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Asset Pricing of Cryptocurrencies and Momentum based Patterns

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Abbreviations

API	Application Programming Interface
CAPM	Capital Asset Pricing Model
CRIX	Cryptocurrency Index
HML	High-minus-Low
LMH	Low-minus-High
SMB	Small-minus-Big

Abbreviations of included assets

BCN	Bytecoin
BTC	Bitcoin
BTS	BitShares
DASH	DASH
DCR	Decred
DOGE	DOGE
ETH	Ethereum
FCT	Factom
LTC	Litecoin
MAID	MaidSafeCoin
SC	Siacoin
XEM	NEM
XLM	Stellar Lumens
XMR	Monero
XRP	Ripple

Summary

This thesis develops a three-factor asset pricing model for cryptocurrencies by using a market factor, a size factor and a factor related to the transaction volume relative to an asset's market capitalisation. This model explains on average about 35% of the variance of weekly returns. Additionally, significant momentum-based returns were revealed by using several formation, holding and weighting periods and different ways of constructing the portfolios. Those returns did not only have abnormal returns up to 74.11 basis points per day by using the aforementioned asset pricing model for risk adjusting, but also have a remarkable Sharpe ratio of more than 3 by using their raw returns. Not only discrete momentum premia were calculated, but also patterns in those premia investigated. Evidence for superior returns of buying past 'winners', a so-called Long-Only approach, in comparison to buying past 'winners' and short-selling past 'losers' was found. Moreover, the analysis suggests investors to utilise a formation period of three weeks and a holding period of two weeks, while ignoring a waiting period. The used data set is covering 15 cryptocurrencies chosen by their market capitalisation and their data availability for a period from April 2016 to July 2017.

1. Introduction

Recently there has been a considerable increase not only in the market capitalisation of so called cryptocurrencies by more than 600% since July 2016 but also an increase in the public attention regarding these assets. In this thesis, I develop an asset pricing model for cryptocurrencies and examine if the momentum anomaly, a pricing pattern which was investigated in most security classes, is observable in cryptocurrencies too.

The European Banking Authority (2014) defines virtual cash as "a digital representation of value that is neither issued by a central bank or a public authority, nor necessarily attached to a fiat currency, but is accepted by natural or legal persons as a means of payment and can be transferred, stored or traded electronically". This paper focuses on a subset of virtual cash called cryptocurrencies, which are additionally characterised by using cryptography to secure the transactions and a price determined by publicly available exchanges. Throughout this thesis, the definition of cryptocurrencies is based on this subset.

Even though the concept of privately issued money is relatively old considering the free banking era in the U.S. in the 19th century (Rolnick and Weber, 2008), the first not only privately issued, but also completely decentralized cryptocurrency utilising the blockchain and a peer-to-peer structure was proposed in a white paper published by somebody going by the pseudonym Satoshi Nakamoto in 2008 (Nakamoto, 2008) called Bitcoin. This ground-breaking development did not only solve the Byzantine Generals' Problem as described by Lamport, Shostak and Pease (2008) by employing an open public available database - the blockchain - but did also intentionally create a link to gold by using the word "mining" for the process of computing a unique number to generate new units and by fixing the total supply of Bitcoin to 21,000,000.

Following up on this invention, new codes and protocols were published and new cryptocurrencies applying the same basic principles issued. Nowadays CoinMarketCap[1], an influential provider of aggregated data regarding these securities, lists more than 900 different assets following the broad definition of this thesis (as of 16/07/2017). All of them are publicly traded on an exchange with non-zero volume. The price of these currencies is defined by supply and demand on exchanges. Given the unclear characteristics of these assets, there is no prevalent asset pricing model yet. Therefore, it is not straightforward to define excess returns. Inspired by Fama and French (1993), a three-factor-model of asset pricing is employed throughout this thesis to risk-adjust the returns of the cryptocurrencies. The utilised model uses a risk-factor based on the cryptocurrency market, one related to the size of a cryptocurrency in market capitalisation terms and one regarding the investors' sentiment. The reasoning behind these factors is based on the assumption of priced risk – investors require a higher reward for

[1] URL: https://coinmarketcap.com/

holding riskier assets. If this assumption is reasonable for cryptocurrencies and if the returns can be explained by a model based on these factors, is challenged by using the first hypothesis:

H1: An asset pricing model with three factors based on market risk, size and sentiment explains returns of every cryptocurrency statistical significantly better than an intercept-only model.

The model with the best fit is then employed to express excess returns. Expressing excess returns is necessary to test for patterns in the so called alpha. Just considering excess returns, expressed by using the described model, helps to distinguish between market anomalies – patterns, which are not explained by standard economic theory – and traditional risk factors (Keim, 2008). Thus, revealing anomaly based patterns require according to Keim (2008) that the null-hypothesis, stating that “returns behave according to a prespecified equilibrium model” is rejected. The prespecified model is the developed model with the best fit. To guarantee independence of the first hypothesis and to have more than one prespecified model, the Capital Asset Pricing Model (CAPM) (Treynor, 1961; Sharpe, 1964 and Lintner, 1965) and the Sharpe Ratio (Sharpe, 1965) are employed besides the determined model as well.

The following analysis, is examining the performance and feasibility of an investment strategy based on the momentum anomaly first described by Jegadeesh and Titman (1993) in a new field, namely cryptocurrencies. While Jegadeesh and Titman (1993) investigated profitable trading strategies by buying past ‘winners’ and short-selling past ‘losers’, Novy-Marx (2012) concludes that the abnormal return is not based on recent past performance but on intermediate past performance and can potentially be explained by under- and overreaction of financial markets. By evaluating different trading strategies with different formation, waiting and holding periods the momentum effect is tested. Thus, the second hypothesis is:

H2 : Momentum trading strategies in cryptocurrencies based on buying past or intermediate winners and selling past or intermediate losers generates economically and statistically significant positive returns.

A data set containing all major cryptocurrencies is used to test both hypotheses. The data set is constructed by including all cryptocurrencies which have data available since 10/04/2016 through the coinmarketcap.com application programming interface (API) and have a market capitalisation of at least $100,000,000.00 on 16/07/2017. In total 15 different assets are included into the analysis.

The analysis revealed that the developed asset pricing model explain on average more than 35% of the variance of returns of cryptocurrencies. In addition it is significantly better than an intercept-only model for every single asset, which is part of the analysis. Significant returns of momentum-based strategies are found. Their returns are statistically significant and additionally superior to momentum strategies in traditional asset markets or holding one of the examined assets alone. Besides different patterns in momentum returns are evaluated and tested.

The remainder of this paper is organized as follows. In the following section, Section 2, the research agenda is presented at a glance. In Section 3, the theoretical framework for the asset pricing model and the momentum effect is presented. Besides some characteristics of cryptocurrencies are discussed. Subsequently, in Section 4 the data is described. In Section 5 the methodology of the asset pricing model and its fit are presented. Section 6 discusses the returns of the different investment strategies and presents different patterns in those returns. Aside from using the developed asset pricing model, a CAPM related approach and Sharpe ratio are considered, too. Finally, Section 7 concludes and discusses reflecting remarks.

2. Research Agenda

The objective of this paper is to study if the momentum anomaly can be observed in cryptocurrencies and is formally expressed by H2 (Section 1). In order to detect an anomaly and distinguish between the anomaly and price patterns that are based on fluctuations in risk and the fundamental value, excess returns have to be expressed by using a suited asset pricing model. Due to the absence of an asset pricing model for cryptocurrencies, a three factor asset pricing model is developed by using different metrics and comparing their fit. The reasonable fit of the developed model is formally expressed by H1 (Section 1). Thus, developing an asset pricing model and providing evidence for H1 can be considered as a step towards the research objective. Following this relation between the hypotheses, the methodology and the results of the asset pricing model are presented entirely before the methodology and the results of the momentum patterns are discussed

3. Literature Review

Since Markowitz (1952) introduced modern portfolio theory by assuming that rational investors diversify their portfolio in the way that no portfolio offers a superior risk-return relationship, several asset pricing models were developed to determine an asset's required return given a certain level of risk or vice versa. Starting with the CAPM which expresses required returns of an asset by comparing it with a risk-free asset, its sensitivity to the market risk and the market return, more sophisticated models were investigated, of which the three-factor-model of asset pricing developed by Fama and French (1993) is the most impactful one for stocks.

Referring to an asset pricing model for stocks while researching cryptocurrencies might seem confusing. Indeed, the name cryptocurrency, suggesting it has characteristics of traditional currencies, is misleading. The U.S. Commodity Futures Trading Commission (CFTC) defines cryptocurrencies as commodities, while the U.S. Internal Revenue Service (IRS) interprets them as property. The unique attributes of cryptocurrencies such as price independence in the sense of low correlation to traditional asset classes, the extreme risk-reward profile or its stand-alone basis of value advocates calling it a new asset class (Burniske and White, 2017). This new asset class incorporates some aspects of traditional equity: The size of a cryptocurrency is also called market capitalisation and is defined by the price of one unit multiplied by the number of outstanding units. Besides, it is mostly traded on the spot on publicly available exchanges even though a market for derivatives exists for the larger cryptocurrencies. Recently analysts developed a metric comparable to the P/E ratio to evaluate a cryptocurrency's price (Vlastelica, 2017). These common characteristics justify an application of the aforementioned Fama and French (1993) three-factor-model of asset pricing to cryptocurrencies. Originally it uses, besides a general market factor, two more elements to determine required rewards: One factor depends on the size of a stock, the other one is related to its Book-to-Market-Ratio. The two new factors are justified as additional, systematic risk factors besides the market risk: Small firms have in general a lower liquidity, a more restricted access to debt financing and it is harder for investors to obtain information (Banz, 1981), therefore investors should require a higher return for holding their stocks. The explanation for the remaining element, the so-called value factor, is less straightforward: Firms with a higher Book-to-Market-Ratio, commonly named value firms, potentially have a higher inherent risk due to low future growth opportunities, so low prospectus earnings. Besides, there are behavioural explanations related to overreaction and investor's sentiment. Value firms can have a high Book-to-Market-Ratio due to a recent loss in their price related to bad news. Investors have the tendency to overreact to such news and produce therefore a mispricing (Fama and French, 1992). In addition, the Book-to-Market-Ratio captures potentially an irrational sentiment of investors: Attention grabbing growth stocks in high tech industries can seem subjectively more attractive than value stocks of traditional industries (Lakonishok, Shleifer, and Vishny, 1994). Furthermore, this finding is backed by the findings of Chen and Shin (2016), who are stating a theoretical model, where sentiment sensitive noise traders produce a mispricing. This mispricing partially explains the Book-to-Market-Ratio factor. This three-factor-model can explain up to 90% in the variation of monthly stock returns (Fama and French, 1993).

Applying asset pricing models is not exclusively done to explain the variation of returns, it can also be applied to observe extraordinary patterns in returns, such as the momentum effect. The momentum effect refers to Isaac Newton's first law which states that a body in motion tends to stay in motion. According to this idea, the momentum effect in the world of finance states that assets, that gained in the past will continue doing so while assets that fall in the past tend to keep falling in the future.

Since first evidence was found in the US stock market (Jegadeesh and Titman, 1993), there was a wide range of research regarding this effect published: Novy-Marx (2012) stated that the future performance is not completely explained by the recent past and that intermediate horizons, which use a lag between the formation period and the holding period, outperform traditional momentum strategies without this waiting period. Fama and French (2012) investigated a strong momentum effect in different developed stock markets except for Japan. Asness, Moskowitz and Pedersen (2013) also found consistent momentum return premia on a global level.

Daniel, Hirshleifer & Subrahmanyam (1998) explain the momentum effect by using behavioural finance: Their two possible explanations are the investor's overconfidence and biased self-attribution. Pastor and Stambaugh (2003) state that the momentum effect is somewhat explained by a liquidity risk factor.

This theoretical groundwork did not only deliver inspiration for an asset pricing model for cryptocurrencies and testing momentum strategies but did exemplify the applied methodology as well.

