IN THE PERIPHERY OF FINANCIAL MARKETS

ASSET PRICING OF CRYPTOCURRENCIES

AXEL BRYHN

OSCAR GONZALES

Bachelor Thesis

Stockholm School of Economics

2019

In the Periphery of Financial Markets: Asset Pricing of Cryptocurrencies

Abstract:

In this thesis we analyze asset pricing of cryptocurrencies. We try to understand and explain what determines the change in return on individual cryptocurrencies by running time-series regressions on their daily returns. The independent variables included are based on the market, size, value and momentum effect. The data set includes the returns on 44 cryptocurrencies between 2017 and 2019 and the findings show that the market risk factor is not significant and has weak explanatory power, while the size, value and momentum factor on average are significant for the greater part of the included cryptocurrencies and have high explanatory power. For one of the size divisions, the modified Fama-French model explains on average 34.8% of the change in return for 37 of 44 cryptocurrencies with a significance level of 5% and 43.7% for 32 of 44 cryptocurrencies on a similar significance level for the modified Carhart model.

Keywords:

Asset pricing, cryptocurrency, CAPM, Fama-French three-factor model, Carhart four-factor model

Authors:

Axel Bryhn (23786)
Oscar Gonzales (23775)

Tutor and Examiner:

Adrien d'Avernas, Assistant Professor, Department of Finance

Bachelor Thesis
Bachelor Program in Business and Economics
Stockholm School of Economics

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1. Introduction

In September 2008, panic spread on the world's financial markets when the U.S. investment bank Lehman Brothers went bankrupt. People lost a lot of money, and the trust and confidence in the established financial institutions took a beating (Earle, 2009). It was no coincidence that just days after the catastrophe, Satoshi Nakamoto[1] released the white paper "Bitcoin: A Peer-to-Peer Electronic Cash System", the idea of a decentralized system to send and receive money without the interference of a third party (Nakamoto, 2008). Bitcoin is the first successful cryptocurrency in the world, and at the time of this writing (15/05/2019), 2176 more cryptocurrencies have been created (CoinMarketCap, 2019). In October 2009, the first purchase of bitcoin with money (U.S. dollars) was registered. 1,006 bitcoins were bought for $1, converting to a price of $0.000994 per bitcoin, an astronomically low figure (Ammous, 2018). At the top of Bitcoin's success, just before the bubble burst on December 16, 2017, one bitcoin was traded for $19,497.40. A staggering increase of almost two billion percent since the first purchase eight years earlier and a compounded annual growth rate of 3,457%. Bitcoin, as well as the other cryptocurrencies, are highly volatile with the possibility of its holder to gain or lose a lot of money. As more and more people flock to these investment opportunities, many interesting questions arise. Consequently, the tentative research question and purpose of this thesis paper is to try answering what determines the change in return on cryptocurrencies.

We will use the capital asset pricing model (CAPM), the Fama-French three-factor model and the Carhart four-factor model to try explaining the change in return on 44 cryptocurrencies from 01/01/2017 to 24/02/2019. This translates to our two hypotheses, namely:

H_1*: The Fama-French three-factor model explains more of the change in return, on average for the 44 cryptocurrencies, than the capital asset pricing model*

[1] A pseudonym, unknown if it is a person or a group of people.

Just like in previous finance literature, where Fama and French (1992) discover that adding a size and value factor explain more of the daily changes in return on U.S. stocks than when only taking the market risk into consideration. The first hypothesis state that this is true for cryptocurrencies as well.

H_2: The Carhart four-factor model explains more of the change in return, on average for the 44 cryptocurrencies, than the Fama-French three-factor model

In the research paper by Carhart (1997), he adds a fourth factor, the momentum factor, taking the past performance of stocks into consideration. We hypothesize that adding this factor explains more than just using the previous three factors.

