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The application of three asset pricing models to cryptocurrencies

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ABSTRACT

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ARE TRADITIONAL ASSETS PRICING MODELS ALSO USEABLE TOOLS IN EXPLAINING THE RETURNS OF CRYPTOCURRENCY? TO ANSWER THIS QUESTION, THREE ASSET PRICING MODELS ARE COMPARED. BY USING TIME SERIES AND CROSS SECTIONAL REGRESSIONS, WE FIND THAT THE CAPM DOES A REASONABLE JOB IN EXPLAINING CRYPTOCURRENCY RETURNS WHILE THE FAMA AND FRENCH THREE FACTOR MODEL AND THE CARHART FOUR FACTOR MODEL SHOW LITTLE ADDITIONAL EXPLANATORY POWER. WE ALSO CONSTRUCTED RISK FACTORS IN DIFFERENT WAYS AND SHOWED THAT THIS CAN LEAD TO HETEROGENEOUS RESULTS. RESULTS WERE ROBUST WHEN THE PORTFOLIOS WERE SORTED BY VOLATILITY INSTEAD OF SIZE/NVT RATIO.

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1 Introduction

During the past few years, cryptocurrencies have gained a lot of popularity amongst both investors and the general public (Hameed & Farooq, 2017). As of today (14-03-2022), the total market capitalization of all crypto currencies is over 1.5 trillion dollars divided over 10000 different coins (coinmarketcap.com). Cryptocurrencies make use of blockchain technology. Blockchain technology is an information recording system that uses a public maintained ledger which allows cryptocurrencies to overcome the double-spending problem, while at the same time does not require a trusted third party. (Cheun, et al, 2017; Gorkhali & Schrestha, 2020). As a results of this decentralized governance, cryptocurrencies are relatively volatile and highly speculative in comparison to fiat currencies. (Yang, 2019).

Bitcoin was first tradeable in 2010 with a value of $0.008. As of today, the highest price that bitcoin has reached was around $65.000 in November 2021. During the years, bitcoin’s price level has seen major explosions but also big crashes. For example, in 2018, bitcoin’s price fell by 65 percent in one month which shows that cryptocurrencies can be very volatile. Also, hacking events have increased this volatility (Corbet, et al, 2020).

The question arises which factors explain the returns of bitcoin and other cryptocurrencies. Smales (2020) shows that returns of other cryptocurrencies highly depend on the returns of bitcoin. Other literature shows relationships between investor behavior and cryptocurrency prices (e.g. Ballis & Antonis, 2020; Pelster, et al, 2019). The Traditional way of valuating assets is the capital asset pricing model (CAPM) of Sharpe (1964) and Litner (1965). Fama and French (1992) have expanded the CAPM model by also adding size and book-to-market equity factors to the model. Carhart (1997) further expanded this model by showing that the momentum factor also has explanatory power. Research has shown that the momentum factor is also an important factor in explaining cryptocurrencies. (Caporale & Plastun, 2020; Cheng, et al, 2019; Lui, et al, 2020&2022; Nguyen, et al, 2020). Gregoriou (2019) shows that investors can obtain excess returns when they account for the five factors of the Fama and French five factor model. The five factor model is an extension of the Fama and French three factor model which also includes profitability and investor patterns factors. However, these results are based on only ten cryptocurrencies which leaves room for additional research on the topic.

Due to cryptocurrencies being relatively new, research on the applicability of asset pricing model factors on cryptocurrencies is still very limited. The paper of Lui, et al, (2020) identifies three risk factors in explaining crypto returns: size, market return and momentum. Shen (2020) show market, size and reversal effects for cryptocurrencies. But as far as the authors knowledge goes, there is no previous work that compares the explanatory power of the CAPM, the Fama and French three factor model and the Carhart four factor model. This research will jump into this gap. Since trading in cryptocurrency is rising in popularity, results of this thesis should be of great interest. The following research question will be answered in this paper:

- Are the CAPM, Fama & French three factor model and the Carhart four factor model applicable to the explaining of cryptocurrency returns?

Due to the different characteristics of the cryptocurrency market, risk factors were constructed manually. Following the method of Fama and French (1993), nine portfolios were created based on size and Network Value to Transactions (NVT) Ratio. Subtracting the risk-free rate from the returns computes the excess returns of these portfolios which is the dependent variable of this research. Following most existing research on asset pricing models and cryptocurrencies, we used the CRIX index as the market factor. This index uses the weighed inclusion of altcoins to give a better representation of the cryptocurrency market as a whole. To measure size, we used market capitalization. And for the value factor, the NVT ratio was used. This ratio is calculated by dividing the market capitalization by the weekly transaction volume. The size and value factors were calculated in two different ways to test for robustness. The momentum factor was calculated for three different lookback periods.

The explanatory power of these asset pricing models was tested by way of time series regression to test the relationship between the variance of the risk factors and the variance in excess cryptocurrency returns. After that, a cross sectional regression was performed to estimate the relationship between mean excess returns and the estimated betas from the time series regression. We find that the CAPM does a reasonable job in explaining cryptocurrency returns while the Fama and French three factor model and the Carhart four factor model show almost no additional explanatory power. Visualization of the cross-sectional regressions confirm these results. Results were robust when replacing the nine portfolios based on size and NVT ratio by ten portfolios based on volatility.

2 Theories and hypotheses

This chapter is a literature review on cryptocurrencies and asset pricing models. First, the concept of blockchain is explained. Second, literature on the question whether cryptocurrencies are a commodity or a currency is reviewed. Third, literature on the ability of factor investing in crypto is reviewed. Fourth, three asset pricing models and their strengths and limitations are explained. And lastly, as a result of the literature review, the hypotheses of this thesis are given.

2.1 blockchain

Blockchain is a subject that lately has attracted a lot of interest in many different industries. However, it seems that the financial industry is the primary user of this system. This can be explained by the emerge of cryptocurrencies (Nofer, et al, 2017). Blockchain was first introduced by Nakamoto (2008) as a system that would allow online payments without the need of a third party. This way, Nakamoto introduced a solution to the double spending problem. Blockchain is an emerging field with a lot of growing potential that can play a big role in many fields of research (Xu, et al, 2019). Blockchain stores information in groups, which are called 'blocks'. When the data-capacity of a blocks is reached, these blocks are closed and linked to a previous filled block. This creates a chain of blocks.

Intermediaries have been the main solution of tracing and verifying ownership of assets. These intermediaries are costly and create credit risk in case they go bankrupt (Nofer, et al, 2017). Blockchain provides a solution for these problems. Users of blockchain use hash functions to digitally sign the previous transaction. Bitcoin makes use of SHA256 algorithms. This is a hashing algorithm that converts any data into a 256 bits string. To prevent that the same bitcoin is spend twice, transactions must be validated before they are published to the network. This validation is done by miners. Miners use digital hardware to solve difficult cryptographic hash puzzles. To incentivize mining, rewards in the form of cryptocurrencies are given in return. The hardware that miners use consume a lot of energy and the process is overall very costly. However, high mining cost together with the blockchain mechanics also provide a shield against hackers. Stoll, et al. (2019) highlights the external costs of bitcoin mining. Their findings show that bitcoins emission levels are comparable to the total emission of Jordan and Sri Lanka.

2.2 Cryptocurrencies: commodity or a digital currency?

Cryptocurrency are digital currencies that use distributed ledgers, blockchain or other technology, to make sure that transactions are safe. Cryptocurrencies have the same function as fiat currencies apart from its decentralized character. Since the launch of bitcoin in 2008, thousands of new coins have been launched. Some of these cryptocurrencies have underlying functions. For example, Chainlink ($LINK), which enables non-blockchain companies to safely connect to the blockchain. But there are also coins without fundamental value, these coins are called ‘shitcoins’. An example of this is Shiba inu ($SHIB). The value of Shiba is based on its big following and memes.

The question arises whether cryptocurrencies behave in a similar way as fiat currencies or that they are more comparable to commodity currencies. Literature shows mixed results. Kwon (2020) estimated conditional autoregressive Value at Risk of return on Bitcoin, the dollar, gold and the stock market index and concludes that the tail behavior of bitcoin is negatively correlating with the dollar and the stock market index. Therefore, bitcoin can be seen as an alternative to the dollar and the stock market. Research of Cermak (2017) concludes that as a result of the high volatility of cryptocurrencies, it cannot fulfill the same functions as fiat currencies such as a medium of exchange, unit of account and a store of value and therefore concludes that cryptocurrencies are more of a digital commodity than a currency. Furthermore, Cermak states that when this volatility decreases, there is not much stopping Bitcoin in becoming a fulfilling alternative to fiat currencies. Previous research also show that cryptocurrencies have similar characteristics as commodity money. Dyhrberg (2016) shows, with use of a GARCH model, that bitcoin and gold have very similar characteristics such as mining, limited supply and decentralization. As a result of these characterizations, cryptocurrencies are a combination of the advantages and disadvantages of currencies and commodities which makes it applicable for portfolio management. Baur, et al, (2018) replicated this study. After expanding the sample and using an alternative framework, they concluded that bitcoin is a highly speculative asset in comparison to gold and the US dollar.

2.3 Factor investing in crypto

This thesis aims to determine what factors explain the returns of cryptocurrencies. Cryptocurrencies are a relatively new phenomenon and research trying to explain what factors cause the returns of cryptocurrencies is growing. Smales (2020) demonstrates that a large portion of cryptocurrency returns is explained by bitcoin returns. This intercorrelation may reduce the effectiveness of divarication in portfolios. Other empirical research also finds intercorrelation between bitcoin and other cryptocurrencies (e.g. Bouri, et al, 2019; Shams, 2019; Barcilar, et al, 2017)

A second factor that has given much attention in academic literature is investor attention. Investor attention has a significant impact on bitcoin realized volatility and returns (Zhu et al, 2021) and vice versa (Lin, 2021). However, Urquhart (2018) shows that investor attention, which is caused by realized volatility and volume, doesn't have predictive power for future volatility or returns.

