An Asset Pricing Model for Cryptocurrencies

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Abstract

Based on stock pricing literature, this research examines if the five factors market, size, momentum, liquidity, and volatility show significant excess returns. Despite the short sample size of less than six years, a significant momentum effect is found. The factors size, liquidity, and volatility are not significant, but do show the expected sign. Then, an asset pricing model is researched to price the cryptocurrency cross-section. I find that the four-factor model containing factors for capturing the market, momentum, liquidity, and volatility contains the smallest pricing error and strongly outperforms the CAPM. The size factor is found to be redundant.

Contents

List of Tables

List of Figures

1 Introduction

In 2008, Nakamoto (2008) published his paper of a peer-to-peer electronic cash system. This version of electrical cash allows for direct payments from one entity to another without going through an intermediary institution. With all the code open-source, one can easily make adjustments and launch a new cryptocurrency, which are called alt-coins, as they are an alternative to Bitcoin. Many of these alt-coins were invented to address pain points in the Bitcoin network such as high energy usage or the limited supply of 21 million Bitcoins (Chuen, Guo, and Wang, 2017). The first alt-coins were cryptocurrencies with small deviations from the original protocol of Bitcoin. Later, completely new cryptocurrencies where build, consensus protocols were reinvented, efficiency increased and smart-contracts introduced. This led to a highly diverse cryptocurrency market. At the moment of writing, there are 5609 different cryptocurrencies trading with a combined market value of 260 billion dollar (CoinMarketCap, 2020c). While they are growing in number they are falling in value (Reuters, 2018).

The cryptocurrency market has drawn an increasing number of new participants, but what really drives prices is still under-examined. A lot of research has been done in more established markets such as the stock market and the bond market. Existing literature shows that the stock market is driven by fundamental economic factors to which investors react differently (Daniel, Hirshleifer, and Subrahmanyam, 2001). Yet, evidence suggests that fundamental economic variables do not affect the price of Bitcoin (Baek and Elbeck, 2015; Cheah and Fry, 2015).

Well known factor investing literature has also made its way into the cryptocurrency market. Factors as market, size, value or momentum have proven itself in the stock- and bond market. (Fama and French, 1992; Jegadeesh and Titman, 1993; Sharpe, 1964). Hubrich (2017) documents that momentum, value, and carry are all relevant, with momentum having the greatest impact of all. Literature on the momentum effect in cryptocurrencies show mixed results. Rohrbach, Suremann, and Osterrieder (2017) and Tzouvanas, Kizys, and Tsend-Ayush (2019) document a significant momentum effect, while Grobys and Sapkota (2019) finds no evidence for a significant momentum effect. Deng, Chuen, Wang, and Zhang (2019) investigate a five-factor model with factors for the market, value, size, contrarian, and attention. They conclude that the market factor, the equally weighted CRIX index, does not help in explaining the variance in excess returns. The other four factors do explain the variation in excess returns. Shen, Urquhart, and Wang (2019b) examine a three-factor model containing the factors market, size, and momentum. They conclude that the model significantly improves when compared to the CAPM.

Much has happened in the last couple of years, the cryptocurrency space has seen an enormous increase in total market value as well as a long bear market. The cryptocurrency market has to some extent matured at least a little bit. Thus, when using new data, it can shed new light on previous literature. In this research the data used is from August 2014 up to March 2020. At each point in time, the 60 most relevant cryptocurrencies are selected based on market value. Some papers, among which Hubrich (2017), have some sort of survivor bias or hindsight benefits, because the sample is constructed with information that was not present at the time of portfolio formation. To prevent survivor bias, the 60 most relevant cryptocurrencies will be re-selected before portfolio formation. This will be done by using historical snapshots cryptocurrencies ranked by Market Capitalization (CoinMarketCap, 2020b).

The research question of this thesis is:

Which factors exist in cryptocurrencies and which model best explains the variation in average excess portfolio returns?

The contribution of this thesis is as follows. First, to the researcher knowledge this is the first inquiry into the volatility factor in cryptocurrencies. Second, most existing literature is either using a small sample, a sample that contains survivor bias or a sample that is retrieved at the begin of the sample. This research is unique by having a survivor bias free sample for a large sample of 315 different cryptocurrencies. Third, some portfolios come with high returns but also with high volatility. In this research all portfolios are leveraged or deleveraged to match the volatility of the market portfolio after taking into account the risk-free rate. All returns can therefore be interpreted as volatility risk-adjusted excess returns. Last, the total value of the cryptocurrency market has seen a big increase since the end of 2017. Therefore, using the historical data till march 2020, can results in new findings.

In this thesis I find the following results. First, I discover a significant momentum effect, this is similar to the finding of Tzouvanas et al. (2019) who also finds a momentum effect in the short run. The factors size, liquidity and volatility show the expected sign but are not significant. This could be due to the lack of power. Secondly, I find that the four-factor model including the four factors for capturing the market, momentum, liquidity, and volatility best explain the variation in cryptocurrency returns. I find that the four-factor model significantly outperforms the CAPM. The model is still easily rejected by the GRS (Gibbons, Ross, and Shanken, 1989) Test, from which can be concluded that it is still an incomplete model. In this research the size factor is found to be redundant. This finding could be a result of the the new data used and the method of selecting a survivor bias free sample.

The remaining paper consist of 4 sections. In Section 2, relevant literature is reviewed for cryptocurrencies as well as for other assets classes. In Section 3, I explain the data. Section 4 consist of the methodology and empirical results concerning the pricing factors. In Section 5, I present the methodology and empirical results regarding the pricing model. Finally, in Section 6, I will conclude the paper, present limitations of the research and suggests areas for future research.

2 Literature

2.1 Efficient Market Hypothesis

The Efficient Market Hypothesis describes how information is processed into asset prices and has three different forms. First of all, the weak form states that all historical public information is included in the price. It is therefore not possible to make abnormal returns based on historical data. Technical analysis, which is solely based on historical data should not give abnormal returns. Secondly, the semi-strong form states that all new information will lead to an almost immediate price change. Thus, in this form even fundamental analysis cannot lead to abnormal returns. Third, the strong form states that all information, public and private, is included in the price. (Malkiel and Fama, 1970)

2.2 Factor Investing

In the 1960's, the basis of factor investing was independently formed by Treynor (1961, 1962), Sharpe (1964), Mossin (1966), and Lintner (1975). Their research formed a one-factor Capital Asset Pricing Model (CAPM) which considered systematic risk (non-diversifiable risk) of an asset using one Beta for price sensitivity to the market portfolio. This market portfolio would theoretically consist out of all assets in the world. This model does not capture unsystematic risk and follows the Efficient Market Hypothesis (EMH). In 1976, the Arbitrary Price Theory (APT) was introduced by Ross (1976). This theory claims that there is more than one risk factor to capture systematic risk. Ross (1976) also states that prices can differ from their fundamental value and that one can benefit from this by taking a long position in the undervalued asset and shorting the overvalued asset. By exploiting arbitrage opportunities, one can still keep a net-zero exposure to systematic risk.

Fama and French (1992) proposed a three-factor model. In this model they included three factors, the market factor from the CAPM, a size factor *(SMB)* and a value factor *(HML)*. For the size factor stocks are sorted on their market value, and the factor can be defined as *Small minus Big*. The value factor is defined as *High minus Low* and stocks are sorted by their book-to-market value. Fama and French (1993) extended their model by adding two bond factors. The bond related risk factors relate to default risk and maturity. Fama and French (2015) proposed a five-factor model, by adding the risk factors for profitability and investment policy to their three-factor model. While the performance of this five-factor model was better than their three-factor model, it is still an incomplete model.

Jegadeesh and Titman (1993) document a momentum strategy, which generates an abnormal return by taking a long position in the past winners and taking a short position in the past losers. This strategy is a direct extension on the research of De Bondt and Thaler (1985) and De Bondt and Thaler (1987). They documented a contrarian strategy, which showed that over 3- to 5-year holding periods stocks that performed poorly over the previous 3 to 5 years achieve higher excess returns than stocks that performed well over the same period. The momentum effect of Jegadeesh and Titman (1993) was analysed over the period of 1965 to 1989. Their results state that selecting assets on the past performance and holding them for 3-12 months yields a significant positive excess return. It is important to notice that these abnormal returns do not come from taking on systematic risk or delayed stock price reaction due to common factors. Reason for this effect could be delayed price reaction to firm-specific information. It was Carhart (1997) who included the momentum factor in a four-factor model. This four-factor model was an extension to the three-factor model of Fama and French (1992). While Carhart (1997) adds the momentum factor to the model, he leaves all risk interpretation to the reader. The question if momentum is a risk factor or an anomaly, is not clearly answered. Yet, Fama and French (2015) still leave it out of their five-factor model despite the high explanatory.

