Master Dissertation
Testing Explanatory Risk Factors for Cryptocurrency Returns

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August 29, 2019

Abstract

This empirical research project examines the construction and adaptation of common risk factors on cryptocurrency returns. The theoretical framework of this research will be based on the Fama and French (1992) and Fama and French (2015) models. The goal of this project is to identify explanatory risk factors within the cryptocurrency realm, which show significance in explaining the return behaviour of a number of selected cryptocurrencies. Apart from the Fama and French (1992) 'three factor' and Fama and French (2015) 'five factor' models, the most recent research conducted on this topic is tested and used to implement a competent factor selection and construction. In essence this research aims at identifying specific explanatory risk factors for individual cryptocurrencies by merging the traditional *Fama and French* factor models with the most recent findings in this area of research based on cryptocurrencies.

Word count: 7.938

Keywords: Bitcoin, Cryptocurrency, Linear Regression, Fama and French Factor Model, Risk Factors.

JEL classification: C22, C5, E42, F31, G1, G2

1 Introduction

The focus of this research project is to identify statistically significant risk factors, which are able to explain the behaviour of cryptocurrency returns. The research commenced by identifying the influence of a number of statistically proven risk factors, which are taken from the Fama and French (1992) and Fama and French (2015) papers on common risk factors within equity returns, and then applied to cryptocurrencies.

Furthermore, research papers on the topic of common risk factors within cryptocurrency returns are observed. There is a number of research papers on this topic found on the internet. Most of which however offer contradictory results to other research conducted. Therefore, this project aims at shining a brighter light upon discovered risk factors found within this area of research and testing their significance. The exact methodology is discussed in detail within Section 4, however the general approach will be to strictly exclude factors which only show independent significance, as also factors which are only significant in combination with other factors. Hence, only truly significant factors are displayed in the results in Section 5. This enables a closer look at the strengths and weaknesses of the most recently conducted research in this area.

There are seven sections in this project. Section 1 offers a general introduction to the focus and aim of this research. The individual sections are summarized as follows. Section 2 gives an in-depth summary of the most influential literature regarding this project. The key findings of the Fama and French 1992 and 2015 papers are discussed and summarized. In addition, the main influences regarding the general procedure, methodology and factor construction based on the most recent research papers are discussed and elaborated on in detail. Section 3 describes the data used in this paper and the sources from which the data is taken. Thereafter, the key assumptions regarding the data are discussed and possible limitations within the data sets and sources are exposed. Specific attention is paid to the data gathered from the market indices CCi30 and CRIX to enable a clear understanding of the methodology and construction used for both indices. Section 4 illustrates the adaptation of the methodology and inspiration gathered from Section 2. A detailed explanation of the procedure, methodology and factor construction is discussed, after which the results for every individual factor are presented and evaluated in section 5. Section 5 interprets the general findings and discusses multicollinearity issues that might arise based on the factor construction. In Section 6 the main findings are summarized. Critically evaluating the main shortcomings within the factor construction and lessons learned from Sections 2 and 4. The implications regarding further research are discussed in Section 7, which also concludes the project. All in all this project aims at identifying the key findings and short-comings of the best practices of finding explanatory risk factors within cryptocurrency returns and attempting to give a competent summary of the key concepts and adaptations.

2 Literature Review

This research was initiated by looking at Eugene F. Fama and Kenneth R. French's *"The Cross-Section of Expected Stock Returns"* (Fama and French, 1992) since it still offers one of the most relevant approaches towards identifying common risk factors within equity returns. Although the paper primarily focuses on risk factors within equity returns only, it is still by far the best source of inspiration for an initial starting point in identifying common risk factors within individual cryptocurrencies. Fama and French (1992) based their research on the Capital Asset Pricing model $E[r_i] = r_f + \beta(r_m - r_f)$ and its approach of associating the behaviour of excess equity returns $E[r_i]$–r_f to a specific excess return on a market portfolio r_m–r_f (where r_i represents the return on stock i, r_m is the market return and r_f the risk free rate). The ground breaking discovery here was the identification of the two additional risk factors to the market factor. Resulting in a model comprising a market factor, a size factor and a growth / value factor with the ability to explain the majority of the behaviour within excess equity returns. Even by today's standards there rarely is a model, which manages to beat the Fama and French (1992) three factor models' explanatory power. Although the model seems to only incorporate three factors the actual factor construction is not as straight-forward as one might assume. The size factor, often referred to as SMB (Small-minus-Big) is based on the observation, that small market capitalization stocks tend to outperform big market capitalization stocks. The growth / value factor on the other hand referred to as HML (High-minus-Low) is associated with the return potential of what Fama and French (1992) call growth and value companies. In essence, the first part of their research paper is based on cross-sectional regressions, in which Fama and French (1992) identify the influence of the two newly discovered risk factors within equity returns. The second part of the paper follows the assumption of significance found by the cross-sectional regressions and applies these as a time series regression to prove that the factors stay significant throughout time.

In a later paper published in 2015, Fama and French (2015) identify another two additional factors for explaining excess equity returns, however also compromising the HML (High-Minus-Low) factor as can be seen from section 7 titled *"HML: a redundant factor"* (Fama and French, 2015). In essence the paper concludes that the initial three factor model proposed in 1992 has in fact still more explanatory power than any of the research building upon the three-factor model. That being said, the newly identified *Momentum* factor, following the believe that well preforming stocks will continue to outperform the market in the future, had shown very strong significance within equity returns.

Following the rise in popularity of cryptocurrencies was an increasing demand for information regarding economic indicators of such digital assets. It was not long until so called "cryptocurrency ranking websites" started emerging from the debts of the internet. Today a variety of cryptocurrency ranking websites can be found online, which all gather their information from a multitude of sources and use a variety of methodologies to construct factors like the market index factor used in the original *Captial Asset Pricing Model.* A paper written by Alexander and Dakos (2019) of the

University of Sussex, takes a closer look at the most widely used and voluminous ranking websites. Critically evaluating the key benefits and shortcomings of the individual approaches these ranking websites take to offer cryptocurrency data.

One of the main takeaways from Alexander and Dakos (2019) "A Critical Analysis of Crypto Data and Sources" for this research is the adjustment of the market index (CRIX) used within the final steps of the analysis. The methodology of how the construction and adjustment of the CRIX index is being handled is documented within *Section 3. Data* of this paper. An additional limitation of the main source of data used in this paper *www.coinmarketcap.com*, discussed within Alexander and Dakos paper is the multitude of sources *coinmarketcap* is using to gather its data. It is suggested that a perhaps narrower source of data streams would be more beneficial due to the complexity, which builds upon collecting all this necessary data (Alexander and Dakos, 2019). In consideration of this information no less than 4 years of cryptocurrency data was observed to account for potential mismatches of data coming from the various sources feeding into the *coinmarketcap.com* price data.

After finding a solid foundation for the explanatory factor creation within the work of Fama and French (1992) and Fama and French (2015) and identifying the limitations and potential pitfalls within the data in use by looking at Alexander and Dakos (2019) "A Critical Investigation of Cryptocurrency Data and Analysis". We decided to look at attempts to implement the Fama and French methodology to cryptocurrencies. Liu et al (2019) discovered a number of significant factors based on a weekly rebalancing, zero investment long-short strategy. In their paper Liu et al (2019) decide to look at the weekly significance of size, momentum, volume and volatility in explaining excess returns in cryptocurrencies. The results show that cryptocurrencies are indeed somewhat predictable using the fundamental factors initially suggested by Fama and French (1992). In their research Liu et al (2019) create various quintile portfolios, dividing the observed cryptocurrencies into portfolios sorted by one factor. They then observe the following weeks returns assuming a long-short zero investment strategy based on the previously constructed factor (Liu et al, 2019). The traditional size factor from Fama and French (1992) e.g. would result in five cryptocurrency portfolios, sorted by their market capitalization. First the cryptocurrencies would be sorted and later split according to the breaking points. The breaking points would simply be decided based on the number of cryptocurrencies available. If e.g. 50 cryptocurrecnies would be observed, each portfolio would consist of 10 cryptocurrencies. If however, the cryptocurrices would not be easily devisable one would include / exclude accordingly. There would be minor influence based on the inclusion or exclusion of a certain cryptocurrency within the portfolio. That being said Liu et al (2019) decide to only consider the upper and lower portfolios for their factor construction. Also the exact methodology is unfortunately not clearly displayed. Hence, for this research other papers were considered to get a better understanding of the factor construction.