Another explanation for crypto returns areis asset pricing model factors. Which is the main focus of this research. Literature supports size, risk and momentum effects in cryptocurrencies. In stock markets, the size effect is an effect where smaller assets outperform larger assets. Research of Li, et al, (2020) concludes that this size effect also exists for cryptocurrencies as coins with a small market cap tend to outperform coins with a large market cap. This negative effect between size and returns was also empirically observed in initial coin offerings (ICO's) as large ICO's tend to be overpriced (Momtaz, 2021). Lui, et al, (2022) explained two reasons for the existence of this size effects. First, the size effect is related to the liquidity effect. And second, the size effect is consistent with a mechanism that shows the trade-off between capital gain and convenience yield. Lui, et al, (2022) also found evidence of a momentum effect. The momentum effect occurs as a result of attention driven overreaction. Nguyen, et al, (2020) also show a short-term momentum effect in crypto returns while controlling for the size effect suggesting that short term momentum explains variation in crypto returns. Caporale & Plastun (2020) show that crypto-prices tend to move in the direction of abnormal returns until the end of the day. Indicating that there is a momentum effect in crypto. The paper of Cheng, et al, (2019) also finds a strong momentum effect when examining bitcoin and Ethereum.

2.3.1 CAPM

A traditional way of valuating assets is the capital asset pricing model (CAPM). This model, introduced by Sharpe (1964) and Lintner (1965), estimates the relationship between the expected return on asset and systematic risk. This relationship results in the following equation:

$$(1)\ E(R) = R_f + \beta * (E(R_m) - R_f)$$

In which E(R) is the expected return, Rf is the risk free rate, β (beta) represents systematic risk and E(Rm) is the expected market return. The CAPM model predicts the following two things. First, expected returns of securities are a positive linear function of market returns. And second, the beta (β) is the only determining factor of the expected return (Ansari, 2000). This model is still broadly used for estimating cost of capital and evaluating portfolios (Fama & French, 2004). However, many research has shown that using only the market beta has proven to be insufficient in explaining market returns (e.g. Fama & French, 1992; Elbannan, 2015). The CAPM follows the efficient market hypothesis (EMH). The EMH assumes that markets are efficient and thus under/overvalued securities do not exist. Therefore, the CAPM assumes that idiosyncratic risk doesn't exist which is unlikely. Ross (1976) introduced a solution to this problem which is called the arbitrage pricing theory (ABT). The APT allows more factors to measure systematic risk. In contrast to the CAPM, the APT assumes that securities can be mispriced and arbitrage opportunities exist. Literature review by Rossi (2016) came to the conclusion that the CAPM is inadequate in explaining excess return of securities as further research has shown that there are more factors that play a part in explaining excessive returns. However, Rossi states that the CAPM is a sufficient tool to introduce asset pricing theory due to its simplicity which makes it a usable tool for e.g. education on asset pricing.

2.3.2 Fama and French three factor model

Fama and French (1993) have expanded the CAPM model by also adding size and book-to-market equity to the model. Their main results show that size and book-market equity both show additional explanatory power on the cross-section of stock returns. These additional factors explain the historical excess return of small stocks over big stocks and value stocks over growth stocks respectively.

$$(2)\ E(R) = R_f + \beta * (E(R_m) - R_f) + + SMB + \beta_{HML} HML + e$$

The size effect reflects the excess return of companies with small market capitalizations over companies with a big market capitalization (SMB). The value effect is reflected by the excess return of companies with high book-market values over companies with low book-to-market values (HML). Empirical research has replicated Fama & French (1993) results across various stock markets. For example: the Indian stock market (Taneja, 2010), New York stock market (Blanco, 2012), Australian stock market (Gaunt, 2004) and the Chinese stock market (Xu & Zhang, 2014)

However, despite that the three factor model was considered to be ground breaking, it also retrieved criticism that the model lacks practical efficiency (Sattar, 2017) and generates heterogeneous results depending on how portfolios are constructed (Blanco, 2012).
After the introduction of their three factor model, Fama and French continued to do research on factor investing. This resulted in the introduction of the Fama and French five factor model (Fama and French, 2015). This model contains the same factors as the three factor model with profitability and investment patterns as additional factors.

2.3.4 Carhart four factor model

As shown in **section 2.3** of this thesis, many previous literature concludes that there is a momentum effect in both stock markets and cryptocurrencies. Carhart (1997) expanded Fama and French's model by adding Momentum as a third additional risk factor to the CAPM model. While Fama and French (1992) tested their model on stocks, Carhart (1997) used mutual funds data. This led to the following formula:

$$(3)\ E(R) = R_f + \beta * (E(R_m) - R_f) + + SMB + \beta_{HML} HML + \beta_{WML} WML + e$$

WML is the additional momentum factor which is based on excess return of winning portfolios over loser portfolios. Bello (2008) compared both the CAPM and the Fama and French three factor model to the Carhart four factor model using domestic actively managed mutual funds testing their quality of prediction. The paper concludes that the Fama and French three factor models outperforms the CAPM and the Carhart four factor model outperforms the Fama and French model. Rehnby (2016) replicated Bello's results by testing the same hypothesis on the Swedish stock market. These results were also shown in the Indonesian stock market (Gumanti, et al, 2017) and the south African stock market (Boamah, 2015).

2.4 Hypotheses

Section 2.3 of this thesis demonstrates that factors that influence stock returns, also seem to have explanatory power regarding cryptocurrency returns. This opens up the opportunity to test whether asset pricing models like CAPM, Fama and French three factor model and the Carhart four factor model are also applicable to cryptocurrency. Previous literature about the connection between these models and cryptocurrencies is scarce. Especially literature that compares all three models. Lui

(2022) tested size, momentum volume and volatility characteristics on cryptocurrency returns. The paper finds that size, momentum and volume characteristic are able to explain cross sectional cryptocurrency returns. However, this research was limited to only ten cryptocurrencies leaving room for replication. Shen, et al, (2020) introduce a three factor model of size, market and reversal effects for the explaining of cryptocurrency returns. Their model strongly outperforms CAPM. Gregoriou (2019) concludes investors can obtain abnormal returns once they account for all the factors of the Fama and French five factor model. However, these results are also only based on ten cryptocurrencies which is only a small representation of the cryptocurrency market as a whole. Based on the literature, the following hypotheses are conducted:

H1: There are market, size, book-to-market equity and momentum effects in cryptocurrency markets.

H2: The Fama and French three factor model outperforms the CAPM model regarding the explaining of cryptocurrency returns

H3: The Carhart four factor model outperforms both the CAPM and Fama and French three factor model regarding the explaining of crypto returns

However, as a result of cryptocurrencies' decentralized nature, there is not a way to calculate book-market ratio for cryptocurrencies. To solve this issue, book-to-market ratio is substituted with the network value to transactions ratio (NVT). The NVT ratio describes the relationship between the transaction value and market capitalization. A high NVT ratio means that the currency has a high value in comparison with its transaction value which indicates overvaluation. A low NVT ratio indicates that the currency is cheap in relation with the transaction value. Because the NVT ratio and the Price equity ratio can be interpreted in a similar way, analysts on this subject see the NVT ratio as a sufficient substitute for the PE ratio. However, an increase in NVT ratio does not necessarily mean that the currency is overvalued since it could also be a result of an increase in long-term holders (Lui & Zhang (2022).

3 Methodology

3.1 Data

Data about the biggest 30 cryptocurrencies based on market cap on t=0 will be collected, covering a period of 4 years. In this case: 19 November 2017 – 31 December 2021 where 14 januari 2018 equals T=0. In Fama and French (1993), data is monthly. However, as a result of the volatile nature of cryptocurrencies, weekly returns will be used. All data needed about the cryptocurrencies is retrieved from (Coinmarketcap, 2022) and (coincodex, 2022). Coinmarketcap (2022) provides a historical snapshot that ranks all cryptocurrencies on their market capitalization any chosen dates. As a result of supply information issues, some coins are left out of the sample. Cryptocurrencies that are pegged to other currencies are also left out of the sample. An example of this is Tether.

Which is a cryptocurrency that is pegged to the dollar. The top 30 cryptocurrencies (based on market cap) that are left compute the sample of this research. **Table 1** provides a list of the cryptocurrencies that were used for the sample of this thesis.

Table 1: Overview of cryptocurrencies used for analysis

Name	Abbreviation	Market Capitalization (on T=0)
Bitcoin	BTC	237,466,518,547.07
Ripple	XRP	89,121,967,114.06
Ethereum	ETH	73,170,132,771.99
Bitcoin Cash	BCH	42,774,236,530.93
Cardano	ADA	18,659,588,487.38
Litecoin	LTC	12,663,197,417.17
IOTA	MIOTA	9,869,763,787.81
NEM	XEM	9,306,424,139.90
Dash	DASH	8,189,388,164.00
Stellar	XLM	6,442,724,493.37
Monero	XMR	5,426,210,002.08
NEO	NEO	4,937,436,141.97
Bitcoin gold	BTG	4,380,775,196.80
Verge	XVG	3,208,728,455.06
TRON	TRX	2,942,336,038.18
NANO	NANO	2,885,869,971.17
Ethereum Classic	ETC	2,765,755,613.58
Omise GO	OMG	2,029,570,238.64
ICON	ICX	2,017,629,553.50
Bitshares	BTS	1,714,041,929.34
Zcash	ZEC	1,495,222,601.73
Stratis	STRAT	1,384,480,444.68
Waves	WAVES	1,259,664,154.05
Bytecoin	BCN	1,081,519,140.38
Dogecoin	DOGE	1,010,010,505.34

Siacoin	SC	952,864,370.88
Status	SNT	779,710,465.24
Steem	STEEM	742,533,311.59
NXT	NXT	705,236,885.02
SALT	SALT	694,306,236.14

Coincodex (2022) was used to obtain historical data about the sample on price, market capitalization, and transaction volume. Market capitalization will be the size indication for cryptocurrencies.

There is no comparable measure for HML. This is because there is no book value for cryptocurrencies. As a replacement of the book-market equity ratio, we will use the NVT ratio. A high NVT ratio indicates that the market cap of a cryptocurrency is outpacing the transaction value (Liu, 2022). NVT ratios were calculated by dividing market cap by daily transaction volume.

Daily data on the CRIX index, which is the index that is used for the market factor, was personally obtained from CRIX. To match the other variables, this data was transformed into weekly data.

The 1 month US treasury bill rate was used for the risk free rate.

3.2 Factor construction

3.2.1 Market factor

Following the research of Fama and French (1993) and Carhart (1997), four risk factors are added to the models. These risk factors are market, size, value and momentum.

For the market factor, the CRIX index is used from Trimborn & Härdle (2018). This is a model that represents the cryptocurrency market by weighed inclusion of altcoins to improve market tracking. Subtracting the risk-free rate from the CRIX index return results in the Market factor.