Blitz and Van Vliet (2007) present empirical evidence on the existence of a low-risk factor. Their research states that stocks with low volatility earn high risk-adjusted returns. This effect is also observed within the US, European and Japanese market in isolation. This effect cannot be explained by other known factors such as size and value. Their results show that stock holders often overpay for risky stocks. Explanations for this could be leverage restrictions, inefficient two-step investment processes or behaviour bias. Clarke, De Silva, and Thorley (2010) replicate the Fama and French (1992) methodology and add a *VMS* (volatile minus stable) factor. This factor shows low to negative results indicating a low-risk premium. The factor is, however, highly correlated with previously established risk factors, which is highly undesirable.

Another volatility strategy, Betting-against-Beta (BAB), was published by Frazzini and Pedersen (2014). According to Frazzini and Pedersen (2014) investors who are prohibited from using leverage or limited in the use of leverage, seek other ways to leverage their portfolios. Instead of leveraging their portfolios the investors bid up high-beta assets. This research is performed by creating a BAB factor, which is a long leveraged portfolio in low-beta assets minus a short portfolio in high-beta assets. They find that the BAB factor produces significant higher risk-adjusted returns in all asset classes.

While most research focuses predominantly on equities, Asness, Moskowitz, and Pedersen (2013) looked into the presence of a momentum effect and a value effect across different asset classes. They find a consistent value and momentum premia across 8 different asset classes and they also find the existence of correlated value and momentum effects in other asset classes. Their result indicate the presence of global risk factors, that are both present within and across asset classes. They furthermore find that the exposure to global funding liquidity risk provides a partial explanation for this correlation structure, but this nevertheless, leaves a lot of room for further explanations.

2.3 Factor Investing in Cryptocurrencies

In this part I review existing literature on factor investing in the cryptocurrency market. It is free and easy to download long historical series on prices of major cryptocurrencies at the daily frequency. Therefore, in the last five years, a large amount of empirical papers have been published (Alexander and Dakos, 2020). Most early research was only focused on the Bitcoin. Some researcher are sceptical if cryptocurrencies represent any real value. Baek and Elbeck (2015) illustrate that Bitcoin is highly speculative and that Bitcoin prices are not driven by fundamental economic variables such as unemployment, inflation, or stock prices. This finding is supported by Cheah and Fry (2015), who suggest that the fundamental value of Bitcoin is equal to zero. Urquhart (2016) indicates that the Bitcoin price is predictable and inefficient, contradicting the EMH. Nadarajah and Chu (2017) and Tiwari, Jana, Das, and Roubaud (2018) among others support the finding that Bitcoin prices are contradicting the EMH. Disadvantages of this early research is the short sample size and in that time Bitcoin was more difficult to trade or arbitrage. It could well be that things have changed over the last years.

Even, if the EMH is rejected, what factors could help explain cryptocurrency returns? An early research of Hayes (2015) indicates that the fundamental factors computational power employed in mining, rate of production, and algorithm used for the protocol drive cryptocurrency returns. Other researches indicate that attention is a price driver for cryptocurrencies proxied by Google Trends data (Deng et al., 2019; Urquhart, 2018) or Twitter data (Shen et al., 2019b), while Wang and Vergne (2017) indicate that it is not attention, but the underlying innovation potential. They even find that attention is negatively associated with returns after controlling for a variety of factors. Demir, Gozgor, Lau, and Vigne (2018) suggest that uncertainty of Economic policy is positively associated with Bitcoin returns. Hacks on cryptocurrencies exchanges are found to increase both the volatility of the cryptocurrency hacked and have a negative influence on the price of the cryptocurrency hacked (Corbet, Cumming, Lucey, Peat, and Vigne, 2019).

Research has also been carried out for factors that have proven themselves in other assets classes. Literature on momentum strategies, which has been demonstrated to have strong predictive power in traditional financial markets, show mixed results. Rohrbach et al. (2017) conducted a research to the momentum effect in the (crypto)currency market. They conclude that there is a momentum effect present in the cryptocurrency market. They, however, only included 7 cryptocurrencies and backtested over the short period of 18 months. Grobys and Sapkota (2019), conducted the research over 143 cryptocurrencies over the period of 2014 to 2018. Their sample only consist of cryptocurrencies that existed prior to 2014. Their findings do not indicate any evidence of significant momentum payoffs nor a significant reversal effect. The formation period ranged between 12 to 1 month and the holding period was 1 month. Tzouvanas et al. (2019) decreased the holding periods to weekly periods, and finds a short-term momentum effect. This indicates an intra-monthly reversal effect.

Well know risk factors: market, size and value, first introduced by Fama and French (1992), also made their way into the cryptocurrency market. Hubrich (2017) examined a four-factor model including the factors: market, momentum, value, and carry. While the value factor sounds like a factor from early Fama and French (1992) research, it is in fact a new factor. The value factor, is calculated as the average excess return of the high book-to-market portfolio minus the average excess return of the low book-to-market portfolio. Since cryptocurrencies do not have a book value, Hubrich (2017) introduced the proxy on-chain transaction volume. This on-chain transaction volume is then compared to the market value in order to create a book-to-market ratio like variable. The carry resembles the return obtained “when underlying fundamentals do not change”, thus the variable has a negative relation to the increase in circulating supply. This is similar to the rate of unit production introduced in the paper of Hayes (2015). Hubrich (2017) selects 12 different cryptocurrencies. All cryptocurrencies are selected at the end of the sample resulting in survivor bias.

Deng et al. (2019) also conducted a research based on pricing factors. They use 110 cryptocurrencies for portfolio formation, which they update monthly. A total of 506 cryptocurrencies are used. Their data is from August 3 2014 to August 26 2018. The portfolios are all value-weighted which allows for a very large influence of large cryptocurrencies such as Bitcoin. A five-factor pricing model is introduced capturing the market, size, liquidity, contrarian, and attention. The factors for capturing size is according to the previous literature of (Fama and French, 1992). The market factor is defined as the excess return of the CRIX index. The liquidity factor is measured by the 7-day liquidity divided by market value. The third factor is a contrarian factor which, indicates a reversal effect that takes place after a momentum effect. There are some inconsistencies within their research concerning the contrarian factor. The 3 x 3 and 4 x 4 sorts show that cryptocurrencies that have performed poor, perform better than cryptocurrencies that have performed well. This shows a contrarian effect. The factor construction shows the opposite. Their contrarian factor is constructed by subtracting the excess return of the losers portfolio from excess return of the winner portfolio. This factor is positive and significantly different from zero, indicating a momentum effect instead of a reversal or contrarian effect. The attention factor is constructed by using global search volumes from Google Trends as a proxy for the attention of cryptocurrencies. On a individual level, the market factor, momentum factor and the attention factor show to be significant. Deng et al. (2019) conclude that in the five-factor model the market factor does not have much explanatory power, but the other four factors do explain the variation in returns. It is strange that they include all variables in the model, since the market factor and the size factor are found to be redundant. A three- of four-factor model could perhaps perform better.

Shen et al. (2019b) examines a three-factor model containing the factors market, size and momentum. This is done by including 1786 cryptocurrencies over the period of April 2013 to March 2019. This sample is obtained at the end of the sample period. This means it is not clear of survivor bias. By using almost all cryptocurrencies present on CoinMarketCap, even micro-cap cryptocurrencies are included that are extremely illiquid. The momentum strategy, with formation periods and holding periods ranging between 1 and 4 weeks. They only document a significant negative momentum effect in the 1-1 strategy. Regarding the three-factor model they conclude that it that it explains cryptocurrencies returns better than the CAPM.

2.4 Cryptocurrency Markets and Limit to Arbitrage

In this section the cryptocurrency market will be described. There are some main differences that influence the way research, which include cryptocurrencies, should be performed. The way cryptocurrencies are traded differ in multiple ways in comparison to stocks. First of all, stocks are mostly traded on only one exchange. An exemption is when companies have a cross-listing, this means a company that is traded on more than one exchange. This is not very common. Cryptocurrencies, on the other hand, are almost always traded on more than one exchange. This leads to different price discoveries.

Secondly, some cryptocurrency exchanges only offer trading against other cryptocurrencies, this is mainly because of regulatory constrains. Most trading volume between cryptocurrencies (other than Bitcoin) occurs against Bitcoin. Exchanges could offer trading against the U.S. Dollar or the Euro, but this brings a large regulatory burden. They need to have strict Know Your Customer (KYC) and Anti-Money Laundering (AML) policies and they often need to get a permit on the market they are active in. One way to undermine these regulations is offering trading pairs against Dollar- or Euro-pegged cryptocurrencies. Tether (USDT), a cryptocurrency pegged to the Dollar, is the most used cryptocurrency to offer Dollar trading.