A paper written by Armilis (2019) from the Warwick Business School titled "Are Cryptocurrencies' returns predictable?" discusses the implementation of cryptocurrency relevant risk factors and constructs a value, momentum and sentiment factor as a result. Armilis (2019) defines momentum as the strongest and most analysed of all the asset pricing anomalies within equity markets. Similar to the momentum factor found within Fama and French (2015) five factor model, the main principle of this factor is the believe that the past winners will continue winning in the future (Armilis, 2019). Armilis (2019) uses a 30-day estimation window for his momentum factor, however only decides on a 2-day holding period of his strategy. He justifies this by relating to the very volatile nature of the cryptoucurrency markets. Similar to the construction of the size factor within the Liu et al (2019) paper, (Armilis, 2019) assumes a zero investment long short portfolio trading strategy. Here the cryptocurrencies are ranked according to their cumulative return of the past month and divided into two: one long and one short portfolio. Different from the previous papers (Armilis, 2019) decides to distribute the weighs of the individual cryptocurrencies within the portfolios based on their rank within the factor. The high cumulative return cryptocurrencies of the past 30-days would so receive a higher weighting up until the median value. The median cryptocurrency would be excluded and the weightings would than proportionally be increased accordingly into the negative weights for the short portfolio. This approach does provide a good insight regarding the construction of the momentum factor.

Bianchi (2018) uses a random-coefficient panel regression model to investigate systematic correlations between cryptocurrencies and other asset classes. From his findings we can observe that cryptocurrencies seem to behave most similar to Gold and Energy than any other asset class. Bianchi (2018) tests for volatility spillover with traditional asset classes, finding high correlations between market capitalization and trading volume both within traditional asset classes and cryptocurrency markets.

3 Data

This section elaborates on the data used in this research project. Since cryptocurrencies are relatively new to the global market, it is still hard to classify them as an asset class, currency or other. Some call cryptocurrencies digital assets, some compare them to fiat currencies and others think the best comparison is found within commodities or gold (Bianchi, 2018). The main focus of this section is to identify the limitations of the data in use and the best way of handling such data. All of this is to ensure a competent implementation of the models in use.

3.1 Price and Return Data

Daily closing price data for a minimum of 4 years was downloaded from *www.coinmarketcap.com* using the API provided by the website. The daily closing prices are used to calculate daily log returns. 7-day averages are taken from the daily returns to proxy the weekly returns for every individual cryptocurrency. The data is standardized by de-meaning and dividing every daily return by the standard deviation for each times series vector.

Coinmarketcap.com is a leading source of cryptocurrency price and volume data. It sources information from over 200 major exchanges and provides daily data on opening, closing, high and low prices, as also volume and market capitalization. Coinmarketcap calculates the price of every cryptocurrency by taking the volume weighted average of the prices reported at each exchange (see 1 below). All cryptocurrencies need to meet specific criteria to be listed. They need to be traded on a public exchange with an API that reports the last traded price and the last 24-hour trading volume. They need to have a non-zero trading volume on at least one supported exchange so that a price can be determined. Due to the fact that coinmarketcap lists both active and inactive cryptocurrencies it has taken much critique recently. As Liu,Tsyvinski and Wu put it "...alleviating concerns about survivor-ship bias" (Liu et al, 2019).

$$Price_{i,t} = \sum_{i=0}^{N} \frac{VOL_{i,t-24h}}{\sum VOL_{i,t-24h}} * Price_{i,t} \tag{1}$$

As was observed by Alexander and Dakos (2019), cryptocurrencies trade on a 24h basis, hence the observed closing price data is based on the prices quoted on coinmarketcap.com every day at 23h:59m:59s. Following Alexander and Dakos (2019), coinmarketcap uses a multitude of sources to gather their price data. These sources do not operate within any regulatory boundary and therefore often quote various different prices for the same cryptocurrency. This leads to instability within the observed price data. The quoted prices will have a direct effect on other indicators like the individual cryptocurrency market capitalization. As Armilis (2019) points out coinmarketcap calculates the individual cryptocurriency market capitalisation as $log(Price) * CirculatingSupply$. To account for the mismatch in information the data used in this research will be no less than 4 years of daily price data.

The resulting cryptocurrencies for the time horizon of this reserach are Bitcoin (BTC), Ether (ETH), Ripple (XRP), Litecoin (LTC), Bitcoin Cash (BCH), EOS, Tether (USDT), Cardano (ADA), Stellar (XLM), DASH, NEO (NEO), IOTA (MIOTA), Ethereum Classic (ETC), NEM (XEM),Zcash (ZEC), Torque (XTZ), Bitcoin Gold (BTG), Dogecoin (DOGE), USD Coin (USDC), Decred (DCR), Aurora (AOA), Lisk (LSK), Bitcoin Dimond (BCD), Egretia (EGT) and HyperCash (HC). The descriptive statistics for all 26 USD and 25 BTC denominated cryptocurrencies can be found in Appendix A.

Figure 1 below shows a graphical comparison of all the 26 USD denominated cryptocurrency prices constructed into an equally weighted price index (left) and an equivalent index for the BTC denominated data (right). The correlation coefficient between the two indices is 0.875. Table 8 and Table 9 within Appendix B show the correlation matrix for the USD and BTC denominated cryptocurrency prices respectively. As can be seen there are considerably high correlations between the highest market capitalization cryptocurrecnies: BTC, ETH, XRP and LTC within both the USD and BTC denominated data. Various high correlations (above 0.7) can be found between the mid to low level market capitalization cryptocurrencies EOS, USDC, DCR, XMR, DASH and HC also. Cryptocurrencies seem to follow very similar behavioural patterns, which should to some extent enable an easier discovery of common explanatory risk factors. An in-depth analysis of the individual cryptocurrencies would potentially benefit the understanding of individual cryptocurrency

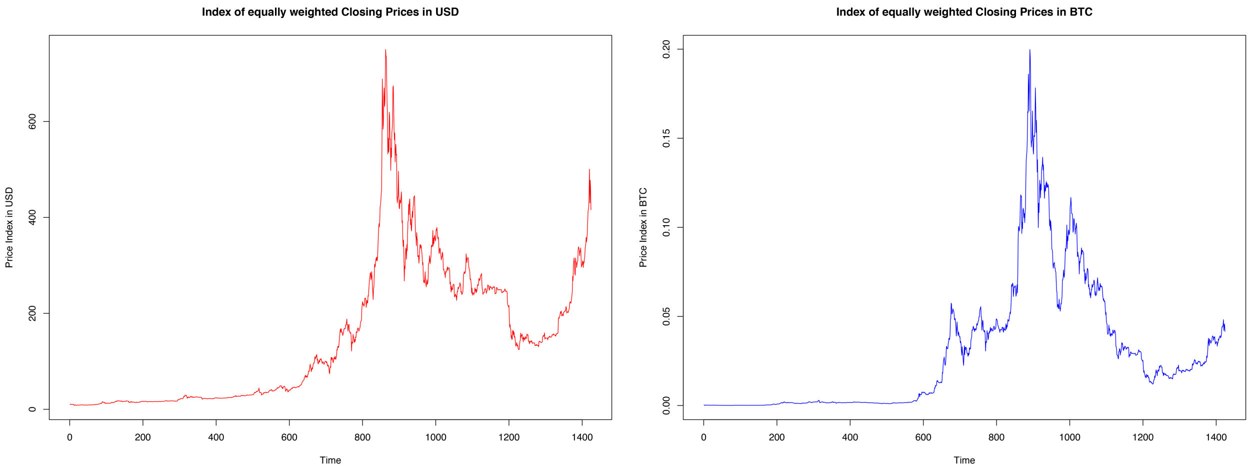

Figure 1: Showing a daily price index composed of equally weighted USD denominated prices (left) and BTC denominated prices (right). The correlation coefficient between the two sets of data is 0.875.

behaviours and help identify potential explanatory risk factors.

As discussed in Section 2, Bianchi (2018) discovered a very high correlations between market capitalization and trading volume within both traditional asset classes and later cryptocurrencies. Figure 2 shows this relationship between Bitcoins market capitalization and volume, taken from the observed data.

Considering the above observations based on the findings of Bianchi (2018) the correlations between volume and market capitalizations for all the 26 observed cryptocurrencies are tested. Table 1 below shows the cross correlations between volume and market capitalization for every individual one of the 26 cryptocurrencies.