4. Data

The data for this empirical analysis is obtained through the API of a provider of data regarding this asset class, namely CoinMarketCap. Their influential website for cryptocurrencies lists and ranks all major representatives of this asset class by providing a volume-per-exchange weighted market price, the market capitalisation and the total trading volume itself. The volume-per-exchange weighted approach is determining an asset *i*'s price by weighting an exchange *j*'s volume *VOL* for this individual asset *i* during the last 24 hours relative to the overall volume for this asset over the last 24 hours on all major exchanges *J* which are charging fees, multiplied with its price. More formally,

$$Coinmarketcap\_Price_{i,t} = \sum_{j=1}^{j=J} \frac{VOL_{i,j,t-24hours}}{\sum_{j=1}^{j=J} VOL_{i,j,t-24hours}} * Price_{i,j,t}$$

This website is only using data from exchanges which are charging trading fees to avoid biases or so called "fake-volume" generated by trading with oneself. All three variables are downloaded and included in my analysis by requesting daily data. The volume-per-exchange weighted approach is correcting for the different prices on exchanges to get a representative market price without being reliant on a single exchanges and its traders. All assets exceeding a market capitalisation of = $100,000,000.00 on 16/07/2017 are included when their data is continuously available since the 10/04/2016. This led to a total data set of 15 different cryptocurrencies (Table 1) over a time span of 65 weeks. The data source has no data available for the dates between 22/2/2017 and 26/2/2017 and on 09/3/2017, so these dates are excluded. CoinMarketCap is not providing explanations regarding this missing data.

Table 1
Overview of potential assets for analysis.

Name	Abbreviation	Rank according to MktCap	MktCap on 16/07/2017	Data available since	Included
Bitcoin	**BTC**	**1**	**$ 33,981,480,390.00**	**10/04/2016**	**x**
Ethereum	**ETH**	**2**	**$ 16,734,656,853.70**	**10/04/2016**	**x**
Ripple	**XRP**	**3**	**$ 6,808,285,331.84**	**10/04/2016**	**x**
Litecoin	**LTC**	**4**	**$ 2,096,342,325.71**	**10/04/2016**	**x**
Ethereum Classic	ETC	5	$ 1,454,532,728.66	24/07/2016	
Dash	**DASH**	**6**	**$ 1,094,223,677.70**	**10/04/2016**	**x**
NEM	**XEM**	**7**	**$ 1,026,341,999.89**	**10/04/2016**	**x**
Monero	**XMR**	**8**	**$ 488,128,181.34**	**10/04/2016**	**x**
IOTA	MIOTA	9	$ 466,627,543.91	16/06/2017	
BitConnect	BCC	10	$ 357,783,914.47	20/01/2017	
Stratis	STRAT	11	$ 314,737,792.06	08/12/2016	
EOS	EOS	12	$ 300,558,825.12	01/07/2017	
Tether*	USDT	13	$ 294,179,484.72	10/04/2016	
Zcash	ZEC	14	$ 285,515,120.59	29/10/2016	
BitShares	**BTS**	**15**	**$ 277,372,145.35**	**10/04/2016**	**x**
Bytecoin	**BCN**	**16**	**$ 239,479,758.61**	**10/04/2016**	**x**
Steem	STEEM	17	$ 234,046,138.93	18/04/2016	
Veritaseum	VERI	18	$ 216,883,100.40	06/08/2017	
Augur	REP	19	$ 210,973,400.00	10/04/2016**	
Waves	WAVES	20	$ 210,101,000.00	02/06/2016	
Qtum	QTUM	21	$ 208,695,570.00	24/05/2017	
Stellar Lumens	**XLM**	**22**	**$ 195,110,883.36**	**10/04/2016**	**x**
Gnosis	GNO	23	$ 185,884,823.56	01/05/2017	
Siacoin	**SC**	**24**	**$ 183,489,283.49**	**10/04/2016**	**x**
Golem	GNT	25	$ 181,900,867.52	18/11/2017	
Dogecoin	**DOGE**	**26**	**$ 171,095,103.78**	**10/04/2016**	**x**
Lisk	LSK	27	$ 158,251,614.51	24/05/2016	
Iconomi	ICN	28	$ 156,001,440.00	30/09/2016	
Byteball	GBYTE	29	$ 155,082,867.46	27/12/2016	
MaidSafeCoin	**MAID**	**30**	**$ 125,149,296.57**	**10/04/2016**	**x**
MCAP	MCAP	31	$ 120,039,825.56	30/05/2017	
Factom	**FCT**	**32**	**$ 119,813,186.35**	**10/04/2016**	**x**
Decred	**DCR**	**33**	**$ 111,229,132.22**	**10/04/2016**	**x**
DigixDAO	DGD	34	$ 95,889,200.00	16/04/2016	
DigiByte	DGB	35	$ 89,824,907.88	10/04/2016	
AntShares	ANS	36	$ 87,139,500.00	09/09/2016	
GameCredits	GAME	37	$ 84,195,893.48	10/04/2016	
Status	SNT	38	$ 83,861,117.30	28/06/2017	
PIVX	PIVX	39	$ 82,758,533.44	23/01/2017	
Ardor	ARDR	40	$ 80,518,660.00	23/07/2016	

* Tether (USDT) is backed by a US-Dollar held by the Tether Ltd. thus it is not part of the analysis
** Augur (REP) has no data available between 17/05/16 and 22/08/16, so it is excluded from the analysis

Table 1: Overview of potential assets for analysis. Out of the 40 largest cryptocurrencies, 15 are selected by using three criteria: Market capitalisation of more than $100,000,000.00, data available since 10/04/16 and continuously available data. Included assets are highlighted in bold.

5. Asset pricing model

Given the uncertain market conditions and the unknown characteristics of cryptocurrencies, different explanatory variables are tested to develop a suited three-factor asset pricing model for cryptocurrencies. The analysis is based on weekly returns averaged per day rather than absolute prices of the cryptocurrencies. These returns are used to construct the factors. The model of the best fit is chosen by considering centered-R^2 statistic. This approach is inspired by Fama & French (2015), who are adding two more factors to their original three-factor-model of asset pricing. They are doing so even though the Gibbons-Ross-Shanken test, a statistic using the null-hypothesis of non-significantly different sum of squared alphas of a time-series to 0, is rejecting the two extra factors. Fama and French justify this by a higher explained variance. Additional to the centered-R^2 statistic, the *F*-values of the models are also studied.

5.1. Factor construction

Inspired by the presented three factor asset pricing model of Fama and French (1993) I use three risk factors of cryptocurrencies to assess their risk-adjusted returns assuming that higher risk is rewarded with higher returns. The first risk factor is the sensitivity to the cryptocurrency market, proxied by using the CRIX, a market capitalisation weighted index of currently (16/07/2017) 65 different cryptocurrencies calculated by the Humboldt University Berlin (Trimborn and Haerdle, 2016). Implementing the size factor is straightforward: By using the market capitalisation of the different cryptocurrencies this second element of the asset pricing model is constructed. The third Fama and French factor is based on the Book-to-Market-Ratio which is likely to be at least partially a proxy for the sentiment regarding an asset. The reasoning for this is that the Book-to-Market-Ratio captures a mispricing due to over-valuation of attention grabbing growth stocks in IT or BioTech industries and an undervaluation of value stocks in more traditional markets, which are considered to be less attractive. Imitating the Book-to-Market-Ratio is done in two possible ways: Firstly, an approximate metrics to determine the fundamental value of a cryptocurrency and then compare it with its market capitalisation is applied. This is done by following the metric described by Vlastelica (2017) stating that the core utility of cryptocurrencies is its ability to move money. Therefore, he suggests to take the market capitalisation of a coin and compare it with its daily transaction volume. Even though this metric is compared to the Price-to-Earnings-Ratio rather than the Book-to-Market-Ratio, both are used to decide whether a stock is overpriced or not and are consequently related. Secondly, one can focus on the behavioural explanation of the value factor and find a proxy for the investor’s sentiment. This can potentially be done by using Google Trends - a data set showing how often a particular search term is entered relative to its peak volume. This data set provides information regarding interest and demand for a cryptocurrency and thus captures investor’s sentiment. This idea is inspired by Woo (2017), who is using Google-Trends to detect price bubbles or undervaluation of Bitcoin. The P/E ratio inspired approach and the Google Trends approach are both tested in this section to determine the model with the best fit.

The factor construction is based on the methodology of Fama and French (1993). The market factor is proxied by using the weekly change of the CRIX index averaged per day. The factor construction is based on weekly returns averaged per day. Weekly returns averaged per day are used by following the methodology as described below Table 2. Weekly returns are used, because the Google Trends data, a data set describing how often a particular search term is entered on Google relative to its peak volume employed to proxy investor's sentiment, is just available in weekly intervals. The returns are averaged per day to make the data more comparable to traditional equity markets and avoid frictions because of the different trading times. Traditional equity is limited to the opening times of stock exchanges which normally span from Monday to Friday from morning to early evening, while cryptocurrencies are traded 24 hours every day.

SMB: The Small-minus-Big factor for t is constructed by ranking the market capitalisation in $t-1$ in descending order and sorting all assets in p portfolios according to their rank. The average daily return of the largest portfolio is then subtracted from the average daily return of the smallest portfolio. This is done for $t=1week$ and for $p=3$ and $p=5$[2]. Doing so led to two different time series for the SMB factor, called SMB_3 and SMB_5 according to their p.

LMH: The Low-minus-High factor, partially referring to the investors' sentiment is calculated in two different ways: First, by using market capitalisation divided by the daily transaction volume, in the following described as PE_LMH, and second by using Google Trends, noted as GT_LMH. The name PE_LMH is referring to Vlastelica's (2017) comparison of the metrics to the P/E ratio. For both analyses a low value refers to a low investor sentiment. This might seem confusing, because the original Fama & French (1993) asset pricing model, where the Book-to-Market-Ratio is used, a high ratio is interpreted as a low sentiment. Therefore the LMH factor is based on the same reasoning as the Fama and French HML (High-minus-Low) factor.

Using the PE_LMH metric, the factor for t is constructed by ranking the market capitalisation divided by the daily transaction volume in $t-1$ in descending order and sorting all assets in p portfolios according to their rank. The weekly return averaged per day of the portfolio with the largest ratio is then subtracted from the weekly return averaged per day of the portfolio with the lowest ratio. This is done for $t=1week$ and for $p=3$ and $p=5$. Doing so led to two different time series for the PE_LMH factor, named PE_LMH_3 and PE_LMH_5 according to their p

The Google Trends data is just available in weekly intervals and is a relative count of a particular search term relative to its peak volume. The change in this count from week to week is calculated and

[2] Fama and French (1993) are using p=2 and p=5 for the size factor and a 30%-40%-30% split and p=5 for the Book-to-Market-Ratio based factor

then ranked in comparison to the other cryptocurrencies and sorted into *p* portfolios according to their rank to test another LMH factor, in the following noted as GT_LMH. The change in this count is employed to make the data comparable between different assets instead of just being relative to its own peak. The weekly return averaged per day in *t* of the portfolio with the largest increase in its search volume in *t-1* is then subtracted from the weekly return averaged per day in *t* of the portfolio with the lowest change in the Google trends data in *t-1*. Unfortunately, this analysis is only possible by sorting the assets into quintiles (*p=5*) due to missing data. Missing data in Google Trends occurs when a particular search term has not exceeded a certain volume, thus the smaller assets do not have a continuously available Google trends data set for the whole time series. Using *t=1week* led to another time series, named GT_LMH_5 according to their *p*, so that finally three data sets for the LMH factor are tested. The six time series regarding the factors (CRIX, SMB_3, SMB_5, PE_LMH_3, PE_LMH_5 and GT_LMH_5) are presented in the first six rows of Table 2; the weekly returns averaged per day of all assets are depicted below the factors in Table 2.

