ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
MSc Economics & Business
Master Specialisation Financial Economics

Factor Investing in the Cryptocurrency Market

Introducing Cryptocurrency-Specific Factors

Author: M. T. Eraslan
Student number: 485291ME
Thesis supervisor: Dr. J. J. G. Lemmen
Second reader: Dr. J. Kil
Finish date: 16 September 2019

PREFACE AND ACKNOWLEDGEMENTS

The reader of this thesis should be acknowledged that the author of this thesis is a cryptocurrency investor.

ABSTRACT

This thesis examines whether factor investing generates excess returns in the cryptocurrency market and whether the cryptocurrency market has become more efficient, by performing Fama-MacBeth (1973) and portfolio regressions, in the cross-section, on a dataset from April 2013 to August 2019. An altered methodology is proposed, where the Bitcoin values of cryptocurrencies are used to construct factor portfolios, whereas usually, USD values of cryptocurrencies are used to construct portfolios. Results show significant results for size and value, in both the USD and BTC approach. Also, significant results are found for a composite factor strategy consisting of size and momentum. Additionally, constructing portfolios according the proposed BTC approach increases cumulative returns in USD. However, future research is needed in this topic, as the used dataset is limited and the constructed value factor is new.

Keywords: Factor Investing, Cryptocurrency, Bitcoin, Behavioural Anomalies, Blockchain
JEL Classification: C33, C38, G40

Table of Contents

List of tables

List of figures

1 Introduction

Satoshi Nakamoto (2008) introduced Bitcoin in a whitepaper as a peer-to-peer electronic cash system, that allows payments to be send without having a financial intermediary, unlike the current financial system. Now, more than 10 years later, the publication of Nakamoto's whitepaper proved to be the inauguration of a new asset class, named the cryptocurrency market. The cryptocurrency market has characterized itself as an exceptionally volatile market (Osterrieder, Lorenz, & Strika, 2017). Over the course of the past ten years, inspired by Nakamoto, thousands of altcoins (cryptocurrencies other than Bitcoin) have been created by developers all over the world. Total Market Capitalization[1] (TMC) peaked at 835.7 billion United States Dollars (USD) on 7 January 2018, whereas this figure was 15.6 billion USD, exactly one year earlier on 7 January 2017. The immensive expansion of the cryptocurrency market in recent years attracted a large number of traders. The low barriers-to-entry in the cryptocurrency market expose the market to speculative traders, what could explain the extreme volatile movements in cryptocurrency prices. Unlike the equity market, do cryptocurrencies not have easy to understand value measures, hindering fundamental investors in determining the value of cryptocurrencies, inducing limits to arbitrage.

Nonetheless, the high volatility and surge in cryptocurrency prices have attracted the attention of institutional investors as well. Intercontinental Exchange (ICE), owned by the New York Stock Exchange (NYSE), is planning to launch[2] their digital assets exchange, named Bakkt, on September 23 2019. LGO Markets[3], another institutional grade digital assets exchange, commenced trading on the 11th of March 2019. Although institutional investors already can trade on other major cryptocurrency exchanges like Bitfinex, Binance, and Bittrex, the surge in legally compliant institution-grade exchanges point towards the gradually increasing maturity of the cryptocurrency market.

This thesis will test the hypothesis of inefficiency in the cryptocurrency market by researching the existence of exploitable behavioural anomalies, by considering a dataset ranging from April 2013 to August 2019. The exploitability of factor investing in the cryptocurrency market has been researched before, yielding significant results on momentum, size and value, depending on the portfolio construction (Hubrich, 2017; Rabener, 2017; Elendner, Trimborn, Ong, & Lee, 2016). However, the belief exists that results could differ significantly, as the market has matured more in the past years and more data is available. The main value this thesis will add to existing literature is the alteration in the used methodology for constructing the factor portfolios. A new approach is proposed, which has, as far

[1]Total Market Capitalization (TMC) equals the sum of all the individual cryptocurrencies' market capitalizations.
[2]https://www.bakkt.com/index
[3]https://medium.com/lgogroup/lgo-markets-platform-is-now-live-5ee4698645f7

as I am aware of, not been implemented before. Also, regarding the value factor, new value measures have been developed in 2018, which could help explain value in the cryptocurrency market.

Specifically, this thesis will contribute to existing literature by analysing the evolvement of the efficiency of the cryptocurrency market, as market conditions have changed compared to times when earlier studies were conducted. Limits to arbitrage, especially, have decreased as there are less short-selling constraints on high-cap cryptocurrencies due to the increase in trading turnover of derivatives exchanges since 2018 (Coinmarketcap, 2019). Recently, on 12 May 2019, an all-time-high in daily turnover was reached on the largest cryptocurrency derivatives exchange Bitmex, indicating a further increase in size of the cryptocurrency futures markets[4]. This does not only hold for Bitcoin, but also for other cryptocurrencies.

Starting from the belief that the existence of return predictability can be explained from systematic errors, cryptocurrency specific factors will be introduced, to test the hypothesis of this thesis. Compared to existing literature, this thesis will provide a new approach in calculating the existence of anomalies in the cryptocurrency market. Namely, in the cryptocurrency market, trading platforms are mainly based on Bitcoin and because of this, cryptocurrencies are traded against Bitcoin. Commonly, in conventional markets, profits are measured in fiat money (i.e., euro or dollar). In the cryptocurrency market, however, investors tend to measure profits in terms of Bitcoin, as cryptocurrencies are mostly traded against Bitcoin. Relying on this, this thesis proposes a slight change in conventional methodology that regularly is used when calculating factor portfolios, by altering the so-called point-of-reference of an investor. Daily data on cryptocurrencies valued in USD and Bitcoin are collected from Coingecko.com and Coinmetrics.io and the same methodology is applied to both datasets.

The research question of this thesis is: *does factor investing in the cryptocurrency market generate abnormal returns?* If not, has the cryptocurrency market then become more efficient? And does the point-of-reference of an investor matter for constructing factor portfolios? A Fama-MacBeth (1973) and portfolio regressions are performed to examine factors on momentum, size and value. To account for autocorrelation and heteroskedasticity, Newey and West (1986) standard errors are used.

Results show that factor investing in the cryptocurrency market does yield excess returns, however, not for all strategies. Significant results are found for size and value. For momentum, no significant results are found. Also, I found that the results differ strongly between equal and value weighted portfolios. The composite factor strategy yields excess returns, only for the combination of size and momentum. Additionally, I found that the proposed approach, where the Bitcoin values of cryptocurrencies are used for the construction of the factor portfolios, yields higher cumulative returns in USD than the traditional methodology to construct factor portfolios.

Since factor investing in the cryptocurrency market still yield returns over the benchmark, I have not found evidence to support the claim that the cryptocurrency market is becoming more efficient.

[4] https://www.cryptoglobe.com/latest/2019/05/bitmex-all-time-record-over-10-billion-in-trading-volume-recorded/

However, correlations (of the USD value) between Bitcoin and other cryptocurrencies have increased over the past years, which could be an indicator of a maturing market. Also, most t-statistics I found are not above 3.0, which might mean that my results are the outcome of data mining, according to Harvey, Liu and Zhu (2016).

The remainder of this thesis is structured as following: In the second chapter, a literature review is described. The third chapter describes the dataset. The fourth chapter consists of the methodology and the fifth chapter describes the results. In chapter six, the conclusion, limitations of the research and suggestions for future research are described.

2 Literature Review

In this chapter, a literature review on factor investing is described. Firstly, factor-investing and its past performance on several asset classes are explained. Then, the drivers of these factors are described. This is followed by an examination of existing literature on factor investing in the cryptocurrency market as well as the limits to arbitrage. Lastly, the construction of cryptocurrency specific factors and literature on cryptocurrency specific value measures are described.

2.1 Factor Investing

Factor investing, also termed evidence-based investing or rule-based investing, is an investing strategy to exploit mispricing using a specified 'factor' (Nielson, Nielsen, & Barnes, 2018). The basis of Factor investing was laid in the 1960's by Jack Treynor (1961; 1962), William F. Sharpe (1964), John Lintner (1965) and Jan Mossin (1966) independently from each other. Their research formed the one-factor CAPM model, which solely considers systematic risk (non-diversifiable risk) of the asset using one beta for price sensitivity relative to the market. This model, hence, does not capture idiosyncratic risk and assumes that markets follow the Efficient-Market-Hypothesis (EMH). According to the EMH, prices reflect all available information and there are no undervalued or overvalued stocks. Also, a strategy aiming to gain excess returns would require an increase in systematic risk (Fama, 1970). In 1976, an extension of the one-factor CAPM model was introduced: The Arbitrage Pricing Theory (APT), which proposes the use of multi-factors to explain stock returns (Ross, 1976). The APT adds more factors to capture systematic risk. The APT assumes that prices can deviate from their fundamental value and arbitrage opportunities can exist. By going long in the undervalued asset and going short in the overvalued asset, a positive expected return can be generated while having a net-zero exposure to systematic risk.

Later, in 1992, Fama and French (1992) proposed the three-factor model which includes a factor on systematic risk, a factor on size (SMB) and a value factor on the book-to-market ratio (HML) of a company. The SMB size factor can be defined as Small Minus Big (small market capitalization minus big market capitalization) and the HML value factor as High Minus Low (high book-to-market ratio minus low book-to-market ratio). These factors capture the historic excess return of small caps over big caps and of value stocks over growth stocks. In 1993, Fama and French added two bond-market factors to the three-factor model (1993). The added bond-market factors are related to maturity and default risk. The Carhart four-factor-model is an extension of the three-factor-model from Fama and French, which includes another factor on momentum (Carhart, 1997). Initially, the momentum factor was studied by Jegadeesh and Titman (1993). They find that strategies which buy stocks that have performed well in the past and sell stocks that have performed poorly in the past generate significant returns over 3- to 12-month holding periods. A momentum strategy consists of ranking assets based on their cumulative raw returns over the past twelve to three months. The momentum strategy has a one-month lag, to avoid short-term reversal effects (Jegadeesh, 1990).

Momentum can be examined both cross-sectionally and longitudinally. Cross-section momentum compares the performance of a set of available assets during a certain time period. Following the cross-section momentum strategy, all assets are sorted based on their performance and only a certain number of stocks is traded. On the other hand, following the (longitudinal) time-series momentum methodology, all available assets are included in the portfolio (Moskowitz, Ooi, & Pedersen, 2012). Time series momentum requires the continuation of the price in a certain direction to fulfil a successful strategy.

Another factor strategy is Betting Against Beta (BAB), also known as the low volatility factor. Frazzini and Pedersen (2014) show that investors that are constrained in the usage of leverage, attempt to magnify returns by trading high-beta assets. However, they find that on US equities, 20 international equity markets, treasury bonds, corporate bonds and futures high beta is associated with low alpha. The Low volatility factor captures excess returns of stocks with a lower than average volatility, beta or idiosyncratic risk (Bender, Briand, Melas, & Subramanian, 2013). A low volatility factor strategy involves longing assets with a low beta and shorting assets with a high beta. Frazzini and Pedersen show that a low volatility factor produces significant positive risk-adjusted returns and that more constrained investors hold riskier assets (Frazzini & Pedersen, 2014).

Blitz and Van Vliet (2007) have conducted a research in which they use a low-volatility factor on global and regional stock markets. They find that low risk stocks generate significantly higher returns than the market portfolio, while high risk stocks significantly underperform (all adjusted for risk). In another paper, Houweling and Van Zundert (2017) examined the factors value, momentum, low-risk and size on the corporate bond market. They find that value, momentum, size and low-risk factors produce significant alphas on high yield corporate bonds and that value, size and low-risk factors produce significant alphas on investment grade corporate bonds. Furthermore, they construct a multi-factor, which consists of a combination of the factors. The multi-factor has diversification benefits on corporate bonds. Namely, a lower tracking error and a higher information ratio than individual factors are achieved. In another research, conducted by Asness, Moskowitz and Pedersen (2013), the researchers examine value, momentum and a ('COMBO') multi-factor across eight diverse markets and asset classes. They find a negative correlation between value and momentum for their dataset, hence the inclusion of the multi-factor in their analysis. Asness et al. find that their multi-factor, consisting of 50% value and 50% momentum, yields significant alpha on their dataset.

2.2 The Drivers of Factors in Factor Investing and Limits to Arbitrage

The persistence of exploitable factor strategies can be explained either by systematic risk or by systematic errors (Bender, Briand, Melas, & Subramanian, 2013). According to the EMH, excess returns should encompass excess systematic risk. Factors included in the one-factor CAPM or in Ross' APT model (1976) seem to not fully explain returns, since abnormal returns still continue to exist in these models. Systematic errors provide a behavioural explanation for the continued existence of these anomalies. Systematic errors are irrationalities in the decision making of traders. Behavioural biases magnify these irrationalities and combined with limits to arbitrage, anomalies persist. Factors described in the first section of the literature review can be explained using literature on behavioural biases. The value anomaly is driven by overreaction, according to Daniel & Titman (2006) and Porta, Lakonishok, Shleifer, & Vishny (1997). Overreaction explains why investors tend to undervalue firms with a poor past performance, despite a high book-to-market ratio. Regarding the momentum anomaly, Barberis, Shleifer, & Vishny (1998) find that this anomaly arises due to the slow revision of investor beliefs after new information arrives. Also, they find that stocks overreact after consistent patterns of good or bad news. Continued overreaction leads to positive return autocorrelation, which is followed by a long-run correction. Hence, short term positive autocorrelations can be consistent with long term negative autocorrelations.

The systematic presence of behavioural biases in traders induces limits to arbitrage (Shleifer & Vishny, 1997). Examples of limits to arbitrage are short-sale constraints and excessive funding costs of arbitrage positions. Exploiting an arbitrage opportunity is risky, as prices can diverge further from fundamental value. Keeping such a position open is costly, as arbitrage is often done using (borrowed) capital. The existence of limits to arbitrage allow anomalies to occur, as this effectively means that the mispricing cannot (due to reasons) be corrected back to fundamental value.

2.3 The Cryptocurrency Markets and Limits to Arbitrage

In this sub-section of the literature review, centralized and decentralized cryptocurrency markets are described. Also, cryptocurrency derivative exchanges and their products are described, together with the typical limits to arbitrage that occur in the cryptocurrency market. For this thesis, only the tradability of cryptocurrencies is relevant. Hence, the different technicalities in blockchain types are not covered.