Table 1: Showing Correlations between Volume and Market Capitalization of Cryptocurrencies

	BTC	ETH	XRP	LTC	BCH	EOS	USDT	ADA	XLM	XMR	DASH	NEO	MIOTA
Corr(Vol,MCAP)	0.73	0.43	0.73	0.52	0.32	0.64	-0.03	0.75	0.51	0.70	0.47	0.40	0.48
	ETC	XEM	ZEC	XTZ	BTG	DOGE	USDC	DCR	AOA	LSK	BCD	EGT	HC
Corr(Vol,MCAP)	0.06	0.61	0.08	0.50	0.49	0.69	0.33	0.12	0.82	0.13	0.10	0.72	0.65

This is important because it will inevitably influence the multicollinearity between the volume and size factors. Both factors are constructed according to the methodologies of Liu et al (2019) and Armilis (2019), using volume and market capitalization as the main input respectively.

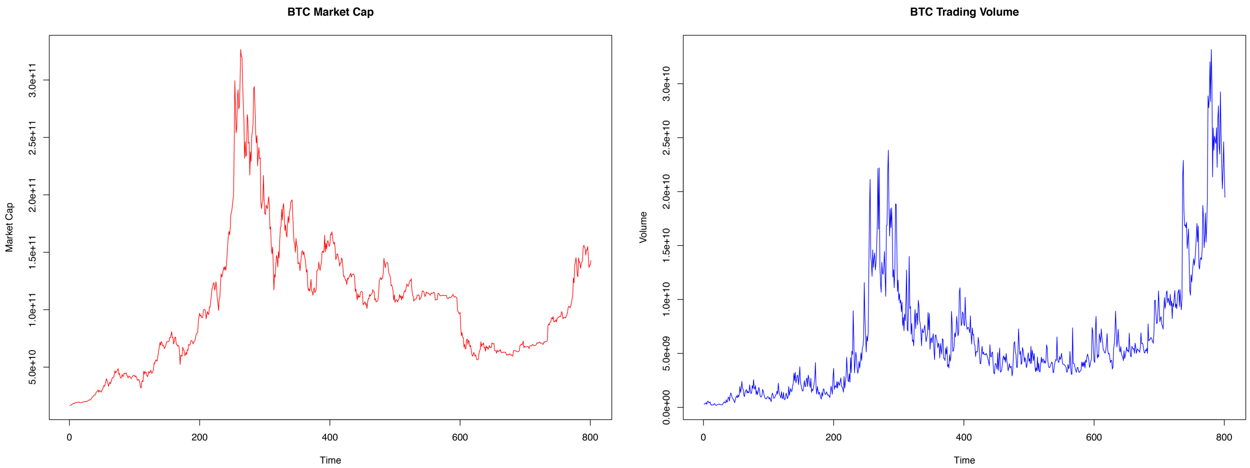

Figure 2: Showing daily Bitcoin Market Capitalization (left) and daily Bitcoin Trading Volume (right). The correlation coefficient between these two sets of data is 0.73.

3.2 Market Index Data

The first risk factor observed in the traditional Fama and French (1992) *three factor model* is the sensitivity to the market. As mentioned in Section 2, Fama and French (1992) base their three factor model on the *Capital Asset Pricing Model*, which is solely based on the market influence on the individual asset. There are various cryptocurrency market indices found on the internet. Following Alexander and Dakos (2019) the most popular and actively used cryptocurrency indices are the CRIX and the CCi30. In this research we first test each index separately and later in combination with additional factors. Alexander and Dakos (2019) suggest that the preferred index should be the CCi30, an index constructed on the basis of 30 market capitalization weighted cryptocurrencies. Alongside the CCi30 this research is also going to test the significance of the CRIX index. The CRIX is a market capitalisation weighted index of over 60 different cryptocurrencies calculated by the Humboldt University Berlin. The portfolio of cryptocurrencies is rebalanced on a 3-month basis, meaning that every 3 months the cryptocurrencies within the market capitalization weighted portfolio are observed and replaced based on their rank of market capitalization in the market (Trimborn and Härdle, 2019). As also mentioned by Alexander and Dakos (2019) the CRIX suffers from insufficiencies and needs to be adjusted from the 30th of January 2018. This is taken into account by lagging the CRIX index from the 30th of January 2018 onwards by one day. Up until the 29th of January 2018 the CRIX will be taken as observed. As already mentioed the CCi30 index is constructed on the basis of 30 different cryptocurrencies, weighted according to their market capitalization.

The CRIX index is based on the Laspeyres Index, which is calculated as follows:

$$INDEX_t^{Laspeyres} = \frac{\sum_i P_{i,t} Q_{i,0}}{\sum_i P_{i,0} Q_{i,0}} \quad (2)$$

where, $P_{i,t}$ is the cryptocurrency price for the individual cryptocurrecny i at time t. $Q_{i,0}$ the quantity of cryptocurrency i at time 0. The Laspeyres formula is adjusted by Trimborn and Härdle (2019) and results in:

$$INDEX_t^{CRIX} = \frac{\sum_i MV_{i,t}}{Divisor} \tag{3}$$

where, $MV_{i,t}$ is the market capitalization of the cryptocurrency i at time t and

$$Divisor = \frac{\sum MV_{i,0}}{1000} \tag{4}$$

(Trimborn and Härdle, 2019).

The CCi30 is rebalanced on a quarterly basis. It is re-weighted every month. Furthermore, it follows the following formula:

$$I(t) = \sum w_i \frac{P(t)}{P(T_0)} \tag{5}$$

where $P(t)$ is the individual cryptocurrency price at time t and w_i is the weight assign to cryptocurrency i. The weights w_i are assigned based on the market capitalization. The market capitalization is computed as an exponentially moving average of the individual market capitalization as follows:

$$M^*(T) = \frac{\sum_{i=0}^{\infty} M_{(T-i)} e^{(-\alpha i)}}{\sum_{i=0}^{\infty} e^{(-\alpha i)}} \tag{6}$$

where, $M(t)$ is the actual market capitalization of cryptocurrency i at time t and M^* is the adjusted market capitalization. α is a decay factor, due to the sum ranging from 0 to ∞. Any reasonable α will make the contribution corresponding to large values of i infinitely smaller (Rivin and Scevola, Rivin and Scevola). A plot of the CCi30 index for a observation window of 200 weeks can be seen in Figure 3. The average weekly returns were calculated based on the daily returns of the data provided by the CCi30 website.

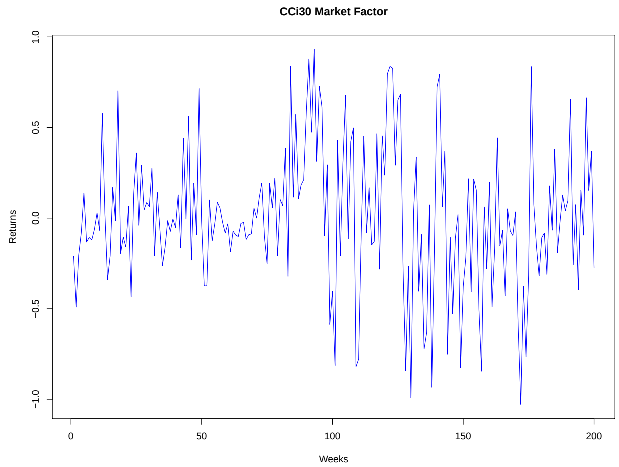

Figure 3: Showing the CCi30 Market Index Factor

4 Methodology and Factor Construction

Due to the high volatility within the cryptocurrency markets some of the returns on these digital assets heavily outweigh the risk free rate. The risk free rate can easily be found by taking the 10 year US Treasury Bond yield for the chosen observation window. This bond yield has been very close to zero in the past 5 years. Therefore, calculating the excess returns of the selected 4 year time horizon of cryptocurrency prices over the risk free rate becomes somewhat of a trivial exercise. We will be looking at pure cryptocurrency returns and focus on finding the statistical significant risk factors, explaining the extraordinarily volatile behaviour of the cryptocurrency market. The deduction of a risk free rate from these returns would be negligible.