3.2.2 small minus big (SMB) & high minus low (HML)

Since the SMB and HML factors that are available on French' website are based on common stocks, it's likely that these factors are not applicable to cryptocurrencies. Therefore, these factors will be calculated manually based on the Fama and French (1993) framework. Furthermore, as a robustness test, size and book-market ratio factors are constructed in two different ways to see which way of factor construction generates the best results.

Size will be measured by sorting all cryptocurrencies on their market capitalization at t=0. First, following Fama and French (1993), all cryptocurrencies are divided into three groups based on size and three groups based on average NVT Ratios. The intersection of these groups results in six portfolios: S/L, S/M, S/H, B/L, B/M and B/H. Difference between the average returns of the Small portfolios (S/L+S/M+S/H) and the big portfolios (B/L+B/M+BH) will compute the small minus big factor SMB1. Second, Following the research of Gregoriou (2019), all cryptocurrencies will be ranked on size. The biggest 30 percent of cryptocurrencies will be added to the “big” portfolio and the smallest 30 percent will be added to the “small” portfolio. Difference in average returns will compute the Small minus big factor SMB2.

The value factor is calculated by subtracting the average return from the low portfolios (SL+BL) from the average return of the high portfolio’s (SH+BH). Second, following the research of Gregoriou (2019), the whole sample will be ranked on average NVT ratios. Thereafter, the bottom 30 percent of average NVT ratios will compute the ‘low’ portfolio. The top 30 percent of average NVT ratios will compute the ‘high’ portfolio. Difference in average returns will result in the HML2 factor.

3.2.3 Win minus lose (WML)

For the momentum factor, all cryptocurrencies will be ranked on their returns from T=-2 – t=0. Top 30 percent will be the ‘winners’ and the bottom 30 percent will be the ‘losers’ (Gregoriou, 2019). The difference in returns will compute the momentum factor WML1. This step is repeated for T-4 (WML2) and T-8 (WML3).

3.2.4 excess cryptocurrency returns.

The risk-free rate is the one month US treasury bill rate.

The main dependent variable is excess cryptocurrency returns. Fama and French (1993) use a 5x5 portfolio construction based on size and book-market ratio. However, since the sample in this research is relatively small, all cryptocurrencies are divided into nine portfolios based on size and NVT Ratio (3x3). Excess returns are calculated by subtracting the risk free rate (rf) from the average returns for each of the nine portfolios. This variable will be measured in dollars($).

3.3 Method

The CAPM model:

$$E(R) - R_f = \beta_{mkt} * (E(R_m) - R_f) + e$$

The Fama and French three Factor model:

$$E(R) - R_f = \beta_{mkt} * \left(E(R_m) - R_f\right) + \beta_{SMB} * (E_{SMB}) + \beta_{HML} * (E_{HML}) + e$$

The Carhart four factor model formula:

$$E(R) - R_f = \beta_{mkt} * \left(E(R_m) - R_f\right) + \beta_{SMB} * (E_{SMB}) + \beta_{HML} * (E_{HML}) + \beta_{WML} * (E_{WML}) + e$$

Where:

$E(R) - R_f = Weekly\ excess\ return\ on\ the\ cryptocurrency\ portfolio$

$\beta_{mkt} * \left(E(R_m) - R_f\right) = Market\ factor$

$\beta_{SMB} * (E_{SMB}) = Size\ factor$

$\beta_{HML} * (E_{HML}) = book - market\ factor$

$\beta_{WML} * (E_{WML}) = Momentum\ factor$

The CAPM, Fama & French three factor model and the Carhart four factor model are estimated by using time series regression analysis. The R-squared obtained from these regressions will give an indication of the explanatory power of these models. The closer it is to 1, the higher the explanatory power is. Next to regression analysis, GRS tests (Gibbons, Ross & Shanken, 1989) will test portfolio efficiency. GRS tests whether the sum of all intercept is jointly equal to zero. If this is the case, the model is able to explain expected returns of the relevant portfolios.

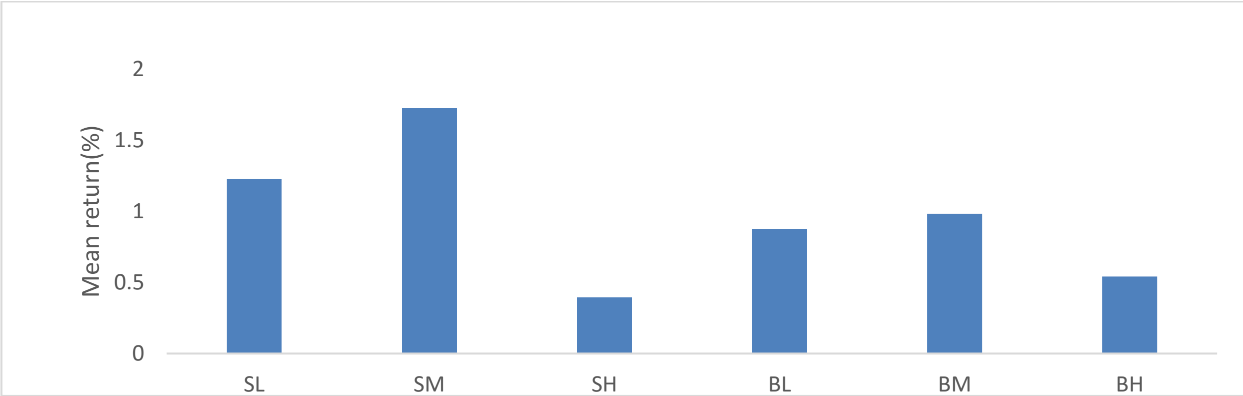
Significance of all tests are measured on a 5% level which is the level of significance that is used in almost every research regarding asset pricing modelling.

4 Results

This section will discuss the results in order to get a better understanding whether asset pricing models can be used to explain cryptocurrency returns and which asset pricing model is the best fit. First, descriptive statistics of the relevant factors are given. Second, regression results between CAPM, Fama and French three factor model and Carhart four factor model are compared. And lastly, the results of the GRS tests.

4.1 Factor analysis

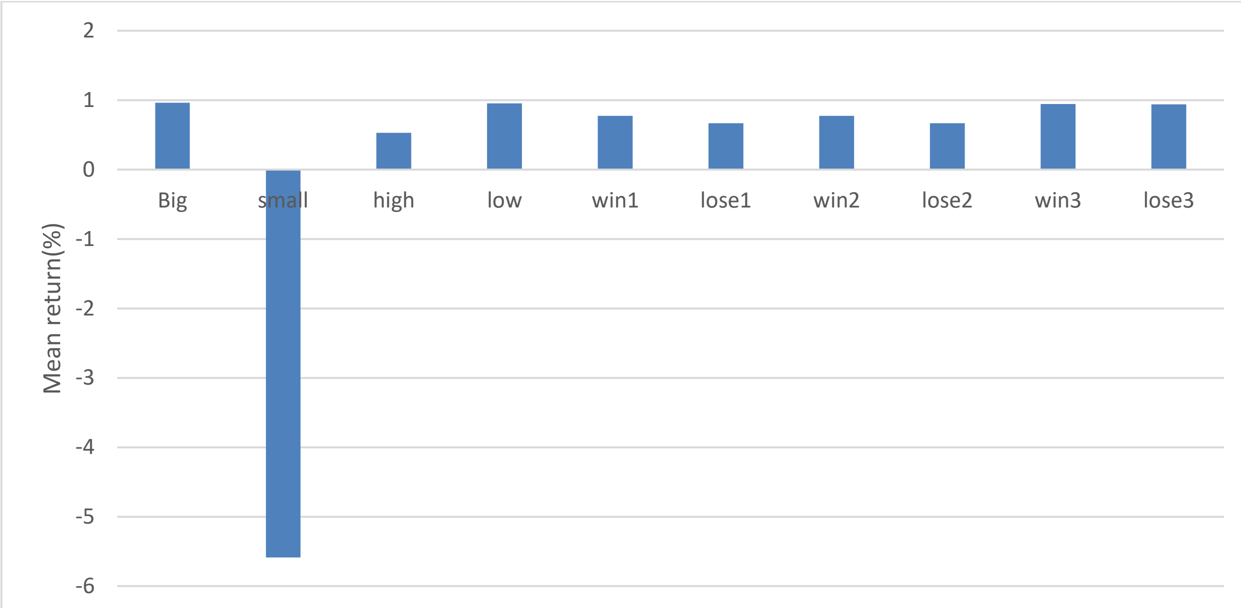
Figure 1: Mean return 2x3 portfolios based on Size and NVT ratio (SMB1 and HML1 construction)



* The first letter indicates the size (small/big). The second letter indicates the average NVT ratio(low, medium high). For example: SM is a portfolio containing small stocks with medium average NVT ratios.

Figure 1 shows the mean returns of the 2x3 portfolios which are made according to Fama and French (1993) based on Size and NVT Ratio. First, these results do not replicate the results of Fama and French (1993) that portfolio with small assets (SL/SM/SH) outperform portfolios with big assets (BL/BM/BH). Second, portfolios with low NVT ratios (SL/BL) seem to outperform portfolios with high NVT ratios (SH/BH). This is the opposite effect to the results found in Fama and French (1993).

Figure 2: Mean return portfolios (SMB2 and HML2 construction)



* The big portfolio indicates the 70th – 100th percentile in size. The small portfolio indicates the 0th -30th percentile in size. Subtracting big portfolio returns from the small portfolio returns results in SMB2. These steps are repeated for average NVT ratios which result in HML2 (high-low). The high portfolio indicates the 70th-100th percentile in average NVT ratios. The small portfolio indicates the 0th-30th percentile in average NVT ratios. The win1 portfolio indicate the 70th-100th percentile of returns between t-2 and t-0 while the lose1 portfolio indicates the 0th-30th percentile of returns between t-2 and t-0. Subtracting the losers portfolio from the winners results in the WML1 factor. These steps are repeated for t-4 (WML2) and t-8 (WML3)

Furthermore, **figure 2** shows the mean returns of the portfolio's that were used to construct the factors SMB2, HML2, WML, WML2 and WML3. First, results clearly show an opposite size-effect as found in the literature (e.g. Momtaz, 2021; Lui, et al, 2022) as the big portfolio is outperforming the small portfolio. Second, the portfolio with the lowest average NVT Ratio outperformed the portfolio containing cryptocurrencies with the highest average NVT. These results contradict the findings reported in the literature.

Third, All "winner" portfolio's outperform their respective "loser" portfolios. Although these results are very small, they are in line with what was found in Carhart (1997) and other literature that found a momentum effect in cryptocurrencies (Nguyen, et al, 2020; Caporale & Plastun., 2020; Cheng, et al, 2019).