Cryptocurrency exchanges differ significantly from traditional stock exchanges. First of all, due to regulatory constraints, cryptocurrencies are mostly traded against other cryptocurrencies. Most trading turnover of cryptocurrencies (other than Bitcoin) occurs against Bitcoin and not against fiat currencies like USD. Altcoins (i.e., cryptocurrencies other than Bitcoin) are mostly traded against Bitcoin, as this is the most convenient for cryptocurrency investors. Regulations applied for USD accepting exchanges do not hold for cryptocurrencies. It is possible for exchanges to handle cryptocurrency to fiat (USD) transactions, but it requires Anti Money Laundering (AML) and Know-Your-Customer (KYC) procedures, what means a complete identity verification using official identity papers. Cryptocurrency exchanges that do not wish to fully verify their customers, make use of stablecoins (also known as cryptocurrencies that are kept "stable", pegged to fiat currency) to trade against Bitcoin and other cryptocurrencies. Stablecoins, like Tether[5] (USDT), are pegged against the

[5] https://tether.to

dollar. By implementing the stablecoin Tether, exchanges prevent having to be compliant with regulations that are forced upon regular trading platforms that require fiat money deposits to buy assets. Although, it is still possible to convert profits to cryptocurrency and withdraw the cryptocurrency to a private wallet. From the private wallet, the investor then could exchange the cryptocurrency to fiat money using a regulated service (e.g., Bitonic.nl in the Netherlands).

Cryptocurrency exchanges yield the opportunity to create an account and transfer funds within minutes, without having to provide verification documents and bank statements. Cryptocurrency exchanges are trading platforms, either centralized or decentralized, where the user trades cryptocurrencies against other cryptocurrencies or conventional fiat currencies. Regularly, like it is with one of the largest cryptocurrency exchange Binance (Coinmarketcap, 2019), is depositing cryptocurrency funds on an account free and is the cost of a withdrawal of funds around 0.0005 Bitcoin per withdrawal. The commission costs differ strongly per exchange, but are 10 basis points per trade on Binance (maker and taker fees are equal), what roughly equals the market average.

There are two types of exchanges, namely centralized exchanges and decentralized exchanges. Centralized exchanges are typically platforms where the platform holds custody over the deposited funds. This kind of platform usually has a withdrawal limit per 24 hours for non-verified users, to prevent money laundering and other illegal activities. At a decentralized exchange, however, the user holds custody over their own funds on the blockchain, by storing their private key (which yields access to the funds) themselves. Hence, decentralized exchanges are of more anonymous character as there are no limitations for users in terms of their account balance. Cryptocurrency markets have extremely low barriers to entry, compared to conventional trading platforms. Particularly, the introduction of the Binance DEX (Binance, 2019), has lowered barriers to entry of regulatory constrained individuals. Currently, there are dozens of other DEX's, like IDEX and Cryptobridge (Coinmarketcap, 2019). However, data on Coinmarketcap shows us that decentralized exchanges are far behind in terms of 24-hour turnover compared to centralized exchanges.

Coinmarketcap shows that in the past 24 hours, 55 cryptocurrency exchanges have a reported trading turnover of more than 100 million USD (2019). This includes the reported volume of derivatives exchanges, which is typically higher due to the usage of borrowed capital (leverage). Coingecko shows that there are 30 decentralized cryptocurrency exchanges, of which five have a higher turnover than one million USD (Coingecko, 2019). Coinmarketcap also shows us that there are currently 1805 cryptocurrencies trading, with an existent market capitalization (circulating supply multiplied with price). 244 of the 1805 currently trading cryptocurrencies have a turnover of higher than one million USD, across all cryptocurrency exchanges. Bitcoin has always remained at the top regarding market capitalization, whereas the other cryptocurrencies in the top ten market capitalization have continuously faced strong competition from other cryptocurrencies. Currently, the other largest cryptocurrencies are Ethereum, Ripple, Bitcoin Cash, Litecoin, EOS, Binance Coin, Tether, Stellar and Cardano (in order from highest to lowest market capitalization in the top ten ranking).

Currently, concerning futures, there are several major cryptocurrency derivatives exchanges, like Bitmex and OKEX. The largest derivatives exchange is Bitmex, with the highest turnover (2.8 billion USD) amongst all cryptocurrency exchanges. Bitmex offers futures on eight major cryptocurrencies: Bitcoin, Cardano, Bitcoin Cash, EOS, Ethereum, Litecoin, Tron and Ripple. Bitmex is the most liquid cryptocurrency derivatives platform. Hence, cryptocurrencies traded on Bitmex have no constraints regarding limits to arbitrage, as they can be shorted on highly liquid derivatives platforms with minimal counterparty risk (the counterparty is the exchange).

2.4 Factor Investing in the Cryptocurrency Market

In this section, existing literature on factor investing in the cryptocurrency market are reviewed. Also, newly introduced cryptocurrency-specific value measures are described, to understand whether these value measures can be implemented in a factor investing strategy.

In a research conducted by Caporale, Gil-Alana, & Plastun (2018), the researchers find that on four cryptocurrencies (Bitcoin, Litecoin, Ripple and Dash), past values correlate with future values. The existence of persistence is an argument on the inefficiency of the cryptocurrency market and also indicate that trend trading strategies are possible. More evidence on the inefficiency of the cryptocurrency markets is provided by Urquhart (2016), Zhang, Wang, Li, & Shen (2018) and Bariviera (2017). Urquhart (2016) shows that Bitcoin is in an inefficient market state but may be in a process of moving towards an efficient market.

Cryptocurrencies do not create value for investors, in the way that there are no expected periodic payments an investor can expect, compared to equities or fixed income. Furthermore, the lack of regulation in the cryptocurrency markets makes it hard for fundamental investors to determine the value behind cryptocurrencies. Thus, the cryptocurrency markets are mainly traded by speculators (Baur, Hong, & Lee, 2018). Baur, Hong, & Lee (2018) find that Bitcoin is mainly used as a speculative investment and not as an alternative currency or medium of exchange. These findings support behavioural biases (systematic errors) to serve as an explanation for the existence of anomalies in the cryptocurrency market (Yang, 2018). Yang tests more than 20 stock price anomalies on cryptocurrency data and finds that the momentum effect produces significant returns, whereas risk-based anomalies are insignificant. Another finding of Yang is that on daily data, momentum has very weak short-term price reversal in cryptocurrencies. This is consistent with the noise trader risk concept, as cryptocurrency markets mainly consist of speculative traders (De Long, Shleifer, Summers, & Waldmann, 1990). Overconfident investors induce noise trader risk for rational arbitrageurs, what makes reversal less likely, as found by Yang (2018). In another research, the size anomaly is found to be present in cryptocurrencies; small-cap cryptocurrencies produce higher than average returns (Elendner, Trimborn, Ong, & Lee, 2016). Concerning the value anomaly, like described earlier in this literature review, cryptocurrencies do not produce a periodical stream of income for investors. Hence, fundamental investors are hindered in determining value. However, particularly since 2018, the popularity of tokens tied to exchanges (which create value) has increased rapidly (Coinmarketcap, 2019). Often, like is the case with Binance Coin and several other cryptocurrencies, the holders of these tokens receive utility, like a discount on transaction fees and a quarterly supply burn, what effectively reduces the number of circulating tokens and has a positive deflationary effect on the token. Hence, this could induce fundamental investors as some cryptocurrencies, opposed to the majority, do have metrics which could provide a measure of value.

The day of the week anomaly is another factor which is present in cryptocurrency markets (Kurihara & Fukushima, 2017). Similar to earlier described literature, Kurihara & Fukushima also find that Bitcoin markets are inefficient (2017). Their data ranges from 17 July 2010 to 29 December 2016. They find that for the first half of their data, markets are more inefficient than the second half of their data. The day of the week anomaly becomes less significant in the second half, which indicates that markets have become more efficient. Caporale & Plastun (2018) find that cryptocurrencies like Ripple, Dash and Litecoin do not display the day of the week anomaly. Bitcoin, on the other hand, does display the day of the week anomaly; Bitcoin's returns are significantly higher on Mondays compared to other days.

In another research, Wang & Vergne explain returns of cryptocurrencies by examining the effects of news coverage ("buzz") on cryptocurrencies (2017). A positive effect on cryptocurrencies' returns is a positive news publication, what leads to an increase in demand in the short-term. They find that innovation positively benefits returns, but not on weekly returns. Also, they find that an increase in supply is associated with an increase in price, what contradicts the theories of supply and demand.

Social media is used frequently for development updates of cryptocurrencies and related platforms. Twitter, for example, is a convenient and fast platform with a wide reach. To research the effect of public information arrival on the cryptocurrency market, Gunay (2019) examined the effect of Twitter posts on the price of Ripple. Gunay found that while the price remained in an upward trend, the effect of public information arrival was positive on the price and that while the price remained in a downward trend, public information arrival did not lead to the market reverting to an upward trend.

2.5 The Construction of Cryptocurrency Specific Factors

A cross-sectional and a longitudinal approach can be implemented in the factor investing strategy. Rohrbach, Suremann and Osterrieder (2017) find that cross-sectional momentum produces higher excess returns than a longitudinal strategy. Specifically, the cross-sectional portfolio generates a higher annualized return and Sharpe ratio than the time series portfolio, Rohrbach et al find. Also, the time series portfolio has larger drawdowns than the cross-sectional portfolio. Hubrich (2017) implements an approach where both the cross-sectional and longitudinal methods are included. Hubrich conducted research on factor investing in the cryptocurrency market, focusing on the value, momentum and carry factors (2017). Hubrich emphasizes the use of a longitudinal and cross-sectional approach in the portfolios. Hubrich finds that adding a longitudinal approach to the portfolio, higher absolute or risk-adjusted returns, alpha and information ratio is achieved. Hubrich finds that momentum is the best performer amongst the researched factors and that carry somewhat produces significant returns as well. It is important to note that Hubrich has researched short-term momentum, as his research is conducted on weekly data and regular momentum investing research is conducted on monthly data. Another finding of Hubrich is that an equal combination of the three factors in a portfolio generates greater risk adjusted returns than a portfolio with the momentum factor alone. This finding shows that combining the factors can generate diversification benefits and yield a higher alpha, just like Asness et al. (2013) find in their research on anomalies in traditional asset classes. In another research, Rabener (2017) has examined the size, momentum, low volatility, mean-reversion and short-term momentum factors in the cryptocurrency market. In line with the research of Hubrich (2017), Rabener also finds that short-term momentum yields significant positive alpha. Rabener constructs momentum based on last days' return and holds the portfolio for a week. Hubrich (2017) defines momentum as prior week's return for each currency, avoiding the trailing daily return per week. Hubrich argues that the trailing daily return per week (mean of the daily returns in a week) would not per se be the best definition of momentum.

Hubrich's carry factor is based on the protocol of cryptocurrencies on coin issuance, which happens through a process called mining (2017). Mining is the processing of transactions on the chain, for which the miners get rewarded cryptocurrency. Not every cryptocurrency can be mined, as some are created and sold through Initial Coin Offerings (ICOs) or Initial Exchange Offerings (IEOs). The mining process has an inflationary effect, as the supply increases. Based on this, Hubrich constructs the carry factor as the negative of the sum total coins issued over the preceding seven days, divided by the outstanding (circulating) coins at the beginning of that seven-day period. Hence, high carry would indicate low inflation.

2.6 Cryptocurrency-Specific Value Measures

The value factor that Hubrich constructed in his research is inspired by the Network Value to Transactions (NVT) ratio (Hubrich used the old term "Market to Transactions value" or "MTV" in his paper from 2017). This ratio, also called the "P/E ratio" of Bitcoin, is market capitalization divided by on-chain transaction volume. Specifically, Hubrich constructed value as market value divided by the trailing 7-day dollar-value transacted on the blockchain. The transactions happening on the Bitcoin network effectively showcase the utility of the network as in the usage and adoption of Bitcoin. The NVT-ratio first made its appearance in February 2017 in a tweet, but was further explained in an article on Forbes later in 2017 by Willy Woo (2017). Later, in 2018, Dimitry Kalichkin improved the NVT-ratio: NVTS (NVT Signal). NVTS provides more insight into predictive signalling of price tops. The NVTS is the network value divided by the 90-day moving average of daily transaction value (Kalichkin, 2018). This ratio is of more predictive character, compared to the NVT-ratio. Another ratio that is being used to value cryptocurrencies like Bitcoin, is the Mayer Multiple. The Mayer multiple is the Bitcoin price divided by the 200-day moving average (Mayer, 2019). Mayer states that the best results are achieved when accumulating Bitcoin whilst the Mayer Multiple is below 2.4, and selling Bitcoin when the multiple reaches values higher than 2.4. Partly inspired by the Mayer Multiple and the NVTS-ratio, in October 2018, Mahmudov and Puell introduced the Market-Value-to-Realized-Value (MVRV) ratio (2018). The MVRV-ratio is the market value divided by the realized value. The market value is the current last known price multiplied by the current circulating supply. The realized value differs significantly from the current market value. Namely, it adjusts for lost and unmoved Bitcoin and also acts as an indicator for where long-term holders bought Bitcoin. Realized value is calculated by summing the products of price per Bitcoin and UTXO (Unspent Transaction Output). The conventional method of calculating market capitalization is the last known price multiplied by circulating supply. However, the conventional method inflates the capitalization as there are many Bitcoin either unmoved for years or lost/unused. Hence, the realized market capitalization represents the current "real" value of Bitcoin, by valuing Bitcoin depending on when it was moved for the last time. By dividing market value by realized value, an indication of Bitcoin's real value emerges. A 1:1 MVRV-ratio would indicate that Bitcoin would be at its realized value. A MVRV-ratio below one indicates that Bitcoin is undervalued, based on these principles. Mahmudov and Puell find that, historically, a MVRV-ratio above 3.7 denotes overvaluation and a MVRV-ratio below one indicates undervaluation (Mahmudov & Puell, 2018).

3 Data

In this chapter, the data used in this thesis is described. Also, are the different benchmarks explained. Additionally, are the different value ratios (explained in the literature review) visualized, to provide insight in how these value measures perform as a metric of value.