All 26 USD and 25 BTC denominated cryptocurrency returns have been regressed on a constant and the constructed factors separately. After which robustness tests were conducted to test the stability of the individual factors in presence of other factors. Table 4 and Table 5 show the results and the significance levels of the individual factors in relation to the observed USD and BTC denominated cryptocurrency returns respectively. The t-statistic is reported in parenthesis below the individual β-estimate. The factor regression is based on linear regression and follows the usual form:

$$r_{i,t} = \alpha_i + \beta_i R_t + \epsilon_{i,t}, \tag{7}$$

where $r_{i,t}$ is the return on the individual cryptocurrency i at time t and R_t is the return on the constructed factor at time t.

4.1 Size Factor

As was mentioned in Section 2 the foundation for the factor construction was taken from the original Fama and French (1992) three factor model. The first factor to be constructed is the size factor, trying to capture the size anomaly behaviour of cryptocurrencies.

Based on the Fama and French (1992) paper, the general assumption would be that the low market capitalization cryptocurrecnies would outperform the high market capitalization cryptocurrencies. Building on this assumption the factor construction will be following Liu et al (2019) by constructing a weekly Small-minus-Big size factor. The only alteration being that the *average* market capitalization will be used for the observation period of one week.

Within the Fama and French (1992) paper the SMB factor is constructed by sorting the observed stocks according to their market capitalization and dividing these sorted stocks into ten different portfolios. Fama and French (1992) sub-sort the stocks within these ten-portfolios based on their regression betas calculated by the previous one-year excess return on the market. This however, will not be useful within the cryptocurrency markets, since cryptocurrency returns tend to be highly volatile. Another reason for not sub-sorting the cryptocurrencies within the size portfolios is the fact that there simply is not enough data on established cryptocurrencies. It could lead to false assumptions within the construction of the size factor when observing that in general "younger" cryptocurrencies tend to generate higher betas. The cryptocurrency beta tends to give a sort-term view on how the individual cryptocurrency is behaving relative to the market index, which is however also constructed based on various assumptions, which are discussed in detail in Section 3. Hence for this research we decided to not sub-sort the size portfolios based on betas. The HML factor is constructed on a similar principle regarding the sub-sorting by betas. It is however previously sorted based on the ratio of the individual stocks $BooktoMarketRatio$. This assumes that companies with a high $BooktoMarketRatio$ are undervalued in the market and have high return potential in the future (growth). Companies with a low $BooktoMarketRatio$ are already priced according to their value and are considered value stocks. Eventually, based on the creation of these portfolios the factors are constructed in the following way:

$SMB = 1/3(SmallValue + SmallNeutral + SmallGrowth) - 1/3(BigValue + BigNeutral + BigGrowth)$.

$HML = 1/2(SmallValue + BigValue) - 1/2(SmallGrowth + BigGrowth)$.

(Fama and French, 1992)

At the beginning of every week t the previous weeks $t-1$ average market capitalizations are observed. Due to the volatile nature of cryptocurrencies, the average weekly market capitalizations are calculated for every individual cryptocurrency. After which, the 26 cryptocurrencies are sorted according to their average market capitalization at t. The 26 cryptocurrencies are then split into two equally weighted portfolios. Resulting in a high market capitalization portfolio of 13 cryptocurrencies and a low market capitalization portfolio of the remaining 13 cryptocurrencies. The investment strategy assumption based on Fama and French (1992) is to long (buy) the low market capitalization portfolio and short (sell) the high market capitalization portfolio. A holding period

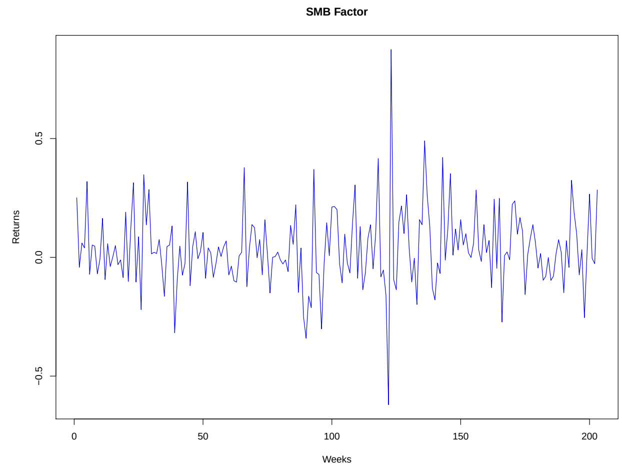

Figure 4: Showing the SMB (Small-minus-Big) Size Factor

of one week is assumed for this strategy. At $t+1$ the average returns based on this zero investment long-short strategy is calculated. When applied to the entire time series of observed returns, these portfolio returns result in a time series vector making up the size factor (SMB). The 26 individual cryptocurrency returns are regressed on a constant and the constructed size factor to test for the significance of this investment strategy. Furthermore, robustness tests were conducted to test the significance of the size factor in presence of additional factors. The same methodology was applied to the 25 BTC denominated cryptocurrency returns and factor construction under BTC denominated returns. The plot of the constructed 200 week SMB factor can be seen in Figure 4.

4.2 Momentum Factor

Armilis (2019) describes momentum to be the most significant factor for explaining cryptocurrency return behaviours. Other papers on the subject like Liu et al (2019) also find strong significance within the explanatory power of this specific factor. Therefore, the construction of the momentum factor is of essential importance. Various different approaches have been taken to construct this factor. This research project will use a combination of the two methodologies displayed by Armilis (2019) and Liu et al (2019). Fama and French (2015) describe the momentum factor as the believe that current winners within the equity markets will continue to outperform the market in the future. Following this believe the general implication is that, similar to the size factor construction two portfolios, one long, one short, are constructed to create a zero investment long-short strategy. Similar to Armilis (2019) both sets of time series data, the USD and BTC one, are sorted according to their cumulative return. Here the cumulative return at $t-1$ is used as a proxy for momentum. Different from Armilis (2019) but in line with the research of Liu et al (2019) the cumulative returns within the first week $t-1$ are being observed to sort the individual cryptocurrecnies into two equally weighted portfolios. At t the two portfolios are used to create a long short investment strategy, buying the high momentum and selling the low momentum portfolio, hence creating the

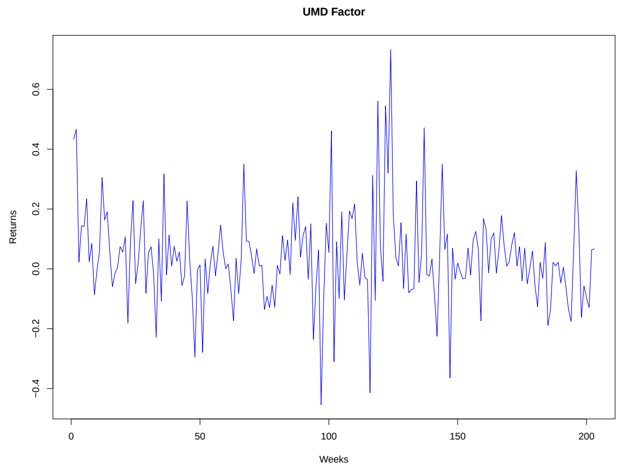

Figure 5: Showing the UMD (Up-minus-Down) Momentum Factor

UMD (Up-Minus-Down) momentum factor. The individual returns for all 26 USD denominated cryptocurrncy returns and 25 BTC denominated cryptocurrency returns have been regressed on a constant and the constructed factor. Furthermore, robustness tests were conducted to test the significance of the constructed factor in presence of other robust factors. Figure 5 shows a plot of the UMD (Up-minus-Down) momentum factor.

4.3 Volume Factor

Volume is defined as the sum of all transactions, which occurred within the last 24h for the observed cryptocurrency. Coinmarketcap offers the historical 24h dollar denominated volume, recorded for every cryptocurrency and available through the coinmarketcap API. As was discussed previously based on the findings of Bianchi (2018) the general assumption is that high volume cryptocurrencies will display a higher market capitalization. Therefore, we assume that the market price of the cryptocurrency would increase equally.

