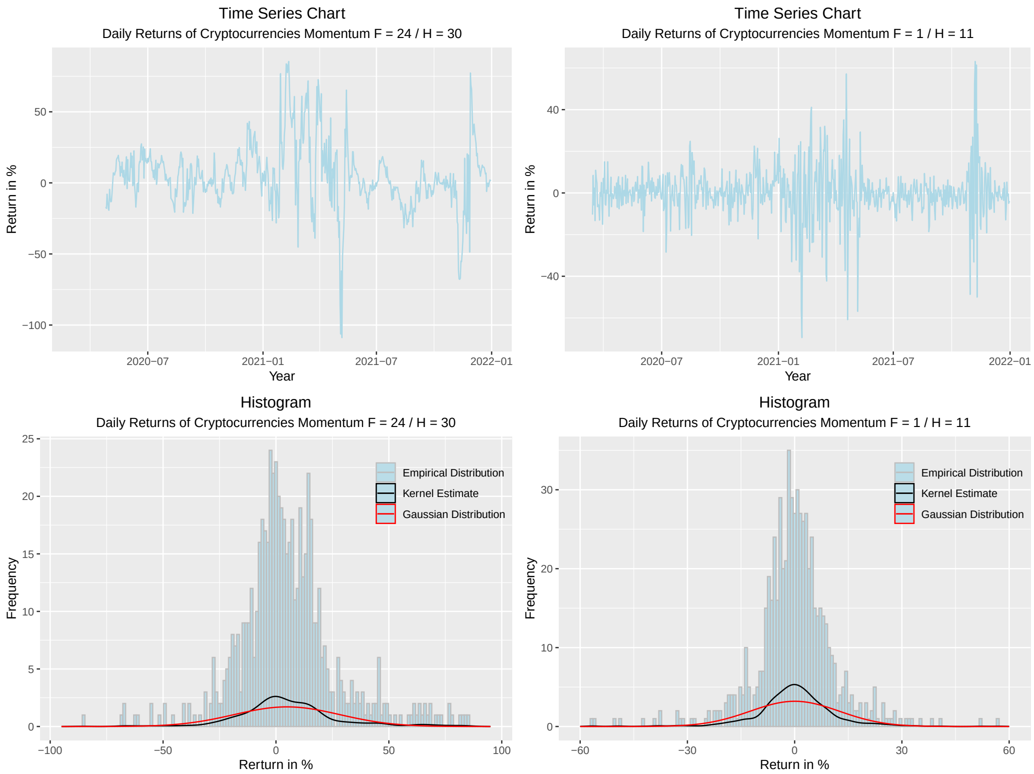


Figure 12: Time Series Plots and Histograms of Cryptocurrencies Momentum Returns (03/2020-12/2021)

This figure shows the time series plot and corresponding histogram of the returns of cryptocurrencies with the highest market capitalization for the best, on the left, and worst momentum strategy, on the right, for the COVID period from March 2020 until December 2021.

For the cryptocurrencies, on the other hand, the best strategy with skewness of 0.10 and kurtosis of 3.42 is quite similar to the normal distribution, which again is a bit surprising since the volatility is very high at 23.37%. For the worst strategy, there is a fairly symmetrical picture with skewness -0.27, the kurtosis of 6.95 is again an indicator for heavy tails and the distribution is clearly not normal.

The mean returns for all tested strategies from different formations and holding periods are presented in Figure 13. As for the other examined two time windows, a somewhat diagonal structure emerges for the stocks: for shorter formation periods, the returns are greater for longer holding periods. Very long formations combined with very long holding periods again produce the worst results. The highest returns are achieved with a short formation period of up to around twelve days and a short holding period of up to around 13 days. The hypothesis that the momentum effect disappears again over time can thus be supported.