Third, cryptocurrencies are traded 24 hours 7 days a week. So their closing prices are usually measured on 23:59:59 UTC. This would normally leave room for only milliseconds of time difference. However, the BTC/USD price data from CoinGecko are time-stamped 00:00:00 UTC. Normally, this would not cause any trouble as one would just look up prices from one coin-ranking site or another. The problem, however, is that the CRIX-index makes use of CoinGecko data (Trimborn and Härdle, 2018). This means that there is either a second difference, which would not be noticeable, or a whole day difference, depending on which day the time-stamp refers to. Either way, it would lead a very big problem. However, on 30 January 2018 something strange happened. Alexander and Dakos (2020) notice that from that day onwards, the prices from Coingecko (and CRIX) went out of sync compared to other prices. Data from the CRIX index is still usable but researchers needs to lag it one day starting on 30 January 2018.

There are two kinds of exchanges, centralized and decentralized. A decentralized exchange (DEX) is something that does not exist for other asset classes. When a transaction happens on a DEX, Cryptocurrencies are kept in private wallets of the investors, and a smartcontract is made to facilitate a transfer. When both investors have transferred their cryptocurrencies to the smart contract address, the transaction will automatically continue. Transactions on a decentralized exchange therefore always happen on the blockchain. Using a DEX is an easy way to bypass all existing regulation. Volume is nevertheless higher on centralized exchanges. It would, especially for Bitcoin, not be possible to do all transactions on a decentralized exchange, since bitcoin does not have the capacity to handle that amount of volume on its blockchain (CoinMarketCap, 2020a). Also, centralized exchanges offer a better user experience. All other exchanges that do not have these characteristics are centralized. Centralized exchanges hold custody over the cryptocurrencies, use their own trading engine and, can apply their own rules. These rules include a deposit or withdrawal fee, deposit or withdrawal limitations and, transaction fee.

Since there are so many exchanges and even more trading pairs, there is not one clear market price. This makes it especially difficult for cryptocurrencies that do not have a Dollar of Euro trading pair. For this reason coin-ranking websites such as *CoinMarketCap*, *CryptoCompare*, and *Coingecko* exist. These websites collect data on prices and volume from exchanges and rank the coins based on market value. Prices and thus market values are calculated as volume-weighted averages from all the exchanges. There are some disadvantages in using price information of coin-ranking sites and these are mainly found in their business models. Investors decide where to trade their cryptocurrency based on the data coin-ranking sites provide. Coin-ranking sites earn money on a referral bases. This arises a conflict of interest. Some exchanges might feel tempted to report inflated volumes to make exchanges appear more liquid than they really are. Exchanges deliberately create artificial volume to rank higher on the coin-ranking sites and therefore attract more traders. When exchange volumes are high, developers of new cryptocurrencies are also willing to pay high listing fees (Alexander and Dakos, 2020; Carter, 2018). Other problems are differences of opinion on circulating supply. According to *CoinMarketCap*, the circulating supply of Ripple (XRP) is approximately 44 billion XRP, while CryptoCompare states that their circulating supply is approximately 100 billion XRP. therefore, the market value of Ripple is 8 billion dollar on *CoinMarketCap* and 19 billion dollar on *CryptoCompare* (CoinMarketCap, 2020c; CryptoCompare, 2020).

Both exchanges and coin-ranking sites have an Application Programming Interface (API) service for retrieving price information. In case of an exchange the API allows retrieval of a limited history of the order book, traded prices, and volumes. Coin-ranking sites offer mostly less detailed data but longer historic time series. It is therefore that most research makes use of the non-traded prices of these coin-ranking sites for portfolio optimisation, efficiency studies, trading strategy development or hedging analysis (Alexander and Dakos, 2020).

According to Ross (1976), arbitrage may not be fully effective in some extreme circumstances. Professionals may want to avoid extreme volatile arbitrage positions. When positions are more volatile, the chances increase that you have to sell your positions underwater. The avoidance of volatile assets could help to explain persistence of high excess returns in securities. Other problems for exploiting arbitrage opportunities are excessive funding cost, since most arbitrage is done using borrowed capital or constraints in taking short positions or leverage positions.

3 Data

In this chapter, all the data that is used for this research is described.

3.1 Data and Sample

3.1.1 CoinMarketCap

In this research daily price data of 315 cryptocurrencies are obtained. As previous mentioned exchange allows retrieval of a limited history and a limited amount of different currencies. By using the coin-ranking site *CoinMarketCap*, data is retrieved of 315 cryptocurrencies from August 2014 to March 2020. Different than Deng et al. (2019) and Shen et al. (2019b) I only pick the 60 largest cryptocurrencies based on market value are used, this is to prevent the influence of micro-cap cryptocurrencies. It is very important to prevent survivor bias in the sample. When you select cryptocurrencies, based on market value, at the end of your time frame you create survivor bias in the sample (Deng et al., 2019). When you select the largest cryptocurrencies at the beginning of the time frame you limit yourself to cryptocurrencies that have been around only in this time frame (Brown, Goetzmann, and Ross, 1995). I correct this by adjusting the top 60 cryptocurrencies on the portfolio formation date. The only cryptocurrencies that are used for portfolio formation are the cryptocurrencies that are in the top 60 on the portfolio formation date. This way portfolios are formed with information that an investor had at his disposal. This is done by making use of the Historical Snapshot pages of *CoinMarketCap* (CoinMarketCap, 2020b). *CoinMarketCap* does not offer any retrieval of data from the historical snapshots by API. Thus, a webscrapper is used to retrieve price data from the *CoinMarketCap* website.

Cryptocurrencies that are pegged to other assets or currencies such as the Dollar or the Euro are excluded from the sample. These are the following cryptocurrencies: Tether, USD Coin, Binance USD, USDK, TrueUSD, DAI, HUSD, and bitUSD. These cryptocurrencies are completely removed from the sample before any portfolio formation has taken place. So there is still a total of 60 cryptocurrencies in the portfolios.

3.1.2 CRIX index

For the calculation of the market factor a market index is required that is representative for the market. Well known indices are Huobi 10 index, Bletchley index, and the CRIX index. The CRIX index is established in July 2014 and is therefore the one with the longest history. The CRIX index is retrieved through the use of the API of CRIX (Trimborn and Härdle, 2018). The CRIX index is a market weighted index consisting of the 10 largest cryptocurrencies based on market value. The reallocation period of the CRIX is 1 month. As mentioned before the CRIX index is out of sync since 30 January 2018. Graph A.1 illustrates that this problem still persist at the time of writing this research. Graph A.1 displays the problem by plotting the spread between the corrected CRIX - BTC(blue) and uncorrected CRIX - BTC(red). The CRIX index is on average 66% Bitcoin, the return spread between the CRIX index and Bitcoin should be minimal. The Graph expose a major increase in spread after the 30 January 2018. When the data is lagged the sudden increase in spread no longer persists. Therefore, the data can still be used when it is lagged by one day, starting from 30 January 2018 onwards.

3.1.3 Additional data

The yield of the 1 month US Treasury bill is used as the proxy for the risk free rate (Fama and French, 1992, 2015). This data is retrieved from Bloomberg.

3.2 Descriptive Statistics

Table 1 displays the descriptive statistics for the CRIX index, Equally-Weighted (EW) market portfolio, Bitcoin (BTC), and the yield of the 1 month US Treasury bill. The CRIX index consist mostly of Bitcoin and therefore shows a very similar mean and Standard deviation. The EW market portfolio has a higher mean and standard deviation than the CRIX index and Bitcoin. Table 2 shows the correlations. The CRIX index and Bitcoin are highly correlated. The correlation between the EW market portfolio and Bitcoin is substantially lower, but still pretty high considering that Bitcoin is only 1/60th of the EW market portfolio. This could indicate that there is a high correlation between Bitcoin and the other cryptocurrencies inside the EW market portfolio.

Table 1: Descriptive statistics

CRIX is the market index for the cryptocurrency market. EW market portfolio is the equally-weighted weekly return on the market portfolio of all sample cryptocurrencies. Bitcoin (BTC) is the cryptocurrency with the largest market value. Yield 1m US T-Bill is the yield of the 1 month US treasury bill. The sample period is from August 2014 to March 2020. Weekly returns are calculated based on daily closing price and denoted in percentage.

Asset	Mean	Std Dev	Min	Max
CRIX	1.519	24.85	-43.99	52.79
EW market portfolio	2.168	31.90	-48.00	89.41
BTC	1.408	24.10	-45.25	74.91
Yield 1m US T-Bill	0.018	0.016	0	0.047

Table 2: Correlations

CRIX is the market index for the cryptocurrency market. EW market portfolio is the equally-weighted weekly return on the market portfolio of all sample cryptocurrencies. Bitcoin (BTC) is the cryptocurrency with the largest market value. The sample period is from August 2014 to March 2020.