Table 2: Risk Factors Summary Statistics

		MEAN	STD DEV	SKEWNESS	T-VALUE	P-VALUE
MARKET FACTOR	RM-Rf	-0.0689	10.9293	0.3320	-0.0908	0.9278
SIZE FACTORS	SMB1	0.3155	6.0869	0.0000	0.7458	0.4566
	SMB2	-6.5508	115.89	0.0033	-0.8133	0.4170
VALUE FACTORS	HML1	-0.583925	6.2940	0.3841	-1.3348	0.1834
	HML2	-0.4249	6.8099	0.1130	-0.8974	0.3705
MOMENTUM FACTORS	WML1	-0.1062	6.2034	0.0148	-0.2462	0.8058
	WML2	0.1012	6.4969	0.0102	0.2240	0.8230
	WML3	0.0022	6.6361	0.0075	0.0048	0.9962

* SMB1/HML1 are the factors constructed by way of 2x3 portfolios based size and NVT ratio

* SMB2/HML 2 are the factors constructed by portfolios based on size at T=0 and average NVT ratio.

*WML1, WML2 and WML 3 are the momentum factors based on a lookback period of 2,4 and 8 weeks respectively.

First, analysis on the risk factors is performed to understand their nature and comparability to the existing literature. **Table 2** shows that the mean return of the Market factor is negative which indicates that during the selected timeframe, the cryptocurrency market was outperformed by the risk-free rate. This can be explained, as a result of cryptocurrencies' volatile nature, by big market crashes, for example on January 2018 and March 2020. However, these results are not significant according to the two tailed T-test.

Furthermore, it is noticeable that the difference in mean return between SMB1 and SMB2 is very high. This is mainly due to the portfolio's that constructed SMB1 contain all cryptocurrencies while the portfolios that constructed SMB2 only contain the highest and lowest 30 percent of cryptocurrencies, based on market capitalization. This indicates that cryptocurrencies between the 30^{th} and 70^{th} percentile performed relatively well in contrast to cryptocurrencies in the 0^{th}-30^{th} percentile. Moreover, momentum factors have very different mean returns as well. This can be explained by the cryptocurrencies that are included in the relevant portfolios. For example, at t-8, the losers portfolio contained Ethereum (ETH), which yielded a relatively high average return overall compared to the other cryptocurrencies. Ethereum (ETH) was not included in the losers portfolio of t-4.

However, all factor variables are not significant, indicating that there is no evidence of market, size, value and momentum effects as described in Fama and French (1993) and Carhart (1997).

Results are heterogeneous for different versions of the same factor, which was also concluded in Blanco (2012).
Furthermore, all factors show a Skewness value between 0 and 1, indicating that the assumption of normal distribution is a good approximation. These results are in line when applying the skewness test to the available SMB, HML and Momentum factors on the Fama French website for the same period as this research showing that the distribution of the cryptocurrency risk factors moves in a similar way as the stock market (Fama & French, 2022)
Finally, STD deviation are higher for cryptocurrencies in comparison to the stock market. This is as expected since cryptocurrencies are more volatile.

Table 3: Pearson's correlation test on risk factors

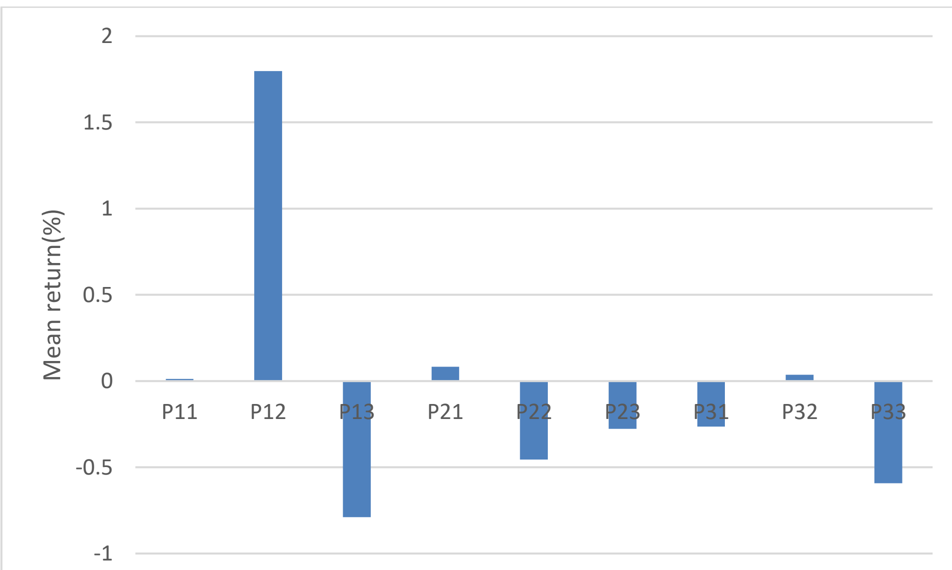
	RM-RM	**SMB1**	**SMB2**	**HML1**	**HML2**	**WML1**	**WML2**	**WML3**
RM-RF	1.0000							
SMB1	0.0100	1.0000						
SMB2	0.0244	-0.0955	1.0000					
HML1	-0.0469	0.1189	-0.513	1.0000				
HML2	0.0148	0.3454	-0.1093	0.8156	1.0000			
WML1	-0.1131	0.1146	-0.0734	0.1037	0.1365	1.0000		
WML2	0.0343	0.1946	0.1713	0.4017	0.1990	-0.2565	1.0000	
WML3	-0.0379	0.1008	0.1314	0.5632	0.2793	-0.0867	0.8380	1.0000

The next step is to check whether these factors are correlated with each other. If this is the case, the r-squared of the time series regression model can be biased. **Table 3** shows large correlation between WML3/HML1 and moderate correlation between WML2/HML1 indicating that putting these variables in the same model can give a false representation of the R-squared. In comparison: the momentum factor in Carhart (1997) is only correlating on a -0.16 level with the value factor while, in this case, this is 0.1037, 0.4017 and 0.5632 for WML1 WML2 and WML3 respectively. This information is very relevant as picking variables that are not correlating with each other will lead to less biased results. Furthermore, correlation between different versions of the same factor is not relevant since these different versions won't be used in the same model. This also counts for combinations between factors that are constructed by way of different methods (HML1 &SMB2).

4.2 Asset pricing models regressions

Descriptive statistics of all nine portfolios are available in **appendix 1A**. All nine portfolios show a skew level between zero and one indicating that they are normally distributed. Standard deviations are very high in comparison with what was observed in the stock market, which is in line with the results in the factor analysis given cryptocurrencies' high volatility. High min and max values also support these findings. **Figure 3** shows no evidence that small cap portfolios (P11/P12/P13) continuously outperform high cap portfolios (P31/P32/P33). Moreover, portfolios with high average NVT Ratios (P13/P23/P33) continuously outperform portfolios with low average NVT Ratios(P11/P21/P31). These results seem to show a opposite value effect as found in the literature (e.g. Fama & French, 1993; Lui, et al, 2022) but are in line what was found in our previous analysis.

Figure 3: Mean return 9 portfolios based on Size and NVT ratio



Portfolios are created by way of 3x3 portfolio construction based on size/NVT ratio (Small-big) and Low-high)
The first number indicates the size percentile and the second number indicates the NVT ratio percentile.
Example: p12 refers to the 0th – 33th percentile on size and 33th-67th percentile in NVT ratio.

4.2.1 CAPM

Table 4: Betas for rm-rf

BETA RM-RF	LOWEST	INTERMEDIATE	HIGHEST

SMALLEST	0.9719***	1.0679***	1.0469***
INTERMEDIATE	1.0453***	1.0686***	1.0272***
BIGGEST	1.1283***	1.007***	1.0200***

Portfolios are created by way of 3x3 portfolio construction. The column indicates size (small-big) and de row indicates NVT ratio (low-high) E.g. Smallest/lowest shows the results of the portfolio containing small sized assets with low average NVT ratios.

*****,**,* - significance on 1, 5 and 10% level**

CAPM time series regression results can be found in **Appendix 2.** The mean R-squared of nine portfolios is 0.5328, meaning that the model explains 53.28 percent of the variability. This is a relatively low score in comparison to the results found in Fama and French (1993) who found an average R-squared of 0.7792. However, it is still a moderate correlation. Importantly, all individual alphas are not significantly different from 0, which means that the model is able to explain the portfolio returns reasonably well. The results are not fully consistent with CAPM though.

Table 4 shows that, for low average NVT ratio portfolios, betas increase when the size of the assets increase as well, indicating that there might be a risk premium for smaller assets which is in line with what was found in Fama and French (1993). This effect reverses as portfolios contain cryptocurrencies with higher average NVT ratios. Furthermore, **table 4** shows that all Mk-RF betas are significant on a 1% level, indicating that the market factor has explanatory power regarding the variance of cryptocurrency returns. After the time-series regression, the next step is a cross-sectional analysis to test whether the market factor can explain cross sectional crypto-returns.

Figure 4: Cross section results CAPM model

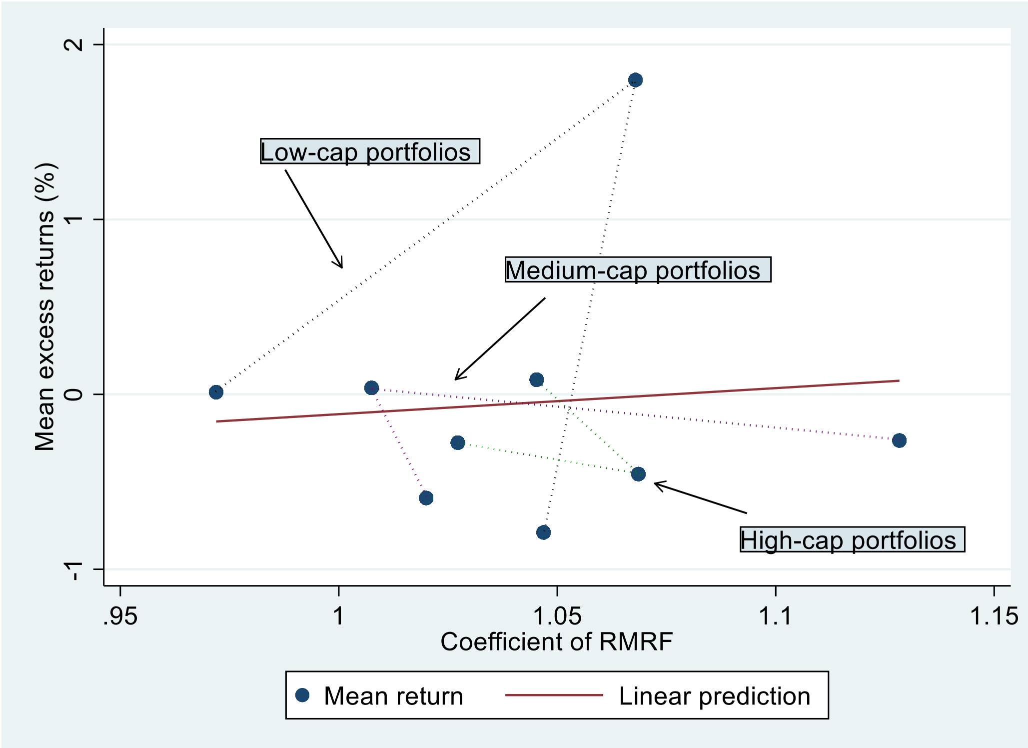


Figure 4 displays this relationship between mean excess returns of the nine portfolios and the estimated market betas. CAPM seems to do a reasonable job in explaining mean excess returns. Furthermore, low-cap portfolios do not systematically outperform medium/high cap portfolios and vice versa, indicating that there is no systematic size effect.