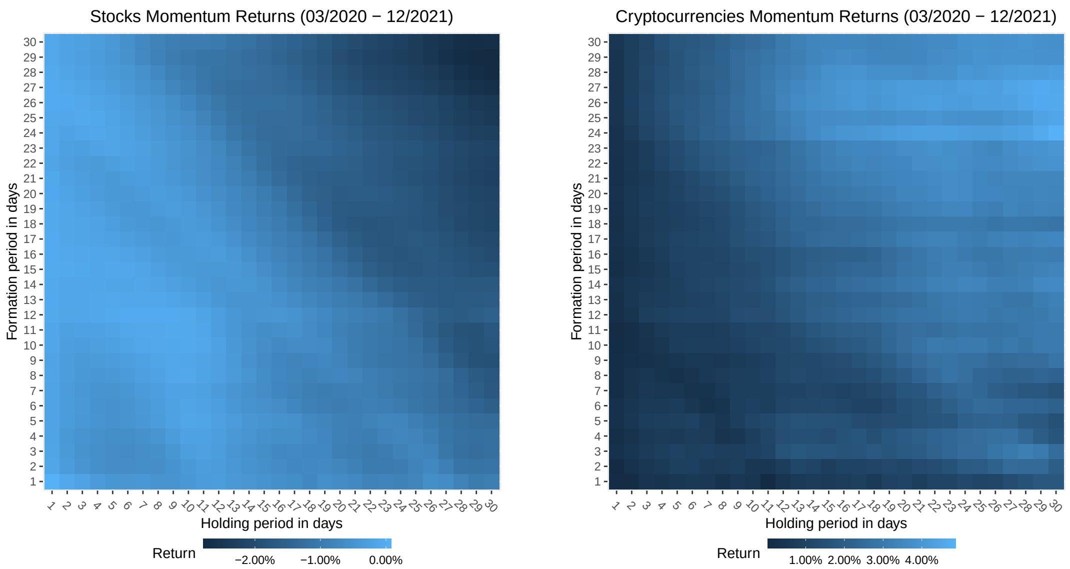


Figure 13: Heat Plots of the Mean Returns (03/2020 - 12/2021)

This figure shows the mean returns of the different combinations of formation and holding period for the S&P500 stocks on the right and cryptocurrencies with the highest market capitalization on the left for the COVID period from March 2020 until December 2021. The lighter the color of the individual boxes, the higher is the respective mean return for the given combination.

For the cryptocurrencies, on the other hand, as in the two previous sections, a pattern that is not as clear as for the shares can be seen. Across all time windows, the most indistinct picture is from the beginning of the pandemic. For holding periods that are too short, up to about ten days, the worst returns are achieved for any formation period, but this still confirms the picture that the holding period has the greatest influence on the success of the momentum strategy of the cryptocurrencies. The highest returns are achieved for holding periods ranging from approximately 13 to 30 days and long formation periods starting at about 24 days.

5.2 Sharpe Ratios of Momentum Returns

As already mentioned in the definition in section 4.3, the Sharpe ratio is a suitable indicator for evaluating the return on an investment in relation to its risk. A major advantage of the Sharpe ratio is that its definition allows comparing investments that come from different markets. In order to take into account the fact that data is used on a daily basis for this study, the annualized Sharpe ratios are presented as well. In the following section, the focus is again on the best and worst momentum strategies of stocks and cryptocurrencies for the respective time periods. However, one should consider at this point that these do not automatically coincide with the best and worst values of the Sharpe ratio. To address this question, as in section 5.1, the Sharpe ratios of all strategies are presented and discussed using a heat plot.

5.2.1 Full Period (01/2018 - 12/2021)

The different Sharpe ratios for the full period of the study for the stocks and cryptocurrencies are depicted in Table 5. The best strategy for the stocks and the worst strategy for cryptocurrencies both have a negative Sharpe ratio despite non-negative returns because both investments were still worse than a risk-free investment in the same period. A negative Sharpe ratio is expected for the stocks' worst strategy since the return is also negative. The best cryptocurrency strategy has a positive Sharpe ratio of 0.133, but this value is not particularly good, which is due to the rather high volatility of over 16%, and is significantly higher than the return itself. The best cryptocurrency strategy is the one to prefer but it does not achieve a desirable Sharpe ratio of > 1, where the return would be higher than the risk.

Table 5: Sharpe Ratios of Momentum Returns (01/2018 - 12/2021)

This table shows the mean risk-free rate, the volatility and the Sharpe ratios for the best and worst momentum strategy for S&P500 stocks and cryptocurrencies with the highest market capitalization for the full time period from January 2018 until December 2021.