3.1 Dataset of 86 Cryptocurrencies

The dataset consists of 86 cryptocurrencies, with daily data from April 2013 to August 2019. All data is retrieved from Coingecko.com and Coinmetrics.io. The data consists of prices in USD, prices in Bitcoin, market capitalizations in USD, market capitalizations in Bitcoin and the MVRV-ratio (only available for nine cryptocurrencies). Returns of cryptocurrencies valued in USD are adjusted by the risk-free rate (4-week T-bill rate). As will be explained in later sections of this thesis, the reason for having two valuations (USD and BTC) in the dataset per cryptocurrency is because of a different than usual way of constructing the factor portfolios. The traditional methodology states to value assets in USD. However, cryptocurrencies are valued (and traded) against Bitcoin as well. Hence, the inclusion of Bitcoin values of cryptocurrencies in the dataset. The traditional methodology is termed the USD approach and the proposed methodology is termed the BTC approach.

All cryptocurrencies other than Bitcoin are termed altcoins or alts. On Coinmarketcap and on Coingecko, there are roughly 2000 cryptocurrencies displayed. Currently, there are more than 2000 cryptocurrencies, but not all cryptocurrencies are listed on Coinmarketcap or Coingecko, due to their low market capitalization and/or low trading turnover. For this thesis, in total 86 cryptocurrencies are handpicked, based on their liquidity when they were trading, to maintain a well-balanced set of available investment opportunities for every (weekly) observation (with the criteria of having a minimum of 24 weekly observations). Hence, no “dead” cryptocurrencies are included in the dataset. All cryptocurrencies included are still trading at the date of writing this thesis.

Table 1 reports descriptive statistics of sixteen cryptocurrencies that are included in the dataset. The descriptive statistics shown in table 1 are based on weekly returns. A notable take from table 1 is that the standard deviation of the weekly return of Bitcoin is far lower than the other cryptocurrencies. Bitcoin’s returns are far less volatile than returns of the altcoin market, because altcoins are not only traded against USD, but also traded against Bitcoin. This causes altcoins’ USD value to swing more volatile when Bitcoin’s USD value is volatile.

Table 1: Descriptive Statistics 16 Large-Cap Cryptocurrencies
The table below reports descriptive statistics of 16 large-cap cryptocurrencies that are included in the dataset. Shown below are statistics based on weekly returns of the USD value of the cryptocurrencies. The total dataset ranges from April 2013 to August 2019.

	Bitcoin	Litecoin	Bitcoin Cash	Ethereum	EOS	Cardano	Ripple	Tron
First observation	28/04/2013	28/04/2013	02/08/2017	07/08/2015	09/07/2017	18/10/2017	04/08/2013	09/11/2017
N	329	329	107	210	110	96	315	93
Mean	2.0%	2.5%	3.7%	4.4%	3.6%	5.4%	4.1%	12.3%
Standard deviation	12.5%	20.7%	29.9%	22.2%	25.9%	46.1%	31.2%	86.0%
Median	0.9%	-0.1%	-0.2%	0.5%	-0.5%	-2.9%	-0.6%	-0.1%
Max	70.6%	188.4%	152.3%	134.8%	109.7%	341.9%	326.7%	734.7%
Min	-41.8%	-46.7%	-53.7%	-34.9%	-38.2%	-36.6%	-45.1%	-55.3%
Return skewness	0.88	3.34	2.44	2.21	1.91	5.43	5.36	7.02
Return Kurtosis	6.62	24.77	11.33	12.41	8.06	36.89	46.43	56.69

	Stellar	Namecoin	Feathercoin	Novacoin	Primecoin	Dogecoin	Dash	DigixDAO
First observation	06/08/2014	28/04/2013	03/05/2013	28/04/2013	11/07/2013	15/12/2013	14/02/2014	18/04/2016
N	262	329	328	319	318	296	287	174
Mean	4.6%	2.1%	3.7%	2.5%	4.6%	3.8%	3.5%	1.5%
Standard deviation	34.5%	28.2%	39.5%	37.1%	47.0%	38.1%	22.1%	18.9%
Median	-1.4%	-1.0%	-3.2%	-2.0%	-3.0%	-0.9%	-0.4%	0.3%
Max	333.1%	344.4%	360.3%	514.8%	537.8%	536.5%	152.8%	60.2%
Min	-76.3%	-55.0%	-73.1%	-86.3%	-49.4%	-47.5%	-48.1%	-65.1%
Return skewness	5.64	7.03	4.47	9.03	7.13	9.77	2.38	0.35
Return Kurtosis	48.73	78.27	32.86	118.45	69.14	131.94	13.59	4.33

3.2 Equal Weighted and Value Weighted Benchmarks

The point of factor investing is to yield returns that are not comparable to the market. There are different methodologies to form benchmarks that represent the market. In this thesis, four benchmark portfolios are formed that represent the market in different ways. Similar to Hubrich (2017), an equal weighted and value weighted benchmark is constructed. The equal weighted benchmark, in formulas (1) and (2), represents the market at every available observation, with an equal allocation to every available cryptocurrency in the dataset. Hubrich, in his paper, terms the value weighted benchmark a capital weighted benchmark, but both are the same. The value weighted benchmark, in formulas (3) and (4), represents the market at every available observation, with an allocation of every available cryptocurrency proportional to the market capitalization of the cryptocurrency. As explained, regressions will be performed on a dataset consisting of cryptocurrencies valued in USD and on a dataset consisting of cryptocurrencies valued in BTC. For the USD approach, all returns (including the markets') are adjusted by the risk-free rate. For the BTC approach, returns are not adjusted by the risk-free rate, as no risk-free rate (to earn "risk-free" cryptocurrency) exists. Later on, in this thesis, the BTC approach will be furtherly explained.

$$(1) \quad EW\_USD\_BM_t = \sum_{i=1}^{I} \frac{R_{i,t} - r_{f,t}}{N_t}$$

$$(2) \quad EW\_BTC\_BM_t = \sum_{i=1}^{I} \frac{R_{i,t}}{N_t}$$

$$(3) \quad VW\_USD\_BM_t = \sum_{i=1}^{I} (R_{i,t} - r_{f,t}) \frac{MCAP_{i,t}}{TCAP_t}$$

$$(4) \quad VW\_BTC\_BM_t = \sum_{i=1}^{I} (R_{i,t}) \frac{MCAP_{i,t}}{TCAP_t}$$

Table 2 shows the return statistics of the equal weighted and value weighted benchmarks. The descriptive statistics are annualized from weekly returns. In this thesis, it is assumed that portfolios are invested for 100%, meaning that the complete portfolios represent the strategy. Hubrich (2017), on the other hand, assumes a 10% allocation to the portfolio's and 90% allocation to cash (assuming zero return on cash). Hence, a direct comparison between Hubrich's descriptive statistics results and table 2 cannot be made.

Again, it should be noted that there are two datasets with the same cryptocurrencies and data lengths. When comparing the USD approach to the BTC approach, it becomes clear that the cryptocurrencies' Bitcoin value is less volatile than the cryptocurrencies' USD value. As cryptocurrencies are traded against Bitcoin, cryptocurrencies' USD value become more volatile, as Bitcoin's USD value is volatile as well. This can clearly be interpreted from table 2.

Table 2: Descriptive Statistics Equal and Value Weighted Benchmarks

The table below reports (annualized) descriptive statistics of the equal weighted and value weighted benchmarks that represent the market. The descriptive statistics are annualized from weekly returns. Results are shown for both the USD approach and for the BTC approach. Two datasets are used, consisting of the same cryptocurrencies with the same data length. The benchmarks following the USD approach are adjusted by the risk-free rate, whereas the benchmarks following the BTC approach are not adjusted by the risk-free rate. The BTC approach aims to yield Bitcoin and as no risk-free rate for yielding Bitcoin exists, no risk-free rate is used. Because of this, the Sharpe ratio can only be calculated for the USD approach. For the BTC approach, a risk-return ratio is calculated instead. The equal weighted benchmark allocates an equal share of every available cryptocurrency to the benchmark portfolio and holds this portfolio until the rebalancing date (weekly). The value weighted benchmark allocates a share, proportionally to the market capitalization of the cryptocurrency, to the portfolio and holds the portfolio until the rebalancing date (weekly). A 100% portfolio allocation is assumed. Skewness and kurtosis are based on weekly returns.

	USD Approach		**BTC Approach**	
	ew_usd_bm	**vw_usd_bm**	**ew_btc_bm**	**vw_btc_bm**
Mean	292%	167%	169%	54%
StDev	161%	97%	128%	39%
Sharpe	1.81	1.73	.	.
Risk-Return ratio	.	.	1.32	1.39
Skewness	21.92	5.89	67.77	25.01
Kurtosis	3.36	0.91	6.33	3.89

3.3 Value Ratios Applied to Bitcoin

In figure 1, are the price of Bitcoin in USD next to the MVRV-ratio displayed. It can clearly be seen that historically, especially during the first half year of 2019, when the MVRV-ratio dropped below one, the price of Bitcoin surged strongly and that when the MVRV-ratio increased above 3.7, a significant decrease in BTCUSD followed. Figure 2 shows the price of Bitcoin in USD and the Mayer Multiple. The Mayer Multiple performs best when Bitcoin is accumulated while the Mayer Multiple is below 2.4 (Mayer, 2019).

Figure 1: BTCUSD and the MVRV-Ratio

The figure below reports the price of Bitcoin valued in USD and the MVRV-ratio. The left vertical axis reports BTCUSD (in logarithmic scale) and the right vertical axis reports the MVRV-ratio (market value divided by realized value). A MVRV-ratio below one indicates undervaluation and a MVRV ratio above 3.7 indicates overvaluation.

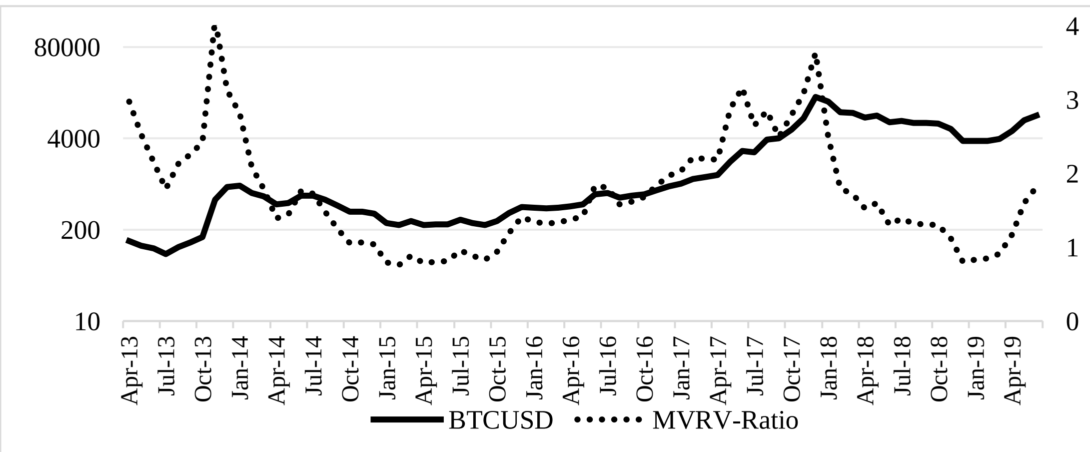
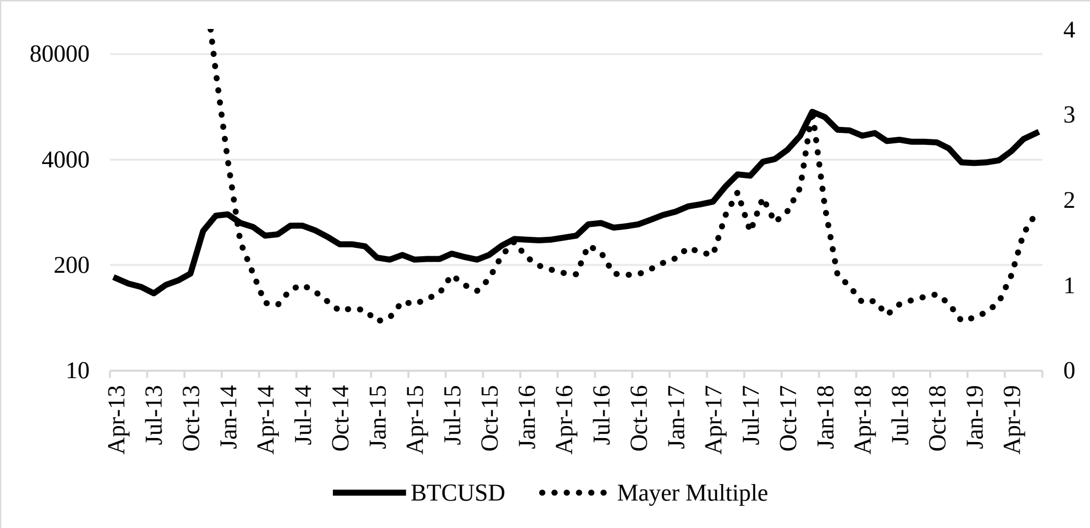
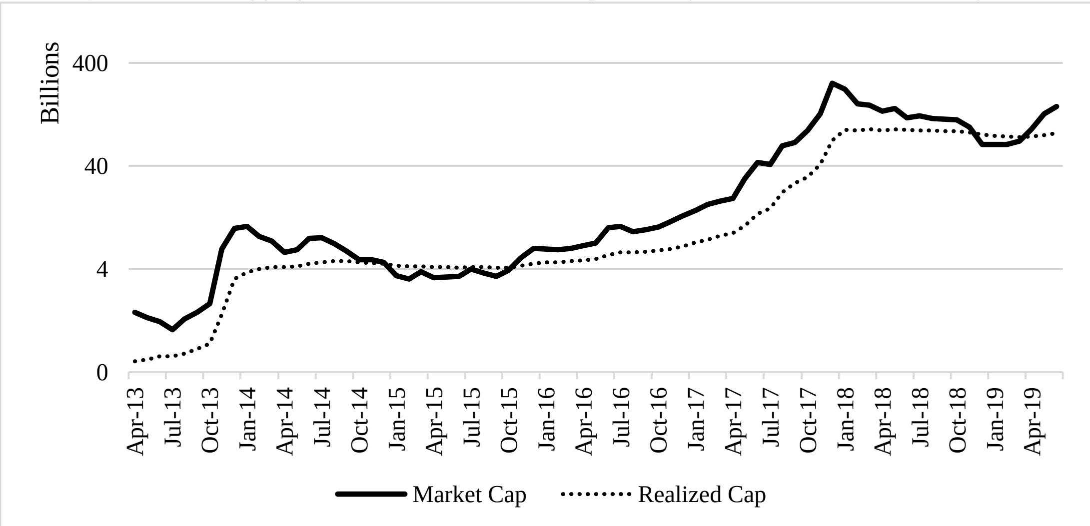


Figure 2: BTCUSD and the Mayer Multiple
The figure below reports the price of Bitcoin valued in USD and the Mayer Multiple. The left vertical axis reports BTCUSD (in logarithmic scale) and the right vertical axis reports the Mayer Multiple (price divided by the 200-day moving average).