However, the market factor in the model is not significant and fails the F-test indicating that there is no significant market premium for cryptocurrency returns.

4.2.2 Fama and French three factor model

Table 5: Betas RM-RF, SMB1 and HML1

BETA RM-RF	LOWEST	INTERMEDIATE	HIGHEST

SMALLEST	0.9574***	1.0693***	1.0589***
INTERMEDIATE	1.0331***	1.0694***	1.0428***
BIGGEST	1.1209***	1.0126***	1.0364***
BETA FOR SMB1	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	0.5557***	2.5052***	0.8308***
INTERMEDIATE	0.6426***	0.3082***	0.6504***
BIGGEST	0.0858	-0.0201	0.07000
BETA FOR HML1	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	-0.4236***	0.5675***	0.6167***
INTERMEDIATE	-0.3164***	0.0941	0.7115***
BIGGEST	-0.2580***	0.0186**	0.5943***

Portfolios are created by way of 3x3 portfolio construction. The column indicates size (small-big) and de row indicates NVT ratio (low-high) E.g. Smallest/lowest shows the results of the portfolio containing small sized assets with low average NVT ratios.
*****,**,* - significance on 1, 5 and 10% level**

Regression results on the Fama and French three factor model can be found in **Appendix 3** (SMB1/HML2) and **Appendix 4** (SMB2/HML2). The betas for RM-RF are comparable to the CAPM model. Results show, when using SMB1 and HML1 as additional risk factors to the CAPM model, that the average R-squared of the model increases to 0.6356. This is an increase of 19.29 percent. The average R-squared in Fama and French (1993) increased to 0.9312 which is an increase of 19.51%. Although the absolute explanatory power of the models used in Fama and French (1993) is a lot higher, relative explanatory power increased in a similar way. All individual alphas are not significantly different from zero which means that the model is able to explain all the returns within the portfolios.

Furthermore, **table 5** shows that the betas of the SMB1 factor is statistically significant on a 1 percent level in six out of nine portfolios. Betas are insignificant for the big portfolios, indicating that SMB1 only has explanatory power regarding portfolios containing small/medium sized cryptocurrencies. Moreover, the beta of the HML factor is statistically significant on a 1 percent level in seven out of nine portfolios and on a five percent level in one out of nine portfolios. Although initial analysis showed no size and value effect, regression analysis show that the model does have some explanatory power regarding the explaining of the variance of cryptocurrency returns.

Table 6: Betas RM-RF, SMB2 and HML2

BETA RM-RF	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	0.9690***	1.0601***	1.0401***

INTERMEDIATE	1.0476***	1.0664***	1.0192***
BIGGEST	1.1304***	1.0043***	1.0146***
BETA SMB2	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	0.0075	0.0077	-0.0051
INTERMEDIATE	-0.0013	0.0029	0.0132
BIGGEST	0.0016	0.0056	0.0046
BETA HML2	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	0.1076	0.6243	0.8716***
INTERMEDIATE	-0.2110**	0.1468	0.4984***
BIGGEST	-0.1786**	0.1858**	0.4608***

Portfolios are created by way of 3x3 portfolio construction. The column indicates size (small-big) and de row indicates NVT ratio (low-high) E.g. Smallest/lowest shows the results of the portfolio containing small sized assets with low average NVT ratios.
*****,**,* - significance on 1, 5 and 10% level**

When using SMB2 and HML2 as additional risk factors to the CAPM model, average R-squared increases to 0.5645 which is an increase of 5.95 percent. This is a low increase compared to the results of SMB1/HML1 and Fama and French (1993). **Table 5** shows that the betas of SMB2 is significant in zero out of nine portfolios. Furthermore, the betas of HML2 is significant on a one percent level in three out of nine portfolios and on a five percent level in five out of nine portfolios. Although these results show little additional explanatory power of the Fama and French (1993) model, they support the conclusion of Blanco (2012) that results heavily rely on the way that the factors are constructed, which was also demonstrated in the initial analysis.
For further analysis, SMB2 and HML2 will be eliminated from the analysis. The next step is to perform a cross-sectional regression between the mean returns of the portfolios and the estimated betas of the time series regression of SMB1 and HML1.

Figure 5: Cross sectional analysis Fama and French three factor model (RM-RF, SMB1 and HML1)

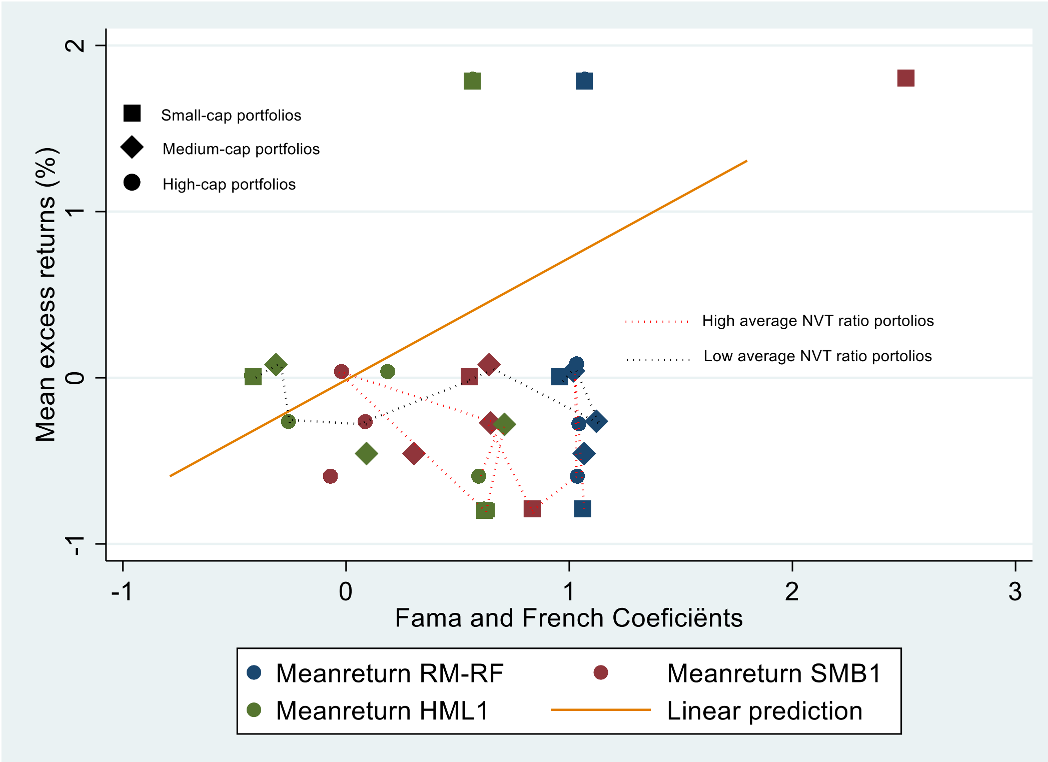


Figure 5 displays this relationship between mean excess returns of the nine portfolios and the estimated market, size and value betas. The graph clearly shows that the Fama and French model is not able to explain cross sectional cryptocurrency returns. Furthermore, low-cap portfolios do not systematically outperform medium/high cap portfolios and vice versa, indicating that there is no systematic size effect. This is also observed for the value effect (high and low average NVT ratios). The cross-sectional regression shows that all factors in the model are significant. Also, results show an R-squared of 0.5748. However, data is clearly heteroscedastic as there is a large difference among the sizes of individual betas. Therefore, the results are biased. For that reason, we reject H2.

4.2.3 Carhart four factor model

Table 7: Betas WML1

BETA RM-RF	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.9839***	1.0747***	1.0509***
INTERMEDIATE	1.0220***	1.0672***	1.0720***
BIGGEST	1.1184***	1.0282***	1.0324***
BETA SMB1	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	0.5101***	2.4960***	0.8445***
INTERMEDIATE	0.6617***	0.3119***	0.6002***
BIGGEST	0.0901	-0.0469	-0.0630
BETA HML1	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	-0.4596***	0.5603***	0.6276***
INTERMEDIATE	-0.3013***	0.0971	0.6719***
BIGGEST	-0.2546***	0.1654*	0.6000***
BETA WML1	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	0.4241***	0.0858	-0.1281
INTERMEDIATE	-0.1782*	-0.0344	0.4672***
BIGGEST	-0.0398	0.2994**	-0.0652

Portfolios are created by way of 3x3 portfolio construction. The column indicates size (small-big) and de row indicates NVT ratio (low-high) E.g. smallest/lowest shows the results of the portfolio containing small sized assets with low average NVT ratios.
*****,**,* - significance on 1, 5 and 10% level**

Regression results on the Carhart four factor model can be found in **Appendix 5** (WML1), **Appendix 6** (WML2) and **Appendix 7** (WML3). For all three factors, betas of SMB1 and HML1 are similar.
Results show, when using a lookback period of two weeks (WML1), that the average r-squared of the model is 0.6422. This is almost equal to the previously founded R-squared of the Fama and French model. In contrast, the average r-squared found in Carhart (1997) is 0.9224. Furthermore, **table 7** shows that the beta of WML1 is only significant in three out of nine portfolios indicating that the momentum factor with a lookback period of two weeks does not explain variance in cryptocurrency excess returns. There is also no systematic relationship between size/value and momentum. These results are contradictory to the findings of Carhart (1997).