	Stocks		Cryptocurrencies	
	best	worst	best	worst
Formation / Holding	5 / 11	28 / 30	10 / 22	1 / 2
Mean risk-free (%)	0.429	0.429	0.429	0.429
Volatility (%)	4.48	7.70	16.21	4.07
Sharpe Ratio	-0.085	-0.237	0.133	-0.095
Annualized Sharpe Ratio	-1.339	-3.76	2.088	-0.31
Scale Factor (Days)	251	251	365	365

A summary of all Sharpe ratios is shown in Figure 14. These are in the range of -0.289 to -0.085 for the stocks, which means that no strategy, regardless of its volatility, is better than investing in a risk-free investment. The structure of the plot is quite similar to that of the mean returns. However, there are a few differences: With a holding period of one day, the Sharpe ratios are most negative and the long holding and formation periods have higher Sharpe ratios compared to other holding and formation combinations than with the mean returns.

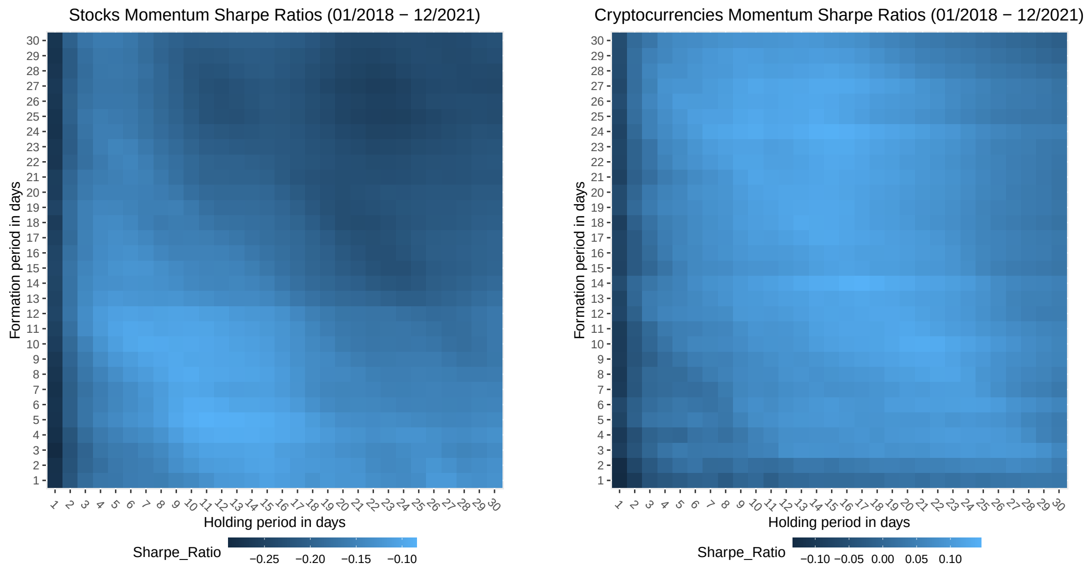


Figure 14: Heat Plots of the Sharpe Ratios (01/2018 - 12/2021)

This figure shows the Sharpe ratios of the different combinations of formation and holding period for the S&P500 stocks on the right and cryptocurrencies with the highest market capitalization on the left for the full time period from January 2018 until December 2021. The lighter the color of the individual boxes, the higher is the respective Sharpe ratio for the given combination.

The values of the Sharpe ratios for the cryptocurrencies range from -0.132 to 0.145 and out of a total of 900 strategies, 833 have a value greater than zero, which means they at least perform better than an investment in a risk-free asset. The problem with cryptocurrencies, despite their high returns, is their high volatility here, which is why the values are never > 1. Interestingly, the one-day holding period has the lowest Sharpe ratios of any formation periods as with the stocks. The Sharpe ratios increase with an increasing holding period from 6 days and become smaller again from around 20 days before they even become negative from around 26 days. Ultimately, however, one can resort to the momentum strategy for cryptocurrencies due to the positive Sharpe ratios.