At the beginning of every week t the previous weeks $t-1$ average 24h volume $Vol_{i,t-1}$ for every individual cryptocurrency i is observed. After which, the 26 cryptocurrencies are sorted according to their average weekly volume $Vol_{i,t-1}$ from highest to lowest. At t the 26 cryptocurrencies are then split into two equally weighted portfolios. Resulting in a high volume portfolio of 13 cryptocurrencies and a low volume portfolio of the remaining 13 cryptocurrencies. The investment strategy assumption is that cryptocurrencies displaying a high $Vol_{i,t-1}$ have a greater potential for high returns in the future. This investment strategy results in long (buying) the high volume portfolio and short (selling) the low volume portfolio. A holding period of one week is assumed for this strategy. At $t+1$ the average weekly returns, based on this zero investment long-short strategy are calculated. When applied to the entire time series of observed returns, these portfolio returns result in a time series vector making up the High-Minus-Low volume factor (HML_{Vol}). The 26 individual cryptocurrency returns are then regressed on a constant and the constructed volume factor to test

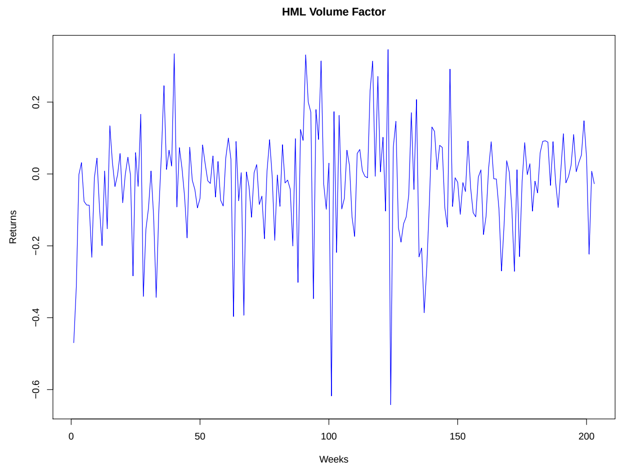

Figure 6: Showing the HML (High-minus-Low) Volume Factor

for the significance of this investment strategy. Furthermore, the robustness of the factor is tests to test the significance of the volume factor in presence of additional factors. The same methodology was applied to the 25 BTC denominated cryptocurrency returns. The factor construction for the 25 BTC denominated cryptocurrency returns was also based on the above methodology. Figure 6 shows the weekly plot of the HML (High-minus-Low) Volume factor.

4.4 Standard Deviation Factor

Liu et al (2019) introduces a volatility factor based on a yearly observation window of the individual cryptocurrency volatility. The exact methodology is unfortunately not explained. The general assumption for a volatility factor is that it will be highly correlated with the volume factor. Volume and volatility tend to move similarly. Therefore, in this research the adaptation of the volatility factor used by Liu et al (2019) will be a factor based on the weekly standard deviation of returns. The main assumption here is that high standard deviation cryptocurrencies will outperform low standard deviation cryptocurrencies. Hence the factor will be constructed as High-Minus-Low (HML_{SD}).

At the beginning of every week t the previous weeks $t-1$ standard deviation $SD_{i,t-1}$ for every individual cryptocurrency i is observed. After which, the 26 cryptocurrencies are sorted according to their standard deviation $SD_{i,t-1}$ from highest to lowest. At t the 26 cryptocurrencies are then split into two equally weighted portfolios. Resulting in a high standard deviation portfolio of 13 cryptocurrencies and a low standard deviation portfolio of the remaining 13 cryptocurrencies. The investment strategy assumption is that cryptocurrencies displaying a high $SD_{i,t-1}$ value have a greater potential for high returns in the future. The resulting strategy assumption is to long (buy) the high standard deviation portfolio and short (sell) the low standard deviation portfolio. Furthermore, a holding period of one week is assumed for this strategy. At $t+1$ the average weekly returns, based on this zero investment long-short strategy are calculated. When applied to the

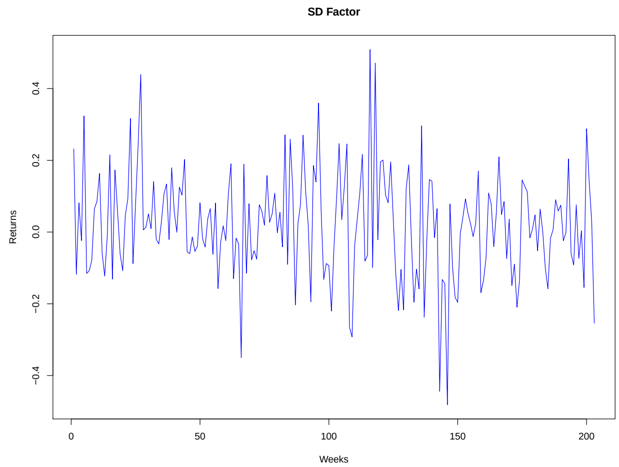

Figure 7: Showing the HML (High-minus-Low) Standard Deviation Factor

entire time series of observed returns, these portfolio returns result in a time series vector making up the High-Minus-Low standard deviation factor (HML_{SD}). The 26 individual cryptocurrency returns are then regressed on a constant and the constructed factor to test for the significance of this investment strategy. Furthermore, robustness tests were conducted to test the significance of the standard deviation factor in presence of additional factors. The same methodology was applied to the 25 BTC denominated cryptocurrency returns. The factor construction for the 25 BTC denominated cryptocurrency returns was also based on the above methodology. Figure 7 shows the weekly plot of the HML (High-minus-Low) standard deviation factor.

5 Results

This section presents the results based on the previous factor construction. Firstly every individual factor result will be discussed. The key findings and shortcomings based on the literature reviewed and factor constructed are displayed. All 26 USD and 25 BTC denominated cryptocurrency returns have been regressed on a constant and the constructed factors separately. After which the robustness of the individual factor in presence of other factors was tested. Table 4 and Table 5 show the results and the significance levels of the individual factors in relation to the observed USD and BTC denominated cryptocurrency returns respectively. The t-statistic is reported in parenthesis below the individual β-estimate.

All factors were tested for significance individually and then later in combination with other factors. If a factor was found to be significant only alone or only in combination with other factors it was considered to be insignificant. Only significant factors were recorded in Tables 4 and 5.

5.1 Market Factor

Throughout the research on the USD denominated data both indices the CCi30 and the lagged CRIX have performed relatively equal. As can be seen from Table 4 both the CCi30 and CRIX show significance for the high market capitalization coins: BTC, ETH, XRP and LTC. This was expected since both indices are constructed based on market capitalization weighted cryptocurrencies. When turning to the BTC denominated price data in Table 5, we can identify quite a significant difference between the explanatory power of the CCi30 and the lagged CRIX index. The CCi30 manages to explain the behaviour of the majority of cryptocurrencies selected in this research. Ranging from the high market capitalization coins like Bitcoin to the lower market capitalization ones. The CRIX on the other hand fails to show satisfactory results, not being able to pass most of the robustness tests conducted. Based on these results the CCi30 is the preferred index when dealing with BTC denominated price data. There is a possibility that explanatory power is lost when dealing with *fiat currency* denominated cryptocurrency price data. Since cryptocurrencies behave very different from traditional asset classes or currencies, it is suggested to view cryptocurrency markets as a separate, independent market, which is not influenced the same way traditional equity, commodity or currency markets are.

5.2 Size Factor

As can be seen from Table 4 the size factor shows significant results for the USD denominated price data for Bitcoin (BTC), USD Coin (USDC) and Stellar (XLM). For the BTC denominated cryptocurrency returns the size factor seems to explain quite a bit more of the individual behaviour of the cryptocurrency returns. A significant relationship was found between the SMB factor and Litecoin (LTC), Bitcoin Cash (BCH), NEM (XEM), USD Coin (USDC) and Bitcoin Dimond (BCD). All mentioned regression results have been tested for robustness and highlighted accordingly (see Table 5). A possible interpretation of the differences between the observed results between the USD and BTC denominated returns might lead to the conclusion that excluding an influential cryptocurrecny giant like Bitcoin could lead to more satisfactory result when trying to explain abnormal behaviours in individual cryptocurrencies. It is also possible that the conversion of the returns to a cryptocurrency base has managed to naturally display the behaviour of the cryptocurrecny market better. The USD denominated returns might be influenced by the movement of the US Dollar and related macroeconomic influences. These however would also be anticipated to vanish considering the extreme volatility differences observed in the data between traditional equity markets and cryptocurrency markets. Similarly to the market factor results it is suggested to use BTC denominated price data for a research based on explanatory factors within cryptocurrency returns.