	CRIX	EW market portfolio	BTC
CRIX	1.00	0.80	0.93
EW market portfolio	0.80	1.00	0.65
BTC	0.93	0.65	1.00

4 Pricing Factors

In this part I discuss the portfolios, the construction of the factors, descriptive statistics of the factors, and the test on redundant factors. It is important to notice that cryptocurrency markets are continuously traded, so markets are open roughly four times longer. Therefore portfolios are adjusted at a seven-day adjustment frequency instead of a one-month adjustment frequency. Since daily returns are used there are 7 possible adjustment days. Each portfolio is used seven times with a different adjustment day. All results are pooled statistics of seven return series. This is similar to the methodology of Jegadeesh and Titman (1993). Because of this, autocorrelation is present in the data. From the seven days of the week, six days are present in other portfolios with different adjustment dates. This by itself leaves the coefficients unbiased but it causes an increase of the variance of the coefficient estimates. Thus, when not corrected for autocorrelation, estimates of the standard error will be smaller than their true value. For this reason Heteroskedasticity and Autocorrelation corrected (HAC) standard errors are used (Newey and West, 1986). Seven lags are used, six lags for the six days overlap and one lag extra to make sure all autocorrelation is captured. This seventh lag should not contain much autocorrelation.

For all portfolios the standard deviation is calculated over the whole sample period. Some portfolios have a higher volatility, especially the portfolios selected on high volatility show volatility up to 2 times as high. The standard deviation of all portfolios range between 0.124 and 0.254, the market portfolio has a standard deviation of 0.137. All portfolios are then leveraged or deleveraged to match the volatility of the market portfolio. This is done after taking into account the risk-free rate. All returns can therefore be interpreted as volatility-risk adjusted excess returns.

Based on previous literature I include the following variables: market *(RM)*, size *(SMB)*, momentum *(WML)*, liquidity *(GMB)*, and volatility *(VMS)*.

a. *Market (RM)*

For constructing the market factor two different indices can be used. First of all, the CRIX index. This is a value-weighted index consisting of the 10 largest cryptocurrencies based on market value. Secondly, the equally-weight weekly return on the market portfolio of all sample cryptocurrencies. This is an equally weighted index, just like the other portfolios used in this research. This index consist of all 60 cryptocurrencies used for portfolio formation. Table 1 and Table 2 show us that the return of the equally-weighted index is approximately 0.6 percent higher, mainly because of the bigger representation of the cryptocurrencies with smaller market value. It is also more volatile. The

CRIX index is highly correlated with BTC, this is because it is a value weighted index and therefore consist mainly out of BTC. Whereas, the EW market portfolio is less correlated with BTC. The EW market portfolio is chosen as the market portfolio since it better represents the cryptocurrency market especially when portfolios are equally-weighted. Therefore, the market factor is defined as the equally-weight weekly return on the market portfolio of all sample cryptocurrencies minus the risk-free rate. The risk free rate is defined as the yield of the one-month treasury bill. The market portfolio and the market factor can be defined as follows:

$$R_{Mt} = \sum_{i=1}^{n} ret_{i,t} * \frac{1}{n} \tag{1}$$

$$RM_t = R_{Mt} - R_{Ft} \tag{2}$$

b. *Size (SMB)*

The *size (SMB)* factor is calculated as the weekly average return of the small market value portfolio *(Small)* minus the big market value portfolio *(Big)*.

c. *Momentum (WML)*

For the momentum factor cryptocurrencies are sorted on performance and divided into well performing cryptocurrencies *Winners* and poor performing cryptocurrencies *Losers*. The Momentum *(WML)* is constructed by subtracting the mean return of the *Losers* from the *Winners*. In stock literature lookback periods vary between one to twelve months. The lookback periods that are examined in this research vary from one week to four weeks. This is for the same reason as the shortened portfolio adjustment frequency. Cryptocurrencies are sorted based on the performance over the following lookback periods, 7 days, 14 days, 21 days and 28 days. The best lookback period is used, based on the highest risk-adjusted excess return. The risk-adjusted excess returns of the *winner* and *Loser* portfolios are displayed in Table 3. The 21 days lookback period has the highest risk-adjusted excess returns and is therefore used for this research.

Table 3: Time-series momentum returns

Average weekly risk-adjusted excess returns for four different lookback periods. Cryptocurrency portfolios are adjusted every seven days and denote the adjustment day as t. A winners and losers portfolio is made based on the 30th and 70th percentiles on t-1. All returns are risk-adjusted returns and denoted in percentages.

Lookback period	Winners	Losers	Winner minus losers
7 Days	2.80	0.99	1.81
14 Days	2.81	1.12	1.69
21 Days	2.95	1.07	1.88
28 Days	2.89	1.05	1.84

d. *Liquidity (GMB)*

The *Liquidity (GMB)* is calculated as the weekly average return of the liquid portfolio (*Good*) minus the illiquid portfolio (*Bad*). The adjusted volume, on which the portfolios are sorted, is calculated by dividing the 7-day average volume by the 7-day average market value. This is similar to Deng et al. (2019). It is defined as follows:

$$V_{adj} = \frac{V_7}{MV_7} \tag{3}$$

e. *Volatility (VMS)*

The volatility factor is constructed by following the literature of Clarke et al. (2010). Cryptocurrencies are sorted on past volatility. The cryptocurrencies are divided into multiple groups. The volatility *(VMS)* is constructed by subtracting the mean return of the *Stable* cryptocurrencies from the *(Volatile)* cryptocurrencies. To find the best lookback period we calculate the factors based on single sorts. This is performed for the following periods, 7 days, 14 days, 21 days, and 28 days. Table 4 contains the risk-adjusted excess returns. All low-risk portfolios show higher risk-adjusted excess returns. According to previous literature, the volatility factor often shows a low-risk premium (Blitz and Van Vliet, 2007). The lookback period with the highest low-risk premium is chosen. This is the 21 days lookback period.

Table 4: Time-series volatility returns

Average weekly risk-adjusted excess returns for four different lookback periods; August 2014 - March 2020, 296 weeks. Cryptocurrency portfolios are adjusted every seven days and denote the adjustment day as t. A high-risk and low-risk portfolio is made based on the 30th and 70th percentiles on t-1. All returns are risk-adjusted returns and denoted in percentages.

Lookback period	low-risk	high-risk	high- minus low-risk
7 Days	2.10	1.96	-0.14
14 Days	2.15	2.06	-0.09
21 Days	2.18	1.93	-0.24
28 Days	2.17	1.96	-0.20

4.1 Factor Definitions

The factor pricing model for the cryptocurrency market can be presented as follows:

$$R_{it} – R_{Ft} = \alpha_i + b_i(R_{Mt} – R_{Ft}) + s_i SMB + w_i WML + g_i GMB + v_i VMS + e_{it}$$

where R_{it}, R_{Ft}, R_{Mt}, SMB, WML, GMB, and VMS stand for the return of the cryptocurrency portfolio, the risk-free rate, the return of market portfolio, size, momentum, liquidity, and volatility, respectively. The intercept α is the return that cannot be explained through the factors.

In the previous section the best lookback period is found based on single sorts grouping. The best lookback period is not selected based on the double sorts. This is to prevent data mining. For constructed the factors I use the method of Fama and French (2015). Independent double sorts is used to create two size groups and three groups for Liquidity, Momentum and Volatility factors. For size the sample median is used as breakpoint. For the other factors the breakpoints are the 30th and 70th percentiles (independent 2 x 3 sorts). Portfolios are also constructed using the 2 x 2 sorts on size and liquidity, momentum and volatility, using sample medians as breakpoints for all variables. The 2 x 2 sorts is added by Fama and French (2015) to test whether factor constructing methods has significant influence on the factors. The 2 x 3 sorts focuses more on the extreme, since the middle 40% is not included. The 2 x 2 sorts include all cryptocurrencies. The 2 x 3 sorts is expected to return larger factor averages. In this research I consider the 2 x 3 sorts the main sorts. Details in Table 5.

Table 5: Construction of size, liquidity and volatility factors

Independent sorts is used to assign cryptocurrencies to two Size groups, and two or three Liquidity, Momentum and Volatility groups. Portfolios are labelled with two letters. The first letter describes the size group, small *(S)* and big *(B)*. The second letter describes the momentum group, winner *(W)*, neutral *(N)*, or loser *(L)*, liquidity, good *(G)*, neutral *(N)*, bad *(B)* and the volatility group, volatile *(V)*, neutral *(N)*, or stable *(S)*. The factors are the *SMB* (small minus big), *WML* (winners minus losers), *GMB* (good minus bad), and *VMS* (volatile minus stable).