The MVRV-ratio and the Mayer Multiple are not applicable to all cryptocurrencies, as not every cryptocurrency has a blockchain similar to Bitcoin where user transaction outputs can be traced, which are required to calculate the MVRV-ratio. A requirement to calculate the Mayer Multiple is having 200 daily observations, to calculate the 200-day moving average. The MVRV-ratio consists of the market value and of the realized value. In figure 3, the market capitalization and the realized capitalization of Bitcoin are displayed. Both datasets are required to calculate the MVRV-ratio, as the MVRV-ratio is essentially the market capitalization divided by the realized capitalization.

Figure 3: Bitcoin's Market Capitalization vs. Realized Capitalization
The figure below reports Bitcoin's Market Capitalization (last known price multiplied by circulating supply) and Realized Capitalization (aggregate value of UTXO's priced by their value when they last moved).



4 Methodology

In this chapter, the methodology used in this thesis is described. First, the methodology of factor investing in the cryptocurrency market is described. Here, a thorough elaboration is given on the implemented methodology, compared to existing literature. Then, an elaboration on the proposed approach is given, which constitutes of a change in point of reference for investors leading to two different approaches, termed the USD approach and the BTC approach. Then, the factor definitions are given. Then, the methodology used for the regressions are described. Firstly, the Fama-MacBeth regressions are described, after which the portfolio regressions are described.

4.1 Applying Factor Investing to the Cryptocurrency Market

Factor investing, also termed rule-based or evidence-based investing, is a methodology in investing that forms portfolios based on given rules, which are believed to generate returns over the benchmark. Typically, factor investing is used in equity markets, but it can be used in other asset classes as well (Asness, Moskowitz, & Pedersen, 2013). Using existing literature on factor investing in the cryptocurrency markets, cryptocurrency specific factors are constructed. However, there are differences between conventional markets and cryptocurrency markets. Namely, conventional markets typically trade five days a week, during business hours. Cryptocurrency exchanges, however, trade constantly and are only not live during maintenance or, very infrequently, during system outages. Because of this, a week of trading in conventional markets almost equals two days of trading in the cryptocurrency markets. Stimulated by this difference, Hubrich (2017) rebalances portfolios at a weekly rate. However, as markets constantly trade, the day of rebalancing could be any day of the week. Because of this, Hubrich implemented each portfolio seven times, with each version having a different rebalancing day. Hubrich then bases his results on pooled statistics of all return series. In this thesis, however, only one day of rebalancing is assumed, namely the last day of the week. Specifically, the prices of the cryptocurrencies every Sunday at UTC 00:00 are used to calculate weekly returns.

In this thesis, portfolios and benchmarks are equal weighted and value weighted. Hubrich employs two weighting schemes for the factor portfolios, namely equal weighted and risk weighted and three weighting schemes for the benchmark portfolios, namely equal weighted, value weighted and risk weighted. Also, Hubrich assumes a 10% allocation to cryptocurrencies for every portfolio. The remaining 90% is allocated to cash. In this thesis, a 100% allocation to cryptocurrencies is assumed. Because of this difference, results of the portfolio regressions and descriptive statistics cannot be directly compared to Hubrich's results.

In this thesis, the momentum, size and value factor strategies are examined. Later in this thesis, the factor definitions are given. The weekly returns of the factor portfolios are ranked in deciles, based on the factor's rules. Then, three portfolios are constructed, where the first portfolio consists of the first three deciles, the second portfolio consists of the fourth till seventh deciles, and the third portfolio consists of the eight till tenth deciles. Additionally, a fourth long-short portfolio is constructed by subtracting the short portfolio from the long portfolio, to create a zero-cost strategy. The main difference between Hubrich's approach and the approach implemented in this thesis is that in this thesis, portfolios are formed cross-sectionally, leaving out the longitudinal (time-series) approach. To understand if the factor strategies predict returns, Fama-MacBeth (1973) and portfolio regressions are performed. The constructed portfolios are regressed against the benchmark. To account for autocorrelation and heteroskedasticity in the error terms, a Newey and West (1986) correction is used with six lags. To understand whether the examined factor strategies generate returns over the benchmark, the results from the regressions are interpreted. The results described in this thesis are all annualized from weekly rebalancing portfolios. The mean and standard deviation (annualized) of the factor portfolios are used to calculate the Sharpe (1964) ratio for the USD approach. The Sharpe ratio gives an understanding of an investment's return in relation to its risk. For the BTC approach, a risk-return ratio is used instead, as the returns on the Bitcoin-traded cryptocurrencies are not adjusted by a Bitcoin-specific risk-free rate, as such a rate does not exist. The portfolio regressions yield alpha, a t-statistic and beta. Jensen's alpha (1968), is the constant term in the regression and can be interpreted as the return of the portfolio over the theoretical expected return. The t-statistic shows the statistical significance of the alpha and the beta shows the volatility of the portfolio relative to the market.

Jensen's Alpha (1968), or alpha, requires, according to its definition, the risk-free rate. In the USD approach, a risk-free rate is included. However, in the BTC approach, risk-free rate is assumed to be zero as no risk-free rate exists when trading to acquire more Bitcoin. However, in the results section for the BTC approach, the constant term of the regression is still named alpha, as alpha can be interpreted as the returns earned over the market.

4.2 The USD Approach and the BTC Approach

This thesis advocates for a new approach of constructing cryptocurrency-specific factor portfolios, adjusting the point of reference when calculating profits. Namely, the proposed approach consists of setting the goal to trade for more Bitcoin, whereas regularly, in traditional markets, traders trade to increase the fiat value of their portfolio. In this thesis, this approach is termed the BTC approach, whereas the traditional methodology is termed the USD approach. The basis backing this new approach stems from the way cryptocurrency exchanges operate, where most cryptocurrency trading turnover occurs against Bitcoin, and not against fiat money (Coingecko, 2019). Another argument is the high correlation between Bitcoin and altcoins in USD value, as being shown in figure 4. Existing literature on factor investing in the cryptocurrency market does not consider the high correlation in USD value between cryptocurrencies, which is essentially caused by the high trading turnover amongst altcoins paired against Bitcoin (effectively causing altcoins to fluctuate with Bitcoin's USD value).

Figure 4: Pearson Correlation Bitcoin and Altcoins
The figure below reports the Pearson correlation between Bitcoin and Altcoins for 2013 and 2019, per year and for the total dataset on daily returns on their USD values. The data is Winsorized at the extreme six observations for Bitcoin and extreme 10 observations for all other cryptocurrencies (as altcoins are more volatile).

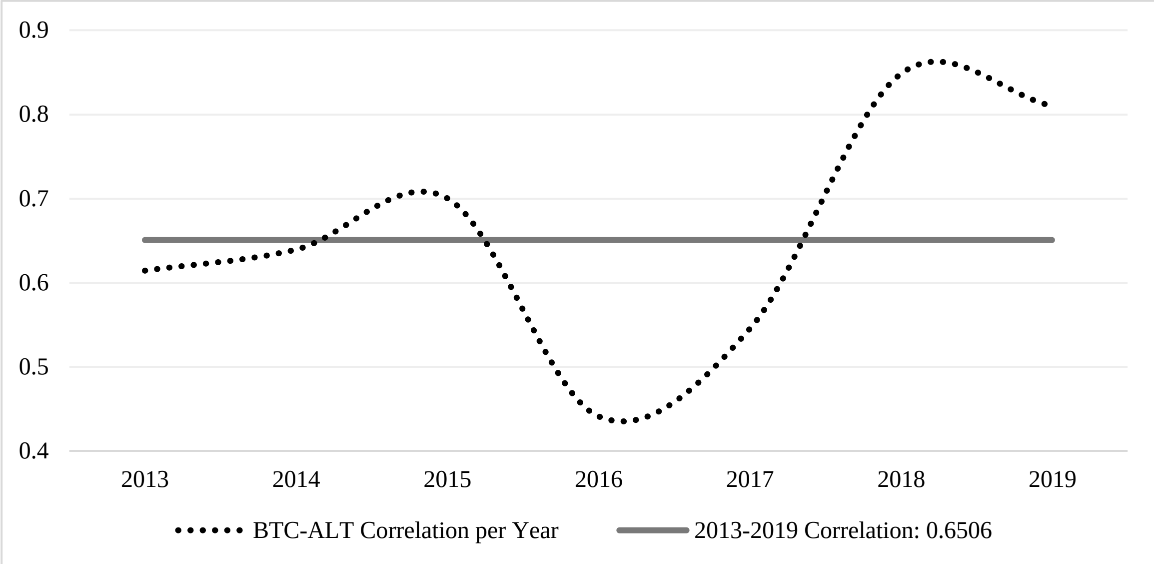


Figure 4 shows the Pearson correlation between daily Bitcoin returns and daily altcoin returns. Over the complete dataset, the correlation equals 0.6506 between Bitcoin's return against USD and altcoin's returns against USD. The decrease in correlation between Bitcoin and altcoins can be explained by the beginning of Bitcoin's uptrend in 2015, which has led to the all-time-high in USD at the end of 2017.

Returns following the USD approach are risk-adjusted by the 4-week T-Bill rate. Returns following the BTC approach are not risk-adjusted, as no risk-free rate to earn more Bitcoin exists. The lending rate of the largest cryptocurrency exchange, Binance, could be implemented as the risk-free rate, for instance. However, the lending rate of cryptocurrency exchange Binance is not completely risk-free, even though it is currently the largest cryptocurrency exchange. For investors of traditional markets, taking the approach of aiming to invest and trade for more Bitcoin might seem odd. However, in the cryptocurrency market, this approach is widely accepted. Examining a different factor portfolio construction method provides insight in how an investors' point of reference could affect the cumulative returns (in USD) of the portfolio compared to when applying the (traditional) USD approach.

4.3 Factor Definitions

In this thesis, three factor strategies are examined: momentum, size and value. In section 4.1, are the differences between Hubrich's (2017) methodology and the methodology of this thesis described. In this section, all formulas are shown of the factors.

In this thesis, three factor strategies are examined, namely momentum size and value. The weights of the factors are formed at every Sunday at UTC 00:00. Per the definition of factor investing, portfolios are formed based on the rules of these factors. Firstly, momentum is defined as last week's return (5), following the same methodology of existing literature (Hubrich, 2017). The momentum factor is ranked weekly based on past weeks' performance. Then, a long portfolio is created based on the top three deciles and a short portfolio based on the bottom three deciles of the momentum factor. Also, a long-short portfolio is generated, by subtracting the short portfolio from the long portfolio, to create a zero-cost strategy.

$$(5) \quad Momentum_t = R_{t-1}$$

$$(6) \quad R_{ew\_momentum,t} = \sum_{i=1}^{I} EW_{i,t} R_{i,t}$$

$$(7) \quad EW_{i,t-1} = \frac{1}{N_{t-1}}$$

$$(8) \quad R_{vw\_momentum,t} = \sum_{i=1}^{I} VW_{i,t} R_{i,t}$$

$$(9) \quad VW_{i,t} = \frac{MCAP_{i,t-1}}{TCAP_{t-1}}$$

Where $R_{ew\_momentum,t}$ is the return of the (equal weighted) momentum factor portfolio in week t, $EW_{i,t}$ is the (equal) weight of the return per cryptocurrency *i*, and N_{t-1} is the number of cryptocurrencies available at period *t-1*. $R_{vw\_momentum,t}$ is the return of the (value weighted) momentum factor portfolio at week *t*, $VW_{i,t}$ is the weight (per value) of the cryptocurrencies *i* in the factor portfolio. $MCAP_{i,t-1}$ represents the market capitalization of the cryptocurrency in the portfolio at period *t-1* and $TCAP_{t-1}$ represents the total market capitalization at period *t-1*.

Secondly, the size factor is based on the market capitalizations. Because portfolios are rebalanced at a weekly rate, the market capitalization at the end of last week is considered for the sorting process. The market capitalizations are ranked from low to high. A long portfolio is created based on the first three deciles, a short portfolio is created based on the last three deciles and a long-short portfolio is generated by subtracting the short portfolio from the long portfolio.

$$(10) \quad Size_t = Market\ capitalization_{t-1}$$

$$(11) \quad R_{ew\_size,t} = \sum_{i=1}^{I} EW_{i,t} R_{it}$$

$$(12) \quad EW_{i,t} = \frac{1}{N_{t-1}}$$

$$(13) \quad R_{vw\_size,t} = \sum_{i=1}^{I} VW_{i,t} R_{it}$$

$$(14) \quad VW_{i,t} = \frac{MCAP_{i,t-1}}{TCAP_{t-1}}$$

Where $R_{ew\_size,t}$ is the return of the (equal weighted) size factor portfolio at week *t*, $EW_{i,t}$ is the (equal) weight of the return per cryptocurrency i, and N_{t-1} is the number of cryptocurrencies available at period *t-1*. $R_{vw\_size,t}$ is the return of the value weighted size factor portfolio, $VW_{i,t}$ is the weight (per value) of the cryptocurrencies i in the portfolio. $MCAP_{i,t-1}$ represents the market capitalization of the cryptocurrencies in the portfolio at the end of last week/beginning of the week and $TCAP_{t-1}$ represents the total market capitalization at *t-1*.