5.2.2 Pre-COVID Period (01/2018 - 02/2020)

For the time leading up to the onset of the COVID pandemic, the Sharpe ratios of the stocks range between -1.004 and -0.262, making neither strategy in the stocks a better choise than a risk-free investment. The best strategy has a Sharpe ratio of -0.519 and the worst of -0.481. Thus, using the Sharpe ratio, one would clearly decide against such a momentum investment. Again, it is the case that the best and worst mean return strategy do not go hand in hand with the best and worst Sharpe ratio. So there are strategies that perform better and worse in terms of the risk to be included.

Table 6: Sharpe Ratios of Momentum Returns (01/2018 - 02/2020)

This table shows the mean risk-free rate, the volatility and the Sharpe ratios for the best and worst momentum strategy for S&P500 stocks and cryptocurrencies with the highest market capitalization for the pre-COVID period from January 2018 until February 2020.

	Stocks		Cryptocurrencies	
	best	worst	best	worst
Formation / Holding	3 / 3	20 / 26	6 / 21	30 / 30
Mean risk-free (%)	0.768	0.768	0.768	0.768
Volatility (%)	1.34	3.38	10.97	14.71
Sharpe Ratio	-0.519	-0.481	0.152	-0.178
Annualized Sharpe Ratio	-8.228	-7.617	2.91	-3.394
Scale Factor (Days)	251	251	365	365

The Sharpe ratios of the cryptocurrencies range between -0.304 and 0.158. This means that the best strategy has almost the best return to volatility relation, and the worst stratgy does not have the worst Sharpe ratio, but still does not achieve a better return than a risk-free investment. Out of 900 strategies, 515 have a positive Sharpe ratio and are at least more profitable than a risk-free investment. But as with the full period, the high volatility is clouding the picture of good returns somewhat. Investors can achieve very high returns with the momentum strategy for cryptocurrencies, but must accept a higher level of risk. It is therefore questionable whether risk-averse investors will get involved.

With regard to the Sharpe ratios of all strategies, which are shown for the stocks and cryptocurrencies in Figure 15, it is noticeable that for both investments, a short holding period of one day leads to the worst values. For stocks, the Sharpe ratios are otherwise relatively similar for all the different strategies. With cryptocurrencies, on the other hand, the differences are somewhat clearer. The Sharpe ratios are particularly high in the 9 to 24 day holding period range and thus have the best ratio between excess return and volatility. For very long holding and formation periods, the values are worse again.

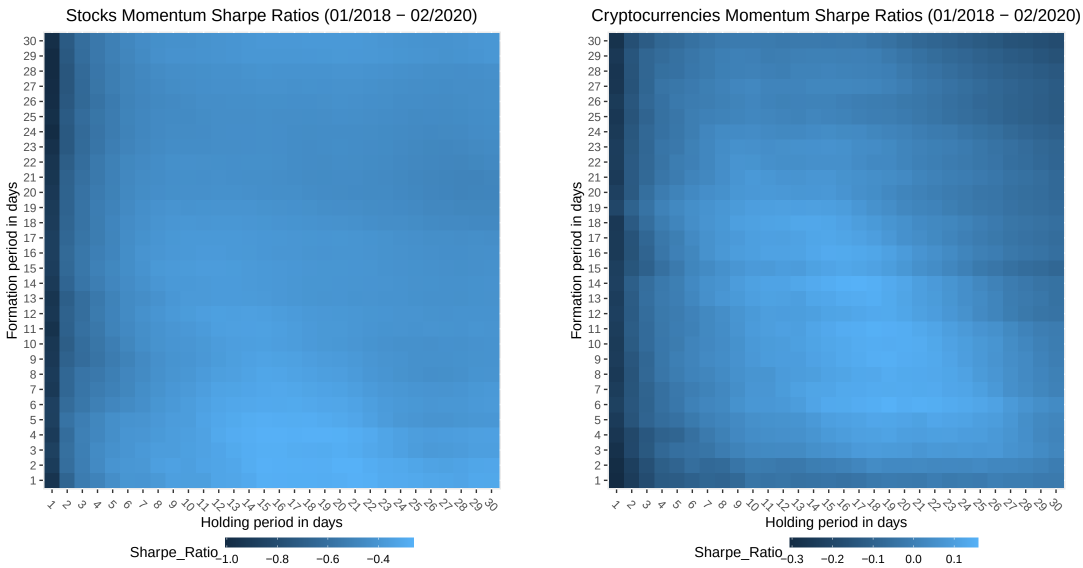


Figure 15: Heat Plots of the Sharpe Ratios (01/2018 - 02/2020)

This figure shows the Sharpe ratios of the different combinations of formation and holding period for the S&P500 stocks on the right and cryptocurrencies with the highest market capitalization on the left for pre-COVID period from January 2018 until February 2020. The lighter the color of the individual boxes, the higher is the respective Sharpe ratio for the given combination.