Table 2

Descriptive statistics for returns and factor time series

Variable	Mean	Std. Dev.	Min	Max
Change of CRIX	0.0055	0.0119	-0.0239	0.0328
SMB_3	0.0069	0.0233	-0.0204	0.0925
SMB_5	0.0081	0.0282	-0.0279	0.1657
PE_LMH_3	0.0113	0.0253	-0.0547	0.0842
PE_LMH_5	-0.0037	0.0328	-0.1582	0.0744
GT_LMH_5*	-0.0052	0.0293	-0.1414	0.0763
BCN Return	0.0190	0.0687	-0.0731	0.3836
BTC Return	0.0041	0.0124	-0.0286	0.0396
BTS Return	0.0101	0.0449	-0.0709	0.2623
DASH Return	0.0094	0.0257	-0.0477	0.0983
DCR Return	0.0118	0.0423	-0.0691	0.1322
DOGE Return	0.0058	0.0213	-0.0578	0.0708
ETH Return	0.0091	0.0254	-0.0432	0.0856
FCT Return	0.0076	0.0279	-0.0626	0.0920
LTC Return	0.0072	0.0235	-0.0371	0.0941
MAID Return	0.0044	0.0204	-0.0601	0.0499
SC Return	0.0134	0.0488	-0.0582	0.2112
XEM Return	0.0133	0.0373	-0.0380	0.1659
XLM Return	0.0097	0.0454	-0.0684	0.2563
XMR Rreturn	0.0104	0.0343	-0.0511	0.1682
XRP Return	0.0109	0.0396	-0.0739	0.1587

Returns are based on weekly returns averaged per day, so Return=(1+(Weekly Return)^(1/7)-1

*Statistics for GT_LMH_5 data is based on 64 observations instead of 65 like for all other variables. GT_LMH_5 is just available for quintiles due to missing data

Table 2: Descriptive Statistics for the weekly time series averaged per day (returns are per day) of all cryptocurrencies and the constructed factors from 10/04/16 to 16/07/17. The abbreviations for the cryptocurrencies can be found in Table 1.

In contrast to the reasoning by Fama and French, PE_LMH_5 and GT_LMH_5 have a negative mean. This describes, that cryptocurrencies with a high transaction volume to their market capitalisation outperformed cryptocurrencies with a low transaction volume to market capitalisation ratio on average, when sorted in quintiles. Same applies to cryptocurrencies with a high increase in their sentiment based on Google trends in comparison to cryptocurrencies with a lower increase or even a drop in their sentiment – They also outperformed the latter ones. These findings can be interpreted by using the findings of Kristoufek (2013), who is investigating a non-linear relationship between Google-Trends data and Bitcoin pricing, but rather a trend dependency. If the price was below its trend, an increased search volume had a negative effect on the price, while it had a positive effect, when the price was upon its trend line. If the relationship between the LMH factors and the price is also more complex than the studied link for other cryptocurrencies, the negative mean of the factors can potentially be explained.

Furthermore, the mean raw return of every single cryptocurrency is positive with at least 0.0041 per day. Such returns are hard to investigate in traditional investment markets and are a sign for a bull market during the analysed period.

5.2. Model Fit

By using the constructed factors and the different time series, weekly regressions with Newey-West standard errors for all cryptocurrencies are applied to get their sensitivity, the so-called beta, to every factor. This type of regression is utilised to be robust for the characteristics of autocorrelation and heteroscedasticity of the time series returns of some assets (test results for these two model misspecifications can be found in Appendix A.1). The White-Koenker test for heteroscedasticity and the Cumby-Huizinga test for autocorrelation are utilised. The maximum number of lags is determined by the optimal lag according to Ng-Perron sequential *t* statistics of the Dickey-Fuller GLS test with a 10% level of significance of the largest representative of my analysis, namely Bitcoin. This led to a maximum lag of three for the weekly data. The different models are compared by using their centered-R^2-measurement of the regressions and their *F*-values.

5.3. Results of the tested APM

The best model has an averaged centered-R^2 above all regressions of 0.3589 and is the model which is using SMB_3 and PE_LMH_3:

$$E(r_{t,i}) = \beta_{Market\ i} * \Delta_{CRIX\ t} + \beta_{SMB_3\ i} * SMB_{3,t} + \beta_{PE\_LMH_3\ i} * PE\_LMH_{3,t}$$

The averaged centered-R^2 of all models is displayed in Table 3. The underlying data including the beta factors for every asset and model can be found in Table 4 and Appendix A.3 and A.4. Aside from its superior averaged centered-R^2, the chosen model is the only model which has a statistically significant *F*-value for every single cryptocurrency (Table 4) – The F (3, 61)-value referring to a significance at the 5% level is 2.91. Therefore it can be indicated that an asset pricing model, using a market factor, a size factor and a factor related to the fundamental value relative to its market capitalisation can explain not only a substantial part of the variance of average weekly returns but is also significantly better than an intercept-only model, so the first hypothesis, stating that 'An asset pricing model with three factors based on market risk, size and sentiment can significantly explain returns of cryptocurrencies' cannot be rejected.

Table 3

Explained variance of the different models - Summary of Tables 4, A.3 and A.4

	SMB_5 and PE_LMH_5	SMB_3 and PE_LMH_3	SMB_5 and GT_LMH_5
Cent. R^2	0.2627	0.3589	0.2372

Table 3: Comparing the different models by using their centered-R^2 measurement

The chosen model and its beta factors deliver already first insights into the price movements. The beta to the market factor is highly significant for Bitcoin. This is not surprising given the fact that its market capitalisation accounts for about 50% (16/07/2017) of the market capitalisation of all cryptocurrencies. The beta factor is also significant for Litecoin and Dogecoin.

Table 4

Time series regressions based on weekly data sorted in thirds

Returns of	CRIX	SMB	LMH	Cent. R^2	F-value
BCN	0.499	2.236**	-0.343	0.506	22.87
BTC	0.663**	0.087	-0.002	0.483	20.93
BTS	0.026	0.806**	0.852**	0.610	34.41
DASH	0.091	-0.4629**	0.599**	0.235	7.55
DCR	-0.264	0.643*	0.365	0.187	5.91
DOGE	0.692**	0.166	0.259*	0.504	22.70
ETH	-0.375	0.069	0.752**	0.457	18.96
FCT	-0.107	0.162	0.611**	0.342	12.09
LTC	0.561*	0.216	0.016	0.141	4.49
MAID	0.016	0.064	0.341**	0.184	5.82
SC	-0.494	0.991**	0.979**	0.626	36.66
XEM	-0.453	0.263	0.737**	0.249	8.06
XLM	0.406	0.324	0.743**	0.317	10.90
XMR	-0.112	-0.417*	0.955**	0.302	10.23
XRP	0.332	0.248	0.572*	0.240	7.74

* refers to a 5% level of significance

** refers to a 1% level of significance

Table 4: Regression results of the chosen model. Assets are listed alphabetical. The t-values are presented in Appendix A.2.

This can potentially be explained by the similarities between Bitcoin and these two assets. They are all based on the same codebase, but Litecoin, one of the first adaptations of Bitcoin, uses a multiplication of four for the maximum of units and just one-fourth of the time until a new unit is generated. Dogecoin, firstly developed as a parody to Bitcoin, is based on the Litecoin code. The significance to the market factor provides some evidence, that these three assets move partially in the same direction and that their pricing is potentially explained by the underlying technology. Additionally, it is surprising that the market beta for Ethereum is not significant considering its share of about 20% of the market capitalisation of all cryptocurrencies. This is possibly caused by its position relative to Bitcoin. They are by far the two largest representatives of this asset class and are often seen as competitors, based on the reasoning that just one technology will be dominant in the future. Therefore, they are often moving in different directions. The correlation of these two assets based on raw returns in the analysed bull market is 0.08 and thus considerably low. Covariance is not existing (<0.001).

The size factor is mostly significant for smaller assets (market capitalisation is presented in Table 1), while it is not for the larger ones with a market capitalisation of more than $5bn (as of 16/07/17 – BTC, ETH, XRP (abbreviations can be found in Table 1)). The LMH factor is significant for all analysed assets except BCN, BTC, DCR and LTC. As aforementioned, BTC and LTC are the oldest assets of the analysis and are therefore more widely accepted as other analysed cryptocurrencies (except for ETH). This potentially leads to a higher base rate in their transaction volume and therefore to less fluctuation. This might be a possible explanation why this factor is not statistically significant.

5.4. Expressing Abnormal Returns

The chosen model and its beta factors (Table 4) are used to determine the abnormal returns of all analysed cryptocurrencies *i* through the time series *t* by calculating:

$$r_{Excess\ t,i} = r_{t,i} - (\beta_{Market\ i} * \Delta_{CRIX\ t} + \beta_{SMB\ i} * SMB_t + \beta_{LMH\ i} * LMH_t)$$

In the traditional Fama and French (1993) three-factor-model the return r and the market return $\Delta_{CRIX\ t}$ are decreased by the risk-free rate. This effect can be neglected given the short holding period of the analyses, the extraordinary risk-return relationship of this asset class and the low interest rate level during the analysed period. Descriptive statistics of the excess returns are presented in Table 5. All included assets have a positive mean raw returns. After risk adjusting, not all means are positive anymore.

Table 5
Weekly excess returns averaged per day

Cryptocurrency	Mean	Std. Dev.	Min	Max
BCN	0.0047	0.0471	-0.1047	0.2023
BTC	-0.0001	0.0087	-0.0369	0.0281
BTS	-0.0052	0.0274	-0.0723	0.1481
DASH	0.0053	0.0220	-0.0488	0.0818
DCR	0.0047	0.0372	-0.0573	0.1185
DOGE	-0.0021	0.0146	-0.0330	0.0524
ETH	0.0022	0.0183	-0.0432	0.0475
FCT	0.0002	0.0221	-0.0541	0.0433
LTC	0.0024	0.0213	-0.0388	0.0811
MAID	0.0000	0.0180	-0.0441	0.0447
SC	-0.0017	0.0292	-0.0975	0.1007
XEM	0.0057	0.0316	-0.0668	0.1556
XLM	-0.0032	0.0367	-0.0832	0.1638
XMR	0.0031	0.0280	-0.0467	0.1347
XRP	0.0009	0.0337	-0.0858	0.1409

Table 5: Descriptive statistics of excess returns based on the model using the SMB_3 and PE_LMH_3 factors.

6. Momentum based strategies

The following section explains the methodology of computing trading strategies and provides an overview about the trading costs connected to implementing those strategies. Afterwards the returns of these investments are discussed and different patterns are elaborated and tested.

6.1. Momentum Methodology

The description of the momentum strategies is based on Jegadeesh and Titman (1993). Their methodology in generally applied. Contrary to Jegadeesh and Titman (1993) the analysis is not using raw returns and test the raw momentum returns against risk factors to reveal this anomaly, but is directly using excess returns of the developed factor model. This is based on the assumption that all expected excess returns $E(r_{Excess\ t,i})$ are zero. Following this assumption, revealing returns significantly different from zero is providing evidence for the existence of an anomaly.

A portfolio of cryptocurrencies is chosen based on their excess returns over the past f weeks, the so called ‘formation period’. Then a holding period of h weeks is utilised to calculate the returns. Later on, a waiting period of w weeks in between is also considered to incorporate the findings of Novy-Marx (2012), who is incorporating a lag between the formation and holding period, so called waiting period, and reveals superior returns in comparison to momentum strategies without a waiting period. The holding portfolio is formatted as follows: the excess returns of the last f weeks are considered to rank the assets in descending order. *N* (Not to be confused with the *p* from the previous section, which is used to construct factors) portfolios are formed, where the top portfolio is defined as 'winners' and the bottom one as 'losers'. After the waiting period has passed, the holding portfolio is formed by buying the winner portfolio and selling the loser portfolio. At the end of the holding period all assets are liquidated. This is defined as a Long-Short strategy.

The strategies are denoted by stating their parameters chronologically: The first number is the formation period *f*, second number is the waiting period *w*, and third number is the holding period *h* – So for example a 3-1-2 strategy would describe a formation period of three weeks, a waiting period of one week and a holding period of two weeks.

The weighting of every asset in the portfolio is equal or based on its market capitalisation relative to all bought assets. So the share s_i of an asset *i* in the holding-portfolio following market capitalisation based weighting is determined by its average market capitalisation over the formation period divided by the sum of average market capitalisation of all holdings. Varying the portfolio size *N* and the weighting is mainly inspired by Israel and Moskowitz (2012).

Besides this long-short approach, a long-only momentum strategy is tested as well, which uses the same methodology but only invests in the 'winner'-portfolio.