Thirdly, the value factor is constructed by ranking the MVRV-ratios of the cryptocurrencies at every Sunday at UTC 00:00. A long portfolio is created, based on the first three deciles, a short portfolio is created based on the top three deciles and a long-short portfolio is generated by subtracting the short portfolio from the long portfolio.

$$(15) \quad Value_t = MVRV\ ratio_{t-1} = \frac{Market\ capitalization_{t-1}}{Realized\ capitalization_{t-1}}$$

$$(16) \quad R_{ew\_value,t} = \sum_{i=1}^{I} EW_{i,t} R_{it}$$

$$(17) \quad EW_{i,t} = \frac{1}{N_{t-1}}$$

$$(18) \quad R_{vw\_value,t} = \sum_{i=1}^{I} VW_{i,t} R_{it}$$

$$(19) \quad VW_{i,t} = \frac{MCAP_{i,t-1}}{TCAP_{t-1}}$$

Where $R_{ew\_value,t}$ is the return of the (equal weighted) value factor portfolio at week *t*, $EW_{i,t}$ is the (equal) weight of the return per cryptocurrency i, and N_{t-1} is the number of cryptocurrencies available at period *t-1*. $R_{vw\_value,t}$ is the return of the value weighted value factor portfolio, $VW_{i,t}$ is the weight (per value) of the cryptocurrencies i in the portfolio. $MCAP_{i,t-1}$ represents the market capitalization of the cryptocurrencies in the portfolio at the end of last week/beginning of the week and $TCAP_{t-1}$ represents the total market capitalization at *t-1*.

4.4 Fama-MacBeth Regressions

To understand whether the factor strategies are able to predict returns, Fama-MacBeth (1973) regressions are performed, using weekly (risk-adjusted) returns as the dependent variable. It should be noted that the Fama-MacBeth regressions are performed only on the USD dataset (cryptocurrencies valued in USD). For the market beta, the equal weighted benchmark is used.

In total, six Fama-MacBeth regressions are performed, to understand how the factor strategies perform. Below are six models shown, with different characteristics. Model (1) has only the market as independent variable. Model (2) has the factor size as the independent variable. Model (3) has only the factor value as the independent variable and model (4) has only the factor momentum as the independent variable. Model (5) represents the characteristics of the Fama and French three-factor model (1993), as model (5) includes a factor on the market, a factor on size and a factor on value as the independent variables. Model (6) represents the characteristics of the Carhart (1997) model, as it has an additional factor on momentum. If, in the cross section, the factor strategies are deemed statistically significant, the factors will be able to positively or negatively predict returns.

$$(1)\quad (R_i - r_f) = \alpha_t + \beta_{ew\_market} * (\bar{R}_{ew\_market} - r_f) + \epsilon$$

$$(2)\quad (R_i - r_f) = \alpha_t + \beta_{logsize} * (\bar{R}_{logsize}) + \epsilon$$

$$(3)\quad (R_i - r_f) = \alpha_t + \beta_{value} * (\bar{R}_{value}) + \epsilon$$

$$(4)\quad (R_i - r_f) = \alpha_t + \beta_{momentum} * (\bar{R}_{momentum}) + \epsilon$$

$$(5)\quad (R_i - r_f) = \alpha_t + \beta_{ew_{market}} * (\bar{R}_{ew_{market}} - r_f) + \beta_{logsize} * (\bar{R}_{logsize}) + \beta_{value} * (\bar{R}_{value}) + \epsilon$$

$$(6)\quad (R_i - r_f) = \alpha_t + \beta_{ew\_market} * (\bar{R}_{ew\_market} - r_f) + \beta_{logsize} * (\bar{R}_{logsize}) + \beta_{value} * (\bar{R}_{value}) + \beta_{momentum} * (\bar{R}_{momentum}) + \epsilon$$

4.5 Portfolio Regressions

Another approach, as commonly seen in factor investing literature, are portfolio regressions. The factor portfolios are regressed on the earlier described benchmarks, to find if the factor portfolios outperform (or underperform) the benchmark. The regressions are run with Newey and West standard errors (1986) to account for autocorrelation and heteroskedasticity. All portfolio regressions are run twice: once where the factor portfolios (including the benchmark) are equally weighted and once where the factor portfolios (including the benchmark) are value weighted. The portfolio regressions where the benchmark is equal weighted resembles the characteristics of the CAPM, which uses an equal weighted benchmark. Value weighting the benchmark leads to a better representation of the market in terms of liquidity, as cryptocurrencies with a larger market capitalization are commonly more liquid in terms of trading turnover compared to cryptocurrencies with a smaller market capitalization. Regressing a value weighted portfolio on a value weighted benchmark has implications on the size factor. Namely, the larger cryptocurrencies get assigned a larger weight within the factor portfolio. The size factor strategy aims to yield returns over the market from going long in small caps and short in large caps. Hence, within the small caps, the larger cryptocurrencies will be assigned more weight. An advantage of this is that more liquid cryptocurrencies get picked by the strategy.

Returns formed according the BTC approach are not risk-adjusted, as the risk-free rate is assumed to be equal to zero. The reasoning behind this assumption is that when trading to acquire more Bitcoin, no financial product exists that will yield risk-free Bitcoin. Not adjusting the BTC returns by the risk-free rate has implications for the interpretation of the performance of the portfolio in relation to its risk. It is not possible to calculate a Sharpe ratio for the BTC approach. Instead, a risk-return ratio is calculated.

The following portfolio regression is performed to find if the factor portfolios generate returns other than theoretically expected. The constructed factor portfolios are regressed against the benchmark. For the value, momentum and size portfolios, regression model (7) is run.

$$(7) \quad R_{p,t} = \alpha_{p,benchmark} + \beta_{p,benchmark} * R_{benchmark,t} + \epsilon_{pt,benchmark}$$

Where $R_{p,t}$ are the returns of the factor strategy (dependent variable) and $R_{benchmark,t}$ are the returns of the benchmark (independent variable) at period t. $\alpha_{p,benchmark}$ is the alpha (constant) of the factor strategy, $\beta_{p,benchmark}$ is the benchmark coefficient (also known as the systematic exposure of the factor strategy to the benchmark) and $\epsilon_{pt,benchmark}$ is the error term of the factor strategy on the benchmark.

This regression is performed to find if significant (positive or negative) alpha exists for the value, momentum and size strategies given the dataset. Hence, the null hypothesis and alternative hypothesis are:

$$\mathrm{H}_0: \alpha_{p,benchmark} = 0$$
$$\mathrm{H}_1: \alpha_{p,benchmark} \neq 0$$

If the null hypothesis is rejected, it means that alpha is significantly different than zero and the factor strategy successfully yields returns other than theoretically expected. The regression produces the alpha (including t-statistic) of the portfolio. The t-statistic indicates how statistically significant the outcome of the regression is. The higher the t-statistic, the more significant the outcome is.

In the results chapter, using the annualized mean and annualized standard deviation of the portfolio, the annualized Sharpe ratio is calculated (Sharpe, 1964). For the BTC approach, as stated earlier, no Sharpe ratio can be calculated as returns are not adjusted by the risk-free rate. Instead, a risk-return ratio is calculated.

5 Results

In this chapter, the results of the Fama-MacBeth (1973) and portfolio regressions are described. In total, 62 regressions are performed: six Fama-MacBeth regressions and 56 portfolio regressions, using Newey and West (1986) standard errors.

5.1 Fama-MacBeth Regressions

To understand if the factors explain returns, Fama-MacBeth (1973) regressions are performed on the dataset with 86 cryptocurrencies, valued in USD. Weekly (risk-adjusted) returns are used as the dependent variable and the factor strategies as the independent variables. Table 3 below shows the results of the regressions. Model (1) shows a positive effect of the market on the weekly returns, yet not statistically significant. Model (2) shows that size has a statistically significant negative effect on the weekly returns, meaning that the larger the market capitalization, in the used dataset, weekly returns are negatively predicted. Models (3) and (4) show that value and momentum have a positive effect on the weekly returns, yet not statistically significant. Model (5) has the characteristics of the Fama and

Table 3: Results Fama-MacBeth Regressions

The table below reports the results of the Fama-MacBeth regressions. The dependent variable is the weekly return and the independent variables are the market, size, value and momentum. Ew_market represents the beta of an equal weighted market portfolio, rebalanced at a weekly rate. Size is calculated by multiplying the circulating supply by the price of the cryptocurrency of last week. Value represents the MVRV-ratio, which is market capitalization divided by realized capitalization. Momentum is based on last week's return. Newey and West (1986) standard errors are used in the regression. Levels of statistical significance are: *** p<0.01, ** p<0.05 and * p<0.1. The used dataset ranges from April 2013 to August 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
ew_market	0.00912				-0.000953	0.000776
	(0.00647)				(0.000944)	(0.000769)
logsize		-0.0150***			-0.00400	-0.0223
		(0.00464)			(0.00285)	(0.0173)
value			0.00530		0.0232	0.0581
			(0.0112)		(0.0156)	(0.0387)
momentum				0.00409		2.073
				(0.0581)		(1.755)
Constant	0.0408***	0.313***	0.0332	0.0512***	0.0964**	0.349
	(0.0132)	(0.0910)	(0.0260)	(0.0187)	(0.0452)	(0.243)
Observations	14,202	14,059	1,790	14,109	1,788	1,783
Adj. R-squared	0.000	0.053	0.337	0.104	0.557	0.779
Number of groups	329	329	329	328	329	328

French (1992) three-factor model, as the independent variables in model (5) are the market, a factor on size and a factor on value. Model (6) has the characteristics of the Carhart (1997) model: the explanatory variables used in model (6) are the market, size, value and momentum.

5.2 Portfolio Regressions

In this section, the (annualized) results of the portfolio regressions are described. Table 4 shows the results of the portfolio regressions, where the factor portfolio returns (dependent variables) are regressed on the market (independent variable), both equal weighted and value weighted, for both the USD approach and the BTC approach. Returns per the USD approach are adjusted by the risk-free, whereas returns used per the BTC approach are not (as the risk-free rate on the BTC approach is assumed to be zero). Hence, instead of a Sharpe ratio, the BTC approach produces a risk-return ratio. To examine the effect of weighting the portfolios based on the market capitalizations of the cryptocurrencies, regressions are performed on equal weighted portfolios and value weighted portfolios. In total, 56 portfolio regressions are performed. The dependent variables used in the regressions are zero-cost strategies and composite factor strategies (combined factors).

For the momentum factor, following the USD approach, no significant alpha is found for the zero-cost strategy. Value weighting the portfolios yields a negative annualized mean of the strategy. A possible explanation for this difference is that because larger cryptocurrencies are included in the value weighted portfolios, both the long portfolio and short portfolio (in the zero-cost strategy portfolio) have lower returns. As described in the prior section of this chapter, for the used dataset, size negatively predicts returns (according the results of the Fama-MacBeth regressions). The momentum factor strategy has, following the BTC approach, an annualized negative alpha of 120% (statistically significant at the p-level of 10%). The yearly Sharpe ratio is extremely low following the USD approach when equal weighting the portfolio and negative when value weighting the portfolio, due to the negative annualized mean of the portfolio. For the momentum strategy, the same holds for the BTC approach. For momentum, the only significant (at the p-level of 10%) strategy is to short the zero-cost strategy on momentum following the BTC approach. However, the low statistical significance of this strategy combined with the low risk-return ratio does not make this an attractive investment strategy.

The size factor strategy, following the USD approach, produces alpha, significant at the p-level of 5%. Remarkable is that for value weighted portfolios, annualized alpha is higher than when equal weighting the portfolios. The size factor strategy buys small market capitalized cryptocurrencies and sells large market capitalized cryptocurrencies. Hence, an interpretation from the results is that from the small cryptocurrencies, the larger capitalized cryptocurrencies perform better in the size strategy, as value weighted portfolios perform better. Results show that size works significantly in the BTC approach as well. In the BTC approach, size yields a higher alpha, however, alpha is not significant when value weighting the portfolios. Another remarkable result is that size yields the highest Sharpe ratio and risk-return ratio, compared to the other factors. Also, when comparing equal to value weighted

Table 4: Results Portfolio Regressions (Annualized)

The table below reports the (annualized) results of the portfolio regressions. The dataset consists of 86 cryptocurrencies, with valuations in USD and BTC. Portfolios are rebalanced at a weekly rate. The zero-cost strategies (long portfolio minus the short portfolio) of the factors is used as the dependent and the market is used as the independent variable (equal weighted and value weighted benchmark). Also, composite factor portfolios are formed: SM (size and momentum) and SMV (size, momentum and value). To account for autocorrelation and heteroskedasticity, Newey and West (1986) standard errors are used. Using the mean and the standard deviation of the factor portfolios, the Sharpe ratio is calculated. Also, do the regressions yield alpha (with a T-statistic) and a beta. Because Newey and West standard errors are used, no R-squared from the regressions could be calculated. The dataset ranges from April 2014 to August 2019. The results are annualized from weekly results. A 100% portfolio allocation to cryptocurrencies is assumed. Levels of statistical significance are: *** p<0.01, ** p<0.05 and * p<0.1.

	USD Approach											
	Equal Weighted						**Value Weighted**					
	Mean	**StDev**	**Sharpe**	**Alpha**	**Tstat**	**Beta**	**Mean**	**StDev**	**Sharpe**	**Alpha**	**Tstat**	**Beta**
Mom	6%	286%	0.02	98%	1.51	-0.31	-116%	195%	-0.60	-96%	-1.46	-0.12
Size	386%	247%	1.56	123%**	2.07	0.90***	414%	471%	0.88	362%**	2.39	0.31
Value	-40%	154%	-0.26	-134%*	-1.92	0.32**	101%	146%	0.70	103%*	1.85	-0.01
SM	196%	158%	1.24	110%***	2.71	0.29	149%	259%	0.58	134%*	1.67	0.1
SMV	118%	117%	1.01	29%	0.83	0.30**	86%	156%	0.55	88%	1.61	-0.02

	BTC Approach											
	Equal Weighted						**Value Weighted**					
	Mean	**StDev**	**R/R**	**Alpha**	**Tstat**	**Beta**	**Mean**	**StDev**	**R/R**	**Alpha**	**Tstat**	**Beta**
Mom	9%	216%	0.04	-120%*	-1.85	0.76***	-188%	312%	-0.60	-167%	-1.40	-0.39
Size	331%	184%	1.8	200%***	4	0.77**	257%	393%	0.65	281%	1.83	-0.43**
Value	-81%	177%	-0.46	-162%**	-2.04	0.48***	75%	156%	0.48	72%	1.34	0.06
SM	170%	169%	1	40%	0.98	0.77***	35%	218%	0.16	57%	0.69	-0.41
SMV	86%	132%	0.65	-27%	-0.83	0.671***	80%	128%	0.62	76%	1.39	0.05

portfolio regression results, size achieves a lower Sharpe ratio and risk-return ratio when the portfolios are value weighted.