Sort	Breakpoint	Factors and their components
2 X 3	Size: sample median	$SMB_{mom} = (SH + SN + SL)/3 - (BH + BN + BL)/3$
		$SMB_{liq} = (SW+SN+SL)/3-(BW+BN+BL)/3$
		$SMB_{vol} = (SH+SN+SL)/3-(BH+BN+BL)/3$
		$SMB = (SMB_{mom} + SMB_{liq} + SMB_{vol})/3$
	Momentum: 30th and 70th percentiles	$WML = (SW + BW)/2 - (SL + BL)/2 = [(SW - SL) + (BW - BL)]/2$
	Liquidity: 30th and 70th percentiles	$GMB = (SG + BG)/2 - (SB + BB)/2 = [(SG - SB) + (BG - BB)]/2$
	Volatility: 30th and 70th percentiles	$VMS = (SV + BV)/2 - (SS + BS)/2 = [(SV - SS) + (BV - BS)]/2$
2 X 2	Size: sample median	$SMB = (SW + SL + SG + SB + SV + SS)/6 - (BW + BL + BG + BB + BV + BS)/6$
	Momentum: sample median	$WML = (SW + BW)/2 - (SL + BL)/2 = [(SW - SL) + (BW - BL)]/2$
	Liquidity: sample median	$GMB = (SG + BG)/2 - (SB + BB)/2 = [(SG - SB) + (BG - BB)]/2$
	Volatility: sample median	$VMS = (SV + BV)/2 - (SS + BS)/2 = [(SV - SS) + (BV - BS)]/2$

4.2 Summary Statistics for Factor Returns

Table 6 contains the average, standard deviations, and t-statistics for weekly returns of the factors. This is done for both the 2 x 2 and 2 x 3 sorts. As mentioned before, the 2 x 3 is the main sorts and the 2 x 2 is present to test whether the construction of the factors influences the outcome. This is similar to Fama and French (2015). The excess returns of the market factor and the momentum factor are significantly different than zero at respectively 5% significance and 1% significance. A significant momentum effect is documented in the period of August 2014 till March 2020. This contradicts some of previous research. Shen, Urquhart, and Wang (2019a) find a strong reversal effect. They use a enormous amount of 1736 cryptocurrencies, all selected before at the beginning of the sample in 2014. This both influences the outcome. It could well be that micro cap cryptocurrencies, that are often very illiquid, do not have show any momentum effect. It could also be that cryptocurrencies selected before 2014 perform different than newer cryptocurrencies selected after 2014. Grobys and Sapkota (2019) who used long lookback periods of 1 to 12 month found no persistence of momentum effect. The results of this research are similar to Tzouvanas et al. (2019) who also used lookback periods and holding periods smaller than a month. This could indicate that there is some intra-month reversal.

The factors size, liquidity, and volatility all show the expected sign, but they are not significant. Similar to Deng et al. (2019) I find a positive but insignificant size factor. Due to the short time series there is a possibility that the tests lack power. They same holds for the volatility factor and the liquidity factor. They both show a negative sign which could indicate a small low-risk and illiquidity premium, yet they are insignificant. While the volatility risk-adjusted returns of size factor, liquidity factor, and volatility factor are not significant different from zero, they can still have explanatory power in combination with other factors.

From Table 6 can be derived that the difference between the different sorting methods is marginal. The volatility risk-adjusted returns of the factors differ little between the two different grouping methods. This is also shown by the correlation between different versions of the same factor in Table 7. The correlations of the different versions of the factors of SMB, WML, GMB and VMS are equal or higher than 0.85. This is high enough to conclude that the different methods of grouping have little effect on the results. Since the market factor is not affected by the grouping methods it is not in the table.

Table 6: Average, standard deviations, and t-statistics for weekly returns

Average, standard deviations, and t-statistics for factor risk-adjusted weekly returns; August 2014 - March 2020, 296 weeks. The factors are the *SMB* (Small minus Big), *WML* (winners minus losers), *GMB* (Good minus Bad), and *VMS* (volatile minus stable). *RM* is the equally-weighted weekly return of the market portfolio of all sample cryptocurrencies minus the yield of the one month US Treasury bill. Newey and West (1986) standard errors are used.

	2 X 3 Factors					2 X 2 Factors				
	RM	SMB	WML	GMB	VMS	RM	SMB	WML	GMB	VMS
Mean	2.16	0.32	1.51	-0.28	-0.34	2.16	0.32	1.30	-0.32	-0.17
Std	31.99	16.58	16.25	17.25	16.63	31.99	14.47	13.25	15.01	13.98
T-stat	3.04	0.87	4.20	-0.72	-0.92	3.04	1.00	4.44	-0.96	-0.56

Table 7: Correlations between different versions of the same factor

Correlations between different versions of the same factor; August 2014 - March 2020, 296 weeks. The factors are the *SMB* (Small minus Big), *WML* (winners minus losers), *GMB* (Good minus Bad), and *VMS* (volatile minus stable).

SMB			WML			GMB			VMS		
	2 x 2	2 x 3		2 x 2	2 x 3		2 x 2	2 x 3		2 x 2	2 x 3
2 x 2	1.00	0.85	2 x 2	1.00	0.87	2 x 2	1.00	0.87	2 x 2	1.00	0.90
2 x 3	0.85	1.00	2 x 3	0.87	1.00	2 x 3	0.87	1.00	2 x 3	0.90	1.00

Table 8 presents the correlation between the five different factors for both sorts. There is an overall low and sometimes negative correlation between the different factors. If correlation is high between factors, there is an increased change they explain the same variation in returns. This is further explored in the next section where is tested for redundant factors.

As mentioned before the variation between the different grouping methods are very small. For this reason it is concluded that the grouping methods has little effect on the characteristics of the factors. Fama and French (2015) consider the 2 x 3 sort the standard. For this reason I continue with the 2 x 3 grouping.

Table 8: Correlations between different factors

Correlations between different factors; August 2014 - March 2020, 296 weeks. The factors are the *SMB* (Small minus Big), *WML* (winners minus losers), *GMB* (Good minus Bad), and *VMS* (volatile minus stable). *RM* is the equally-weighted weekly return of the market portfolio of all sample cryptocurrencies minus the yield of the one month US Treasury bill. Newey and West (1986) standard errors are used.

2 X 3 Factors

	RM	SMB	WML	GMB	VMS
RM	1.00	-0.07	-0.06	0.21	-0.06
SMB	-0.07	1.00	0.23	0.17	0.08
WML	-0.06	0.23	1.00	0.41	0.39
GMB	0.21	0.17	0.41	1.00	0.18
VMS	-0.06	0.08	0.39	0.18	1.00

2 X 2 Factors

RM	SMB	WML	GMB	VMS
1.00	-0.04	-0.01	0.12	-0.01
-0.04	1.00	0.14	0.10	0.02
-0.01	0.14	1.00	0.37	0.33
0.12	0.10	0.37	1.00	0.23
-0.01	0.02	0.33	0.23	1.00

4.3 Redundant Factors

In this section we only continue with the factors based on the 2 x 3 sorts. I examine whether one of the factors is redundant by regressing individual factor portfolios on the other four factors. The intercept of the regressions in Table 9 show the return premium after accounting for the other four factors. The results for the market factor and the momentum factor do not change compared to Table 6. The market factor and the momentum factor both have a significant alpha at a significance level of 1%. This indicates that both factors still offer a premium after taking into account the other factors. The liquidity factor and volatility factor both show different results compared to Table 6. Both factors were not significantly different from zero, but after taking into account the other factors do show a significant alpha. This is probably due to the high expose to the momentum factor. The liquidity factor and the volatility factor have a significant exposure to the momentum factor of 0.402 and 0.352 respectively. The results in Table 9 indicate that the size factor is redundant since the intercept is not significantly different from zero. Because of the small sample size further analysis is needed before it can safely be concluded whether the size factor is completely redundant.

Table 9: Tests on redundant factors

Using four factors in regressions to explain average returns on the fifth; August 2014 - March 2020, 296 weeks. The factors are the *SMB* (Small minus Big), *WML* (winners minus losers), *GMB* (Good minus Bad), and *VMS* (volatile minus stable). RM is the equally-weighted weekly return of the market portfolio of all sample cryptocurrencies minus the yield of the one month US Treasury bill. Newey and West (1986) standard errors are used.

	Intercept	RM	SMB	WML	GMB	VMS
RM						
coef	2.270		-0.140	-0.226	0.456	-0.091
t-statistic	4.03		-0.92	-2.29	-3.42	0.65
SMB						
coef	0.189	-0.047		0.168	0.104	-0.017
t-statistic	0.62	-0.92		1.98	0.87	-0.17
WML						
coef	1.799	-0.065	0.147		0.352	0.320
t-statistic	6.78	-2.20	2.20		5.72	5.79
GMB						
coef	-1.201	0.150	0.104	0.402		0.040
t-statistic	-3.32	3.83	0.87	4.73		0.36
VMS						
coef	-0.806	-0.029	-0.016	0.352	0.038	
t-statistic	-2.77	-0.67	-0.17	5.50	0.37	

5 Pricing Model

In this section the performance of different pricing models is tested.