Given the unknown characteristics of this asset class, no research based assessment of promising time frames can be done. Kristoufek (2013), who is investigating the relationship between Google Trend data regarding Bitcoin, the Wikipedia search volume of Bitcoin and its price movements is using daily and weekly data. Due to data limitations caused by the weekly interval-scaled Google Trends data set, which is limiting the factor construction to weekly time series, weekly intervals are the shortest periods that can be used. All in all, different simulations are applied and in total 192 different parameter composition for the long-and-short momentum strategy and another 192 different parameter composition for the long-only momentum strategy are compared - trading strategies based on *f* in weeks=(1, 2, 3, 4), *w* in weeks=(0, 1, 2) and *h* in weeks (1, 2, 3, 4), *N*= (3, 5) are compared by weighting assets equally and based on their market capitalisation relative to the total holdings.

6.2 Evaluation of Strategies

For evaluating the trading strategies only excess returns are used: The assets get ranked according to their excess return and then the excess returns of the strategies are evaluated. The excess returns are expressed by using the SMB_3 and PE_LMH_3 asset pricing model. For further insights excess returns are also expressed by using CAPM-risk-adjustment. The CAPM can be used to adjust for the systematic risk of an asset by comparing it to a market proxy. The CRIX index is proxying the market again. To allow comparisons to other trading strategies, the Sharpe ratio based on raw returns calculated, too. The Sharpe ratio measures the return per unit of volatility. The effect of interest rate is again neglected.

When interpreting the Sharpe ratio, one has to be careful: It is a descriptive metric using returns and volatility but says nothing about statistical significance.

6.3. Trading costs

The most influential exchanges for cryptocurrencies, which are including all considered assets are Poloniex, Inc.[3] and Bittrex, Inc.[4] (TheMerkle, 2016). While Bittrex is charging a fee of 0.25% of a trade’s volume, Poloniex is using a graded scheme with decreased fees for traders with a larger volume by considering the last 30 days. Additionally, Poloniex distinguishes between Maker, the creator of an order, and the Taker, which order is matched to the existing order to fulfil the trade. Makers pay a lower fee to reward investors for bringing liquidity into the market. For Makers with a volume of less than 600 Bitcoin per month Poloniex charges 0.15%, for Takers with a volume below the same threshold 0.25% are charged. Just using Poloniex and assuming that the shares of being Taker and Maker are equal while trading with a volume below 600 Bitcoin leads to an average fee of 0.20% of a trade’s volume.

All trading strategies are evaluated over a time span of 65 weeks. The trading strategies with a formation period of just one week already started trading after one week, while the ones with a four weeks formation period and a two weeks waiting period just started trading after six weeks. The trading strategies with a one week holding period required a weekly realignment and thus higher trading fees, while a longer holding period leads to lower trading fees. These effects are depicted in Table 6 while assuming that after every holding period all assets are sold and the new holdings are bought.

[3] URL: https://poloniex.com/

[4] URL: https://bittrex.com/

Table 6
Trading fees per strategy

		Sum of holding periods in weeks				Total number of realignments of the portfolio			
		h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
w=0	f=1	64	64	64	64	64	32	22	16
	f=2	63	63	63	63	63	32	21	16
	f=3	62	62	62	62	62	31	21	16
	f=4	61	61	61	61	61	31	21	16
w=1	f=1	63	63	63	63	63	32	21	16
	f=2	62	62	62	62	62	31	21	16
	f=3	61	61	61	61	61	31	21	16
	f=4	60	60	60	60	60	30	20	15
w=2	f=1	62	62	62	62	62	31	21	16
	f=2	61	61	61	61	61	31	21	16
	f=3	60	60	60	60	60	30	20	15
	f=4	59	59	59	59	59	30	20	15

		Total trading costs over entire holding period				Tradings costs in basis points per day			
		h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
w=0	f=1	12.80%	6.40%	4.40%	3.20%	2.86	1.43	0.98	0.71
	f=2	12.60%	6.40%	4.20%	3.20%	2.86	1.45	0.95	0.73
	f=3	12.40%	6.20%	4.20%	3.20%	2.86	1.43	0.97	0.74
	f=4	12.20%	6.20%	4.20%	3.20%	2.86	1.45	0.98	0.75
w=1	f=1	12.60%	6.40%	4.20%	3.20%	2.86	1.45	0.95	0.73
	f=2	12.40%	6.20%	4.20%	3.20%	2.86	1.43	0.97	0.74
	f=3	12.20%	6.20%	4.20%	3.20%	2.86	1.45	0.98	0.75
	f=4	12.00%	6.00%	4.00%	3.00%	2.86	1.43	0.95	0.71
w=2	f=1	12.40%	6.20%	4.20%	3.20%	2.86	1.43	0.97	0.74
	f=2	12.20%	6.20%	4.20%	3.20%	2.86	1.45	0.98	0.75
	f=3	12.00%	6.00%	4.00%	3.00%	2.86	1.43	0.95	0.71
	f=4	11.80%	6.00%	4.00%	3.00%	2.86	1.45	0.97	0.73

Table 6: Total holding period, number of realignments and trading costs in percent of volume traded over entire holding period and in basis points per day per strategy

6.4. Returns of Long-Short Momentum Strategies

192 Long-Short momentum strategies are simulated by using the excess returns of the developed asset pricing model for risk-adjustment according to the formula from Section 5.4. The return of a momentum strategy $r_{Mom,\,t}$ is calculated for every week t by adding the excess returns of all holdings multiplied by their current share $s_{t,\,i}$ in the holdings.

$$r_{Mom,t} = \sum_{i}^{I} s_{t,i} \ * r_{Excess\ t,i} \ \ for\ all\ i, \dots, I\ in\ holdings$$

The most profitable one promises on average an abnormal return of 62.92 basis points per day (the returns and the *t*-values are presented in the Appendix, this section focuses on patterns and averages), while being highly significantly (p=.002) different from zero by using a student's t-test. The most profitable strategy by using a CAPM approach leads to an abnormal return of 63.64 basis points per day and is also highly significant (p<.001) different from zero. The highest Sharpe ratio out of these Long-Short strategies is 3.171, which is higher than the one of every single analysed asset (Appendix A.5).

This is considered to be extraordinary high, considering that for example Berkshire Hathaway, the holding company of Warren Buffett, has realised a long-term Sharpe ratio of 0.76 (Frazzini, Kabiller & Pedersen, 2013). The statistical significance paired with the magnitude of these results, which are hard to find in other asset classes, provides evidence for the second hypothesis: There are indeed momentum trading strategies in cryptocurrencies based on buying past or intermediate winners and selling past or intermediate losers that are generating economic and statistic significant positive returns. Starting with this evidence, not only concrete returns are discussed but especially patterns in returns are evaluated.

In total 192 Long-Short momentum strategies are simulated by using f=(1,2,3,4), w=(0,1,2), h=(1,2,3,4), N=(3,5). These parameters are applied to equal weighted and market capitalisation weighted portfolio formation on the APM-risk-adjusted returns. The results are presented in Table 7. The average abnormal return of all tested strategies is 15.68 basis points per day. 38 strategies are creating on average a negative daily return. The highest abnormal return is 62.92 basis points per day and origins from the 2-0-4 strategy with market capitalisation based weighting, while the most negative return is created by the 2-1-3 strategy with market capitalisation based weighting.

In Table 7, different patterns can be observed as depicted by the variation of colours (shading): A lower waiting period seem to be superior to a longer one, a holding period of one or two weeks appears to work best, while three weeks look like the worst. Additionally, the table suggests that a formation period of three weeks outperforms other formation periods. Equal weighting seems to outperform market capitalisation based weighting on average. Besides these findings, it appears that holding less assets, which performed more extreme in the past (forming five portfolios (N=5) instead of three (of N=3)) generates superior returns.

			3 Assets Long, 3 Assets Short				5 Assets Long, 5 Assets Short				
			h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4	Average
Equal	w=0	f=1									16.71
		f=2		26.01				26.15			29.23
		f=3									35.22
		f=4									23.15
	w=1	f=1									13.06
		f=2		20.28				19.08			22.13
		f=3									32.25
		f=4									11.28
	w=2	f=1									10.14
		f=2		15.38				11.57			8.97
		f=3									22.17
		f=4									12.62
Mkt Cap	w=0	f=1									7.29
		f=2		23.43				13.66			29.47
		f=3									30.81
		f=4									6.60
	w=1	f=1									-2.02
		f=2		10.72				7.90			17.83
		f=3									25.40
		f=4									-3.96
	w=2	f=1									-9.86
		f=2		9.33				4.71			10.25
		f=3									16.94
		f=4									10.75
Average Equal			25.89	26.24	9.38	20.72	25.86	24.45	7.89	17.52	
Average Mkt.Cap			18.68	17.84	4.39	17.07	9.36	8.24	6.29	11.14	

Table 7: Daily returns in basis points per strategy of Long-Short strategies based on the developed asset pricing model. The colour of the returns varies with the return of the strategy: The highest return of all tested parameters and strategies (Long-Short and Long-Only, APM and CAPM) has a return of 187.56 basis points per day and is defined as 'green', the most negative return is a return of -44.86 basis points per day and is defined as 'red'. In between the colours vary continuously. The numbers in the middle of the black outlined box are the average returns of all strategies in that section. The black bar in the middle is presenting the border between the two weighting mechanisms. All strategies upon the black bar are weighting assets equally, while all strategies below the bar weighting assets according to their own market capitalisation relative to the market capitalisation of all holdings. The concrete results including *p*-values can be found in the Appendix A.6.1 and A.6.2. All returns are before transaction costs (see section 5.2).

These results are in general backed up by the CAPM based approach (Overview: Appendix A.8.1; Details: Appendix A.8.2 and A.8.3), even though the effects for market capitalisation based weightings are less strong. Sharpe ratio is also superior for equal weighting, where a formation period of three weeks works best as well (Appendix A.10). Besides this measure suggests that a holding period of one or two weeks has a better risk-return relationship than a longer holding period. In contrast to earlier findings, holding five assets long and five assets short (N=3) is preferred in comparison to holding less assets (N=5). This is potentially explained by the lower variance caused by a higher diversification, which is positively rewarded by Sharpe ratio.

6.5. Returns of Long-Only Momentum Strategies

In this section 192 Long-Only momentum strategies are discussed. They are based on the same parameters as in the previous section but grounded on the assumption that an investor invests only in the ‘winner’ portfolio. The results are presented in Table 8. The average abnormal return of all Long-Only strategies based on the APM-risk-adjusted returns is 19.76 basis points per day and therefore about 4 basis points higher than the one of Long-Short strategies. The highest abnormal return is again created by the 2-0-4 strategy with market capitalisation based weighting. In total 40 strategies resulted in negative mean returns. The highest negative return origins from a 1-2-4 strategy with market capitalisation based weighting creating an average abnormal loss of -36.11basis points per day.

The Long-Only strategies show similar patterns as the Long-Short strategies. There seems to be a negative effect of longer waiting periods, equal weighting appears to dominate market capitalisation based weighting, a shorter holding period appears to work better than a longer one, while a holding period of three weeks seems to perform the worst. The table also suggests that a formation period of three weeks is preferable. In contrast to Long-Short strategies, holding five assets (*N*=3) instead of three assets (*N*=5) results on average in higher returns for Long-Only strategies. These patterns are generally also observable when considering Sharpe ratio (Appendix A.11) and the CAPM based approach (Overview, Appendix A.9.1; Details Appendix A.9.2 and A.9.3), even though the effects, especially for the superior formation period of three weeks are less pronounced. Besides one observes, that the difference between the APM based approach and the CAPM based risk-adjustment is considerable large for Long-Only strategies: The averages return of all Long-Short strategies based on the APM-adjusted returns is 15.68, while the one for the CAPM-adjusted returns is 19.76, the average return of all Long-Only based on the APM-returns is 23.31, although the average abnormal return of the strategies using the CAPM-risk-adjustment is 109.49.