The closest previous work to what we have done is found in a master thesis by Stoffels (2017) from Erasmus University Rotterdam. In the thesis he studies asset pricing on the weekly returns of 15 cryptocurrencies between April 2016 and July 2017 using the Fama-French three-factor model. Our thesis is different in three main ways. Firstly, the thesis offers a wider scope timewise, from January 2017 to February 2019, a time period when the cryptocurrency market has changed a lot. Secondly, it covers a wider set of cryptocurrencies than has earlier been studied. Usually, only the largest cryptocurrencies are being analyzed, while in this thesis smaller ones are included as well. Thirdly, the momentum factor is added to the models.

The results confirm the two hypotheses for a majority of the included cryptocurrencies. Meaning that the Fama-French three-factor model explains more of the change in return on cryptocurrencies than CAPM and that the Carhart four-factor model in turn, explains more than the Fama-French three-factor model. However, the results are not significant for all individual cryptocurrencies.

The modified Fama-French model, when excluding the cryptocurrency index (CRIX), is significant for 37 of 44 cryptocurrencies and on average explains 34.8% of the change in return. The modified Carhart model is significant for 32 of 44 cryptocurrencies and explains 43.7%.

In conclusion, the results are new because the models have obtained a higher explanatory value of the change in return on cryptocurrencies than previous literature. But also, confirming that even though cryptocurrencies are highly volatile, financial methods are applicable on this phenomenon. Something that might be of interest in the future.

The remainder of this thesis is organized as follows: Section 2 provides an introductory explanation of what cryptocurrencies are, together with a description of blockchain technology. Section 3 describes the financial theories on which this thesis is based, as well as previous literature within the subject. Section 4 and 5 describe the used data and research method. Section 6 and 7 describe the results and interpretations of the findings. Lastly, section 8 and 9 describe limitations of this thesis and the conclusions.

2. Background

2.1. What is a cryptocurrency?

Cryptocurrency derives from the two words cryptography and currency. According to the Oxford Dictionary (2019), cryptography is “the art of writing or solving codes”. When you send a cryptocurrency, you send the value as a code which is later verified and processed through a so-called peer-to-peer network. This is all based on the blockchain technology, which is explained more in detail in section 2.2.

The main quality of cryptocurrencies, and what makes them different from already established financial intermediaries, is that they are based on a decentralized platform, enabling people to send fast transactions at a low cost (Gates, 2017). Although, some cryptocurrencies focus more on anonymity and others on the speed of which financial transactions are sent and received, they all derive from the same purpose of sending digital value from one entity to another without the interference of a third party (such as a bank).

Despite its name and primary function of sending value, a cryptocurrency cannot directly be classified as a traditional currency. In order for something to be classified as a currency it has to fulfill three requisites: (1) it has to be a medium of exchange, (2) needs to have salability over time and space, (3) and function as a store of value (Ammous, 2018). Bitcoin, along with the altcoins (all cryptocurrencies that are not Bitcoin), fulfill the first two requisites but not fully the latter. The value that determines a cryptocurrency today depends on supply, demand and many unknown factors. In other words, there is no underlying stable value. Consequently, the price of a cryptocurrency could be worth $19,497.40 but also $0.000994, as we have seen throughout the lifetime of Bitcoin.

Since the end of the Bretton-Woods system, the value of fiat[2] currencies are not backed up by gold. However, the trust we confine in financial institutions and the fact that you pay taxes in the currency decided by the government make the currency more secure (Ammous, 2018). For this reason, comparing a regular fiat currency with a cryptocurrency is somewhat of a bold statement. Hence, the classification of a

[2] A currency without an intrinsic value that has been established as money, often by government regulation, such as USD, SEK, or EUR.

cryptocurrency as a highly volatile asset class is more suitable, and this definition is used throughout the thesis.

Even though they are highly volatile and lacking one of the proper requisites to be classified as a currency, the cryptocurrencies' main objective from the beginning was to transfer digital value, and this is still an important characteristic of today's cryptocurrencies. Hence, they still function as a currency in some respects (mainly as a medium of exchange), and this is an important observation for the factor construction later in the thesis. Different suggestions for classifications of cryptocurrencies are discussed further in section 3.2.