5.2.3 COVID Period (03/2020 - 12/2021)

As the last point in this section, the Sharpe ratios for the time from the beginning of the pandemic in March 2020 are discussed, which are shown in Table 7. Starting with the stocks, these values range from -0.345 to 0.021. Both minimum and maximum take on the respective peak values over all periods considered. On the one hand, this is due to the significantly higher volatility during this period for the worst value. The very low average interest rate of the risk-free investment is probably the main reason for the best value, even if only this one strategy has a positive Sharpe ratio. Overall, however, the risk-free rate has a positive effect on all strategies, since it was almost zero at the time but the Sharpe ratios suggest to not go into such an investment.

The values of the Sharpe ratios of the cryptocurrencies range between -0.001, which is the value of the worst strategy, and 0.248, which is also the best for all examined periods. The risk-free interest rate seems to have a strong influence, which means that overall only one strategy does not have a positive Sharpe ratio. With a value of 0.207, the best strategy is less risky than for the previous periods discussed. But as stated before, the low risk-free interest rate has a certain influence here and could mask the high

Table 7: Sharpe Ratios of Momentum Returns (03/2020 - 12/2021)

This table shows the mean risk-free rate, the volatility and the Sharpe ratios for the best and worst momentum strategy for S&P500 stocks and cryptocurrencies with the highest market capitalization for the COVID period from March 2020 until December 2021.

	Stocks		Cryptocurrencies	
	best	worst	best	worst
Formation / Holding	1 / 1	29 / 29	24 / 30	1 / 11
Mean risk-free (%)	0.033	0.033	0.033	0.033
Volatility (%)	1.97	8.36	23.37	12.46
Sharpe Ratio	0.021	-0.338	0.207	-0.001
Annualized Sharpe Ratio	0.337	-5.348	3.952	-0.016
Scale Factor (Days)	251	251	365	365

volatility. Ultimately, due to the Sharpe ratios, it would be recommendable to invest in cryptocurrencies with momentum if a decision has to be made.

The Sharpe ratios of all strategies shown in Figure 16 again show a diagonal structure for the stocks, as it does for the average returns. The worst values are again achieved for very long formation and holding periods, but rather short combinations also show an increased risk.