Table 8: betas WML2 and WML3

BETA WML2	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	-0.1142	0.8042***	-0.0090

INTERMEDIATE	0.6560***	0.2157	1.0921***
BIGGEST	0.1937***	0.3826***	0.1832
BETA WML3	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	0.0366	1.1156***	-0.0823
INTERMEDIATE	0.5568***	0.2490	1.0092***
BIGGEST	-0.1212	0.5707**	0.1934

Portfolios are created by way of 3x3 portfolio construction. The column indicates size (small-big) and de row indicates NVT ratio (Low-high) E.g. Smallest/lowest shows the results of the portfolio containing small sized assets with low average NVT ratios.
*****,**,* - significance on 1, 5 and 10% level**

When using a lookback period of four (WML2) and eight weeks (WML3) average r-squared of the model is 0.6621 and 0.6636 respectively. Betas of WML2 are significant in five out of nine portfolios and betas of WML3 are significant in four out of nine portfolios.
These results are contradictory to findings in the existing literature on momentum effects in cryptocurrencies (e.g. Carhart, 1997; Nguyen et al., 2020; Caporale & Plastun, 2020; Cheng, et al, 2019). As results between WML1, WML2 and WML3 are comparable we eliminate WML2 and WML3 for further analysis as the initial analysis showed that these factors correlate with the HML1 factor and this may lead to biased results. The next step is a cross-sectional analysis between mean average excess return of the portfolios and the betas of the Carhart four factor model.

Figure 6: Cross sectional analysis Carhart four factor model (RM-RF, SMB1, HML1 and WML1)

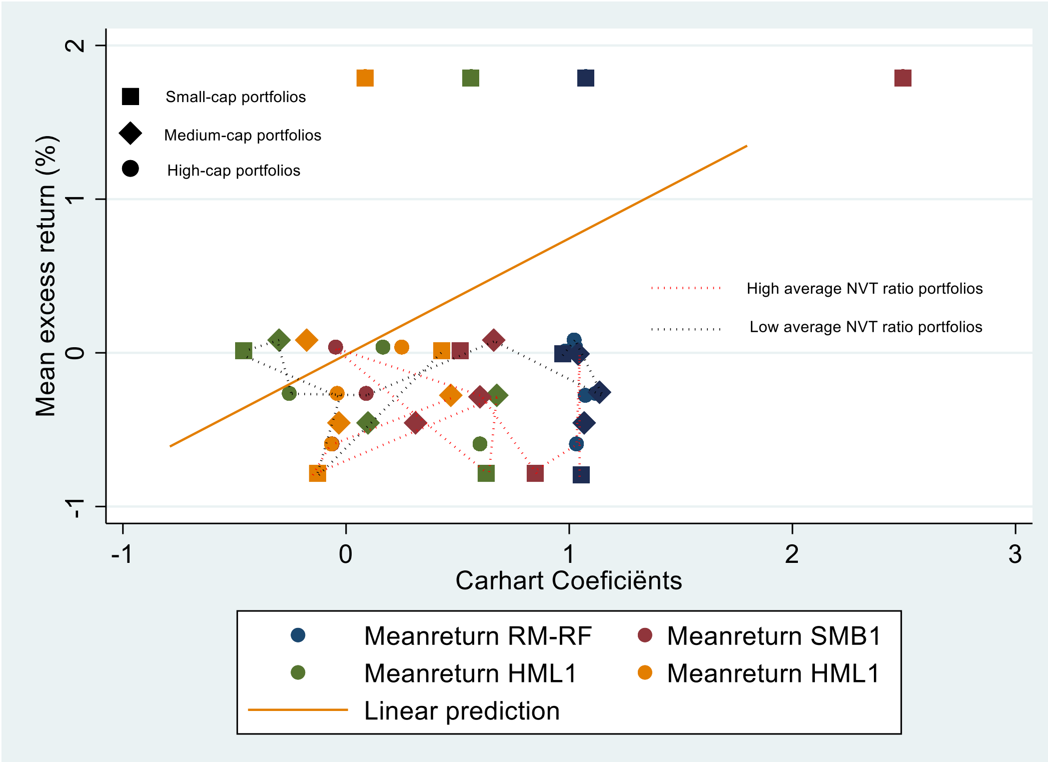


Figure six displays this relationship between mean excess returns of the nine portfolios and the estimated market, size and value betas. The graph shows clearly that the Carhart model is not able to explain cross sectional cryptocurrency returns. These results are as expected since the Fama and French model is already rejected and the betas for the momentum effect are not significant. Furthermore, low-cap portfolios systematically do not outperform medium/high cap portfolios and vice versa, indicating that there is no systematic size effect. This is also observed for the value effect (high and low average NVT ratios). The cross-sectional regression shows that all factors in the model are significant. Also, results show a R-squared of 0.5103, indicating that the model is able to explain 51% of the variance. However, data is clearly heteroscedastic as there is a large difference among the sizes of individual betas. Therefore, the results are biased. There is no systematic relationship between the estimated betas and the mean excess returns of the portfolios. For that reason, we reject H3.

4.2.4 GRS test

Table 9: Grs test

Model	GRS value	*GRS P-Value*
CAPM	1.5209	*0.1426*
Three factor model	1.2809	*0.2493*
Four factor model	1.3040	*0.2369*

Table 9 shows the GRS test for all the models that have been tested in this chapter. GRS statistic tests whether the sum of all intercept is jointly equal to zero. These results indicate that the average absolute value of the intercepts does not significantly differ from zero. The model confirms earlier results that CAPM seems to do a reasonable job while the Fama and French three factor model and the Carhart four factor model show little additional explanatory power.

5 Robustness test

To test for robustness, instead of 3x3 portfolio construction based on size and NVT ratio as dependent variable, the cryptocurrencies in the sample will be divided into ten portfolios based on average volatility which generate portfolios PA-PJ. Descriptive statistics about these portfolios can be found in **Appendix 1B.** First, mean returns indicate that there is no systematic relationship between volatility and returns.

Regression results for CAPM, available in **Appendix 9A,** show an average r-squared of 0.5293. This is comparable to the CAPM model tested in **section 4.2.1** of this thesis (0.5328). All ten betas are significant indicating that they have explanatory power for the variance in cryptocurrency returns of the portfolios. Moreover, it is noticeable that the explanatory power of the CAPM model decreases when assets in the portfolios get more volatile. An explanation for this can be that the CRIX model only consists out of the biggest cryptocurrencies and thus does not contain the relatively small and very volatile assets that are included in these portfolios.

Appendix 9B and **9C** provide the regression results for the Fama and French three factor model for the factors SMB1/HML1 and SMB2/HML2 respectively. The average R-squared of the model including SMB1/HML1 is 0.5882 which is almost the same as the R-squared of the CAPM model indicating that the Fama and French factors give little additional explanatory power to the CAPM model which is in line with what was found in **Section 4.2.2** of this thesis. The average r-squared of the model including SMB2/HML2 is even lower (0.5514). Moreover, the beta of the SMB2 factor was only significant in one out of the ten portfolios. In line with the initial analysis, SMB2 and HML2 will not be used for the robustness check on the Carhart four factor model.

Appendix 9D, 9E and **9F** provide the regression results for the Carhart four factor model for the 2-week (WML1), 4 week (WML2 and 8 week (WML3) momentum factors. Average R-squared is 0.5899, 0.6162 and 0.6088 for models including the two-week, 4-week and 8-week momentum factor respectively. These results support the results of Section **4.2.3** that the momentum factor provides almost no additional explanatory power.

The robustness results are in line which what was found in **chapter 4,** which improves the reliability of the results of this research.

6 Conclusion

This research shows no significant evidence of a size, value or momentum effect in the cryptocurrency market indicating that there are still undiscovered factors that explain cryptocurrency returns.

First, initial analysis shows that both size factors are insignificant. Mean returns of the portfolios that constructed SMB2 even show that the big portfolio is outperforming the small portfolio which is the opposite of what is found in the literature. Second, there was also no evidence found for a value effect as mean returns of both value factors are negative and insignificant. And lastly, although all winner portfolios slightly outperformed their respective loser portfolios, all three momentum factors were insignificant as well. There is also no systematic relationship between the length of the lookback period and the mean return of the momentum portfolios. Cross section regression analysis confirms these results as all cross-section regressions demonstrate that low-cap, high average NVT ratio and winner portfolios systematically do not outperform their respective high-cap, low average NVT and loser portfolios. Moreover, constructing factors in different ways led to heterogeneous results which is in line with the literature.

Furthermore, regression results show that CAPM seems to do a decent job in explaining cryptocurrency returns. All the estimate betas in the time series regression are significant on a 1 percent level. Although the r-squared is lower than what was found in the literature, time series and cross section regression show a systematic positive relationship between excess returns and the market beta.

We also conclude that the Fama and French three factor model shows little additional explanatory power. Although the R-squared showed a similar relative improvement as the original paper, cross-section analysis demonstrated that the betas of the value and size factors take a random walk which indicates that the regression results were biased.

The Carhart model performed even worse, as all three momentum factors showed additional explanatory power to the Fama and French model. Results of the cross-section analysis demonstrated no systematic relationship between mean returns and the betas of the momentum factors.

After reconstructing the dependent variable based on volatility, we find that the CAPM still performs decent while the Fama and French and the Carhart model show little additional explanatory power. Although CAPM does a reasonable job, further research is needed to access other factors that influence the returns of cryptocurrencies.