5.3 Momentum Factor

As can be seen in both the USD denominated data set in Table 4 and the BTC denominated data set in Table 5, the momentum factor passes most of the robustness tests. That being said, it does not fully manage to explain the majority of the cryptocurrency behaviours. Delivering significant and robust results for 7 out of the 26 USD denominated cryptocurrecnies: XRP, BCH, USDT, DASH, ZEC, DCR and BCH. However only explaining 5 out of the 25 BTC denominated cryptocurrency behaviours: LTC, EOS, DASH, LSK and HC. Different from the other explanatory risk factors the momentum factor seems to not suffer from a limitation based on the USD or BTC denomination. Since cumulative returns are used as a proxy for momentum, the volatile nature of the cryptocurrency market is not affected by the base in use. Both the USD and BTC denominated data sets offer relatively similar results. The factor does not manage to meet the anticipated explanatory power based on the research papers observed. Nevertheless, it is one of the most robust factors, which is based on the fact that is is not as dependent on the base of denomination.

5.4 Volume Factor

As can be seen from Tables 4 and 5 the volume factor is among the most explanatory factors in this research project. It shows very strong significance above the 0.05 level for 12 out of the 26 USD denominated cryptocurrencies. It however only shows significance for 6 out of 25 BTC denominated cryptocurrencies. As mentioned by Bianchi (2018) and also displayed in Section 3, volume and market capitalization tend to be highly correlated. This will be further discussed in Subsection 5.6 focusing only on the factor correlations. Although being one of the most significant factors, the volume factor is also highly correlated to the size factor. Explanatory power might be lost due to this multicollinearity issue.

5.5 Standard Deviation Factor

The standard deviation factor shows significance for only 3 out of the 26 USD denominated cryptocurrencies. No significance is discovered for the BTC denominated cryptocurrencies. Based on the findings of Liu et al (2019) it is to be anticipated that a yearly observation window would be more beneficial for this factor. The inclusion of a volume factor would lead to the assumption that the standard deviation factor would be trivial. When observing the factor correlations in Subsection 5.6 however, no particular correlation is found between the volume and standard deviation factors. Further research regarding this factor would be suggestion based on the fact that cryptocurrencies are among the most volatile assets observed. Concerning this particular research project however no evidence of a strong significance was found.

5.6 Factor Correlation

The following correlations have been calculated to identify multicollinearity issues within the factors.

As anticipated based on the findings of Bianchi (2018) we discovered a very high correlation between the size and volume factor within the BTC denominated data (see Table 3). When analysing the correlation matrix of the USD denominated cryptocurrencies in Table 2, no multicollinearity issue is found between the size and volume factor. Observing the significance of the volume factor for the USD denominated data (see Table 4) the volume factor seems to outperform the size factor and would suggest to be preferred. Within the BTC denominated data (see Table 5) no particular

Table 2: Correlation Matrix for Factors created based on USD denominated returns.

	Size	Momentum	Market	Volume	StDev
Size	1.00	0.04	-0.15	-0.07	-0.22
Momentum	0.04	1.00	0.03	-0.31	-0.14
Market	-0.15	0.03	1.00	0.36	0.15
Volume	-0.07	-0.31	0.36	1.00	0.11
StDev	-0.22	-0.14	0.15	0.11	1.00

Table 3: Correlation Matrix for Factors constructed based on BTC denominated returns.

	Size	Momentum	Market	Volume	StDev
Size	1.00	-0.32	0.24	0.81	0.27
Momentum	-0.32	1.00	0.10	-0.38	0.07
Market	0.24	0.10	1.00	0.19	0.17
Volume	0.81	-0.38	0.19	1.00	0.19
StDev	0.27	0.07	0.17	0.19	1.00

preference is evident. This result further strengthens the conclusion that BTC denominated data is to be preferred in any future model construction or research. A rather surprising result is the low correlation between the volume and standard deviation factor in both the USD and BTC denominated data. This hints at the fact that volume and standard deviation tend to move separately in the cryptocurrency world. The weekly standard deviation was anticipated to be significant, hence further investigations would be necessary in this regard.

Table 4: The table below summarizes all β-estimates for the 26 USD-denominated cryptocurrencies. Only statistically significant results are displayed. The t-stat for every β-estimate is shown in parenthesis below the β-estimate. Positive estimates describe a cryptocurrency behaviour similar to the factor and its assumptions during the factor construction. Negative estimates describe a behaviour opposite to the factor for the individual cryptocurrency. The estimate weight displays the strength by which any given cryptocurrency is behaving similar or different from the factor. E.g. A negative estimate of 0.522 for Bitcoin (BTC) illustrates that Bitcoin is moving in the opposite direction to the SMB (Small-Minus-Big) factor with a strength of 0.522. An estimate of 1 would describe the cryptocurrency behaving exactly the same as the factor.

	BTC	ETH	XRP	LTC	EOS	USDT	ADA	XMR	DASH	NEO	ETC	ZEC	XTZ	BTG	USDC	DCR	BCD
Market	0.042	0.603	0.666	0.677					-0.146						-0.220		
	(18.031)	(12.694)	(12.366)	(14.037)					(-1.922)						(-3.329)		
Size	-0.522														-0.589		
	(-3.322)														(-3.783)		
Momentum								-0.490	-0.537	-0.367		-0.526				-0.336	-0.291
								(-2.986)	(-2.956)	(-2.005)		(-3.45)				(-2.023)	(-1.736)
Volume	0.862	0.704	0.765	0.935	0.343		0.441	0.740	0.624	0.562	0.400		0.289	0.329			
	(5.317)	(4.557)	(4.402)	(5.86)	(1.816)		(2.459)	(4.404)	(3.291)	(2.952)	(2.274)		(1.996)	(1.81)			
StDev		0.380	0.404			0.316											
		(2.321)	(2.199)			(1.689)											

Table 5: The table below summarizes all β-estimates for the 25 BTC-denominated cryptocurrencies. Only statistically significant results are displayed. The t-stat for every β-estimate is shown in parenthesis below the β-estimate. Positive estimates describe a cryptocurrency behaviour similar to the factor and its assumptions during the factor construction. Negative estimates describe a behaviour opposite to the factor for the individual cryptocurrency. The estimate weight displays the strength by which any given cryptocurrency is behaving similar or different from the factor.

	ETH	XRP	LTC	BCH	EOS	USDT	ADA	XLM	XMR	DASH	NEO	MIOTA	XEM	ZEC	XTZ	DOGE	USDC	DCR	AOA	LSK	BCD	EGT	HC
Market	0.216	0.258		-1-59-e01		-0.174	-0.190	-0.042	-0.037	-0.055	-0.029	-0.026	-0.026	-0.042	-0.017	-0.024	-0.095	-0.046		-0.046		-0.031	-0.023
	(3.361)	(3.903)		(-2.559)		(-2.428)	(-2.708)	(-5.294)	(-5.498)	(-4.318)	(-2.459)	(-3.547)	(-1.723)	(-3.459)	(-1.949)	(-2.114)	(-4.887)	(-2.546)		(-2.845)		(-3.448)	(-2.224)
Size			1.457	1.119									0.206				-0.389		-0.111		-0.174		
			(4.882)	(3.956)									(2.918)				(-4.238)		(-2.163)		(-1.676)		
Momentum					-1.82					-0.108											-0.195		0.082
					(-5.873)					(-1.777)											(-1.904)		(1.722)
Volume		1.193	1.197		1.066	1.212	1.241			-0.108													
		(4.550)	(4.620)		(3.753)	(4.335)	(4.523)			(-2.043)													
StDev																							

6 Conclusion

This research project focused on the implementation and adaptation of various risk factors inspired by the iconic Fama and French (1992) and Fama and French (2015) models. It took a closer look at the most recent research papers applying methodologies based on Fama and French to cryptocurrencies and adjusting them accordingly. In summary the key take-aways from this research project are as follows.

Based on Bianchi (2018) cryptocurrencies would best be compared to gold or energy commodities. Furthermore, as mentioned by Bianchi (2018) a strong correlation was found between the cryptocurrency market capitalization and trading volume, resulting in an also very high multicollinearity found between the size and volume factor observed in this research.

An overarching finding of this research project has been the usage of BTC denominated data over that of fiat currency denominated data. The above mentioned multicollinearity issue has only been found within BTC denominated data tests, which results in the observation that not finding such an issue within USD denominated data is rather questionable.

All factors were tested for significance individually and then later in combination with other factors. If a factor was found to be significant only alone or only in combination with other factors it was considered to be insignificant. This ensured that the significance found within all factors was truly robust throughout different dimensions.