Bitcoin, as the most famous example, is a mineable cryptocurrency. This means that the number of outstanding bitcoins increases until the mining process ends around the year 2140, when the number of outstanding bitcoins reaches 21 million (Ammous, 2018). When you send a bitcoin to someone, this transaction is registered on a decentralized platform, namely on the blockchain. The mining process itself can be explained as solving a very complex mathematical puzzle to add the transaction to the blockchain (Coindesk, 2019). Anyone, which nowadays mainly are large groups of computers able to process huge quantities of information, can participate in the mining in a peer-to-peer network. The objective is to verify the authenticity of the transaction by solving the puzzle that is associated with the transaction. By running randomized numbers the computers try to find the right code that is unique for that transaction. The computers that solve the puzzle receive bitcoins as a reward. At the time of this writing (15/05/2019), the reward is 12.5 bitcoins, which is worth approximately $100,000 (Coindesk, 2019). This process of finding the right number is called *mining* and the people who do this are called *miners*. Since Bitcoin has a finite amount of coins that will ever exist, academics have drawn parallels with gold, hence, the analogy of mining for bitcoin just like you mine for gold has become widespread (Ammous, 2018).

2.2. The blockchain technology

To truly understand the underlying concept and future potential of blockchain it is helpful to look at it from a historical perspective, and realize that one of the fundamental factors that has ensured the success of the human race is based on trust. The one thing that makes us humans dominate the world is the fact that we are able to co-operate in large numbers, and work with strangers towards joint goals (Harari, 2014). This itself relies on our shared belief in stories and large systems such as nations and money. These large systems are today entirely centralized, meaning that there is an intermediary for our interactions with each other. This is an efficient way of enabling humans to interact with each other, since we do not necessarily have to trust the other party we are interacting with, it is enough that we trust the intermediary, for example, the bank or the government (Harari, 2014). But still, without the intermediary, many processes could be made even more efficient and less costly. This is where blockchain comes in.

Blockchain is in essence an infrastructure for trust between entities. The technology is entirely decentralized and distributed. This means that it allows for settling transactions within a peer-to-peer network, without the need of a trusted intermediary (Coindesk, 2019). This lets people trust the content without having to trust the other people using it. Blockchain furthermore allows for owning, and proving ownership of digital assets, such as cryptocurrencies.

The blockchain is like a neutral third party that does not need to know who does what, or why they are doing it, as long as the rules are followed (De Geer, 2018). The blockchain is categorized by three main principles. Firstly, it is an open book filled with transactions, similar to a bank's database. Secondly, it is available for everyone, no matter the reason, similar to internet. Thirdly, it is controlled by everyone who uses it, similar to Wikipedia (De Geer, 2018).

Sending a cryptocurrency via the blockchain is much like sending an email. You inquire for the recipient's public key, which functions as their email address, and thereafter you send any amount of cryptocurrency you want from your own public key to their public key. Your private key functions as the password to your email account, and using this code you can access your coins. Thus, one of the main problems prior to launching Bitcoin was how you restricted people from not sending the same coin to multiple public keys, just like you can send the same email to hundreds of other email addresses. This is what is referred to as the double-spending problem, and what Nakamoto solved with the use of blockchain technology (Nakamoto, 2008).

2.3. Why we believe it is relevant

Cryptocurrencies are still relatively new, in particular as a field of research, and there are many unanswered questions and unexplored areas to be examined. With this thesis, we aim to contribute to the financial field of cryptocurrencies, and inspire others to do the same. We want to shed light on this financial market and enlighten people about this phenomenon. We view cryptocurrencies as relevant, not only considering the rapid growth in recent years, but also due to the potential as a future part of our financial systems and maybe even our everyday lives

Throughout history we have seen proof of several great inventions that have completely changed the way we live and view the world, but it is usually difficult to realize the true impact they will have until we look at it in retrospect. Only time will tell if cryptocurrencies will be one of the great inventions to look back on in the future or not, but it surely has made a mark as something new within the world of finance. Also, despite one's view on the future of cryptocurrencies, at the time of this writing (15/05/2019), the total market capitalization of all cryptocurrencies in the world is more than $240 billion (CoinMarketCap, 2019). We consider this a justification for gaining deeper knowledge within the subject.