7 Limitations and further research

The first limitation to this study is the sample size. Although the 30 cryptocurrencies that were used for the sample make up for a big part of the total market capitalization of cryptocurrencies, they do not represent the cryptocurrency market as a whole. As far as the authors knowledge goes, there is no website that provides automatic data extraction for multiple cryptocurrencies at the same time

as data in this research was extracted manually from coincodex.com. It is recommended for future research to increase the sample size to improve the representation of the cryptocurrency market.
Second, the time frame of this thesis is only three years. This is due to the cryptocurrency market being relatively new. Future research will be able to increase the timeframe as the crypto-market develops over the coming years.
Third, the portfolios used in this thesis are based on their data at t=0. In contrast, the portfolios that Fama and French (1993) use to estimate their risk factors are updated on a yearly basis. Due to the volatile nature of the cryptocurrency market, we would recommend future research to update the size and value portfolios on a weekly basis. For the momentum factor, it is recommended to update the portfolios on the same timeframe as the lookback period. Moreover, for the market factor, the CRIX index was used. The altcoins that are included in this model represent a big portion of the total market capitalization of the cryptocurrency market but they do not represent the whole sample. For that reason, future research can use the value weighted excess returns of the portfolios as the dependent variable.
Furthermore, for the cross-section analysis, a single cross section regression between the average mean returns and the estimated betas was performed. We would suggest further research to perform Fama Macbeth (1973) rolling regressions on the asset pricing model to provide additional information on the risk premia of each of the included risk factors.
Based on the results of this thesis, we also recommend further research on other factors that may explain cryptocurrency. For example, the five factor model of Fama and French (2015) which includes profitability and investment patterns as additional risk factors to the three factor model. Another interesting topic is to look at the behavioral side of crypto investing. For example, Ballis & Antonis (2020) conclude that investors in the cryptocurrency market invest irrationally and blindly mimic other investors' decisions. Pelster, et al, (2019) find that the majority of crypto investors is driven by excitement-seeking. These results indicate that behavioral factors may explain pricing anomalies of crypto returns that the CAPM cannot explain.

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Appendix

Appendix 1A: Descriptive statistics for 9 portfolios based on Size and NVT ratio

	MEAN	STD DEV	SKEWNESS	MIN	MAX
P11	0.0124%	15.2150	0.0037	-42.4409	60.9119
P12	1.7973%	26.0392	0.0000	-44.6366	242.7433
P13	-0.7896%	15.2596	0.2530	-55.1609	52.7634
P21	0.0838%	15.1001	0.2935	-50.7288	50.6924
P22	-0.4556%	14.9950	0.0147	-57.4079	50.6924
P23	-0.2764%	17.4549	0.0017	-52.9599	68.9294
P31	-0.2639%	14.1875	0.1886	-42.0758	45.7348
P32	0.0373%	13.4153	0.0180	-46.4298	56.1007
P33	-0.5925%	15.1760	0.0007	-49.7885	56.0722

* The first number indicates the size percentile and the second number indicates the NVT ratio percentile. Example: p12 refers to the 0th – 33th percentile on size and 33th-67th percentile in NVT ratio.

Appendix 1B: Descriptive statistics for 10 portfolios based on volatility

	MEAN	STD DEV	SKEWNESS	MIN	MAX
PA	-0.2639%	11.7472	0.1726	-39.5716	30.4540
PB	0.1528%	13.6325	0.8022	-41.2735	39.0887
PC	-1.1443%	13.8690	0.0137	-51.4742	58.7990
PD	-0.0715%	15.2115	0.7521	-46.1666	42.0322
PE	-0.6401%	15.5458	0.0317	-50.3573	61.1735
PF	0.0226%	15.3274	0.0240	-51.8202	54.6034
PG	-0.3566%	15.8444	0.0071	-52.2836	64.5512
PH	0.7905%	9.3468	0.0000	-23.4122	44.2790
PI	-0.3642	16.4297	0.0296	-51.4363	58.8254
PJ	0.8747	21.8430	0.0000	-49.7764	190.4236

* All 30 cryptocurrencies are sorted by volatility. Afterwards they are divided in 10 portfolios. PA contains the least volatile assets while PJ contains the most volatile assets.

Appendix 2: Time series regression results CAPM:

$$E(R) - R_f = \beta_{mkt} * \left(E(R_m) - R_f\right)$$

ALPHA	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.0794	1.8710	-0.7174
INTERMEDIATE	0.1559	-0.3819	-0.2056
BIGGEST	-0.1861	0.1068	-0.5221

BETA RM-RF	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.9719***	1.0679***	1.0469***
INTERMEDIATE	1.0453***	1.0686***	1.0272***
BIGGEST	1.1283***	1.007***	1.0200***

R-SQUARED	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.4849	0.2009	0.5601
INTERMEDIATE	0.5703	0.6047	0.4108
BIGGEST	0.7543	0.6721	0.5374

Portfolios are created by way of 3x3 portfolio construction. The column indicates size (small-big) and de row indicates NVT ratio (low-high) E.g. Smallest/lowest shows the results of the portfolio containing small sized assets with low average NVT ratios.
*****,**,* - significance on 1, 5 and 10% level**

Appendix 3: Regression results Fama and French 3 factor model (SMB1 and HML1)

$$E(R) - R_f = \beta_{mkt} * \left(E(R_m) - R_f\right) + \beta_{SMB1} * (E_{SMB1}) + \beta_{HML1} * (E_{HML1}) + e$$

ALPHA	LOWEST	INTERMEDIATE	BIGGEST
SMALLEST	-0.3443	1.8710	-0.6186
INTERMEDIATE	-0.2325	-0.4241	0.0057
BIGGEST	-0.3643	0.2224	-0.1519

BETA RM-RF	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.9574***	1.0693***	1.0589***
INTERMEDIATE	1.0331***	1.0694***	1.0428***
BIGGEST	1.1209***	1.0126***	1.0364***
BETA SMB1	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.5557***	2.5052***	0.8308***
INTERMEDIATE	0.6426***	0.3082***	0.6504***
BIGGEST	0.0858	-0.0201	0.07000
BETA HML1	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	-0.4236***	0.5675***	0.6167***
INTERMEDIATE	-0.3164***	0.0941	0.7115***
BIGGEST	-0.2580***	0.0186**	0.5943***

R-SQUARED	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.5517	0.5756	0.7567
INTERMEDIATE	0.6434	0.6195	0.5380
BIGGEST	0.7655	0.6765	0.5934

Portfolios are created by way of 3x3 portfolio construction. The column indicates size (small-big) and de row indicates NVT ratio (low-high) E.g. Smallest/lowest shows the results of the portfolio containing small sized assets with low average NVT ratios.

*****,**,* - significance on 1, 5 and 10% level**

Appendix 4: Regression results Fama and French three factor model (SMB2 and HML2)

$$E(R) - R_f = \beta_{mkt} * \left(E(R_m) - R_f\right) + \beta_{SMB2} * (E_{SMB2}) + \beta_{HML2} * (E_{HML2}) + e$$

ALPHA	LOWEST	INTERMEDIATE	BIGGEST
SMALLEST	-0.1739	2.1861	-0.3813
INTERMEDIATE	0.0580	-0.3005	0.0921
BIGGEST	-0.2726	0.2219	-0.2964

BETA RM-RF	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.9690***	1.0601***	1.0401***
INTERMEDIATE	1.0476***	1.0664***	1.0192***
BIGGEST	1.1304***	1.0043***	1.0146***
BETA SMB2	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.0075	0.0077	-0.0051
INTERMEDIATE	-0.0013	0.0029	0.0132
BIGGEST	0.0016	0.0056	0.0046
BETA HML2	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.1076	0.6243	0.8716***
INTERMEDIATE	-0.2110**	0.1468	0.4984***
BIGGEST	-0.1786**	0.1858**	0.4608***

R-SQUARED	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.4924	0.2275	0.7183
INTERMEDIATE	0.5751	0.6055	0.4474
BIGGEST	0.7593	0.6792	0.5758

Portfolios are created by way of 3x3 portfolio construction. The column indicates size (small-big) and de row indicates NVT ratio (low-high) E.g. Smallest/lowest shows the results of the portfolio containing small sized assets with low average NVT ratios.

*****,**,* - significance on 1, 5 and 10% level**

Appendix 5: Regression results Carhart four factor model (SMB1, HML1 and WML1)

$$E(R) - R_f = \beta_{mkt} * \left(E(R_m) - R_f\right) + \beta_{SMB1} * (E_{SMB1}) + \beta_{HML1} * (E_{HML1}) + \beta_{WML1} * (E_{WML1}) + e$$

ALPHA	LOWEST	INTERMEDIATE	BIGGEST
SMALLEST	-0.3041	1.4201	-0.6308
INTERMEDIATE	-0.2494	-0.4274	0.0500
BIGGEST	-0.3681	0.2460	-0.1581

BETA RM-RF	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.9839***	1.0747***	1.0509***
INTERMEDIATE	1.0220***	1.0672***	1.0720***
BIGGEST	1.1184***	1.0282***	1.0324***
BETA SMB1	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	0.5101***	2.4960***	0.8445***
INTERMEDIATE	0.6617***	0.3119***	0.6002***
BIGGEST	0.0901	-0.0469	-0.0630
BETA HML1	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	-0.4596***	0.5603***	0.6276***
INTERMEDIATE	-0.3013***	0.0971	0.6719***
BIGGEST	-0.2546***	0.1654*	0.6000***
BETA WML1	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	0.4241***	0.0858	-0.1281
INTERMEDIATE	-0.1782*	-0.0344	0.4672***
BIGGEST	-0.0398	0.2994**	-0.0652

R-SQUARED	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.5789	0.5739	0.7545
INTERMEDIATE	0.6469	0.6178	0.5629
BIGGEST	0.7647	0.6880	0.5921

Portfolios are created by way of 3x3 portfolio construction. The column indicates size (small-big) and de row indicates NVT ratio (low-high) E.g. Smallest/lowest shows the results of the portfolio containing small sized assets with low average NVT ratios.
*****,**,* - significance on 1, 5 and 10% level**

Appendix 6: Regression results Carhart four factor model (SMB1, HML1 and WML2)

$$E(R) - R_f = \beta_{mkt} * \left(E(R_m) - R_f\right) + \beta_{SMB1} * (E_{SMB1}) + \beta_{HML1} * (E_{HML1}) + \beta_{WML2} * (E_{WML2}) + e$$

ALPHA	LOWEST	INTERMEDIATE	BIGGEST
SMALLEST	-0.3116	1.1816	-0.6160
INTERMEDIATE	-0.4205	-0.4859	-0.3071
BIGGEST	-0.4198	0.1128	-0.2044

BETA RM-RF	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.9609***	1.0445***	1.0592***
INTERMEDIATE	1.0130***	1.0628***	1.0091***
BIGGEST	1.1149***	1.0008***	1.0308***
BETA SMB1	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.5737***	2.3781***	0.8322***
INTERMEDIATE	0.5388***	0.2741**	0.4778***
BIGGEST	0.0552	-0.0806	-0.0990
BETA HML1	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	-0.3782***	0.2466	0.6203***
INTERMEDIATE	-0.5782***	0.0081	0.2757**
BIGGEST	-0.3353***	0.0338	0.5211
BETA WML2	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	-0.1142	0.8042***	-0.0090
INTERMEDIATE	0.6560***	0.2157	1.0921***
BIGGEST	0.1937***	0.3826***	0.1832