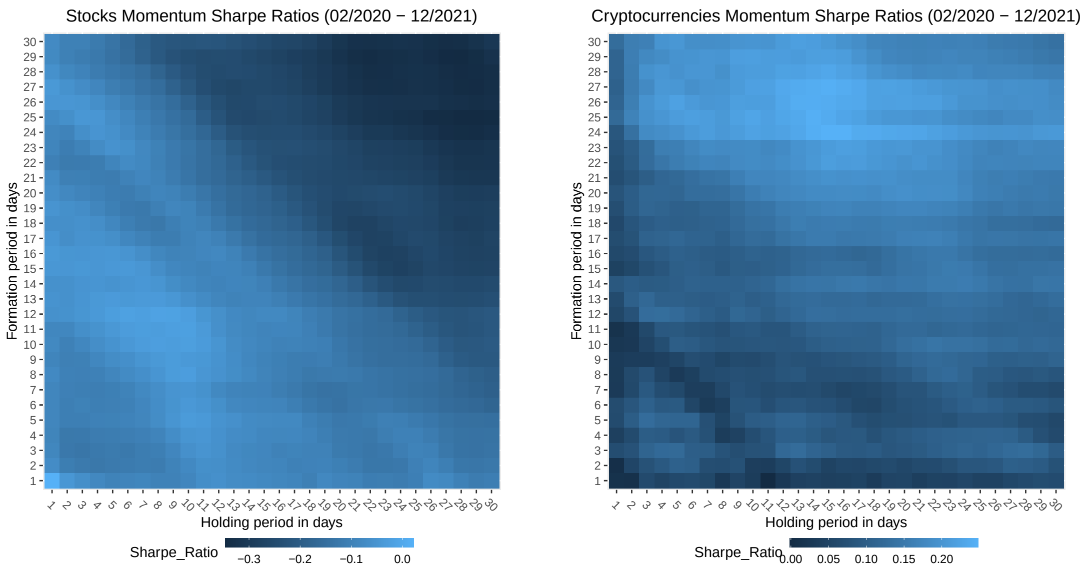


Figure 16: Heat Plots of the Sharpe Ratios (03/2020 - 12/2021)

This figure shows the Sharpe ratios of the different combinations of formation and holding period for the S&P500 stocks on the right and cryptocurrencies with the highest market capitalization on the left for the COVID period from March 2020 until December 2021. The lighter the color of the individual boxes, the higher is the respective Sharpe ratio for the given combination.

With cryptocurrencies, the picture is again not quite as clear even if one can see a somewhat diagonal structure for rather short holding and formation periods, as with the stocks. However, the opposite seems to be the case here, with rather short holding and formation periods showing the worst Sharpe ratios. In the ratio of excess return to volatility, a formation period of 24 days in connection with all holding periods except one day performs best. In general, formation periods of 24 days and more have the best Sharpe ratios for holding periods of up to around 17 days.

5.3 Limitations

The study is also subject to a couple of limitations, some of which will now be discussed briefly. A problem that has been completely abstracted here are taxes and transaction costs that inevitably arise when buying and selling securities. This would of course reduce the returns generated and cause them to be less than shown here, but Asness et al. [2013] nevertheless showed that momentum is a viable strategy, even when such costs are taken into account. Furthermore, it is assumed that it is possible to sell and short stocks and cryptocurrencies at any time, which does not always have to be the case.

The study is purely limited to the stocks listed in the S&P 500 in April 2022 and to cryptocurrencies that were the largest by market capitalization at the same time. On the one hand, the empirical results are only valid for these two specific markets and this has the disadvantage that there is a certain upward trend that may not have existed in 2018 from when the data was evaluated and is therefore anticipated. Using the example of shares, one can imagine this as follows: A share that may not even be included in the S&P 500 in 2018 will be included at some point later due to its good performance, but will be included in the study for the full time period. Of course, this brings with it a certain artifical positive trend into the data, since one anticipates that the share will develop well. The same applies to the market capitalization of cryptocurrencies: whether these were all among the largest in 2018 has not been further investigated. The data has also not been adjusted, which also includes extreme observations and also differs in the number of observations between stocks and cryptocurrencies, since the latter are available for each day and data from stocks is only available for trading days. The mean values are therefore calculated over different numbers of observations and could be distorted. However, the mean values were formed over several hundereds of observations, which means that this limitation may not be that important.

Another point is the formation of the portfolios, which are formed for the stocks from the best and worst 50 and for the cryptocurrencies from the best and worst 10. For equities, this corresponds to around 10%, whereas for cryptocurrencies it is around 33%, which can make a difference, since the limit for equities is much stricter. But one has to keep in mind that there are many more shares available than cryptocurrencies and an even stricter subdivision may not make sense at all. Furthermore, the focus is entirely on the cross-sectional momentum and it would also be interesting to do an analysis using time-series momentum. In general, it is also questionable whether the approach used here for ranking the securities is the optimal one.

More or less apples are compared with oranges over the individual periods examined, since the focus is on the best and worst set momentum strategies for stocks and cryptocurrencies and these always differ. How the strategies behave over other time windows was therefore ignored. In general, the choice of sub-periods can be questioned as a whole, since the focus is now solely on the pandemic. Possibly even finer subdivisions would have been useful and correct. One could also have gone into how the two markets mutually influence each other and, for example, correlate with one another.