3. Theoretical framework and previous literature

There have been numerous previous studies and reports on cryptocurrencies, ranging from topics on how cryptocurrencies can be used as alternative investments to what makes up the fundamental value of cryptocurrencies. These are used as a groundwork for the study and presented in section 3.2. However, since the purpose of this thesis is to investigate what determines the change in return, we also rely on several traditional financial theories as a foundation for our research.

3.1. Theoretical framework

In this section, we explain the underlying theories of our research, based on the evolution of portfolio theory and asset pricing, including the work of Markowitz (1952), Sharpe (1964), Lintner (1965), Fama and French (1992 and 1993) and Carhart (1997). To be able to apply an asset pricing model on cryptocurrencies, it is essential to understand the fundamentals of asset pricing.

Markowitz (1952) laid out the foundation for the modern portfolio theory in his research paper "Portfolio Selection". The main idea is that an investor is basing his or her investment decision on two criteria: the return and variance of the asset. If two portfolios have an identical return, a rational investor will choose the portfolio with the lowest variance, since the variance is associated with higher risk. If an investor is going to invest in a portfolio with a relatively higher variance, he or she will demand a higher return as a compensation for the higher undertaken risk. The research paper also states that investors will invest in an efficient portfolio, in other words a portfolio that has the highest expected return for a given level of variance.

Following Markowitz's findings, and based on the research papers by Sharpe (1964) and Lintner (1965), one of the most widely used financial concepts was developed, CAPM. Similarly to Markovitz, CAPM describes the relationship between risk and return. In CAPM the risk studied is the systematic risk and the individual asset's relation to it, which is measured through its beta. The expected return of an asset can be expressed as a linear function of the risk-free rate of return and the beta of the asset multiplied by the expected market risk premium (the market return subtracted by the risk-free rate). The main intuition behind the model is that the expected return is determined by only one risk factor, namely the market risk.

Another widely used model is the Fama-French three-factor model, which considers more than the market as a risk factor when explaining the change in return on stocks. Fama and French (1992) present in their paper "The Cross-Section of Expected Stock Returns" their three-factor model, explaining changes in stock returns based on three risk factors: a market factor, a size factor and a value factor, obtained through cross-sectional regressions. The market factor is represented by the excess return of the market, the size factor is represented by the risk associated with the size of the company, and lastly the value factor is represented by the book-to-market ratio (BE/ME). Together, these factors predict a bigger portion of the change in return compared to models that only consider the market factor.

Fama and French divide the analyzed stocks into different portfolios based on the above-mentioned factors, where size is divided based on the median market capitalization of the stocks (small and big stocks), and the value factor is based on the BE/ME, dividing the stocks into groups of growth stocks (low BE/ME), neutral stocks, and value stocks (high BE/ME). In 1993, they extended their research by using the time-series regression approach of Black et al. (1972). Their findings confirm that the average return has a negative relationship with size, in other words, small-cap stocks tend to outperform bigger stocks. Stocks with higher BE/ME tend to outperform those with lower BE/ME, meaning that there is a strong positive relationship between value stocks and return. In conclusion, small-cap value stocks outperform all other types of stocks.

Carhart's four-factor model (Carhart, 1997) is an extension of the Fama-French three-factor model which takes a momentum factor into consideration. The momentum factor is based on the findings of Jegadeesh and Titman (1993), that buying stocks that have performed well in the past and sell stocks that have performed poorly in the past generate significant positive returns.

3.2. Previous literature

The academic field of cryptocurrencies is relatively young, for this reason the articles and reports written have rarely been published in the most prominent journals in economics and finance, especially regarding asset pricing. Therefore, a large part of the previous literature that has been written about the topic derives from unpublished research reports and theses. Below, a summary of the previous literature is presented to highlight important findings relevant to this study.