R-SQUARED	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.5514	0.5739	0.7519
INTERMEDIATE	0.7135	0.6248	0.6729
BIGGEST	0.7709	0.7034	0.5965

Portfolios are created by way of 3x3 portfolio construction. The column indicates size (small-big) and de row indicates NVT ratio (low-high) E.g. Smallest/lowest shows the results of the portfolio containing small sized assets with low average NVT ratios.
*****,**,* - significance on 1, 5 and 10% level**

Appendix 7: Regression results Carhart four factor model (SMB1, HML1 and WML3)

$$E(R) - R_f$$
$$= \beta_{mkt} * \left(E(R_m) - R_f\right) + \beta_{SMB1} * (E_{SMB1}) + \beta_{HML1} * (E_{HML1}) + \beta_{WML3} * (E_{WML3}) + e$$

ALPHA	LOWEST	INTERMEDIATE	BIGGEST
SMALLEST	-0.3565	1.0399	-0.5912
INTERMEDIATE	-0.4182	-0.5072	0.3309
BIGGEST	-0.4047	0.0321	-0.2164

BETA RM-RF	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.9577***	1.0774***	1.05830***
INTERMEDIATE	1.0373***	1.0712***	1.0502***
BIGGEST	1.1218***	1.0168***	1.0378***
BETA SMB1	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	0.5543***	2.4633***	0.8339***
INTERMEDIATE	0.6617***	0.2989***	0.6125***
BIGGEST	0.0813	-0.0415	-0.0773
BETA HML1	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	-0.4452***	-0.0890	0.6651***
INTERMEDIATE	-0.6441***	-0.0524	0.1176
BIGGEST	-0.3293***	0.1493	0.4805***
BETA WML3	**LOWEST**	**INTERMEDIATE**	**HIGHEST**
SMALLEST	0.0366	1.1156***	-0.0823
INTERMEDIATE	0.5568***	0.2490	1.0092***
BIGGEST	-0.1212	0.5707**	0.1934

R-SQUARED	LOWEST	INTERMEDIATE	HIGHEST
SMALLEST	0.5496	0.6296	0.7528
INTERMEDIATE	0.6832	0.6260	0.6379
BIGGEST	0.7666	0.7302	0.5964

Portfolios are created by way of 3x3 portfolio construction. The column indicates size (small-big) and de row indicates NVT ratio (low-high) E.g. Smallest/lowest shows the results of the portfolio containing small sized assets with low average NVT ratios.
*****,**,* - significance on 1, 5 and 10% level**

Appendix 8: Results cross sectional regressions

Cross sectional results Fama & French 3 factor model (RM-RF, SMB1, HML1)

MEANRETURN	COEFFICIENT	STD ERROR
BETA RM-RF	1.4898	0.3933

*****,**,* - significance on 1, 5 and 10% level**

R squared: 0.0071

Cross sectional results Fama & French 3 factor model (RM-RF, SMB1, HML1)

MEANRETURN	COEFFICIENT	STD ERROR
BETA RM-RF	-0.6858***	0.2061
BETA SMB1	0.8686***	0.0121
BETA HML1	-0.3950***	0.0215

*****,**,* - significance on 1, 5 and 10% level**

R-squared: 0.5748

Cross sectional results Carhart four factor model (RM-RF, SMB1, HML1 and WML1)

MEANRETURN	COEFFICIENT	STD ERROR
BETA RM-RF	1.1092***	0.2406
BETA SMB1	0.8597***	-0.5072
BETA HML1	-0.4424***	0.0209
BETA WML1	0.5612	0.03744

*****,**,* - significance on 1, 5 and 10% level**

R-squared: 0.5153

Appendix 9A: Regression results CAPM with alternative portfolios based on volatility (RM-RF)

PORTFOLIO	COEFFICIENT RM-RF	R-SQUARED
PA	0.9873***	0.8430
PB	1.0349***	0.6869
PC	0.9474***	0.5553
PD	1.0951***	0.6169
PE	1.0806***	0.5751
PF	1.0296***	0.5368
PG	1.1384***	0.6147
PH	0.2895	0.1146
PI	1.1002	0.5334
PJ	0.9285	0.2158

* All 30 cryptocurrencies are sorted by volatility. Afterwards they are divided in 10 portfolios. PA contains the least volatile assets while PJ contains the most volatile assets.
*****,**,* - significance on 1, 5 and 10% level**

Appendix 9B: Regression results Fama and French three factor model with alternative portfolios based on volatility (RM-RF, SMB1 and HML1)

PORTFOLIO	COEFFICIENT RM-RF	COEFFICIENT SMB1	COEFFICIENT HML1	R-SQUARED
PA	0.9834***	0.0350	-0.1371**	0.8469
PB	1.0335***	0.0798	-0.0382	0.6853
PC	0.9571***	0.1046	0.3808***	0.5852
PD	1.0981***	0.3458***	0.1795*	0.6410
PE	1.0916***	0.4229***	0.4929***	0.6471
PF	1.0285***	0.6573***	0.0936	0.6053
PG	1.1410***	0.0729	0.1133	0.6141
PH	0.2756***	0.4481***	-0.4225***	0.2498
PI	1.1019***	0.8663***	0.2426**	0.6544
PJ	0.9250***	1.3082***	0.1347	0.3536

* All 30 cryptocurrencies are sorted by volatility. Afterwards they are divided in 10 portfolios. PA contains the least volatile assets while PJ contains the most volatile assets.
*****,**,* - significance on 1, 5 and 10% level**

Appendix 9C: Regression results Fama and French three factor model with alternative portfolios based on volatility (RM-RF, SMB2 and HML2)

PORTFOLIO	COEFFICIENT RM-RF	COEFFICIENT SMB2	COEFFICIENT HML2	R-SQUARED
PA	0.9885***	-0.0004	-0.1236**	0.8466
PB	1.0342***	0.0027	-0.0001	0.6844
PC	0.9451***	0.0021	0.1953***	0.5602
PD	1.0981***	0.3458***	0.1795*	0.6410
PE	1.0920***	0.0051	0.2040**	0.6277
PF	1.0281***	0.0010	0.1443	0.5364
PG	1.1368***	0.0006	0.0126	0.6130
PH	0.2876***	0.0011	0.1757*	0.1178
PI	1.0933***	0.0075	0.5356***	0.5790
PJ	0.9253***	-0.0176	0.8446***	0.2889

* All 30 cryptocurrencies are sorted by volatility. Afterwards they are divided in 10 portfolios. PA contains the least volatile assets while PJ contains the most volatile assets.

*****,**,* - significance on 1, 5 and 10% level**

Appendix 9D: Regression results Carhart four factor model with alternative portfolios based on volatility (RM-RF, SMB1, HML1 and WML1)

PORTFOLIO	COEFFICIENT RM-RF	COEFFICIENT SMB2	COEFFICIENT HML2	COEFFICIENT WML1	R-SQUARED
PA	0.9846***	0.0329	-0.1386***	0.01944	0.8463
PB	1.0351***	0.0769	-0.0405	0.0272	0.6863
PC	0.9603***	0.0992	0.3765***	0.0505	0.5837
PD	1.0824***	0.3728***	0.2001**	-0.2507**	0.6495
PE	1.0788***	0.4450***	0.5103***	-0.2050*	0.6519
PF	1.0353***	0.6456***	0.0843	0.1086	0.6052
PG	1.1504***	0.05685	0.1007	0.1488	0.6155
PH	0.2786***	0.4430***	-0.4265***	0.0470	0.2470
PI	1.0881***	0.8901***	0.2614**	-0.2215**	0.6545
PJ	0.9551***	1.2562***	0.0935	0.4835**	0.3594

* All 30 cryptocurrencies are sorted by volatility. Afterwards they are divided in 10 portfolios. PA contains the least volatile assets while PJ contains the most volatile assets.

*****,**,* - significance on 1, 5 and 10% level**

Appendix 9E: Regression results Carhart four factor model with alternative portfolios based on volatility (RM-RF, SMB1, HML1 and WML2)

PORTFOLIO	COEFFICIENT RM-RF	COEFFICIENT SMB2	COEFFICIENT HML2	COEFFICIENT WML2	R-SQUARED
PA	0.9840***	0.0294	-0.1301**	-0.0176	0.8492
PB	1.0202***	0.0119	-0.2095**	0.4293***	0.7185
PC	0.9535***	0.0858	0.3333***	0.1191	0.5857
PD	1.0761***	0.2329**	-0.1054	0.7140***	0.7165
PE	1.0808***	0.3675***	0.3529***	0.3507***	0.6632
PF	1.0100***	0.5626***	-0.1455	0.5989***	0.6569
PG	1.1308***	0.0206	-0.0187	0.3307***	0.6275
PH	0.2834***	0.4880***	-0.3219***	-0.2521***	0.2716
PI	1.0830***	0.7689***	-0.0033	0.6162***	0.6969
PJ	0.9426***	1.3971***	0.3590**	-0.5627***	0.3764

* All 30 cryptocurrencies are sorted by volatility. Afterwards they are divided in 10 portfolios. PA contains the least volatile assets while PJ contains the most volatile assets.

*****,**,* - significance on 1, 5 and 10% level**

Appendix 9F: Regression results Carhart four factor model with alternative portfolios based on volatility (RM-RF, SMB1, HML1 and WML3)

PORTFOLIO	COEFFICIENT RM-RF	COEFFICIENT SMB2	COEFFICIENT HML2	COEFFICIENT WML3	R-SQUARED
PA	0.9833***	0.0354	-0.1300**	-0.0121	0.8462
PB	1.0365***	0.0640	-0.2858***	0.4208***	0.7128
PC	0.9587***	0.0967	0.2556**	0.2129*	0.5904
PD	1.0981***	0.3458***	0.1795*	0.6817***	0.7006
PE	1.0944***	0.4082***	0.2614**	0.3934***	0.6649
PF	1.0337***	0.6303***	-0.3269***	0.7146***	0.6698
PG	1.1426***	0.0650	-0.010	0.2094*	0.6175
PH	0.2743***	0.4548***	-0.3171***	-0.1791*	0.2573
PI	1.1049***	0.8513***	0.0067	0.4001***	0.6658
PJ	0.9206***	1.3301***	0.4785**	-0.5847***	0.3627

* All 30 cryptocurrencies are sorted by volatility. Afterwards they are divided in 10 portfolios. PA contains the least volatile assets while PJ contains the most volatile assets.

*****,**,* - significance on 1, 5 and 10% level**