Significance was found for all factors within USD denominated data. The market, volume, momentum and weekly standard deviation factors for the USD denominated data were all significant past the 0.05 level. For the BTC denominated data significance was only found for the market, size, volume and momentum factors, however not for the weekly standard deviation factor. Since the conclusion of the previous parts puts greater trust within the BTC denominated data it is to assume that the standard deviation factor is in fact not significant on a weekly basis. Liu et al (2019) present results based on what they call a volatility factor, which is significant past the 0.05 level. The actual factor construction is unfortunately not clearly displayed. This should potentially be further investigated, since standard deviation would be assumed to be a good explanatory variable for an instrument as volatile as cryptocurrencies.

Following the research of Liu et al (2019) and Armilis (2019) the momentum factor was weaker than anticipated within both the USD and BTC denominated data. The size factor showed satisfactory results for both sets of data, explaining only 2 out of 26 of the USD denominated but therefore 6 out of 25 of the BTC denominated cryptocurrency returns.

Last but not least the market factor has shown the strongest significance of all explanatory factors. Following the findings of Alexander and Dakos (2019), we have also concluded that the CCi30 is to be preferred as a cryptocurrency market index over the other popular alternatives. Although not particularity highlighted within Section 5, the market factor by itself is able to explain the majority of the behaviour of cryptocurrency returns. Resulting in an Adjusted R-squared of 0.62 and 0.44 for high market capitalization cryptocurrencies like BTC or ETH respectively.

7 Further Research Suggestions

This section was created due to the time limitation of this research. The main aim is to suggest further research and ideas to help improve research conducted within the topic of explanatory risk factors for cryptocurrency returns.

7.1 Carry Factor

Armilis (2019) discusses carry as being a strongly significant factor for explaining abnormal behaviours within cryptocurrency returns. The carry factor reflects the measure of “inflation”, based on the number of new coins generated. As Armilis (2019) writes: ”It is reasonable to believe that as new coins will be generated, the total supply will increase and the currency would lose its nominal value.” Armilis (2019) follows the methodology reported by (Hubrich, 2017), defining high carry to be a low coin issuance reported by a cryptocurrency. Reflecting the above mentioned assumptions, the carry factor is constructed as the negative of the sum of total coin generated over the previous 7 days, divided by the total coin outstanding at the beginning of that 7-day period. Here, the signals are once again ranked and the portfolio is formed in the same way as for momentum and value. Armilis (2019)

7.2 Sentiment Factor

Armilis (2019) also discusses the implementation of a sentiment factor based on a raw data set found within the paper of Wang and Vergne (2017). He describes the data to be focusing on the ”buzz” surrounding cryptocurrencies. Nasekin and Chen (2018) focus on a deep learning based cryptocurrency sentiment algorithm. Due to the highly volatile nature of cryptocurrencies a sentiment factor seems not only necessary but vital to understand the behaviour of cryptocurrency returns. Armilis (2019) finds significance within the sentiment factor based on a one-day observation window. Nevertheless, the approach taken by Nasekin and Chen (2018) seems more appropriate considering the complexity of the information surrounding cryptocurrencies today. Nasekin and Chen (2018) run recessional significance tests to analyse the statistical significance of their sentiment algorithm in comparison to the CRIX index and find strong significance. This concludes that there indeed is reason to include a sentiment factor within an analysis like this. A suggestion for further reserach would be the application of the mentioned algorithm to the CCi30 index to again compare the significance of predictability. Furthermore, the implementation of such an algorithm might lead to the substitution of high correlation factors like the volume or volatility factors mentioned in this research project. Looking at techniques like principal component analysis might be useful in this regard.

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Appendices

A Descriptive Statistics

Table 6: Descriptive Statistics for the 26 USD denominated Cryptocurrencies

	BTC	ETH	XRP	LTC	BCH	EOS	USDT	ADA	XLM	XMR	DASH	NEO	MIOTA
Mean	0.0026	0.0033	0.0027	0.0024	-0.0029	-0.0014	-0.0023	-0.0022	0.0062	0.0003	0.0009	-0.0027	0.0005
Median	0.0025	-0.0007	-0.0034	0.0000	-0.0031	0.0000	0.0000	-0.0034	-0.0007	0.0000	-0.0015	-0.0022	-0.0030
StDev	0.0396	0.0746	0.0722	0.0569	0.1814	0.1533	0.2724	0.1453	0.1064	0.1054	0.1744	0.1528	0.1206
Kurtosis	4.7841	68.1088	41.1783	11.8540	830.9117	511.2384	863.7437	372.3313	159.2996	671.0647	768.8921	531.0758	253.7630
Skewness	-0.2128	-3.4056	3.0438	1.2355	-25.0170	-20.5685	-22.3175	-15.2740	7.5677	-21.3784	-23.6108	-18.7040	7.8468

	ETC	XEM	ZEC	XTZ	BTG	DOGE	USDC	DCR	AOA	LSK	BCD	EGT	HC
Mean	-0.0029	0.0052	-0.0029	0.0021	-0.0086	0.0062	0.0017	-0.0045	0.0033	-0.0005	-0.0054	0.0070	-0.0005
Median	-0.0001	-0.0034	0.0000	-0.0026	-0.0022	0.0000	0.0000	-0.0012	-0.0033	0.0000	-0.0029	0.0016	-0.0013
StDev	0.3009	0.2307	0.1875	0.1610	0.2993	0.1649	0.2973	0.2607	0.1750	0.2376	0.3244	0.1221	0.1514
Kurtosis	1204.5114	728.5457	697.5679	493.2120	512.5787	1021.1722	648.6234	486.0569	362.3147	626.5384	435.6638	116.9790	194.7553
Skewness	-33.2450	24.2888	-20.2661	17.5946	-19.9430	29.4715	-9.0303	-17.5680	12.8448	17.2525	-3.2892	5.2263	-1.4747

Table 7: Descriptive Statistics for the 25 BTC denominated Cryptocurrencies

	ETH	XRP	LTC	BCH	EOS	USDT	ADA	XLM	XMR	DASH	NEO	MIOTA	ETC
Mean	0.0383	0.0000	0.0107	0.7661	0.0076	0.0034	0.0000	0.0004	0.1037	0.2692	0.0246	0.0024	0.0024
Median	0.0315	0.0000	0.0094	0.0023	0.0005	0.0013	0.0000	0.0002	0.0176	0.0290	0.0002	0.0014	0.0000
StDev	0.0289	0.0000	0.0043	1.3535	0.0100	0.0065	0.0001	0.0006	0.1532	0.4117	0.0636	0.0022	0.0062
Kurtosis	0.4403	0.5883	-0.7247	6.6403	2.4234	20.6999	3.7907	6.4814	2.7520	4.5564	12.5622	1.2667	3.5870
Skewness	0.9333	0.8566	0.4247	2.4263	1.4832	3.7846	2.0077	2.4709	1.8203	2.0576	3.5419	1.2937	2.2885

	XEM	ZEC	XTZ	BTG	DOGE	USDC	DCR	AOA	LSK	BCD	EGT	HC
Mean	0.0222	0.3588	0.0155	0.0004	0.0000	0.0060	0.0417	0.0006	0.0015	0.0005	0.0008	0.0081
Median	0.0097	0.1493	0.0054	0.0000	0.0000	0.0005	0.0069	0.0003	0.0007	0.0000	0.0005	0.0004
StDev	0.0409	0.5619	0.0229	0.0061	0.0001	0.0092	0.0567	0.0008	0.0021	0.0010	0.0009	0.0206
Kurtosis	134.7955	4.4862	15.9049	282.8009	10.3540	1.0376	1.5075	11.1916	4.7507	2.8677	10.3782	16.3805
Skewness	9.2435	2.1609	3.4777	16.8486	3.3799	1.5348	1.4272	2.8211	2.1894	2.0549	2.9086	3.8240