5.1 Summary Statistics of Portfolio Returns

This section examines the patterns in risk-adjusted returns the model is designed to explain. In this part the same double sorts method is used as for the construction of the factors. Considering the relatively small sample size of 60 cryptocurrencies in all portfolios combined, I adopt the 3 x 3 sorts to form 9 portfolios. These 9 portfolios are then used for testing the performance of the pricing models (Fama and French, 2015). Table 10 shows the volatility risk-adjusted weekly excess returns of the 9 equal-weighted portfolios from the 3 x 3 grouping. The portfolios are grouped according to the Size and Momentum (Panel A), Size and Liquidity (Panel B), and Size and Volatility (Panel C). The results indicate that portfolios containing cryptocurrencies with small market capitalisation (8 times) yield higher volatility risk-adjusted returns than cryptocurrencies with large market capitalisation (1 time). In Panel A, cryptocurrencies with past high returns show high volatility risk-adjusted returns. In Panel B, volatility risk-adjusted returns tend to increase when liquidity decreases. In Panel C, cryptocurrencies with low volatility show higher volatility risk-adjusted returns.

Table 10: Excess returns of 3 X 3 portfolios

Average weekly volatility risk-adjusted excess returns for equally-weighted portfolios formed on (a) size, liquidity, (b) size, momentum and (c) size, volatility; August 2014 - March 2020, 296 weeks. Portfolios are adjusted every 7 days denoted as t. Cryptocurrencies in each Size group are allocated independently to the three groups Liquidity, Momentum and Volatility on t - 1. Returns are denoted in percentage.

	Small	2	Big
Panel A: Size - Momentum			
Low	1.45	0.32	0.92
2	1.82	1.61	1.78
High	2.31	2.43	2.45
Panel B: Size - Liquidity			
Low	1.88	1.89	1.75
2	2.31	1.18	1.78
High	1.59	1.51	1.50
Panel C: Size - Volatility			
Low	2.32	1.87	1.63
2	2.26	1.36	2.15
High	2.00	1.78	1.03

5.2 Model Performance Summary

In this part the explanatory power of the factor models is examined. First the performance of the CAPM is analysed. After that the model is expanded with relevant factors. According to Section 4.3, size *(SMB)*, was the only redundant factor. So, a four-factor model, excluding size, is introduced. The four-factor model can be specified as follows:

$$R_{it} – R_{Ft} = \alpha_i + b_i(R_{Mt} – R_{Ft}) + w_i WML + g_i GMB + v_i VMS + e_{it}$$

Section 5.1 shows the pattern in returns that the models are trying to explain. This same 3 x 3 portfolios are used in this section to test the performance of the models. There are two methods to test the explanatory power of a model. First of all, the Gibbons, Ross and Shanken (GRS) Test (Gibbons et al., 1989), which examines if all intercepts are equal to zero at the same time. According to Fama and French (2015), models are simplified propositions about expected returns. For this reason proposed models often get easily rejected by the GRS test. What is more important, is the relative performance of the models. For this reason, Fama and French (2015) introduced following three estimates, $A|a_i|$, $A|a_i|/A|\bar{r}_i|$, $A(a_i)^2/A(\bar{r}_i)^2$. $A|a_i|$ is the absolute mean of the intercept of the 9 portfolios where a_i is the intercept of portfolio i. $\bar{r}_i$ is portfolio i's deviation from the cross-section average and is defined as $\bar{r}_i = \bar{R}_i - \bar{R}$. Where $\bar{R}_i$ is the average return of portfolio i and $\bar{R}$ is the average of all the portfolios. $A|a_i|/A|\bar{r}_i|$ is the average of the absolute value of the intercept a_i divided by the average absolute value of r_i. $A(a_i)^2/A(\bar{r}_i)^2$ is the average square root of the intercepts a_i divided by the square root of the $\bar{r}_i$.

Table 11 display all estimates for the CAPM and the four- and five factor model. The average absolute intercept, $A|a_i|$, of the CAPM is between 0.328 and 0.557. In comparison to the CAPM, the four-factor model shows big improvements. The average absolute intercepts decreases by 0.072 to 0.330 percentage points. Furthermore, $A|a_i|/A|\bar{r}_i|$ range between 44% and 93%. Hence, the four-factor model leaves 44-93% of the dispersion of average excess returns unexplained. The CAPM and the five-factor model have an estimate that exceeds 1. This interpretation, that more than 100 percent of the dispersion of average excess returns is unexplained, sounds strange. Yet, Fama and French (2015) also mention that some of their estimates exceed 1. They do not interpret these estimates. All models perform poorly on the *Size-Liquidity* portfolios.

Measurement errors have a negative influence on both the absolute intercept $A|a_i|$ and the absolute deviation $A|r_i|$. The estimated intercept, a_i, is the actual intercept, α_i, plus an estimation error, $a_i = \alpha_i + \epsilon_i$. The absolute deviation is, similarly, a combination of expected deviation of the mean, μ_i, and an estimation error, $\bar{r}_i = \mu_i + \epsilon_i$. These measurement errors can be adjusted for by using both the squared intercept and squared deviation. The $A(\hat{\alpha}^2)/A(\hat{\mu}^2)$ estimates the proportion of the variance of the expected return that is not explained by the model. Because of the correction for the measurement error and because units of return are squared, it can give a more positive image of the models. For the four-factor model the $A(\hat{\alpha}^2)/A(\hat{\mu}^2)$ ranges between 0.241 and 0.843, which means the that the model leaves 24 till 84 percent of the variance of the expected return unexplained. The GRS statistic, for the three portfolios, is between 2.715 and 3.176. These all exceed the critical value at a 5% level of 1.88. According to this statistic all intercepts are not jointly equal to zero. Because of the overlapping periods, the GRS test statistic is biased. It therefor rejects the hypothesis, that the intercepts are unequal to zero, too fast.

Table 11: Tests of the four- and five-factor model

Summery statistics for test of four- and five-factor model to explain weekly excess returns on 9 *size-Momentum* portfolios, 9 *size-Liquidity* portfolios, and 9 *size-volatility* portfolios; August 2014 - March 2020, 296 weeks. The GRS statistic test whether the expected values of 9 intercept estimates are equal to zero. The average absolute value of the intercepts, $A|a_i|$. The average absolute value of the intercept, a_i over the absolute value of $\bar{r}_i$, which is the average return on portfolio i minus the average of the portfolio returns. $A(\hat{\alpha}^2)/A(\hat{\mu}^2)$, which is $A(\hat{a_i}^2)/A(\hat{r_i}^2)$, the squared value of the intercept over the squared value of $\bar{r}_i$, adjusted for sampling error in the numerator and denominator.

	GRS	$A\|a_i\|$	$A\|a_i\|/A\|\bar{r}_i\|$	$A(\hat{\alpha}^2)/A(\hat{\mu}^2)$
Panel A: CAPM				
Size-Momentum	10.441	0.557	1.032	1.115
Size-Liquidity	4.290	0.328	1.554	1.802
Size-Volatility	4.612	0.358	1.088	1.022
Panel B: Four-factor model (excluding size)				
Size-Momentum	3.176	0.237	0.438	0.241
Size-Liquidity	2.715	0.256	0.934	0.843
Size-Volatility	2.745	0.272	0.824	0.592

All factors are included in the four-factor model that have been indicated to be useful in the previous section. The estimates are also calculated for the three- and five-factor model to see whether the model performs better by including or excluding additional factors. Table 12 Panel D shows, as expected, that adding the redundant factor size does not improve the model. From this I can conclude that the size factor really is redundant. Deng et al. (2019) who also uses a similar survivor bias free sample also indicate that size could be redundant. They nevertheless included it in their five-factor model. Shen et al. (2019b), who selected 1763 cryptocurrencies at the beginning of the sample, does find the size factor to have explanatory power. This shows that method of selecting cryptocurrencies probably influences the model results.

Table 12 also displays the results for the three-factor models. Panel A, Panel B, and Panel C show that excluding any other factors than the size factor does not improve the performance either. From this can be concluded that the four-factor pricing model is the model containing the smallest pricing errors and therefore best explains the variance in cryptocurrency returns. This confirms the results in Section 4.3, where only the size factor showed to be a redundant factor. Just like Hubrich (2017) I find the strongest performance of the momentum factor and in accordance to most previous literature I find that a multi-factor pricing model better explains cryptocurrency prices than the CAPM (Deng et al., 2019; Hubrich, 2017; Shen et al., 2019b).

Table 12: Tests of the three-factor model

Summery statistics for three-factor model to explain weekly excess returns on 9 *Size-Momentum* portfolios, 9 *Size-Liquidity* portfolios, and 9 *Size-Volatility* portfolios; August 2014 - March 2020, 296 weeks. The GRS statistic test whether the expected values of 9 intercept estimates are equal to zero. The average absolute value of the intercepts, $A|a_i|$. The average absolute value of the intercept, a_i over the absolute value of $\bar{r}_i$, which is the average return on portfolio i minus the average of the portfolio returns. $A(\hat{\alpha}^2)/A(\hat{\mu}^2)$, which is $A(\hat{a_i}^2)/A(\hat{r_i}^2)$, the squared value of the intercept over the squared value of $\bar{r}_i$, adjusted for sampling error in the numerator and denominator.