			3 Assets Long Only				5 Assets Long Only				
			h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4	Average
Equal	w=0	f=1									29.84
		f=2		35.94				38.32			38.74
		f=3									47.62
		f=4									32.32
	w=1	f=1									24.51
		f=2		22.69				28.19			24.76
		f=3									36.76
		f=4									15.74
	w=2	f=1									12.22
		f=2		18.71				19.36			15.60
		f=3									31.05
		f=4									17.26
Mkt Cap	w=0	f=1									8.48
		f=2		26.58				20.46			40.85
		f=3									31.98
		f=4									12.75
	w=1	f=1									-7.70
		f=2		8.81				10.10			20.32
		f=3									21.87
		f=4									3.32
	w=2	f=1									-16.18
		f=2		9.15				-1.14			7.04
		f=3									20.51
		f=4									4.64
Average Equal			36.70	31.40	11.67	23.36	38.60	34.63	15.04	26.23	
Average Mkt.Cap			25.79	16.86	-1.23	17.96	16.14	12.50	5.00	5.56	

Table 8: Daily returns in basis points per strategy of Long-Only strategies based on the developed asset pricing model. The colour of the returns varies with the return of the strategy: The highest return of all tested parameters and strategies (Long-Short and Long-Only, APM and CAPM) has a return of 187.56 basis points per day and is defined as 'green', the most negative return is a return of -44.86 basis points per day and is defined as 'red'. In between the colours vary continuously. The numbers in the middle of the black outlined box are the average returns of all strategies in that section. The black bar in the middle is presenting the border between the two weighting mechanisms. All strategies upon the black bar are weighting assets equally, while all strategies below the bar weighting assets according to their own market capitalisation relative to the market capitalisation of all holdings. The concrete results including *p*-values can be found in the Appendix A.7.1 and 7.2. All returns are before transaction costs (see section 5.2).

6.6. Patterns in Returns

Based on 192 Long-Short strategies and 192 Long-Only strategies, evaluated by using a three-factor asset pricing model, the CAPM and Sharpe ratio, five sub-hypotheses regarding patterns of returns are formulated and tested. The results are presented in Table 9 by stating the alternative hypothesis. The Null-hypotheses are equal means for all five sub-hypotheses. The patterns are tested by using Fisher's exact test by comparing the medians of returns of the APM-based strategies.

Table 9
Tested hypothesis regarding return patterns

	Alternative hypothesis. The Null-hypothesis is no difference in the median of returns	p-value of H_0
1	Long-Only strategies have significantly higher returns than Long-Short strategies.	0.041
2	Holding a 'winner' and a 'loser' portfolio containing three assets results in significantly higher returns than holding a 'winner' and a 'loser' portfolio containing five assets.	0.156
3	A waiting period of 0 weeks causes signifcantly higher returns than a waiting period of 1 week. Same applies when comparing a waiting period of 1 and 2 weeks.	$p(R_{w=0}=R_{w=1})=0.002$ $p(R_{w=0}=R_{w=2})<0.001$ $p(R_{w=1}=R_{w=2})=0.134$
4	A formation period of three weeks generates significantly higher returns than other formation periods.	$p(R_{f=3}=R_{f=1})<0.001$ $p(R_{f=3}=R_{f=2})=0.056$ $p(R_{f=3}=R_{f=4})<0.001$
5	Equal weighting induces significantly higher returns than market capitalisation based weighting .	<0.001

All hypotheses are tested based on the APM-adjusted returns

Table 9: Investigated patterns are tested by using the returns of the simulated strategies based on the APM-adjusted returns

Long-Only strategies performed significantly better than Long-Short strategies at the 5% level (alternative hypothesis 1). The difference in excess returns of strategies using N=3 and N=5 (alternative hypothesis 2) is not significant. While a waiting period of zero weeks is strongly significantly better than a waiting period of one or two (alternative hypothesis 3a and 3b). The effect between one and two weeks is statistically not significant (alternative hypothesis 3c). A formation period of three weeks is strongly significantly better than a formation period of one or four weeks (alternative hypothesis 4a and 4c). The effect in comparison to a two week formation period is just significant at the 10% level (alternative hypothesis 4b). When all holdings are weighted equally returns are significantly higher than those from market capitalisation based weighting (alternative hypothesis 5).

7. Conclusion and Discussion

Even though the asset class of cryptocurrencies is relatively young and shows different characteristics than more traditional asset classes, a model inspired by the three-factor-model from Fama and French (1993) shows a reasonable fit to the returns of 15 cryptocurrencies, chosen by their size, their age and their data availability. Different momentum premia are found in the data set from 10/04/16 to 16/07/17 by using a variety of parameters. For example, a strategy utilising a two week formation period and a four week holding period generates an abnormal return of 62.92 basis points per day, which is more than 850% per annum. Besides these discrete strategies, different patterns in momentum returns are investigated. Long-Only strategies outperformed Long-Short strategies based on the magnitude of returns and their Sharpe ratio, suggesting that the momentum is stronger for recent 'winners'. The findings of Novy-Marx, who is stating a stronger momentum effect for intermediate past horizons, could not be examined in cryptocurrencies – strategies without a waiting period between the formation- and the holding period worked best. A formation period of three weeks outperformed formation periods of one, two and four weeks, where the effect for one and four weeks is strongly significant. These patterns suggest that recent medium horizon have the ability to forecast returns for short holding periods. This ability works best for recent 'winners' and equal weighting. Why these patterns occur is not clear. One potential explanation is based on the characteristics of cryptocurrencies: Their core utility is the ability to move economic value, thus the fundamental value of such assets increases when the market acceptance and the user base increases. Recent gains potentially lead to a growth in these factors, thus the fundamental value increases.

Furthermore, the momentum effect can potentially be explained by behavioural explanations such as overreaction to news and investor sentiment. The time spans might be caused by the time news about cryptocurrencies need to spread: The information channels for cryptocurrencies are less efficient than the ones from traditional security markets. While for example stock listed companies are forced to publish new information immediately (ad-hoc) which occur almost in real time to their investors, news about cryptocurrencies spread through social media and need their time to be verified. Besides there is a lower scrutiny of professional analysts evaluating these assets, which makes it harder to correctly price new information. Given the considerable large returns of some cryptocurrencies in the analysed period, there are probably also some positive feedback traders involved – traders that see a price rising in the past and thus jump in to participate in this opportunity. This can potentially explain why the observed effect is stronger for Long-Only strategies.

When the results are interpreted, one has to put into account that the market conditions were more than friendly during the analysed period. The CRIX index grew by more than 600% during that time. Besides, it was an almost continuous growth on market level. Additionally, selecting the assets based on their data availability and their age potentially creates a selection bias: The cryptocurrencies which suffered from hacker attacks or had other problems are probably excluded from the analysis due to the data selection process. Furthermore, using excess returns by assuming that returns, significantly different from zero, are providing evidence for an anomaly is a joint-hypothesis testing. The anomaly cannot be studied without testing the asset pricing model as well. This joint-testing problem cannot completely be avoided by using other approaches such as the CAPM or Sharpe ratio.

To get insights into the explanations for the momentum effect in this asset class, it is potentially beneficial to look at individual trading data or combine the analysis with a more sophisticated proxy for the news sentiment. This analysis lacks in providing reasons for the observed patterns. Moreover, this analysis misses to incorporate the different characteristics of the analysed assets. Some, for example NEM (XEM) are not mineable, therefore its units outstanding has not changed during the analysed period, while others, for example Bitcoin (BTC) are mineable and had consequently an increase in their units outstanding. This supply effect has potentially an effect on prices.

In conclusion, it should be stressed that returns of cryptocurrencies can up to a medium degree be explained by the cryptocurrency market itself, the size of a cryptocurrency and its transaction volume relative to its market value. Furthermore, the risk-adjusted returns show patterns that were also investigated in traditional equity markets, even though the evaluated time periods are smaller, while the magnitude of those patterns is larger. Why these structures, which are promising abnormal returns, occur, could not be answered. In general, a better understanding of cryptocurrencies and their price drivers is necessary to evaluate its investment opportunities. While assuming that this asset class will grow in the future, the data availability and the information regarding this asset class will become more professional, I want to close with emphasizing that this asset class gives researchers the almost unique possibility to observe a new asset class growing.

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Appendix

Appendix A.1

Table A.1

	p-value of White-Koenker test for heteroscedasticity	p-value of Cumby-Huizinga test for autocorrelation
BCN	<0.0001***	0.4095
BTC	0.0586*	0.0614*
BTS	0.0209**	0.8162
DASH	0.0161**	0.0258**
DCR	0.1246	0.9408
DOGE	0.1961	0.4633
ETH	0.0005***	0.3995
FCT	0.2455	0.9655
LTC	0.0961*	0.5585
MAID	0.9617	0.8887
SC	0.0001***	0.3158
XEM	0.1366	0.094*
XLM	0.0004***	0.1293
XMR	0.2075	0.3462
XRP	0.1112	0.2695

Table A.1: Test results for all assets for the White-Koenker test for heteroscedastivity and the Cumby-Huizinga test for autocorrelation.

Appendix A.2

Table A.2

Time series regressions based on weekly data sorted in thirds

Returns of	CRIX	SMB_3	PE_LMH_3	Cent. R^2	F-value
BCN	0.4985246 (0.80)	2.23598** (7.22)	-0.3425187 (-1.04)	0.5062	22.87
BTC	0.6625801** (5.74)	0.0873113 (1.53)	-0.0017675 (-0.03)	0.4831	20.93
BTS	0.0261944 (0.07)	0.806085** (4.48)	0.8518474** (4.46)	0.6103	34.41
DASH	0.09097 (0.31)	-0.4629027** (-3.21)	0.5994207** (3.91)	0.2350	7.55
DCR	-0.2637758 (-0.53)	0.643114* (2.63)	0.365062 (1.41)	0.1870	5.91
DOGE	0.6917337** (3.55)	0.165649 (1.72)	0.2589149* (2.53)	0.5042	22.70
ETH	-0.3749012 (-1.54)	0.0693742 (0.58)	0.7520433** (5.89)	0.4571	18.96
FCT	-0.1068959 (-0.36)	0.1617778 (1.11)	0.6109904** (3.96)	0.3421	12.09
LTC	0.561145* (1.98)	0.2156753 (1.54)	0.0160557 (0.11)	0.1407	4.49
MAID	0.0159385 (0.07)	0.0639959 (0.54)	0.3414867** (2.72)	0.1842	5.82
SC	-0.4942452 (-1.27)	0.9910431** (5.17)	0.9790774** (4.81)	0.6257	36.66
XEM	-0.4528538 (-1.08)	0.2625545 (1.26)	0.7369077** (3.34)	0.2487	8.06
XLM	0.4060904 (0.83)	0.3244653 (1.35)	0.7428906** (2.90)	0.3170	10.90
XMR	-0.1122329 (-0.30)	-0.4169119* (-2.27)	0.9547946** (4.89)	0.3020	10.23
XRP	0.3315283 (0.74)	0.2481847 (1.12)	0.5721227* (2.43)	0.2400	7.74

t-values in parantheses

* refers to a 5% level of significance

** refers to a 1% level of significance

Table A.2: Regression results of the model using the PE_LMH factor and portfolio sorting in thirds.

Appendix A.3

Table A.3

Time series regressions based on weekly data sorted in quintiles

Returns of	CRIX	SMB_5	PE_LMH_5	Cent. R^2	F-value
BCN	1.626099** (3.58)	0.7004669** (3.15)	-1.189844** (-6.34)	0.6402	38.96
BTC	0.6856369** (7.11)	0.0818691 (1.73)	-0.0085479 (-0.21)	0.4991	22.26
BTS	1.504675** (3.42)	0.3507092 (1.63)	-0.0436773 (-0.24)	0.2116	6.72
DASH	0.4711337 (1.79)	-0.0530966 (-0.41)	0.2500622* (2.30)	0.1391	4.45
DCR	0.1328308 (0.33)	0.922399** (4.71)	0.3058547 (1.85)	0.2625	8.59
DOGE	1.13208** (6.41)	0.0643341 (0.74)	-0.1227104 (-1.68)	0.4331	17.3
ETH	0.5888354* (2.14)	0.0406046 (0.30)	0.0121846 (0.11)	0.0382	1.85
FCT	0.5114975 (1.85)	0.4088219** (3.01)	0.2525818* (2.20)	0.1902	6.01
LTC	0.4524367* (2.20)	0.5063484** (5.02)	0.1641332 (1.93)	0.3673	13.38
MAID	0.3902731 (1.82)	0.1835428 (1.74)	0.036568 (0.41)	0.0868	3.03
SC	1.057194* (2.27)	0.7514138** (3.29)	0.061478 (0.32)	0.2496	8.1
XEM	0.6938654 (1.83)	0.1125423 (0.61)	-0.3831951* (-2.45)	0.1535	4.87
XLM	1.423244** (3.10)	0.2913251 (1.30)	0.0011799 (0.01)	0.1593	5.04
XMR	0.463747 (1.41)	0.365784* (2.28)	0.5707597** (4.21)	0.2466	7.98
XRP	1.040058** (2.78)	0.4601799* (2.51)	-0.1543746 (-1.00)	0.2634	8.63

t-values in parantheses

* refers to a 5% level of significance

** refers to a 1% level of significance

Table A.3: Regression results of the model using the PE_LMH factor and portfolio sorting in quintiles.