B Price Correlations

Table 8: Correlation Matrix for Prices denominated in USD

	BTC	*ETH*	*XRP*	*LTC*	*BCH*	*EOS*	*USDT*	*ADA*	*XLM*	*XMR*	*DASH*	*NEO*	*MIOTA*	*ETC*	*XEM*	*ZEC*	*XTZ*	*BTG*	*DOGE*	*USDC*	*DCR*	*AOA*	*LSK*	*BCD*	*EGT*	*HC*
BTC	1.00																									
ETH	0.88	1.00																								
XRP	0.82	0.88	1.00																							
LTC	0.94	0.92	0.86	1.00																						
BCH	-0.54	-0.45	-0.42	-0.46	1.00																					
EOS	-0.46	-0.31	-0.32	-0.38	0.32	1.00																				
USDT	0.45	0.56	0.39	0.52	-0.24	-0.25	1.00																			
ADA	-0.57	-0.47	-0.47	-0.49	0.55	0.22	-0.15	1.00																		
XLM	0.28	0.02	0.13	0.20	-0.28	-0.29	-0.14	-0.33	1.00																	
XMR	-0.48	-0.45	-0.46	-0.45	0.37	0.47	-0.15	0.45	-0.27	1.00																
DASH	-0.48	-0.45	-0.44	-0.44	0.49	0.42	-0.19	0.46	-0.18	0.94	1.00															
NEO	-0.44	-0.38	-0.33	-0.36	0.38	-0.07	-0.19	0.47	-0.20	0.00	0.06	1.00														
MIOTA	0.64	0.54	0.56	0.53	-0.48	-0.49	0.07	-0.55	0.21	-0.50	-0.49	-0.34	1.00													
ETC	-0.31	-0.26	-0.23	-0.26	0.61	-0.10	-0.14	0.39	-0.18	-0.18	-0.08	0.68	-0.20	1.00												
XEM	0.50	0.48	0.45	0.40	-0.40	-0.25	0.04	-0.47	0.16	-0.46	-0.44	-0.32	0.71	-0.20	1.00											
ZEC	-0.48	-0.37	-0.43	-0.44	0.22	0.53	-0.01	0.49	-0.33	0.80	0.74	-0.12	-0.56	-0.29	-0.45	1.00										
XTZ	0.71	0.67	0.63	0.70	-0.19	-0.24	0.45	-0.24	-0.04	-0.12	-0.13	-0.19	0.28	-0.14	0.13	-0.20	1.00									
BTG	-0.01	0.00	0.00	0.00	-0.03	-0.01	0.02	0.01	-0.04	-0.07	-0.08	0.18	-0.01	0.08	-0.02	-0.04	0.00	1.00								
DOGE	0.21	-0.01	0.08	0.19	-0.20	-0.21	-0.12	-0.24	0.79	-0.22	-0.12	-0.12	0.05	-0.13	0.05	-0.26	-0.08	-0.05	1.00							
USDC	-0.45	-0.45	-0.42	-0.43	0.44	0.41	-0.24	0.34	-0.14	0.88	0.88	0.01	-0.42	-0.12	-0.38	0.66	-0.18	-0.08	-0.10	1.00						
DCR	-0.64	-0.54	-0.53	-0.56	0.51	0.44	-0.19	0.68	-0.35	0.80	0.77	0.16	-0.60	-0.01	-0.53	0.79	-0.24	-0.07	-0.27	0.77	1.00					
AOA	0.61	0.68	0.54	0.65	-0.35	-0.35	0.35	-0.39	-0.07	-0.35	-0.35	-0.28	0.52	-0.17	0.43	-0.35	0.33	0.00	-0.10	-0.33	-0.43	1.00				
LSK	0.18	0.19	0.12	0.11	-0.15	-0.19	-0.13	-0.19	-0.02	-0.20	-0.19	-0.09	0.56	-0.02	0.38	-0.23	-0.05	0.00	-0.06	-0.11	-0.22	0.24	1.00			
BCD	0.40	0.46	0.26	0.33	-0.23	-0.21	0.46	-0.12	-0.26	-0.33	-0.36	-0.13	0.26	0.03	0.31	-0.08	0.24	0.05	-0.24	-0.40	-0.32	0.27	0.16	1.00		
EGT	0.48	0.36	0.29	0.42	-0.39	-0.17	0.34	-0.32	0.38	-0.28	-0.27	-0.33	0.11	-0.27	0.13	-0.13	0.24	-0.02	0.40	-0.30	-0.39	0.15	-0.07	0.30	1.00	
HC	-0.38	-0.34	-0.29	-0.30	0.36	-0.10	-0.16	0.36	-0.12	-0.08	0.02	0.88	-0.34	0.67	-0.32	-0.18	-0.16	0.04	-0.01	-0.03	0.11	-0.27	-0.10	-0.13	-0.24	1.00

Table 9: Correlation Matrix Prices denominated in BTC

	ETH	*XRP*	*LTC*	*BCH*	*EOS*	*USDT*	*ADA*	*XLM*	*XMR*	*DASH*	*NEO*	*MIOTA*	*ETC*	*XEM*	*ZEC*	*XTZ*	*BTG*	*DOGE*	*USDC*	*DCR*	*AOA*	*LSK*	*BCD*	*EGT*	*HC*
ETH	1.00																								
XRP	0.70	1.00																							
LTC	0.66	0.68	1.00																						
BCH	-0.49	-0.46	-0.27	1.00																					
EOS	-0.34	-0.49	-0.38	0.57	1.00																				
USDT	0.31	0.04	0.29	-0.08	-0.17	1.00																			
ADA	-0.53	-0.47	-0.19	0.59	0.28	-0.05	1.00																		
XLM	-0.19	0.09	-0.04	-0.14	-0.09	-0.25	-0.08	1.00																	
XMR	-0.44	-0.60	-0.52	0.41	0.74	-0.14	0.38	0.02	1.00																
DASH	-0.45	-0.58	-0.46	0.55	0.76	-0.13	0.45	0.03	0.95	1.00															
NEO	-0.42	-0.26	0.04	0.42	0.13	0.01	0.67	-0.17	0.07	0.14	1.00														
MIOTA	-0.33	-0.04	-0.15	-0.08	-0.21	-0.22	0.16	0.08	-0.18	-0.20	0.44	1.00													
ETC	-0.46	-0.28	-0.01	0.68	0.20	-0.01	0.66	-0.21	0.01	0.12	0.78	0.29	1.00												
XEM	0.38	0.40	0.15	-0.25	-0.22	-0.13	-0.26	0.13	-0.27	-0.26	-0.20	0.07	-0.21	1.00											
ZEC	-0.33	-0.53	-0.46	0.29	0.67	-0.09	0.39	0.08	0.87	0.85	0.00	-0.18	-0.11	-0.23	1.00										
XTZ	-0.30	-0.37	-0.21	0.48	0.55	-0.04	0.43	0.01	0.52	0.62	0.14	-0.23	0.14	-0.17	0.60	1.00									
BTG	-0.07	-0.03	0.06	0.04	0.11	0.00	0.10	-0.04	-0.02	-0.03	0.21	0.13	0.14	-0.03	0.00	-0.02	1.00								
DOGE	-0.06	0.13	0.23	-0.17	-0.22	-0.15	-0.17	0.56	-0.20	-0.19	-0.11	-0.03	-0.12	0.06	-0.19	-0.16	-0.02	1.00							
USDC	-0.44	-0.58	-0.50	0.51	0.83	-0.14	0.29	0.00	0.92	0.91	0.07	-0.18	0.07	-0.26	0.79	0.54	-0.02	-0.19	1.00						
DCR	-0.54	-0.64	-0.46	0.59	0.71	-0.11	0.67	-0.01	0.78	0.80	0.32	-0.06	0.27	-0.30	0.81	0.77	-0.01	-0.22	0.78	1.00					
AOA	0.32	0.24	0.26	-0.27	-0.21	0.05	-0.26	-0.11	-0.03	-0.04	-0.23	-0.05	-0.27	0.13	-0.04	-0.11	-0.04	-0.13	-0.04	-0.23	1.00				
LSK	-0.35	-0.26	-0.06	0.40	0.18	-0.14	0.52	-0.17	0.14	0.21	0.76	0.52	0.61	-0.08	0.08	0.20	0.14	-0.17	0.17	0.34	-0.08	1.00			
BCD	-0.29	-0.20	0.10	0.55	0.05	0.14	0.66	-0.30	-0.11	-0.01	0.78	0.27	0.91	-0.15	-0.17	0.07	0.17	-0.16	-0.09	0.18	-0.25	0.58	1.00		
EGT	0.27	0.07	0.04	-0.18	-0.01	0.11	-0.28	0.03	-0.16	-0.18	-0.25	-0.35	-0.25	0.00	-0.10	-0.21	-0.05	0.14	-0.17	-0.23	-0.19	-0.35	-0.19	1.00	
HC	-0.42	-0.27	0.02	0.43	0.14	0.00	0.64	-0.16	0.07	0.15	0.91	0.37	0.77	-0.20	-0.01	0.24	0.09	-0.11	0.09	0.36	-0.24	0.71	0.75	-0.23	1.00