Blockchain was for the first time successfully conceptualized by Nakamoto in the fall of 2008, through the invention of Bitcoin, and is by many thought to be the most secure and stable of the cryptocurrencies. Nakamoto created a system that could transfer digital value directly between two parties without a central authority via the blockchain technology (Nakamoto, 2008).

Stoffels (2017) develops a three-factor asset pricing model for cryptocurrencies by using a market factor, a size factor and a factor related to the transaction volume relative to an asset's market capitalization. The data used is weekly returns on 15 cryptocurrencies from April 2016 to July 2017. The model explains on average 35% of the change in weekly returns. Furthermore, the momentum factor is analyzed by using several formations, holding and waiting periods, and different ways of constructing the portfolio, to see that abnormal returns can be achieved by using certain momentum based strategies.

One fundamental part of this research is the categorization of cryptocurrencies and whether they ought to be classified as a currency, a commodity or an asset. Since an asset pricing model is used, the underlying assumption is that cryptocurrencies are classified as an asset class. Yermack (2013) published one of the first research papers on cryptocurrencies and in which the author assesses whether Bitcoin is a real currency or not. Although at the time of writing, the transaction volume was far below today's level, it still demonstrates many of the typical characteristics we see today. The conclusion is partly that Bitcoin has zero correlation with widely used currencies and gold, and that it in general behaves more like a speculative investment than a currency. On this note, Glaser et al. (2014) also state that users of digital currencies are primary interested in alternative investments, rather than an alternative transaction system. Burniske and White (2017) identify cryptocurrencies as a distinct asset class, as it meets the criteria for being an asset, namely its investability, but differs from traditional assets in terms of politico-economic features, correlation of price movements, and risk-reward profiles.

Asplund and Ivarsson (2018) analyze what drives the price of cryptocurrencies. Their conclusion is that the size of the cryptocurrency market, trading volume, and attention (news articles and views on Wikipedia) all have significant effect on the price, but macroeconomic factors such as correlation with gold and oil prices do not have an effect. Klein et al. (2018) also find that Bitcoin behaves completely different from gold, and positively correlates with bear markets. On the other hand, Bianchi (2018), who investigates the relationship between cryptocurrencies and traditional asset classes and commodities, finds that there is a positive, but weak, relationship between returns on cryptocurrencies and returns on gold and energy. Similarly, Dyhrberg (2016) tries to determine what type of asset Bitcoin is by investigating its hedging capabilities. The conclusion is that Bitcoin can be used as a hedge against the *Financial Times Stock Exchange Index*, and it can also be used as a hedge against the U.S. dollar in the short-run. The author emphasizes that Bitcoin possesses some of the hedging capabilities as gold. The findings of Baur et al. (2017) contradict those of Dyhrberg (2016) and conclude, similarly to Klein et al. (2018) and Asplund and Ivarsson (2018), that Bitcoin's price behavior and return are not anywhere near those of gold nor currencies.

Liu and Tsyvinski (2018) support the findings that cryptocurrencies do not have any exposure to the returns on commodities and currencies, but also find that one of the most important drivers of the return on cryptocurrency is the momentum effect. For stocks, the momentum effect is well-known and have been researched and proved several times. Daniel et al. (1998) and Asness et al. (2013) are two examples of research papers that dwell upon this topic. Not to forget Jegadeesh and Titman (1993), and Carhart's (1997) method of including the momentum factor as an extension of the Fama-French three-factor model either.

Despite the fact that several different research papers have tried to conclude the price drivers and classification of cryptocurrencies, the results are somewhat ambiguous. Still, the majority of the previous literature indicates that cryptocurrencies should be classified as an asset class, since it lacks the characteristics of and connections to commodities or currencies. Starting from this definition, the aim of this research is to clarify what determines the change in return on cryptocurrencies, and investigate which financial models have the highest explanatory power for this purpose. The timing of our research is important, since we today have access to prices both before and after the peak of Bitcoin in December 2017. Lastly, this research is not limited to Bitcoin or a few of the largest cryptocurrencies, the data set includes all cryptocurrencies with a market capitalization above $5 million that were created before 2017, resulting in a sample of 44 cryptocurrencies. We thereby contribute to previous literature in three ways. Firstly, by considering a larger sample of cryptocurrencies within the research. Secondly, by using a timeframe that is both longer than before studied and that includes the important peak and drop in prices of 2017. Thirdly, the model is extended by incorporating a momentum factor.