Appendix A.4

Table A.4

Time series regressions based on weekly data sorted in thirds

Returns of	CRIX	SMB$_5$	GT_LMH$_5$	Cent. R^2	F-value
BCN	0.5615699 (1.04)	1.372769** (6.09)	-0.7242874** (-3.29)	0.4928	21.4000
BTC	0.7123567** (7.46)	0.0952531* (2.40)	0.0574227 (1.48)	0.5162	23.4000
BTS	1.37685** (3.14)	0.3527454 (1.93)	-0.1891936 (-1.06)	0.2245	7.0800
DASH	0.6573127* (2.39)	-0.2078453 (-1.82)	0.0772301 (0.69)	0.0729	2.6500
DCR	0.3713465 (0.90)	0.7512083** (4.40)	0.1387524 (0.83)	0.2333	7.3900
DOGE	0.9986553** (5.63)	0.1242178 (1.68)	-0.1234759 (-1.71)	0.4355	17.2000
ETH	0.6456864* (2.34)	0.04122 (0.36)	0.0848547 (0.76)	0.0467	2.0300
FCT	0.6838503* (2.37)	0.2457229* (2.05)	0.0447863 (0.38)	0.1264	4.0400
LTC	0.4756851* (2.26)	0.3848184** (4.40)	-0.1221572 (-1.43)	0.3498	12.3000
MAID	0.4794971* (2.25)	0.1730084 (1.95)	0.1189357 (1.37)	0.1108	3.6200
SC	0.9851108* (2.12)	0.6801047** (3.52)	-0.2020564 (-1.07)	0.2605	8.4000
XEM	0.5053771 (1.27)	0.3685088* (2.22)	0.0496478 (0.31)	0.0716	2.6200
XLM	1.349941** (2.93)	0.2696425 (1.41)	-0.138791 (-0.74)	0.1662	5.1900
XMR	0.6551021 (1.78)	-0.0316635 (-0.21)	-0.2271604 (-1.52)	0.0631	2.4200
XRP	0.6640818 (1.93)	0.5000956** (3.50)	-0.508399** (-3.64)	0.3879	14.3100

t-values in brackets

* refers to a 5% level of significance

** refers to a 1% level of significance

Table A.4: Regression results of the model using the GT_ LMH factor and portfolio sorting in quintiles.

Appendix. A.5

Table A.5

Sharpe Ratio for all analysed cryptocurrencies based on raw returns

BCN	BTC	BTS	DASH	DCR	DOGE	ETH	FCT	LTC	MAID	SC	XEM	XLM	XMR	XRP
1.99	2.40	1.62	2.63	2.02	1.95	2.57	1.96	2.22	1.54	1.98	2.57	1.53	2.19	1.98

Table A.5: Sharpe ratio for all analysed cryptocurrencies based on raw returns.

Appendix A.6.1

			3 Assets Long, 3 Assets Short				5 Assets Long, 5 Assets Short				
			h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4	Average
Equal	w=0	f=1	23.52	25.04	-0.74	19.34	23.53	25.53	5.98	11.47	16.71
			(0.176)	(0.16)	(0.96)	(0.28)	(0.05)	(0.05)	(0.58)	(0.39)	
		f=2	32.23	39.78	8.25	33.32	38.28	36.62	13.87	31.51	29.23
			(0.083)	(0.041)	(0.670)	(0.047)	(0.008)	(0.015)	(0.347)	(0.017)	
		f=3	37.80	40.02	33.34	39.23	37.74	35.32	25.54	32.80	35.22
			(0.062)	(0.053)	(0.076)	(0.039)	(0.011)	(0.015)	(0.106)	(0.013)	
		f=4	32.01	22.28	16.81	13.96	35.79	26.82	17.36	20.17	23.15
			(0.137)	(0.273)	(0.383)	(0.451)	(0.019)	(0.077)	(0.201)	(0.160)	
	w=1	f=1	23.54	28.84	-6.14	11.03	16.75	19.45	0.46	10.57	13.06
			(0.162)	(0.124)	(0.687)	(0.521)	(0.203)	(0.144)	(0.965)	(0.412)	
		f=2	38.94	31.12	-5.92	28.14	36.44	31.96	-7.43	23.81	22.13
			(0.044)	(0.101)	(0.751)	(0.105)	(0.014)	(0.046)	(0.609)	(0.082)	
		f=3	26.59	34.89	45.88	31.20	31.42	36.98	28.99	22.01	32.25
			(0.194)	(0.059)	(0.007)	(0.094)	(0.039)	(0.014)	(0.049)	(0.115)	
		f=4	9.31	11.11	-2.24	18.22	17.10	12.40	5.64	18.66	11.28
			(0.643)	(0.587)	(0.914)	(0.329)	(0.251)	(0.417)	(0.688)	(0.203)	
	w=2	f=1	22.34	26.09	-10.21	5.20	18.62	20.59	-12.11	10.63	10.14
			(0.211)	(0.141)	(0.522)	(0.749)	(0.145)	(0.129)	(0.323)	(0.367)	
		f=2	21.14	14.82	-3.45	8.13	19.25	18.80	-6.02	-0.92	8.97
			(0.294)	(0.340)	(0.840)	(0.635)	(0.223)	(0.187)	(0.653)	(0.941)	
		f=3	19.34	24.98	32.83	27.78	17.43	22.78	15.02	17.20	22.17
			(0.259)	(0.138)	(0.102)	(0.119)	(0.257)	(0.129)	(0.345)	(0.203)	
		f=4	23.90	15.96	4.17	13.13	18.00	6.15	7.33	12.33	12.62
			(0.278)	(0.423)	(0.822)	(0.542)	(0.284)	(0.640)	(0.593)	(0.452)	
	Average		25.89	26.24	9.38	20.72	25.86	24.45	7.89	17.52	

p-values in parantheses

Table A.6.1: Returns and p-values for Long-Short strategies with equal weighting using APM-adjusted returns.

Appendix A.6.2

			3 Assets Long, 3 Assets Short				5 Assets Long, 5 Assets Short				
			h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4	Average
MktCap	w=0	f=1	10.32	-6.61	4.69	-17.51	21.24	16.47	24.88	4.83	7.29
			(0.615)	(0.69)	(0.81)	(0.34)	(0.16)	(0.19)	(0.16)	(0.69)	
		f=2	39.38	36.58	1.18	62.92	26.55	23.09	8.45	37.61	29.47
			(0.088)	(0.103)	(0.959)	(0.002)	(0.178)	(0.206)	(0.680)	(0.015)	
		f=3	55.43	46.62	19.97	56.68	13.06	19.29	7.47	27.91	30.81
			(0.056)	(0.052)	(0.430)	(0.010)	(0.452)	(0.271)	(0.695)	(0.065)	
		f=4	33.13	26.43	5.93	-0.31	7.30	-13.33	-8.20	1.87	6.60
			(0.251)	(0.397)	(0.779)	(0.989)	(0.672)	(0.494)	(0.600)	(0.926)	
	w=1	f=1	8.98	-19.22	-2.69	-5.61	14.51	-20.41	9.60	-1.33	-2.02
			(0.671)	(0.271)	(0.896)	(0.764)	(0.345)	(0.155)	(0.652)	(0.906)	
		f=2	18.99	38.18	-29.47	51.53	27.74	18.82	-7.11	23.92	17.83
			(0.357)	(0.071)	(0.166)	(0.014)	(0.090)	(0.236)	(0.693)	(0.084)	
		f=3	35.12	34.90	33.22	24.51	35.78	17.29	6.57	15.83	25.40
			(0.136)	(0.133)	(0.118)	(0.231)	(0.060)	(0.294)	(0.672)	(0.298)	
		f=4	-8.20	0.92	-6.69	-2.88	-10.26	-11.48	4.04	2.86	-3.96
			(0.750)	(0.972)	(0.768)	(0.910)	(0.602)	(0.566)	(0.819)	(0.888)	
	w=2	f=1	1.67	-20.03	-8.75	-19.27	-9.82	-13.52	-5.83	-3.31	-9.86
			(0.926)	(0.274)	(0.648)	(0.313)	(0.533)	(0.366)	(0.751)	(0.776)	
		f=2	10.44	39.00	-6.39	31.89	-21.67	19.43	-0.19	9.51	10.25
			(0.650)	(0.048)	(0.737)	(0.121)	(0.218)	(0.181)	(0.990)	(0.485)	
		f=3	18.33	27.74	38.31	22.34	-0.61	13.07	13.38	2.95	16.94
			(0.463)	(0.246)	(0.126)	(0.327)	(0.972)	(0.452)	(0.473)	(0.852)	
		f=4	0.51	9.52	3.32	0.61	8.47	30.14	22.40	10.98	10.75
			(0.982)	(0.719)	(0.870)	(0.982)	(0.617)	(0.077)	(0.119)	(0.599)	
	Average		18.68	17.84	4.39	17.07	9.36	8.24	6.29	11.14	

p-values in parantheses

Table A.6.2: Returns and p-values for Long-Short strategies with market capitalisation based weighting using APM-adjusted returns.

Appendix A.7.1

			3 Assets Long Only				5 Assets Long Only				
			h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4	Average
Equal	w=0	f=1	49.01	39.55	9.22	29.91	34.53	37.31	19.76	19.42	29.84
			(0.048)	(0.112)	(0.658)	(0.274)	(0.037)	(0.028)	(0.215)	(0.336)	
		f=2	54.79	38.82	11.01	34.28	59.22	49.90	24.11	37.82	38.74
			(0.045)	(0.173)	(0.691)	(0.188)	(0.009)	(0.032)	(0.252)	(0.079)	
		f=3	48.02	43.52	32.47	58.09	56.00	52.60	39.48	50.81	47.62
			(0.115)	(0.146)	(0.240)	(0.039)	(0.013)	(0.015)	(0.093)	(0.016)	
		f=4	63.05	36.39	21.34	5.59	54.52	37.14	15.25	25.29	32.32
			(0.037)	(0.205)	(0.430)	(0.835)	(0.022)	(0.100)	(0.483)	(0.270)	
	w=1	f=1	41.71	40.28	2.29	14.63	35.61	29.65	13.72	18.17	24.51
			(0.063)	(0.190)	(0.914)	(0.576)	(0.040)	(0.174)	(0.414)	(0.376)	
		f=2	31.05	28.53	-15.83	26.56	54.64	45.27	-3.38	31.23	24.76
			(0.257)	(0.286)	(0.558)	(0.307)	(0.015)	(0.053)	(0.874)	(0.120)	
		f=3	25.29	34.42	49.15	29.11	43.02	45.17	37.52	30.43	36.76
			(0.423)	(0.226)	(0.049)	(0.275)	(0.070)	(0.062)	(0.089)	(0.147)	
		f=4	15.53	21.55	-0.92	19.73	21.10	18.00	2.26	28.71	15.74
			(0.575)	(0.431)	(0.974)	(0.477)	(0.346)	(0.415)	(0.916)	(0.223)	
	w=2	f=1	24.19	26.21	-7.61	-7.23	26.95	27.47	-1.62	9.41	12.22
			(0.426)	(0.380)	(0.757)	(0.768)	(0.232)	(0.241)	(0.936)	(0.637)	
		f=2	37.47	16.55	-2.57	9.79	30.87	26.76	0.42	5.54	15.60
			(0.237)	(0.478)	(0.919)	(0.721)	(0.201)	(0.234)	(0.982)	(0.786)	
		f=3	22.85	29.72	43.20	31.93	27.88	35.27	26.28	31.28	31.05
			(0.410)	(0.270)	(0.145)	(0.238)	(0.243)	(0.139)	(0.237)	(0.143)	
		f=4	27.47	21.22	-1.72	27.93	18.83	11.02	6.70	26.63	17.26
			(0.382)	(0.46)	(0.94)	(0.31)	(0.42)	(0.59)	(0.73)	(0.23)	
	Average		36.70	31.40	11.67	23.36	38.60	34.63	15.04	26.23	

p-values in parantheses

Table A.7.1: Returns and p-values for Long-Only strategies with equal weighting using APM-adjusted returns.