Value is based on the Market-Value-Realized-Value ratio. Value yields remarkable results, namely the equal weighted portfolios, following the USD and BTC approach, have a negative annualized alpha (significant at the p-level 10% and 5%, respectively). When value weighting the portfolios, however, the yearly alpha is positive, but higher (and statistically significant at the p-level of 5%) for the USD approach. This means that buying undervalued and selling overvalued cryptocurrencies with a large(r) market capitalization (value weighted), leads to positive yearly alpha on the portfolio. When equal weighting the portfolios, however, shorting the portfolio yields even higher returns, significant at a p-level of 10%.

The composite factor strategies SM (size and momentum) and SMV (size, momentum and value) are portfolios that consist of a combination of the factor strategies size, momentum and value. As explained in the literature review of this thesis, combining factor strategies might improve the results due to possible diversification benefits. SM, which consists of size and momentum, yields the highest annualized alpha (significant at the p-level of 1%) on equal weighted portfolios following the USD approach. When value weighting the SM factor portfolio, a higher annual alpha is achieved, however, this alpha is not statistically significant. Also, value weighting the SM factor portfolio decreases the risk-return ratio from 1 to 0.16. SMV shows similar results, where the risk-return ratio decreases when value weighting the portfolios, yet slightly. SMV does not yield significant yearly alpha, however, value weighting the portfolios increases the t-statistic and hence its statistical significance, yet not sufficiently to consider the strategy statistically significant. Conclusively, combining all three factor strategies into one composite factor strategy does not generate excess returns in the USD approach and no returns over the benchmark in the BTC approach.

5.3 Cumulative Returns BTC vs USD Approach

In this section, to display the effect of implementing the BTC approach on the cumulative returns of the portfolio, the cumulative returns (in USD) of the size factor strategy are shown in figures 5 and 6. The equal weighted strategy is shown in figure 5 and the value weighted strategy is shown in figure 6.

Every week, one dollar is invested in the strategies. Portfolios are rebalanced at a weekly rate, meaning that, in figures 5 and 6, one USD is invested in the strategies every week. Then, the returns (in USD) are summed up per week, leading to the cumulative returns (in USD) in figures 5 and 6. Shown in the figures are the strategy following the BTC approach, the USD approach and the benchmark (all portfolios are both equal weighted and value weighted). The cumulative returns are shown to gain an understanding in how the strategies perform against each other and against the benchmark. According the BTC approach, portfolios are held in Bitcoin, which is why the cumulative returns of this strategy are more volatile than the cumulative returns of portfolios formed according the USD approach. According the BTC approach, the (initial) goal is to trade for more Bitcoin. Results from table 4 show that size yields significant alpha, and thus yields abnormal returns on portfolios formed in Bitcoin. Hence, when Bitcoin is in an upwards trend, the portfolio appreciates more in USD. However, when Bitcoin is in a downwards trend, the strategy accumulates more Bitcoin, what effectively leads to a strong increase in cumulative returns once Bitcoin’s trend shifts from downwards to upwards, as can be seen from both figures 5 and 6 in the period after 2015.

Figure 5: Cumulative Returns (in USD) Size Factor Strategy Equal Weighted

The figure below shows the cumulative returns (valued in USD) of the size factor strategy on equal weighted portfolios. The BTC approach constructs portfolios based on the BTC value of the cryptocurrencies, whereas the USD approach constructs portfolios based on the USD values of the cryptocurrencies. The strategies are implemented from December 2013 to August 2019. Every week, one dollar is invested in the weekly rebalancing strategies. The returns (in USD) are then summed up, every week, leading to the cumulative returns (in USD) below. The BTC approach holds portfolios in Bitcoin, as cryptocurrencies are traded against Bitcoin in the BTC approach. Hence, at the beginning of every week, one USD worth of Bitcoin is bought and then traded with. In the figure below, for the BTC approach, the USD value of the profits in Bitcoin are shown.

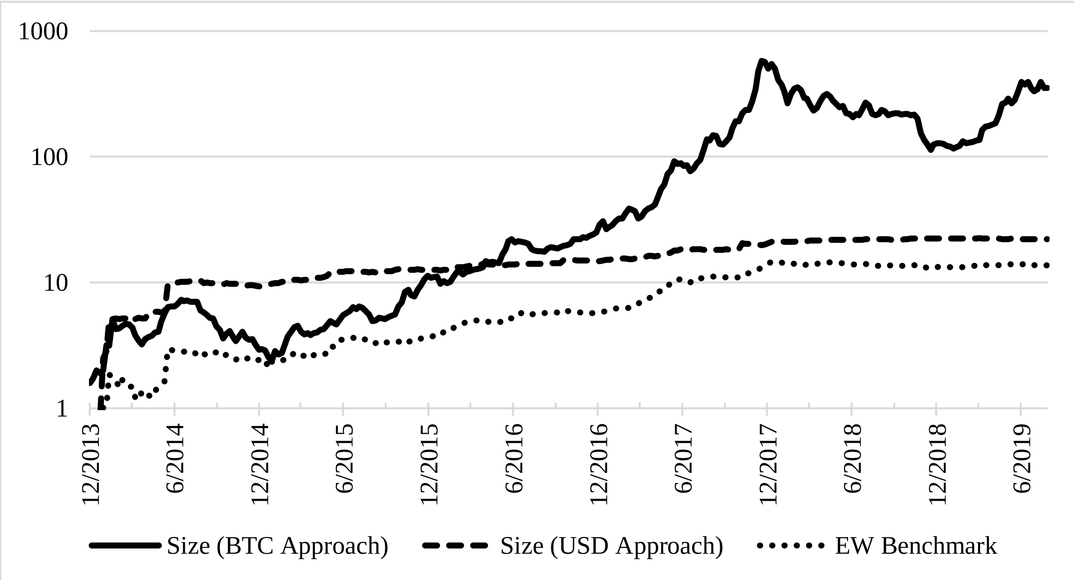
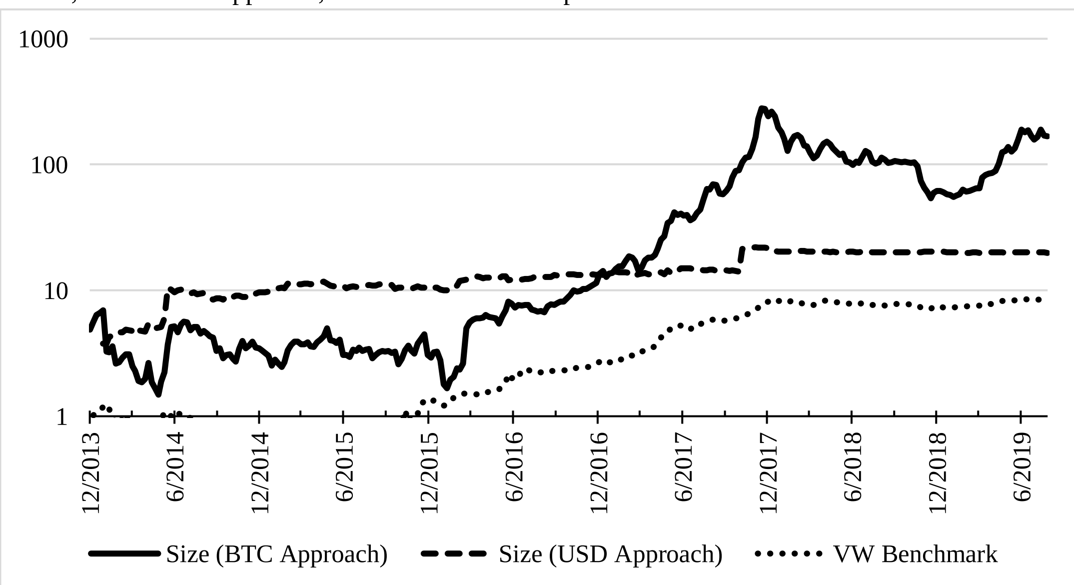


Figure 6: Cumulative Returns (in USD) Size Factor Strategy Value Weighted

The figure below shows the cumulative returns (valued in USD) of the size factor strategy on value weighted portfolios. The BTC approach constructs portfolios based on the BTC value of the cryptocurrencies, whereas the USD approach constructs portfolios based on the USD values of the cryptocurrencies. The strategies are implemented from December 2013 to August 2019. Every week, one dollar is invested in the weekly rebalancing strategies. The returns (in USD) are then summed up, every week, leading to the cumulative returns (in USD) below. The BTC approach holds portfolios in Bitcoin, as cryptocurrencies are traded against Bitcoin in the BTC approach. Hence, at the beginning of every week, one USD worth of Bitcoin is bought and then traded with. In the figure below, for the BTC approach, the USD value of the profits in Bitcoin are shown.



Figures 5 and 6 show that in the long run, the BTC approach strongly outperforms the USD approach in terms of cumulative returns in USD. All strategies outperform the benchmark, on equal weighted and value weighted portfolios, what can also be interpreted from the results of the regressions in table 4. The equal weighted portfolios (figure 5) have higher cumulative returns than the value weighted portfolios (figure 6). This is because larger cryptocurrencies, in terms of market capitalization, are assigned a higher share of the portfolio. This can also be interpreted from the results of the Fama-MacBeth regressions in section 5.1.

5.4 Summary of the Results

Three factor strategies are examined: momentum, value and size. Also, two composite factor strategies are formed, using these three factor strategies. Using a dataset ranging from April 2013 to August 2019, in total 62 regressions are performed: six Fama-MacBeth (1973) regressions and 56 portfolio regressions, using Newey and West standard errors (1986).

The results of the Fama-MacBeth regressions show that size negatively predicts returns, statistically significant at a p-level of 1%. The market, value and momentum positively predict returns, however, not statistically significant. Using portfolio regressions, the factor strategies' performance is examined, both equal weighted and value weighted. In table 4, only the results of the zero-cost strategies and the composite factor strategies are shown. Only on the BTC approach using equal weighted portfolios, momentum yields a negative annualized alpha statistically significant at a p-value of 10%. Size yields annualized alpha when constructing portfolios using the USD approach at a statistical significance of 5% (on both equal and value weighted portfolios). Remarkably, when constructing size portfolios according the BTC approach, significant annualized alpha (at the p-level of 0.1%) is found on equal weighted portfolios and no significant results are found on value weighted portfolios. Value yields negative alpha on equal weighted portfolios and positive alpha on value weighted portfolios, with significant results on the USD approach and only significant results on the equal weighted portfolio strategy for the BTC approach. The composite factor strategies SM and SMV yield the most significant results for the SM (size and momentum) portfolio, on equal weighted portfolios constructed using the USD approach. The highest Sharpe ratio and risk-return ratio is reached using the Size strategy, on all considered strategies.

Figures 5 and 6 show that the BTC approach strongly outperforms the USD approach and the benchmark in terms of cumulative returns in USD. The results shown for the cumulative returns are only shown for the size strategy, as the results on the size factor strategy are the most significant.

6 Conclusion and Limitations of Research

6.1 Conclusion

In this thesis, I aim to answer the question: *Does factor investing generate excess returns in the cryptocurrency market?* If not, has the cryptocurrency market become more efficient over the past years? To answer this question, I perform Fama-MacBeth (1973) and portfolio regressions on cross-sectional portfolios. Next to the conventional method, a new factor construction approach is implemented, where the factor portfolios are calculated using the Bitcoin values of cryptocurrencies, whereas, usually, factor portfolios are calculated using the USD values of cryptocurrencies. The motivation behind this new approach stems from the way cryptocurrency exchanges operate. Namely, most cryptocurrency exchanges operate in Bitcoin (and/or other cryptocurrencies), where deposits and withdrawals happen in cryptocurrency. Added to this, the high trading turnover happening of cryptocurrencies paired against Bitcoin, gives reason for investors to value their cryptocurrency portfolio in Bitcoin. Both equal and value weighted portfolios are examined, to gain a thorough understanding of different portfolio construction methods.

My results show that momentum does not generate excess returns following the USD approach on equal and value weighted portfolios. Similarly, Hubrich (2017) also does not find significant results on equal weighted portfolios (similar USD approach). However, Hubrich finds significant results for momentum when including a longitudinal approach to the cross-sectional approach (a "complete" portfolio). It should be noted that, as is described in section 4.1, Hubrich's methodology of rebalancing the portfolios slightly differs, what makes comparing results difficult. However, it remains interesting to examine the significance of the alpha's in Hubrich's paper. For value, I find significant annualized alpha on the USD approach (at a p-level of 10%), and only significant annual alpha on equal weighted portfolios for the BTC approach. It should be noted that this result is of low significance and might be the result of data mining. Also, Hubrich constructed his value factor differently (yet very similar), and did not find significant results as well (on both equal and value weighted portfolios in the cross-section). The best results were produced by the size factor strategy, yielding significant annualized alpha (at a p-level of 5%) on the USD approach and significant annual alpha (at a p-level of 0.1%) on the BTC approach, equal weighted. My results are in line with the results of Elendner et al. (2016), who also found significant results for the factor size. The composite factor strategies seem to only work when combining momentum and size on equal weighted portfolios following the USD approach.

The difference in cumulative returns between the BTC approach and the USD approach show that implementing the BTC approach to the portfolio leads to higher cumulative returns in USD. The downside of this strategy is that if the value of Bitcoin depreciates in USD, the strategy's cumulative returns in USD decrease as well. However, as the BTC approach accumulates more Bitcoin over time, downside risk is limited as more Bitcoin is acquired (and held) in the portfolio.

It should be noted that the used dataset is a fairly small dataset, which is why the findings might be the result of data mining. I find that the results strongly depend on how the factor portfolios are constructed. Because of this, the threshold to consider a strategy to be working, should be higher than usual, as is being argued by Harvey, Liu and Zhu (2016). They state that the minimum t-statistic for a new factor should be at least 3.0. If that threshold would be applied to the results of this thesis, only one strategy would pass, namely size (BTC approach, equal weighted).

No evidence has been found to support the claim that the cryptocurrency market has become more efficient. Factor investing strategies generate significant alpha, meaning that the market (the benchmark) can still be outperformed.