4. Data

4.1. Sample construction

The data set has been collected from CoinMarketCap (2019), a website providing daily information of all cryptocurrencies trading on exchanges from April 28, 2013 until today. Closing prices, market capitalizations and traded volumes (all three quantified in USD on a daily basis) for 44 cryptocurrencies have been collected between January 1, 2017 and February 24, 2019 (784 observations). The number of cryptocurrencies have been limited to 44 because all of these have, at the time of the data collection (24/02/2019), a total market capitalization of more than $5 million and available data from January 1, 2017. Cryptocurrencies with a market capitalization below $5 million were excluded because it was decided that these currencies have a too low market capitalization, and thus not relevant for the scope of this thesis. The main trade-off considered for the data selection was reaching a sufficient number of cryptocurrencies, without including too many irrelevant ones in terms of influence on the overall market. Thus, the cut-off at $5 million was reasonable, even though the exact cut-off is somewhat arbitrary. Furthermore, younger cryptocurrencies created after 01/01/2017 were chosen to be excluded. Since currencies that were established before the bubble burst in the end of 2017 were desirable, data that stretched back to the beginning of 2017 was required. Moreover, the price changes before 2017 were fairly modest (as can be seen in Figure 1 in section 4.3), and by excluding this time period it will probably not lead to a significant difference in result.

For a detailed description and view of the included assets and their market capitalization as well as the differences among each cryptocurrency individually see Table A1 in appendix 11.2. The average daily return is ranging from 0.01% to 0.72%, together with an average standard deviation ranging from 4.54% to 15.58%. All cryptocurrencies have experienced a drop and rise of at least 20% on a single day. Bytecoin experienced the largest change in daily return with a drop of 91% and a spike of 160%. These numbers highlight one of the difficulties with cryptocurrencies as of today: they are incredibly volatile and it is difficult to predict how they will perform in the future. Another important aspect to consider is the enormous size difference and the concentration of the total market value of the larger cryptocurrencies.