Appendix A.7.2

			3 Assets Long				5 Assets Long				
			h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4	Average
Mkt Cap	w=0	f=1	33.44	-10.85	5.50	-2.15	23.83	9.38	30.71	-21.99	8.48
			(0.259)	(0.687)	(0.824)	(0.936)	(0.239)	(0.546)	(0.150)	(0.216)	
		f=2	53.56	50.04	12.57	74.11	33.77	42.62	18.19	41.94	40.85
			(0.089)	(0.142)	(0.688)	(0.028)	(0.202)	(0.131)	(0.481)	(0.116)	
		f=3	47.85	29.02	16.54	60.58	30.80	36.05	0.27	34.76	31.98
			(0.186)	(0.334)	(0.590)	(0.065)	(0.208)	(0.126)	(0.991)	(0.105)	
		f=4	42.68	32.99	-3.33	-17.32	26.94	13.68	-5.56	11.93	12.75
			(0.250)	(0.362)	(0.900)	(0.555)	(0.259)	(0.599)	(0.812)	(0.651)	
	w=1	f=1	7.64	-26.20	-5.48	-7.06	3.96	-24.00	12.73	-23.19	-7.70
			(0.787)	(0.327)	(0.826)	(0.783)	(0.836)	(0.265)	(0.563)	(0.181)	
		f=2	18.73	37.38	-35.70	53.34	38.34	30.05	-5.74	26.19	20.32
			(0.511)	(0.183)	(0.209)	(0.071)	(0.105)	(0.211)	(0.805)	(0.251)	
		f=3	19.12	40.40	25.64	27.17	46.46	13.14	-0.84	3.87	21.87
			(0.569)	(0.218)	(0.324)	(0.395)	(0.100)	(0.588)	(0.967)	(0.864)	
		f=4	3.97	7.38	-18.18	-7.18	12.11	8.54	4.65	15.28	3.32
			(0.900)	(0.808)	(0.514)	(0.810)	(0.643)	(0.742)	(0.847)	(0.564)	
	w=2	f=1	10.98	-20.00	-11.91	-36.11	-10.89	-18.49	-14.56	-28.46	-16.18
			(0.669)	(0.446)	(0.610)	(0.143)	(0.634)	(0.416)	(0.532)	(0.111)	
		f=2	39.43	26.79	-15.00	29.02	-16.93	5.06	-4.64	-7.44	7.04
			(0.222)	(0.358)	(0.563)	(0.338)	(0.470)	(0.834)	(0.820)	(0.747)	
		f=3	38.38	40.52	28.58	28.56	-3.61	18.59	16.78	-3.75	20.51
			(0.264)	(0.232)	(0.335)	(0.399)	(0.885)	(0.459)	(0.471)	(0.873)	
		f=4	-6.30	-5.15	-14.02	12.57	8.95	15.43	8.05	17.59	4.64
			(0.824)	(0.86)	(0.56)	(0.68)	(0.72)	(0.52)	(0.71)	(0.50)	
Average			25.79	16.86	-1.23	17.96	16.14	12.50	5.00	5.56	

p-values in parantheses

Table A.7.2: Returns and p-values for Long-Only strategies with market capitalisation based weighting using APM-adjusted returns.

Appendix A.8.1

			3 Assets Long, 3 Assets Short				5 Assets Long, 5 Assets Short				
			h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4	Average
Equal	w=0	f=1									33.60
		f=2		38.14				40.44			39.15
		f=3									49.84
		f=4									34.57
	w=1	f=1									21.63
		f=2		30.00				32.34			35.49
		f=3									40.59
		f=4									26.98
	w=2	f=1									19.80
		f=2		20.16				19.90			8.20
		f=3									31.23
		f=4									20.89
Mkt Cap	w=0	f=1									10.46
		f=2		19.48				12.98			29.18
		f=3									15.48
		f=4									9.81
	w=1	f=1									8.05
		f=2		17.78				17.70			34.49
		f=3									17.34
		f=4									11.07
	w=2	f=1									16.98
		f=2		17.05				13.70			20.47
		f=3									8.71
		f=4									15.35
Average Equal			35.72	29.43	26.82	25.76	36.98	32.68	27.01	26.91	
Average Mkt.Cap			26.64	17.43	24.24	4.09	21.46	11.12	13.00	13.59	

Table A.11.1: Overview about Long-Short strategies with CAPM-adjusted returns.

Appendix A.8.2

			3 Assets Long, 3 Assets Short				5 Assets Long, 5 Assets Short				
			h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4	Average
Equal	w=0	f=1	49.92	53.63	18.39	32.45	36.78	39.34	24.99	13.31	33.60
			(0.013)	(0.00)	(0.32)	(0.05)	(0.01)	(0.00)	(0.07)	(0.25)	
		f=2	39.01	46.66	25.96	32.95	43.75	52.93	33.07	38.89	39.15
			(0.077)	(0.042)	(0.241)	(0.030)	(0.013)	(0.007)	(0.063)	(0.004)	
		f=3	53.43	52.19	35.58	56.20	55.94	52.00	37.40	56.00	49.84
			(0.013)	(0.014)	(0.019)	(0.004)	(0.005)	(0.005)	(0.006)	(0.000)	
		f=4	39.66	20.91	44.11	9.28	48.80	45.74	34.30	33.78	34.57
			(0.051)	(0.260)	(0.040)	(0.644)	(0.011)	(0.012)	(0.056)	(0.061)	
	w=1	f=1	10.49	37.80	9.55	36.59	14.94	23.51	18.77	21.39	21.63
			(0.625)	(0.101)	(0.620)	(0.055)	(0.319)	(0.128)	(0.173)	(0.095)	
		f=2	54.98	24.15	20.50	23.53	63.64	41.38	24.97	30.72	35.49
			(0.009)	(0.201)	(0.348)	(0.136)	(0.000)	(0.017)	(0.141)	(0.030)	
		f=3	34.59	42.74	48.26	31.30	44.82	48.93	37.42	36.66	40.59
			(0.143)	(0.018)	(0.043)	(0.105)	(0.039)	(0.003)	(0.037)	(0.022)	
		f=4	39.25	18.02	33.35	14.85	39.38	22.86	24.09	24.00	26.98
			(0.055)	(0.304)	(0.071)	(0.501)	(0.018)	(0.112)	(0.127)	(0.160)	
	w=2	f=1	24.80	20.56	16.68	31.04	12.03	10.89	22.94	19.46	19.80
			(0.210)	(0.310)	(0.462)	(0.093)	(0.388)	(0.464)	(0.183)	(0.115)	
		f=2	9.40	5.21	9.25	-5.44	15.44	22.46	12.26	-2.97	8.20
			(0.606)	(0.660)	(0.665)	(0.723)	(0.304)	(0.074)	(0.473)	(0.807)	
		f=3	43.34	21.43	41.70	20.56	43.12	24.10	31.45	24.17	31.23
			(0.049)	(0.190)	(0.066)	(0.305)	(0.020)	(0.073)	(0.073)	(0.132)	
		f=4	29.79	9.91	18.46	25.80	25.12	8.08	22.45	27.47	20.89
			(0.088)	(0.558)	(0.362)	(0.200)	(0.105)	(0.571)	(0.180)	(0.098)	
	Average		35.72	29.43	26.82	25.76	36.98	32.68	27.01	26.91	

p-values in parantheses

Table A.11.2: Returns and p-values for Long-Short strategies with equal weighting using CAPM-adjusted returns.

Appendix A.8.3

			3 Assets Long, 3 Assets Short				5 Assets Long, 5 Assets Short				
			h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4	Average
MktCap	w=0	f=1	26.76	3.17	39.98	-36.95	12.57	-0.69	45.46	-6.61	10.46
			(0.235)	(0.89)	(0.13)	(0.09)	(0.45)	(0.96)	(0.02)	(0.73)	
		f=2	25.56	22.88	35.91	49.80	10.23	21.01	30.34	37.67	29.18
			(0.298)	(0.275)	(0.078)	(0.013)	(0.546)	(0.205)	(0.089)	(0.031)	
		f=3	33.10	42.97	-18.55	31.68	23.32	20.79	-44.86	35.38	15.48
			(0.129)	(0.068)	(0.503)	(0.141)	(0.145)	(0.235)	(0.019)	(0.062)	
		f=4	25.43	5.73	34.43	-10.28	12.90	-1.23	3.88	7.60	9.81
			(0.256)	(0.767)	(0.115)	(0.460)	(0.471)	(0.932)	(0.767)	(0.652)	
	w=1	f=1	1.62	-0.98	24.99	-23.70	12.40	11.71	31.08	7.26	8.05
			(0.953)	(0.967)	(0.403)	(0.306)	(0.497)	(0.455)	(0.197)	(0.696)	
		f=2	49.50	32.99	30.82	36.23	43.47	31.93	18.54	32.48	34.49
			(0.023)	(0.098)	(0.089)	(0.061)	(0.012)	(0.076)	(0.295)	(0.065)	
		f=3	25.39	22.35	30.09	-2.63	47.05	7.54	0.29	8.62	17.34
			(0.441)	(0.308)	(0.173)	(0.880)	(0.174)	(0.637)	(0.982)	(0.591)	
		f=4	16.92	20.48	20.29	0.05	13.34	-0.28	5.33	12.44	11.07
			(0.450)	(0.301)	(0.299)	(0.997)	(0.415)	(0.984)	(0.666)	(0.456)	
	w=2	f=1	35.30	-9.85	23.63	-14.58	45.20	6.32	38.71	11.13	16.98
			(0.146)	(0.637)	(0.403)	(0.506)	(0.010)	(0.732)	(0.035)	(0.569)	
		f=2	24.51	35.30	35.20	18.74	9.13	22.86	17.60	0.39	20.47
			(0.211)	(0.057)	(0.042)	(0.252)	(0.574)	(0.191)	(0.305)	(0.980)	
		f=3	28.05	14.66	26.55	-4.98	9.72	-3.55	-0.66	-0.11	8.71
			(0.178)	(0.482)	(0.215)	(0.743)	(0.531)	(0.802)	(0.957)	(0.993)	
		f=4	27.57	19.43	7.61	5.64	18.23	17.10	10.36	16.83	15.35
			(0.124)	(0.157)	(0.628)	(0.778)	(0.237)	(0.206)	(0.367)	(0.296)	
	Average		26.64	17.43	24.24	4.09	21.46	11.12	13.00	13.59	

p-values in parantheses

Table A.11.3: Returns and p-values for Long-Short strategies with market capitalisation based weighting using CAPM-adjusted returns.

Appendix A.9.1

			3 Assets Long Only h=1	h=2	h=3	h=4	5 Assets Long Only h=1	h=2	h=3	h=4	Average
Equal	w=0	f=1									134.54
		f=2		136.13				137.15			143.10
		f=3									145.04
		f=4									123.89
	w=1	f=1									125.36
		f=2		117.89				122.94			127.26
		f=3									124.68
		f=4									104.36
	w=2	f=1									121.59
		f=2		106.78				107.21			97.38
		f=3									111.31
		f=4									97.71
Mkt Cap	w=0	f=1									118.57
		f=2		131.97				105.51			135.80
		f=3									119.48
		f=4									101.12
	w=1	f=1									100.63
		f=2		96.25				91.74			103.01
		f=3									103.06
		f=4									69.28
	w=2	f=1									93.84
		f=2		85.67				74.63			77.89
		f=3									77.78
		f=4									71.10
Average Equal			134.13	121.10	114.92	110.91	133.38	127.14	114.24	114.97	
Average Mkt.Cap			121.20	106.74	98.69	91.91	101.14	88.68	87.73	84.95	

Table A.12.1: Overview about Long-Only strategies with CAPM-adjusted returns.