6.2 Limitations of Research and Suggestions for Future Research

Factor investing is, due to the frequent rebalancing of the portfolio, costly for the investor. This thesis does not consider transaction costs, which on average are 10 basis points per trade (for makers and takers). Hence, in practice, it would be harder to outperform the benchmark. Also, does this thesis not consider spillage costs, which depend on liquidity. Even though the dataset consists of high-volume cryptocurrencies, liquidity might not always be present in the orderbooks of some cryptocurrency pairs and thus, in practice, it might be costly to enter large positions. Also, does this thesis not consider the costs of moving the funds of the portfolio from an exchange to another exchange. For instance, the strategy could rebalance the portfolio towards a different cryptocurrency exchange (as not all cryptocurrencies are available on every exchange). This would lead to withdrawal costs, which are roughly 0.0005 Bitcoin per withdrawal (depositing cryptocurrency is free). Also, on-chain transactions could be performed, which are costly as well. Another limitation of this research is that only cross-sectional portfolios are considered. It would be interesting to consider time series strategies, as this could very well lead to different results.

Another limitation of this research is the absence of the risk-free rate for the BTC approach. Traders aiming to trade for more Bitcoin do not have risk-free possibilities to acquire more Bitcoin. Hence, in this thesis, the risk-free rate is assumed to be zero. In future research, possibly the lending rate of (ideally large) cryptocurrency exchanges can be used instead. Even though cryptocurrency exchanges are definitely not risk-free, it remains interesting to implement the lending rates instead, to furtherly examine the effects of having a different than usual valuation reference of the investment portfolio.

Regarding the constructed factors, all factors can be constructed differently and this would in turn lead to different results. Because of this, it would be interesting to explore the field of value in the cryptocurrency market more. In this thesis, the MVRV-ratio is implemented to understand whether this strategy outperforms the market. In future research, adding a variable on miner revenues in the value factor could lead to a better understanding of the effect miners have on the price of Bitcoin.

References

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and Momentum Everywhere. *The Journal of Finance, 68*(3), 929-985.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of Investor Sentiment. *Journal of Financial Economics, 49*(3), 307-343.

Bariviera, A. F. (2017). The inefficiency of Bitcoin revisited: A dynamic approach. *Economic Letters, 161*, 1-4.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions & Money, 54*(C), 177-189.

Bender, J., Briand, R., Melas, D., & Subramanian, R. A. (2013). *Foundations of Factor Investing.* MSCI Index Research.

Binance. (2019, February 20). *Binance Launches DEX Testnet for the New Era of Peer-to-Peer Cryptocurrency Trading*. Retrieved April 2019, from Binance: https://www.binance.com/en/blog/304867000443084800/Binance-Launches-DEX-Testnet-for-the-New-Era-of-PeertoPeer-Cryptocurrency-Trading

Blitz, D. C., & Van Vliet, P. (2007). The Volatility Effect: Lower Risk without Lower Return. *The Journal of Portfolio Management, 34*(1), 102-113.

Caporale, G. M., & Plastun, A. (2018). The Day of the Week Effect in the Cryptocurrency Market. *Finance Research Letters*, 1-12.

Caporale, G. M., Gil-Alana, L., & Plastun, A. (2018). Persistence in the Cryptocurrency Market. *Research in International Business and Finance*, *46*, 141-148.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance, 52*(1), 57-82.

Coingecko. (2019, May 5). *Cryptocurrency Exchanges by Trading Volume (Spot)*. Retrieved May 2019, from Coingecko: https://www.coingecko.com/en/exchanges

Coinmarketcap. (2019, May 5). *Top 100 Cryptocurrency Exchanges by Trade Volume*. Retrieved May 2019, from Coinmarketcap: https://coinmarketcap.com/

Daniel, K., & Titman, S. (2006). Market Reactions to Tangible and Intangible Information. *The Journal of Finance, 61*(4), 1605-1643.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. *The Journal of Political Economy, 98*(4), 703-738.

Elendner, H., Trimborn, S., Ong, B., & Lee, T. M. (2016, October). *The cross-section of crypto-currencies as financial assets: An overview.* Retrieved from ResearchGate: https://www.researchgate.net/publication/318521916_The_Cross-Section_of_Crypto-Currencies_as_Financial_Assets_An_Overview

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance, 25*(2), 383-417.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance, 47*(2), 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56.

Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy, 81*(3), 607-636.

Frazzini, A., & Pedersen, L. H. (2014). Betting Against Beta. *Journal of Financial Economics, 111*(1), 1-25.

Gunay, S. (2019, June). Impact of Public Information Arrivals on Cryptocurrency Market: A Case of Twitter Posts on Ripple. *East Asian Economic Review, 23*(2), 149-168.

Harvey, C. R., Liu, Y., & Zhu, H. (2016). ... and the Cross-Section of Expected Returns. *The Review of Financial Studies, 29*(1), 5-68.

Houweling, P., & Van Zundert, J. (2017). Factor Investing in the Corporate Bond Market. *Financial Analysts Journal, 73*(2), 1-49.

Hubrich, S. (2017). 'Know When to Hodl 'Em, Know When to Fodl 'Em': An Investigation of Factor Based Investing in the Cryptocurrency Space. *SSRN Electronic Journal*.

Jegadeesh, N. (1990). Evidence of Predictable Behavior of Security Returns. *The Journal of Finance, 45*(3), 881-898.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance, 48*(1), 65-91.

Jensen, M. C. (1968). The Performance of Mutual Funds in the Period 1945-1964. *The Journal of Finance, 23*(2), 389-416.

Kalichkin, D. (2018, February 4). *Rethinking Network Value to Transactions (NVT) Ratio.* Retrieved from Medium: https://medium.com/cryptolab/https-medium-com-kalichkin-rethinking-nvt-ratio-2cf810df0ab0

Kurihara, Y., & Fukushima, A. (2017). The Market Efficiency of Bitcoin: A Weekly Anomaly Perspective. *Journal of Applied Finance & Banking, 7*(3), 57-64.

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics, 47*(1), 13-37.

Mahmudov, M., & Puell, D. (2018, October 2). *Bitcoin Market-Value-to-Realized-Value (MVRV) Ratio*. Retrieved from Medium: https://medium.com/adaptivecapital/bitcoin-market-value-to-realized-value-mvrv-ratio-3ebc914dbaee

Mayer, T. (2019, June 6). *Mayer Multiple*. Retrieved from https://mayermultiple.info

Moskowitz, T. J., Ooi, H. Y., & Pedersen, L. H. (2012). Time Series Momentum. *Journal of Financial Economics, 104,* 228-250.

Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica, 34*(4), 768-783.

Nakamoto, S. (2008). *Bitcoin: A Peer-to-Peer Electronic Cash System.* Satoshi Nakamoto.

Newey, W. K., & West, K. D. (1986). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *NBER Technical Paper Series*, 1-12.

Nielson, D., Nielsen, F., & Barnes, B. (2018). *An overview of factor investing.* Fidelity Investments Canada ULC.

Osterrieder, J., Lorenz, J., & Strika, M. (2017). Bitcoin and Cryptocurrencies — Not for the Faint-Hearted. *International Finance and Banking, 4*(1), 56-94.

Porta, R. L., Lakonishok, J., Shleifer, A., & Vishny, R. (1997). Good News for Value Stocks: Further Evidence on Market Efficiency. *The Journal of Finance, 52*(2), 859-874.

Rabener, N. (2017). *Quant Strategies in the Cryptocurrency Space: Factor Investing in the Wild West of Financial Markets*. Retrieved from FactorResearch: https://www.factorresearch.com/research-quant-strategies-in-the-cryptocurrency-space

Rohrbach, J., Suremann, S., & Osterrieder, J. (2017). Momentum and Trend Following Trading Strategies for Currencies Revisited - Combining Academia and Industry. *International Finance eJournal, 9*(72), 1-22.

Ross, S. A. (1976). The Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory, 13*(3), 341-360.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance, 19*(3), 425-442.

Shleifer, A., & Vishny, R. W. (1997). The Limits of Arbitrage. *The Journal of Finance, 52*(1), 35-55.

Treynor, J. L. (1961). Market Value, Time, and Risk. Unpublished manuscript dated 8/8/61, No. 95-209.

Treynor, J. L. (1962). Toward a Theory of Market Value of Risky Assets. Unpublished manuscript.

Urquhart, A. (2016). The Inefficiency of Bitcoin. *Economic Letters, 148*(C), 80-82.

Wang, S., & Vergne, J. P. (2017). Buzz Factor or Innovation Potential: What Explains Cryptocurrencies' Returns? *PloS one, 12*(1), e0169556.

Woo, W. (2017, September 29). *Is Bitcoin In A Bubble? Check The NVT Ratio.* Retrieved from Forbes: https://www.forbes.com/sites/wwoo/2017/09/29/is-bitcoin-in-a-bubble-check-the-nvt-ratio/#af3a68b6a23f

Yang, H. (2018, December 12). Behavioral Anomalies in Cryptocurrency Markets. *SSRN Electronic Journal*. Retrieved from SSRN: https://ssrn.com/abstract=3174421

Zhang, W., Wang, P., Li, X., & Shen, D. (2018). The inefficiency of cryptocurrency and its cross-correlation with Dow Jones Industrial Average. *Physica A, 510*(C), 658-670.

Appendix 1: Overview Dataset

Table 5: Overview of cryptocurrencies in the dataset

The table below reports all used cryptocurrencies and their symbols. The underlined cryptocurrencies are the cryptocurrencies that have data available on the MVRV-ratio to construct the value factor.

	Name	Symbol		Name	Symbol		Name	Symbol
1	Bitcoin	BTC	**31**	DigixDAO	DGD	**61**	Bitcoin Gold	BTG
2	Bitcoin Cash	BCH	**32**	Steem	STEEM	**62**	ICON	ICX
3	Cardano	ADA	**33**	Siacoin	SC	**63**	NANO	NANO
4	EOS	EOS	**34**	Decred	DCR	**64**	KuCoin Shares	KCS
5	Ethereum	ETH	**35**	Ethereum Classic	ETC	**65**	Loopring	LRC
6	Litecoin	LTC	**36**	Waves	WAVES	**66**	Dentacoin	DCN
7	Tron	TRX	**37**	LBRYCredits	LBC	**67**	Waltconchain	WTC
8	Ripple	XRP	**38**	Ren	REN	**68**	Substratum	SUB
9	Peercoin	PPC	**39**	Zcash	ZEC	**69**	Zilliqa	ZIL
10	Namecoin	NMC	**40**	Ardor	ARDR	**70**	Ontology	ONT
11	Feathercoin	FTC	**41**	Komodo	KMD	**71**	Pundi X	NPXS
12	Novacoin	NVC	**42**	Stratis	STRAT	**72**	Storm	STORM
13	Primecoin	XPM	**43**	NEO	NEO	**73**	Bitcoin SV	BSV
14	Dogecoin	DOGE	**44**	Viacoin	VIA	**74**	Maker	MKR
15	Nxt	NXT	**45**	IOTA	MIOTA	**75**	Tezos	XTZ
16	Counterparty	XCP	**46**	Golem	GNT	**76**	Bitcoin Diamond	BCD
17	Vertcoin	VTC	**47**	Basic Attention Token	BAT	**77**	IOST	IOST
18	Dash	DASH	**48**	Veritaseum	VERI	**78**	Wanchain	WAN
19	Reddcoin	RDD	**49**	Ubiq	UBQ	**79**	Huobi Token	HT
20	Digibyte	DGB	**50**	Ark	ARK	**80**	Ravencoin	RVN
21	MaidSafeCoin	MAID	**51**	Verge	XVG	**81**	Bibox Token	BIX
22	Bytecoin	BCN	**52**	Zcoin	XZC	**82**	Cosmos	ATOM
23	Vericoin	VRC	**53**	Qtum	QTUM	**83**	Holo	HOT
24	Monero	XMR	**54**	OmiseGO	OMG	**84**	BitTorrent	BTT
25	Bitshares	BTS	**55**	Metal	MTL	**85**	Aelf	ELF
26	Stellar	XLM	**56**	Binance Coin	BNB	**86**	Enigma	ENG
27	Nem	XEM	**57**	Bancor	BNT			
28	Factom	FCT	**58**	0x	ZRX			
29	Syscoin	SYS	**59**	Chainlink	LINK			
30	Lisk	LSK	**60**	VeChain	VET			

Appendix 2: Descriptive Statistics

Table 6: Descriptive Statistics

The table below reports basic descriptive statistics on weekly returns of the cryptocurrencies used in the dataset.