	GRS	$A\|a_i\|$	$A\|a_i\|/A\|\bar{r}_i\|$	$A(\hat{\alpha}^2)/A(\hat{\mu}^2)$
Panel A: Three-factor model (excluding size and momentum)				
Size-Momentum	18.226	0.677	1.251	1.531
Size-Liquidity	3.233	0.256	1.211	1.446
Size-Volatility	5.316	0.380	1.151	1.138
Panel B: Three-factor model (excluding size and liquidity)				
Size-Momentum	2.827	0.254	0.469	0.220
Size-Liquidity	8.218	0.513	2.427	4.229
Size-Volatility	2.013	0.231	0.699	0.443
Panel B: Three-factor model (excluding size and volatility)				
Size-Momentum	2.843	0.224	0.414	0.217
Size-Liquidity	2.265	0.182	0.860	0.852
Size-Volatility	5.218	0.415	1.259	1.379
Panel C: Five-factor model				
Size-Momentum	3.883	0.277	0.512	0.243
Size-Liquidity	2.620	0.258	1.223	1.167
Size-Volatility	4.750	0.238	0.720	0.437

5.3 Regression Details

In Table 13 the CAPM regression results are displayed for the nine *Size-Momentum* portfolios. The CAPM has problems with explaining the returns of the low and high momentum portfolios, resulting in significant intercepts for five out of nine portfolios. The four-factor model, including a momentum factor (details in Table 14), does a significantly better job in explaining the results. For seven out nine portfolios, the null hypothesis, that intercept is equal to zero, cannot be rejected. The average absolute intercept improves from 0.557 to 0.237 (Details in Table 11). The market factor is both in the CAPM and the four-factor model significant for all nine portfolios. This could be due to the way some altcoins are listed. Most altcoins only have a trading pair with Bitcoin. When Bitcoin falls in value the dollar value of the altcoins falls with it. In the four-factor model the momentum factor has a significant coefficient in six out of nine times. As expected, it especially helps to explain the returns of Low and High momentum portfolios. The momentum factor also captures some of the differences in excess return on the small cryptocurrency portfolios compared to the big cryptocurrency portfolios. None of the other factors show a big difference in the value of the coefficient between big cryptocurrency portfolios and the small cryptocurrency portfolios. This can also be concluded from the *Size-Liquidity* and *Size-Volatility* portfolios (Details in Table 16 and Table 18). The coefficient of the liquidity factor is significant zero times, and the coefficient of the volatility factor is significant only twice, indicating low explanatory power of the two factors.

Table 13: Regression results CAPM for Size-Momentum portfolios

Regression results CAPM for nine *Size-Momentum* portfolios; August 2014 - March 2020, 296 weeks. *RM* is the equally-weighted weekly return on the market portfolio of all sample cryptocurrencies minus the one-month Treasury bill rate. On the right hand side of the table are the corresponding t-values, which indicate if the intercept or coefficient are significantly different from zero. Newey and West (1986) standard errors are used.

Size →		Small	2	Big	Small	2	Big
		α			$t(\alpha)$		
	Low	-0.309	-1.465	-0.790	-1.04	-5.21	-2.63
Intercept	2	0.015	-0.194	-0.041	0.07	-0.79	-0.17
	High	0.882	0.644	0.656	2.92	2.30	2.04
		b			$t(b)$		
	Low	0.800	0.811	0.776	16.77	21.26	16.37
RM	2	0.826	0.821	0.829	22.38	18.37	20.18
	High	0.651	0.812	0.813	8.87	17.70	21.04

Table 14: Regression results five-factor for Size-Momentum portfolios

Regression results five-factor model for nine *Size-Momentum* portfolios; August 2014 - March 2020, 296 weeks. The factors are the *WML* (winners minus losers), *GMB* (good minus bad), and *VMS* (volatile minus stable). *RM* is the equally-weighted weekly return on the market portfolio of all sample cryptocurrencies minus the one-month Treasury bill rate. On the right hand side of the table are the corresponding t-values, which indicate if the intercept or coefficient are significantly different from zero. Newey and West (1986) standard errors are used.

Size →		Small	2	Big	Small	2	Big
		α			$t(\alpha)$		
	Low	0.617	-0.601	0.155	1.60	-2.02	0.48
Intercept	2	-0.117	-0.422	0.016	-0.56	-2.04	0.07
	High	-0.019	0.033	0.157	-0.08	0.14	0.56
		b			$t(b)$		
	Low	0.765	0.793	0.773	17.60	24.01	17.02
RM	2	0.827	0.813	0.815	21.77	25.91	18.63
	High	0.666	0.831	0.834	11.61	24.82	20.04
		w			$t(w)$		
	Low	-0.538	-0.533	-0.591	-5.54	-8.44	-7.43
WML	2	0.087	0.048	-0.056	1.90	1.10	-1.03
	High	0.629	0.414	0.294	5.52	8.07	3.99
		g			$t(g)$		
	Low	0.130	0.006	-0.103	1.52	0.07	-0.92
GMB	2	0.019	-0.040	0.029	0.36	-0.65	0.47
	High	0.099	0.008	0.074	1.06	0.18	-0.99
		v			$t(v)$		
	Low	0.028	0.072	0.148	0.33	0.80	1.24
VMS	2	0.007	-0.343	-0.198	0.07	-3.72	-2.92
	High	0.111	0.100	0.038	1.21	1.89	0.57

For the nine *Size-Liquidity* portfolios the results are somewhat similar. As seen before in Table 11 the average absolute intercept improves from 0.328 to 0.256. This is a smaller improvement than for the *Size-Momentum* portfolios. This is due to the smaller deviation in returns in the nine *Size-Liquidity* than in the nine *Size-Momentum* portfolios (Details in Table 10). Therefore, the CAPM has less trouble in explaining the *Size-Liquidity* portfolios compared to the *Size-Momentum* portfolios.

In Table 15 and Table 16 the CAPM and the four-factor regression results are displayed for the nine *Size-Liquidity* portfolios. For the four-factor model, eight out of nine portfolios, the null hypothesis cannot be rejected that the intercept is equal to zero. This is slightly better than the CAPM with seven out of nine portfolios. For the four-factor model, the coefficient of the market factor is significant for all portfolios. The coefficient of the momentum factor is significant once, the coefficient of the liquidity factor six out of nine times, and the volatility factor three our of nine times.

Table 15: Regression results CAPM for Size-Liquidity portfolios

Regression results CAPM for nine *Size-Liquidity* portfolios; August 2014 - March 2020, 296 weeks. *RM* is the equally-weighted weekly return on the market portfolio of all sample cryptocurrencies minus the one-month Treasury bill rate. On the right hand side of the table are the corresponding t-values, which indicate if the intercept or coefficient are significantly different from zero. Newey and West (1986) standard errors are used.

Size →		Small	2	Big	Small	2	Big
		α			$t(\alpha)$		
	Low	0.486	0.129	0.458	1.48	0.40	1.11
Intercept	2	0.595	-0.659	-0.113	2.06	-2.58	-0.42
	High	-0.076	-0.248	-0.370	-0.24	-0.90	-1.32
		b			$t(b)$		
	Low	0.641	0.808	0.595	13.45	21.70	10.16
RM	2	0.790	0.849	0.872	18.60	25.00	24.32
	High	0.768	0.811	0.860	13.63	15.11	21.30

Table 16: Regression results four-factor model for *size-liquidity* portfolios

Regression results four-factor model for nine *Size-Liquidity* portfolios; August 2014 - March 2020, 296 weeks. The factors are the *WML* (winners minus losers), *GMB* (good minus bad), and *VMS* (volatile minus stable). *RM* is the equally-weighted weekly return on the market portfolio of all sample cryptocurrencies minus the one-month Treasury bill rate. On the right hand side of the table are the corresponding t-values, which indicate if the intercept or coefficient are significantly different from zero. Newey and West (1986) standard errors are used.

Size →		Small	2	Big	Small	2	Big
		α			$t(\alpha)$		
	Low	-0.207	-0.164	0.274	-0.74	-0.58	0.80
Intercept	2	0.471	-0.593	0.016	1.71	-2.43	0.06
	High	0.238	-0.215	-0.121	0.77	-0.93	-0.45
		b			$t(b)$		
	Low	0.728	0.866	0.697	13.67	21.22	8.99
RM	2	0.794	0.851	0.854	17.35	26.95	24.74
	High	0.712	0.755	0.823	25.95	21.05	20.18
		w			$t(w)$		
	Low	0.127	0.045	-0.072	1.21	0.80	-0.78
WML	2	0.074	-0.052	-0.109	1.31	-1.06	-2.82
	High	0.033	0.129	-0.061	0.48	2.17	-0.91
		g			$t(g)$		
	Low	-0.679	-0.441	-0.684	-2.99	-4.24	-2.93
GMB	2	-0.003	-0.039	0.011	-0.04	-0.74	0.23
	High	0.516	0.468	0.065	5.94	6.85	3.27
		v			$t(v)$		
	Low	-0.244	0.001	0.353	-2.35	0.01	1.64
VMS	2	-0.004	-0.037	-0.191	-0.04	-0.52	-4.07
	High	0.266	-0.115	-0.040	4.03	-1.17	-0.63

For the nine *Size-Volatility* portfolios the results are very similar. As seen before in Table 11 the average absolute intercept improves from 0.358 to 0.272. Similar to the *Size-Liquidity* portfolios, the effect is smaller than for the *Size-Momentum portfolios*. This is due to the smaller variation in returns.