Appendix A.9.2

			3 Assets Long Only h=1	h=2	h=3	h=4	5 Assets Long Only h=1	h=2	h=3	h=4	Average
Equal	w=0	f=1	166.29	164.42	119.67	143.31	132.87	127.02	115.51	107.21	134.54
			(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	
		f=2	162.89	162.23	132.28	117.73	151.13	164.01	127.84	126.71	143.10
			(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
		f=3	155.69	145.24	110.57	150.50	158.40	152.29	137.44	150.16	145.04
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
		f=4	145.25	104.21	126.96	70.86	154.31	150.97	120.22	118.32	123.89
			(0.000)	(0.009)	(0.003)	(0.061)	(0.000)	(0.000)	(0.002)	(0.003)	
	w=1	f=1	131.20	148.56	114.63	148.38	115.13	115.92	112.00	117.04	125.36
			(0.001)	(0.000)	(0.005)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	
		f=2	139.22	120.60	116.62	100.43	161.63	143.00	116.05	120.49	127.26
			(0.000)	(0.000)	(0.008)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	
		f=3	117.55	115.96	142.20	105.66	136.65	141.99	119.93	117.51	124.68
			(0.006)	(0.004)	(0.002)	(0.010)	(0.002)	(0.000)	(0.001)	(0.001)	
		f=4	113.62	96.84	89.88	84.84	131.28	114.49	94.63	109.27	104.36
			(0.008)	(0.013)	(0.030)	(0.037)	(0.000)	(0.001)	(0.011)	(0.004)	
	w=2	f=1	128.96	136.34	115.72	138.32	110.35	110.90	118.22	113.95	121.59
			(0.001)	(0.003)	(0.007)	(0.002)	(0.000)	(0.002)	(0.002)	(0.001)	
		f=2	115.73	87.14	104.73	70.83	108.08	109.67	104.94	77.90	97.38
			(0.002)	(0.008)	(0.014)	(0.020)	(0.001)	(0.002)	(0.004)	(0.008)	
		f=3	121.27	93.73	124.88	94.16	135.51	111.29	109.00	100.60	111.31
			(0.008)	(0.007)	(0.010)	(0.022)	(0.002)	(0.002)	(0.008)	(0.006)	
		f=4	111.92	77.96	80.86	105.90	105.26	84.19	95.13	120.46	97.71
			(0.006)	(0.04)	(0.05)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	
Average			134.13	121.10	114.92	110.91	133.38	127.14	114.24	114.97	

p-values in parantheses

Table A.12.2: Returns and p-values for Long-Only strategies with equal weighting using CAPM-adjusted returns.

Appendix A.9.3

			3 Assets Long				5 Assets Long				
			h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4	Average
MktCap	w=0	f=1	187.56	164.82	146.54	122.53	98.44	76.83	98.09	53.70	118.57
			(7.174)	(0.000)	(0.000)	(0.004)	(0.012)	(0.020)	(0.004)	(0.078)	
		f=2	160.07	146.21	117.19	123.67	127.52	151.67	131.90	128.15	135.80
			(0.001)	(0.001)	(0.008)	(0.005)	(0.003)	(0.000)	(0.001)	(0.002)	
		f=3	146.79	123.44	91.46	143.27	125.36	124.28	76.92	124.31	119.48
			(0.001)	(0.004)	(0.019)	(0.001)	(0.001)	(0.002)	(0.047)	(0.002)	
		f=4	164.43	112.13	99.60	61.84	122.42	92.46	73.06	83.03	101.12
			(0.000)	(0.022)	(0.020)	(0.121)	(0.002)	(0.012)	(0.056)	(0.033)	
	w=1	f=1	126.02	142.68	122.55	102.50	72.40	76.02	92.46	70.44	100.63
			(0.006)	(0.001)	(0.002)	(0.013)	(0.025)	(0.011)	(0.004)	(0.012)	
		f=2	99.83	86.03	83.23	89.40	121.43	121.88	103.74	118.57	103.01
			(0.013)	(0.037)	(0.047)	(0.023)	(0.001)	(0.002)	(0.006)	(0.002)	
		f=3	106.35	107.01	99.92	94.45	168.74	87.83	72.93	87.23	103.06
			(0.041)	(0.020)	(0.021)	(0.033)	(0.014)	(0.022)	(0.048)	(0.020)	
		f=4	89.08	66.39	64.90	59.72	83.13	59.57	62.88	68.59	69.28
			(0.053)	(0.120)	(0.110)	(0.105)	(0.030)	(0.091)	(0.093)	(0.069)	
	w=2	f=1	126.58	115.15	134.78	79.36	82.06	58.04	98.45	56.26	93.84
			(0.002)	(0.011)	(0.002)	(0.031)	(0.007)	(0.071)	(0.007)	(0.033)	
		f=2	65.83	71.48	86.37	58.17	66.03	94.63	99.87	80.75	77.89
			(0.102)	(0.075)	(0.040)	(0.127)	(0.069)	(0.012)	(0.009)	(0.021)	
		f=3	108.07	90.38	81.87	75.06	77.37	53.00	72.91	63.58	77.78
			(0.020)	(0.037)	(0.052)	(0.061)	(0.053)	(0.141)	(0.053)	(0.068)	
		f=4	73.79	55.18	55.81	92.91	68.80	67.95	69.57	84.81	71.10
			(0.066)	(0.17)	(0.11)	(0.01)	(0.06)	(0.06)	(0.05)	(0.02)	
	Average		121.20	106.74	98.69	91.91	101.14	88.68	87.73	84.95	

p-values in parantheses

Table A.12.3: Returns and p-values for Long-Only strategies with market capitalisation based weighting using CAPM-adjusted returns.

Appendix A.10

			3 Assets Long, 3 Assets Short					5 Assets Long, 5 Assets Short					
			h=1	h=2		h=3	h=4	h=1	h=2		h=3	h=4	Average
Equal	w=0	f=1	2.24	2.34		0.85	1.59	2.06	2.55		1.65	1.03	1.79
		f=2	1.67	1.81	**1.68**	0.94	1.89	1.78	2.31	**1.94**	1.26	2.41	1.76
		f=3	2.30	2.17		2.04	2.58	2.30	2.32		2.03	2.67	2.30
		f=4	1.59	0.99		1.69	0.11	1.87	1.94		1.41	1.41	1.38
	w=1	f=1	0.41	1.60		0.41	1.63	0.88	1.57		1.23	1.45	1.15
		f=2	2.59	1.16	**1.26**	0.69	1.29	3.17	1.99	**1.63**	1.24	1.62	1.72
		f=3	1.26	2.13		1.80	1.38	1.59	2.48		1.91	1.64	1.77
		f=4	1.43	0.66		1.39	0.32	1.81	1.27		1.11	1.05	1.13
	w=2	f=1	1.13	1.04		0.56	1.49	1.00	0.77		1.36	1.00	1.04
		f=2	0.30	0.60	**0.76**	0.12	-0.44	0.77	1.56	**1.03**	0.56	-0.61	0.36
		f=3	1.45	1.07		1.16	0.92	1.99	1.30		1.66	1.07	1.33
		f=4	1.16	-0.01		0.72	0.89	1.26	0.62		1.00	1.21	0.86
MktCap	w=0	f=1	0.89	-0.82		1.24	-2.05	0.50	-1.50		1.69	-2.54	-0.32
		f=2	0.45	0.68	**0.23**	1.33	1.23	0.16	0.07	**-0.33**	0.58	0.44	0.62
		f=3	1.05	0.37		-1.99	0.40	-0.70	-0.75		-2.07	0.14	-0.45
		f=4	0.64	0.14		0.74	-0.21	-1.70	-0.38		-0.92	0.21	-0.19
	w=1	f=1	-0.34	-1.05		0.72	-1.48	-0.64	-1.14		1.32	-1.49	-0.51
		f=2	1.55	1.02	**-0.04**	0.94	1.09	0.96	0.12	**-0.11**	-1.12	0.22	0.60
		f=3	-0.05	-0.37		-1.14	-1.37	0.25	-0.48		-0.40	-0.70	-0.53
		f=4	-0.21	0.33		0.18	-0.48	-0.34	0.41		0.21	1.11	0.15
	w=2	f=1	0.65	-1.04		0.44	-1.44	1.21	-1.10		1.18	-1.07	-0.15
		f=2	0.76	1.15	**0.06**	1.49	-0.16	-0.39	-0.38	**-0.20**	-1.29	-1.27	-0.01
		f=3	0.08	-0.77		-1.61	-1.18	-1.13	-0.82		-0.29	-0.33	-0.76
		f=4	1.59	1.00		-0.61	0.63	0.07	0.68		0.73	1.02	0.64
Average Equal			1.46	1.30		1.03	1.14	1.71	1.72		1.37	1.33	
Average Mkt.Cap			0.59	0.05		0.14	-0.42	-0.15	-0.44		-0.03	-0.36	

Table A.13: Sharpe ratio for Long-Short strategies based on raw returns

Appendix A.11

			3 Assets Long Only					5 Assets Long Only					
			h=1	h=2	h=3	h=4		h=1	h=2	h=3	h=4		Average
Equal	w=0	f=1	3.61	3.60	2.83	3.20		3.24	3.63	3.32	3.10		3.32
		f=2	3.37	3.55	2.96	3.30	**3.22**	3.35	3.71	3.24	3.49	**3.35**	3.37
		f=3	3.66	3.36	3.27	3.61		3.54	3.47	3.51	3.57		3.50
		f=4	3.44	2.87	2.94	1.89		3.31	3.37	2.94	2.84		2.95
	w=1	f=1	3.07	3.30	2.71	3.07		3.43	3.54	3.27	3.18		3.20
		f=2	3.66	3.44	2.61	3.21	**2.87**	4.10	3.72	3.02	3.41	**3.26**	3.40
		f=3	2.76	2.84	3.00	2.55		2.97	3.28	3.33	2.83		2.94
		f=4	2.81	2.69	2.19	2.10		3.40	3.29	2.55	2.87		2.74
	w=2	f=1	3.23	3.04	2.60	2.97		3.59	2.92	3.05	2.98		3.05
		f=2	2.96	2.88	2.31	2.31	**2.57**	3.20	3.05	2.77	2.42	**2.90**	2.74
		f=3	2.41	2.67	2.15	2.26		3.13	3.01	2.83	2.56		2.63
		f=4	2.74	1.98	1.98	2.62		2.69	2.65	2.51	3.04		2.53
MktCap	w=0	f=1	3.97	3.60	3.29	2.75		2.71	2.31	3.00	1.23		2.86
		f=2	3.13	3.04	2.57	2.56	**2.97**	2.73	2.74	2.57	2.66	**2.44**	2.75
		f=3	3.19	2.62	1.73	3.15		2.41	2.27	1.88	2.76		2.50
		f=4	3.18	2.50	2.40	1.59		2.00	2.41	1.89	1.99		2.24
	w=1	f=1	2.75	3.14	2.95	2.41		1.89	2.37	2.98	2.10		2.57
		f=2	2.61	2.38	2.02	2.31	**2.23**	2.64	2.24	1.97	2.64	**2.22**	2.35
		f=3	1.97	1.97	1.78	2.13		1.92	2.17	1.94	2.36		2.03
		f=4	2.05	1.82	1.70	1.69		2.04	2.16	1.96	2.19		1.95
	w=2	f=1	3.05	2.70	2.95	2.14		2.77	1.75	2.83	1.91		2.51
		f=2	1.91	1.91	2.10	1.58	**2.05**	1.73	1.91	1.89	2.20	**2.10**	1.90
		f=3	1.82	1.73	1.45	1.91		1.87	1.79	2.19	2.21		1.87
		f=4	1.88	1.45	1.71	2.51		1.84	2.04	2.23	2.44		2.01
Average Equal			3.14	3.02	2.63	2.76		3.33	3.30	3.03	3.03		
Average Mkt.Cap			2.63	2.40	2.22	2.23		2.21	2.18	2.28	2.22		

Table A.13: Sharpe ratio for Long-Only strategies based on raw returns