	Bitcoin	**Bitcoin Cash**	**Cardano**	**EOS**	**Ethereum**	**Litecoin**	**Tron**	**Ripple**
First observation	28/04/2013	02/08/2017	18/10/2017	09/07/2017	07/08/2015	28/04/2013	09/11/2017	04/08/2013
N	329	107	96	110	210	329	93	315
Mean	2.0%	3.7%	5.4%	3.6%	4.4%	2.5%	12.3%	4.1%
Standard deviation	12.5%	29.9%	46.1%	25.9%	22.2%	20.7%	86.0%	31.2%
Median	0.9%	-0.2%	-2.9%	-0.5%	0.5%	-0.1%	-0.1%	-0.6%
Max	70.6%	152.3%	341.9%	109.7%	134.8%	188.4%	734.7%	326.7%
Min	-41.8%	-53.7%	-36.6%	-38.2%	-34.9%	-46.7%	-55.3%	-45.1%
Return skewness	0.88	2.44	5.43	1.91	2.21	3.34	7.02	5.36
Return kurtosis	6.62	11.33	36.89	8.06	12.41	24.77	56.69	46.43
	Peercoin	**Namecoin**	**Feathercoin**	**Novacoin**	**Primecoin**	**Dogecoin**	**Nxt**	**Counterparty**
First observation	28/04/2013	28/04/2013	03/05/2013	28/04/2013	11/07/2013	15/12/2013	04/12/2013	15/02/2014
N	329	329	328	319	318	296	297	287
Mean	1.9%	2.1%	3.7%	2.5%	4.6%	3.8%	3.5%	2.3%
Standard deviation	21.8%	28.2%	39.5%	37.1%	47.0%	38.1%	29.7%	26.7%
Median	-1.1%	-1.0%	-3.2%	-2.0%	-3.0%	-0.9%	-2.1%	-0.9%
Max	178.4%	344.4%	360.3%	514.8%	537.8%	536.5%	206.5%	219.7%
Min	-51.7%	-55.0%	-73.1%	-86.3%	-49.4%	-47.5%	-59.7%	-50.5%
Return skewness	2.89	7.03	4.47	9.03	7.13	9.77	3.18	2.98
Return kurtosis	19.96	78.27	32.86	118.45	69.14	131.94	17.72	21.62
	Vertcoin	**Dash**	**Reddcoin**	**Digibyte**	**MaidSafeCoin**	**Bytecoin**	**Vericoin**	**Monero**
First observation	20/01/2014	14/02/2014	10/02/2014	06/02/2014	28/04/2014	17/06/2014	16/05/2014	21/05/2014
N	291	287	288	288	275	270	274	273
Mean	8.0%	3.5%	5.6%	5.9%	1.8%	4.6%	12.2%	3.2%
Standard deviation	71.9%	22.1%	37.3%	46.5%	15.6%	38.5%	147.5%	20.9%
Median	-2.8%	-0.4%	-1.2%	-1.8%	1.2%	-0.4%	-1.1%	0.6%
Max	900.7%	152.8%	305.9%	542.6%	55.3%	421.1%	2388.5%	138.8%
Min	-62.8%	-48.1%	-44.3%	-50.2%	-43.2%	-40.2%	-53.9%	-53.6%
Return skewness	8.80	2.38	4.08	6.88	0.29	6.49	15.37	2.05
Return kurtosis	98.32	13.59	28.79	70.69	3.80	63.01	247.81	11.76

Table 6 ***(continued)***

	Bitshares	Stellar	Nem	Factom	Syscoin	Lisk	DigixDAO	Steem
First observation	21/07/2014	06/08/2014	01/04/2015	06/10/2015	20/08/2014	06/04/2016	18/04/2016	18/04/2016
N	263	262	229	202	260	172	174	174
Mean	3.7%	4.6%	4.6%	4.3%	4.2%	2.4%	1.5%	8.2%
Standard deviation	32.3%	34.5%	23.6%	31.1%	29.4%	26.2%	18.9%	92.7%
Median	-1.5%	-1.4%	0.5%	-1.4%	0.3%	-1.5%	0.3%	-4.5%
Max	257.6%	333.1%	128.5%	324.7%	240.7%	163.4%	60.2%	1155.7%
Min	-46.7%	-76.3%	-38.5%	-48.8%	-56.9%	-78.8%	-65.1%	-53.4%
Return skewness	4.36	5.64	1.89	5.92	2.96	2.06	0.35	11.04
Return kurtosis	30.78	48.73	8.08	58.47	20.80	12.95	4.33	136.68

	Siacoin	Decred	Ethereum Classic	Waves	LBRYCredits	Ren	Zcash	Ardor
First observation	26/08/2015	10/02/2016	24/07/2016	02/06/2016	07/07/2016	02/03/2018	29/10/2016	23/07/2016
N	208	184	160	168	163	77	146	149
Mean	5.9%	3.7%	2.6%	2.6%	1.9%	2.1%	0.4%	3.2%
Standard deviation	35.6%	22.0%	19.7%	23.2%	32.6%	20.3%	21.2%	23.8%
Median	-0.6%	0.2%	-0.2%	-0.3%	-1.5%	-0.3%	-2.2%	1.8%
Max	245.5%	114.6%	115.4%	128.0%	180.6%	66.0%	76.6%	116.3%
Min	-44.6%	-44.2%	-35.1%	-80.2%	-61.1%	-39.2%	-74.2%	-50.6%
Return skewness	3.31	1.59	1.74	1.40	2.11	0.57	0.57	1.29
Return kurtosis	18.15	7.31	9.64	9.27	10.50	3.23	5.67	7.05

	Komodo	Stratis	NEO	Viacoin	IOTA	Golem	Basic Attention Token	Veritaseum
First observation	05/02/2017	12/08/2016	09/09/2016	18/07/2014	14/06/2017	18/11/2016	08/06/2017	18/06/2017
N	132	157	153	265	114	143	115	113
Mean	4.8%	5.4%	5.5%	3.3%	2.6%	3.9%	1.9%	1.4%
Standard deviation	29.7%	32.3%	29.4%	25.7%	30.4%	25.5%	20.4%	29.2%
Median	0.5%	0.5%	0.3%	0.9%	-0.8%	0.6%	1.1%	-4.2%
Max	157.5%	244.4%	166.7%	109.3%	223.1%	116.7%	78.8%	122.4%
Min	-50.2%	-38.4%	-51.4%	-58.1%	-46.2%	-44.1%	-33.2%	-52.1%
Return skewness	2.54	3.33	2.13	1.06	3.76	1.40	1.06	1.71
Return kurtosis	12.62	22.27	10.38	5.51	26.04	7.03	4.88	7.26

Table 6 *(continued)*

	Ubiq	Ark	Verge	Zcoin	Qtum	OmiseGO	Metal	Binance Coin
First observation	07/09/2014	22/03/2017	25/10/2014	06/10/2016	14/06/2017	16/07/2017	15/07/2017	16/09/2017
N	253	126	248	150	114	109	110	101
Mean	4.6%	4.2%	9.5%	10.9%	1.6%	2.7%	0.9%	37.7%
Standard deviation	29.4%	32.0%	53.7%	92.5%	26.5%	25.8%	24.0%	336.6%
Median	-0.1%	-0.7%	-1.0%	0.4%	-1.0%	0.2%	-1.6%	1.3%
Max	237.6%	219.4%	472.7%	1083.6%	141.8%	181.4%	116.9%	3378.6%
Min	-51.5%	-42.7%	-63.7%	-54.8%	-43.9%	-43.8%	-42.9%	-52.6%
Return skewness	3.03	3.31	4.75	10.51	2.03	3.41	1.42	9.83
Return kurtosis	20.36	20.10	34.41	122.13	10.39	23.15	7.55	98.05
	Bancor	**0x**	**Chainlink**	**VeChain**	**Bitcoin Gold**	**ICON**	**NANO**	**KuCoin Shares**
First observation	27/06/2017	17/10/2017	09/11/2017	18/11/2017	18/11/2017	28/10/2017	15/07/2017	08/11/2017
N	112	96	93	89	93	95	110	93
Mean	-0.4%	1.7%	5.3%	-0.8%	-1.0%	2.7%	9.3%	7.3%
Standard deviation	16.4%	20.0%	25.2%	22.1%	24.7%	30.6%	50.5%	57.7%
Median	0.1%	-0.5%	0.8%	-2.2%	-0.7%	-3.4%	0.2%	-2.1%
Max	52.5%	77.3%	108.0%	64.9%	160.9%	194.1%	354.8%	417.6%
Min	-34.6%	-34.2%	-41.1%	-98.6%	-67.9%	-44.8%	-43.0%	-39.9%
Return skewness	0.38	0.92	1.52	-0.42	2.88	2.92	4.46	5.68
Return kurtosis	3.39	4.62	6.56	7.02	21.50	17.96	26.95	37.79
	Loopring	**Dentacoin**	**Waltconchain**	**Substratum**	**Zilliqa**	**Ontology**	**Pundi X**	**Storm**
First observation	30/10/2017	29/10/2017	08/11/2017	19/11/2017	11/02/2018	23/3/2018	24/3/2018	04/01/2018
N	94	94	93	91	80	74	74	85
Mean	1.1%	10.5%	1.1%	-0.3%	-0.5%	1.4%	3.0%	-2.1%
Standard deviation	26.1%	98.4%	23.8%	25.9%	18.7%	22.6%	40.6%	27.4%
Median	-0.9%	-4.8%	-1.5%	-4.4%	-0.5%	-2.0%	-1.1%	-2.3%
Max	147.9%	875.5%	89.2%	132.4%	59.9%	82.4%	301.2%	174.0%
Min	-39.8%	-56.4%	-44.8%	-50.7%	-44.4%	-35.4%	-45.9%	-47.8%
Return skewness	2.35	7.54	1.32	1.89	0.56	1.34	5.53	3.18
Return kurtosis	13.10	65.36	5.56	9.81	3.89	5.71	40.83	21.68

Table 6 *(continued)*

	Bitcoin SV	Maker	Tezos	Bitcoin Diamond	IOST	Wanchain	Huobi Token	Ravencoin
First observation	10/11/2018	20/12/2017	28/10/2017	03/12/2017	23/01/2018	26/03/2018	09/02/2018	21/03/2018
N	41	87	95	89	82	73	80	74
Mean	4.4%	0.3%	1.9%	6.6%	-0.5%	-0.7%	2.4%	3.1%
Standard deviation	27.1%	14.8%	22.4%	64.1%	20.1%	21.5%	14.8%	26.9%
Median	-1.1%	-0.1%	-2.0%	-1.0%	0.1%	-1.3%	1.0%	-5.1%
Max	78.2%	45.3%	76.3%	395.1%	65.2%	82.1%	63.5%	121.7%
Min	-54.7%	-41.7%	-58.2%	-80.3%	-47.7%	-42.7%	-29.2%	-39.9%
Return skewness	0.90	0.31	0.83	3.86	0.24	1.03	1.00	2.08
Return kurtosis	3.96	3.95	4.83	20.97	4.09	5.48	5.80	8.95
	Bibox Token	**Cosmos**	**Holo**	**BitTorrent**	**Aelf**	**Enigma**		
First observation	23/01/2018	22/02/2019	30/04/2018	01/02/2019	07/01/2018	08/11/2017		
N	82	26	68	29	85	93		
Mean	-0.5%	1.9%	1.3%	1.8%	-2.1%	2.6%		
Standard deviation	19.7%	22.4%	24.1%	19.5%	18.6%	26.3%		
Median	-2.5%	-1.6%	-2.7%	-2.1%	-1.1%	-0.3%		
Max	57.3%	55.5%	110.9%	61.7%	54.7%	124.8%		
Min	-34.4%	-35.4%	-42.8%	-30.4%	-47.1%	-35.5%		
Return skewness	0.80	0.56	1.80	1.29	0.18	2.14		
Return kurtosis	3.66	2.72	8.87	5.20	3.28	10.29		

Appendix 3: Results of all Portfolio Regressions

Table 7: Results Tercile Portfolio Regressions (Annualized)

The table below reports the (annualized) results of the tercile portfolio regressions. The dataset consists of 86 cryptocurrencies, with valuations in USD and BTC. Portfolios are rebalanced at a weekly rate. The tercile portfolios of the factors are used as the dependent and the market is used as the independent variable (equal weighted and value weighted). To account for autocorrelation and heteroskedasticity, Newey and West (1986) standard errors are used. Using the mean and the standard deviation of the factor portfolios, the Sharpe ratio is calculated. For the BTC approach, a risk-return ratio is calculated, using the mean and the standard deviation of the portfolios. The regressions yield alpha (with a t-statistic) and a beta. Because Newey and West standard errors are used, no R-squared from the regressions can be calculated. The dataset ranges from April 2014 to August 2019. The results are annualized from weekly results.

	USD Approach											
	Equal Weighted						Value Weighted					
	Mean	**StDev**	**Sharpe**	**Alpha**	**Tstat**	**Beta**	**Mean**	**StDev**	**Sharpe**	**Alpha**	**Tstat**	**Beta**
MomP1	343%	256%	1.34	-37%	-1.08	1.30***	259%	244%	1.06	62%	0.91	1.18***
MomP2	185%	138%	1.33	-23%	-0.96	0.71***	147%	218%	0.67	-40%	-0.80	1.12***
MomP3	349%	220%	1.59	61%*	1.67	0.99***	144%	191%	0.75	-34%	-0.81	1.06***
SizeP1	500%	40%	12.37	80%**	1.96	1.44***	640%	455%	1.41	424%***	2.70	1.28***
SizeP2	249%	161%	1.55	-27%	-1.04	0.95***	335%	252%	1.33	137%*	1.68	1.19***
SizeP3	114%	112%	1.02	-43%*	-1.67	0.54***	224%	190%	1.18	61%	0.91	0.97***
ValueP1	139%	144%	0.96	-54%*	-1.89	0.66***	187%	173%	1.08	15%	0.31	1.03***
ValueP2	138%	136%	1.02	24%	0.45	0.39***	85%	123%	0.69	-109%***	-2.88	0.93***
ValueP3	179%	139%	1.29	80%	1.20	0.34***	36%	125%	0.29	-95%**	-2.53	0.96***

	BTC Approach											
	Equal Weighted						Value Weighted					
	Mean	**StDev**	**R/R**	**Alpha**	**Tstat**	**Beta**	**Mean**	**StDev**	**R/R**	**Alpha**	**Tstat**	**Beta**
MomP1	236%	141%	1.68	86%***	2.88	0.89***	261%	296%	0.88	168%	1.49	1.70**
MomP2	48%	102%	0.47	-59.8%**	-2.51	0.64***	63%	167%	0.38	-30%	-0.59	1.71**
MomP3	244%	246%	0.99	-33.86%	-0.80	1.65***	73%	114%	0.64	1%	0.04	1.31***
SizeP1	346%	195%	1.78	143%***	3.65	1.21***	441%	333%	1.33	378%***	2.72	1.18***
SizeP2	134%	183%	0.73	-75.4%**	-2.31	1.24***	229%	207%	1.11	112%	1.55	2.16***
SizeP3	16%	81%	0.19	-57.7%***	-2.58	0.43***	184%	221%	0.83	97%	1.16	1.61***
ValueP1	34%	118%	0.28	-66.6%**	-2.20	0.59***	80%	131%	0.61	-3%	-0.08	1.52***
ValueP2	1%	89%	0.01	-30.9%	-0.86	0.19*	-27%	146%	-0.18	-99%	-1.45	0.87***
ValueP3	115%	131%	0.88	95.2%	1.48	0.12	18%	140%	0.13	-47%	-0.93	1.05***

Appendix 4: Descriptive Statistics Risk-Free Rate

Table 8: Descriptive Statistics Risk-Free Rate
The table below reports the descriptive statistics of the (weekly) risk-free rate used in this thesis. The risk-free rate is based on the 4-Week Treasury Bill rate, retrieved from FRED (Federal Reserve Bank of St. Louis). As this rate is annualized, the rate is divided by 52 to get the weekly risk-free rate. The dataset is from April 2013 to August 2019.

	N	**Mean**	**StDev**	**Kurtosis**	**Skewness**
Risk-Free Rate	330	0.0136%	0.0161%	2.26	0.91