6 Discussion & Conclusion

Even after almost 30 years of research, momentum remains an interesting investment strategy that is far from clear on how best to ultimately use it. There is no real consensus in the literature as to whether cross-sectional, time-series or earning momentum is the optimal strategy and how they replace each other or possibly expand on each other. There are also many different approaches to ranking and the resulting sorting, which probably each have their own justification, but the one universal momentum strategy that outshines all the other has not yet been found. The idea of this study was to use the simple approach of Jegadeesh and Titman [1993], since one can be critical when it comes to whether it makes sense to constantly change a procedure and try to improve it. Ultimately, all other approaches are based on the original methodology, which is why it cannot be that bad in itself. In order to check how momentum performs on a daily basis and whether there are differences in the underlying asset, momentum was applied to stocks of the S&P 500 and the 30 largest cryptocurrencies by market capitalization with a surprising result: no momentum effect can be observed for the stocks. On the contrary, the strategy brings in negative returns, which speaks more for the contrarian strategy as a successful investment method. Various sub-periods in which attempts are made to eliminate economically turbulent times do not change this. However, when the markets are in crisis, volatility increases, which is to be expected, although the momentum strategy of the stocks surprisingly performs better than expected at this time.

On the other hand, there are the considerable positive returns when applying momentum to cryptocurrencies, even if they suffer from their extreme volatility over all periods, which may be a deterrent for risk-averse investors. However, stocks and cryptocurrencies do have some things in common: apart from one single case, the distributions of returns are clearly not normally distributed with some stylized facts such as excess kurtosis, which peaks with cryptocurrencies, especially when the strategy performs worst. The distributions are usually quite symmetrical, even if they are slightly skewed to the left or right. In addition, returns are concentrated around a mean of zero in all cases. Stocks appear to be less volatile overall, which is especially evident in the period before COVID broke out. Choosing the optimal formation and holding period remains a big mystery. In the case of shares, you can see a somewhat diagonal structure, so if the formation period becomes smaller, the holding period can easily become a little longer. This effect is less visible with cryptocurrencies. Perhaps it would be more interesting to concentrate on this aspect in research instead of constantly looking for and finding new ranking and past performance measure methods. There is also the question of whether one should focus on a time interval or on the number of points in time. Really big findings are still missing, especially since one can work with much finer data today than 30 years ago.

The volatility of momentum was now often mentioned and in order to be able to assess the risk of the strategy, the Sharpe ratios were calculated and analyzed. One might say that it is not a particularly meaningful instrument, but it is certainly suitable for making an initial recommendation for action. A big plus of the Sharpe ratio is certainly that it is independent of any markets and one can therefore compare investments quite well with each other and if it were so useless, it would hardly be treated in finance courses at universities around the world. *"Keep it simple"* may be the magic saying here. After the average yields are consistently poor, the Sharpe ratios do not provide a better picture of the momentum equity strategy, investors should keep their hands off them, at least in the period under review. Only in the COVID period are there positive Sharpe ratios, which is probably due to the almost non-existent risk-free rate. The same picture again for cryptocurrencies, the high volatility is clouding the picture of positive returns. Whether risk-averse investors want to invest in something like this remains questionable, in no single phase is the Sharpe ratio > 1, which means: the risk is always higher than the return. But if one was forced to, one could consider it. The bottom line is that the following conclusion can be drawn: First, momentum does not generate positive returns or if one is not willing to take a very high level of risk. At least if one wants to use the strategy to build new portfolios with shares in the S&P 500 or the 30 major cryptocurrencies every day. Second, the efficient market hypothesis does not hold up whichever way one turns it. Negative yields also speak against an efficient market that has processed all the information. And, ultimately, one just has to turn the strategy around and one already has the desired positive returns, but then the strategy has a different name. Research should now deal with the following open questions for the future instead of constantly inventing new methods: What is the optimal unit of time? The past has proven that momentum works, even if it did not work in this specific case with shares, but it did with cryptocurrencies. So maybe it's better to use weekly or monthly data? Or is the study just highlighting a bad period and daily data is best? Another aspect would be to find out how much suitable the cryptocurrencies are as a hedge if the portfolios are made up of a mixture of stocks and these. Perhaps this has two positive effects: good returns and less volatility. And then it finally needs a kind of hyperparameter tuning to find the optimal combination of formation and holding period, but probably one for each asset class. In conclusion, momentum is very interesting topic, has a right to exist, every investor should keep it in mind and it is worth the time to explore it further. One idea would certainly be to start trying to create a large overall picture from these many small individual parts.

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