Table 17 and Table 18 show the CAPM and the four-factor regression results are displayed for the nine *Size-Volatility* portfolios. The results are again very similar. For the four-factor model, all nine portfolios, the null hypothesis cannot be rejected that the intercept is equal to zero. This is better than the CAPM with seven our of nine portfolios. For the four-factor model, the coefficient of the market factor is significant for all portfolios. The coefficient of the momentum factor is significant for three out of nine portfolios, the coefficient of the liquidity factor two out of nine times, and the volatility factor is significant for all portfolios.

Table 17: Regression results CAPM for Size-Volatility portfolios

Regression results CAPM for nine *Size-Volatility* portfolios; August 2014 - March 2020, 296 weeks. *RM* is the equally-weighted weekly return on the market portfolio of all sample cryptocurrencies minus the one-month Treasury bill rate. On the right hand side of the table are the corresponding t-values, which indicate if the intercept or coefficient are significantly different from zero. Newey and West (1986) standard errors are used.

Size →		Small	2	Big	Small	2	Big
		α			$t(\alpha)$		
	Low	0.631	0.092	-0.280	2.06	0.33	-1.05
Intercept	2	0.561	-0.535	0.284	1.92	-1.99	1.09
	High	0.265	-0.075	-0.534	0.91	-0.28	-1.37
		b			$t(b)$		
	Low	0.769	0.808	0.870	18.26	14.66	20.15
RM	2	0.773	0.861	0.849	20.17	28.94	25.82
	High	0.788	0.841	0.710	14.85	17.85	17.08

Table 18: Regression results five-factor for Size-Volatility portfolios

Regression results five-factor model for nine *Size-Volatility* portfolios; August 2014 - March 2020, 296 weeks. The factors are the *WML* (winners minus losers), *GMB* (good minus bad), and *VMS* (volatile minus stable). *RM* is the equally-weighted weekly return on the market portfolio of all sample cryptocurrencies minus the one-month Treasury rate. On the right hand side of the table are the corresponding t-values, which indicate if the intercept or coefficient are significantly different from zero. Newey and West (1986) standard errors are used.

Size →		Small	2	Big	Small	2	Big
		α			$t(\alpha)$		
	Low	0.264	-0.247	-0.018	1.05	-1.20	-0.08
Intercept	2	0.428	-0.492	0.208	1.60	-1.94	0.88
	High	0.395	-0.075	-0.321	1.43	-0.30	-0.92
		b			$t(b)$		
	Low	0.768	0.790	0.840	21.29	21.33	19.42
RM	2	0.769	0.862	0.836	17.87	31.83	23.30
	High	0.786	0.848	0.763	23.93	22.91	17.60
		w			$t(w)$		
	Low	0.092	0.099	-0.176	1.44	2.14	-3.66
WML	2	0.060	-0.066	0.024	0.71	-1.41	0.43
	High	0.075	0.072	-0.133	1.22	1.53	-2.10
		g			$t(g)$		
	Low	-0.106	-0.010	0.079	-1.19	-0.16	1.62
GMB	2	0.019	-0.057	0.046	0.20	-1.18	0.58
	High	0.178	0.067	0.125	2.30	1.14	-2.26
		v			$t(v)$		
	Low	-0.545	-0.624	-0.344	-6.96	-7.15	-5.66
VMS	2	-0.129	-0.126	-0.216	-2.10	-2.56	-3.85
	High	0.504	0.388	0.595	6.45	6.00	4.65

6 Conclusion and Limitations of research

6.1 Conclusion

In this thesis I answer the question: *Which factors exist in cryptocurrencies and which model best explains the variation in average excess portfolio returns?* To answers this, I perform portfolio regression on cross-sectional portfolios. To increase power, overlapping periods are used. By using data from only the historical snapshot of CoinMarketCap (2020b), I prevent survivor bias or any form of hindsight benefits. Portfolios are all equally weighted and all matched to the volatility of the market portfolio. The 60 most relevant cryptocurrencies, based on market value, are selected for portfolio formation. This top 60 is continually replaced by the current top 60. This adds up to a total of 315 different cryptocurrencies used in this research. Daily returns are used from August 2014 to March 2020.

The factors size, momentum, liquidity and volatility have proven to work across a wide range of asset classes. I find a significant momentum effect. These results match Tzouvanas et al. (2019) who also found a momentum effect over a short holding period. The size, liquidity, and volatility factor show the expected sign, but they are not significant. This could be due to the lack of power caused by the short sample size of less than 6 years.

In the test for redundant variables only the size factors shows to be redundant. The other factors: market, momentum, liquidity, and volatility all show to have a significant return premium when other factors are taken into account. The four-factor model containing factors for market, momentum, liquidity, and volatility best explain the variance in excess returns of the portfolios. The four-factor model performs significantly better than the CAPM. Based on the GRS statistic, the four-factor model still gets easily rejected, this indicates that the model is still incomplete. This is partly because of the biased GRS estimate. The market factor performs very well in explaining returns, which could be due to the nature of some altcoins listings. Most altcoins only have a trading pair with Bitcoin. When Bitcoin falls in value the dollar value of the altcoins falls with it.

6.2 Limitations of Research

There are some limitations to this research. First of all, the data that I use is extracted from *CoinMarketCap* and not directly from exchanges. This result in non-traded prices, which can slightly differ from the actual price data from the exchanges.

Second, there are arbitrage restrictions. It is not possible, for all cryptocurrencies, to open a short position. A long-short portfolio on momentum would therefore in practice not always be possible.

Third, all returns are overestimated since trading cost is not taken into account. These cost include transaction cost, bid/ask spreads, and deposit or withdrawal fee. Fees on the Binance are approximately 0.1 percent. When extracting your cryptocurrencies from an exchange you often pay a withdrawal fee (deposit is free). This is 0.001 BTC for Binance, which is, on a small amount, quite high compared to the trading fees (Binance, 2020).

Fourth, most altcoins only have trading pairs with Bitcoin and not with the dollar. It could therefore also be relevant how cryptocurrencies are priced in terms of Bitcoin instead of their Dollar value.

Last, all portfolios are equally weighted. This is to prevent, the otherwise very big influence of large market value cryptocurrencies on the portfolio returns. This, however, can influence the outcome of the research.

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A Appendix

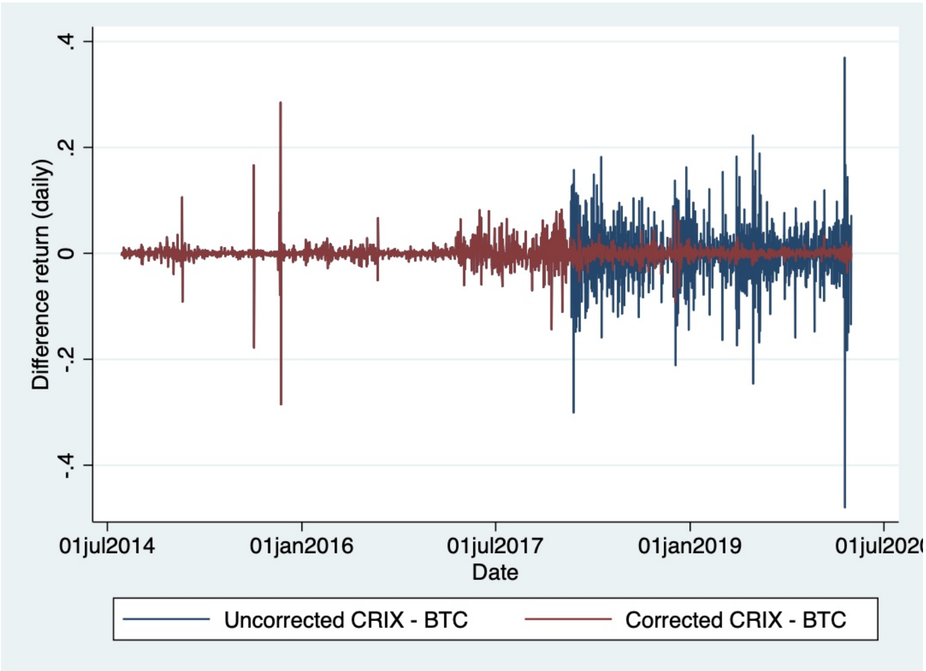

Figure A.1: CRIX - BTC spread in return