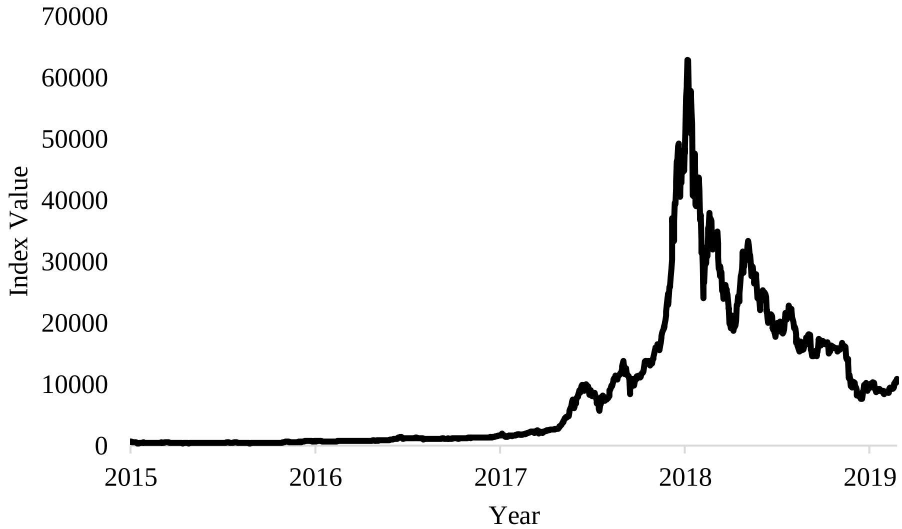
4.2. CoinMarketCap

For a cryptocurrency to be listed on CoinMarketCap (2019) it must meet two criteria: (1) fit the definition of a cryptocurrency according to Lansky (2018) and (2) be actively traded on at least two exchanges that CoinMarketCap supports. For an exchange to be supported it has to be able to expose the latest prices continuously, provide 24 hours' volume of each cryptocurrency, and been in operation for a minimum of 60 days. Just meeting these criteria is not a guarantee to be listed, but each exchange and cryptocurrency is thoroughly analyzed by looking at factors ranging from community interest and trading volume, to age and uniqueness. Also, only exchanges that charge a transaction fee are included, since this minimizes the risk of fraudulent trading volumes to manipulate prices. CoinMarketCap provides updated information for each cryptocurrency frequently, and the data runs through several verification processes before being made available. In section 11.1 in appendix the process of how each relevant metric is calculated to confirm its validity is presented. Although there exist several requisites and processes to confirm the validity of the data obtained from CoinMarketCap it could be subjected to errors. To the best of our knowledge, CoinMarketCap is the best data provider of cryptocurrency market data and thus used for this thesis.

4.3. CRIX

CRIX is a market index for cryptocurrencies created and updated on a daily basis by Humboldt-Univeristät zu Berlin, a school of business and economics (CRIX, 2019). CRIX is calculated by weighting each cryptocurrency by their market capitalization. At the time of the data collection (24/02/2019), the market index consisted of 55 cryptocurrencies. However, the number of included assets varies. The price development of CRIX is seen in Figure 1, with the price spike around the end of 2017 and the following decline.

Figure 1: CRIX Index (01/01/2015 to 24/02/2019)



4.3.1. Credibility and reliability

To the best of our knowledge, CRIX is the most reliable proxy of the market index for cryptocurrencies. Hence, it is used in the thesis for this reason. Humboldt-Univeristät zu Berlin, being the oldest and second to largest university in Berlin, adds credibility to the market index together with the fact that one of their professors, Dr. Wolfgang Härdle, is responsible for its content. The methodology used in the calculations of the index, together with the fact that the cryptocurrencies included are available on display, adds reliability to the data since it is transparent and could be replicated by anyone having access to daily data of included cryptocurrencies from providers such as CoinMarketCap.

5. Methodology

In the following section the process of applying and adjusting financial models to explain changes in cryptocurrencies' returns is described. The method is based on the Fama-French three-factor model, which serves as the foundation of the research. From this, a more appropriate version for cryptocurrencies has been derived. Using this model, different factors were tested to conclude which ones exhibit the highest adjusted R-squared values, in other words how much the independent variable can explain of the variance in the dependent variable. The process contains three parts: (1) creating six different portfolios based on size and value, (2) calculating the average return for each portfolio to generate the factors and (3) using the cryptocurrency index as a proxy of the market risk factor. These factors are then used to run time-series regressions on the individual cryptocurrencies to see if and how much the factors explain the change in return. The results are then used to evaluate potential adjustments that could be made to increase the explanatory power of the model, for example changes regarding the portfolio constructions, adding variables that could explain the returns better, omitting irrelevant variables, and adding the momentum factor.

5.1. Factor construction

The purpose of the original Fama-French model is to consider three essential factors regarding the market return, the size of the asset, and the book-to-market ratio (BE/ME) of the asset. As explained in the section 3.1, these factors are represented by the market risk premium, the small-minus-big factor (SMB), and the high-minus-low factor (HML). A usual approach when using the Fama-French three-factor model to assess stock returns is to obtain data of the factors from Kenneth R. French's website (2019). The factors are calculated based on stocks listed on *New York Stock Exchange*, *American Stock Exchange* and *NASDAQ*. In this thesis, it is not a plausible approach, since the stock market does not necessarily reflect the characteristics of cryptocurrencies. Therefore, these factors were constructed using cryptocurrency market data.

5.1.1. Size

To calculate the size factor, the cryptocurrencies are first sorted based on their market capitalization. In the original Fama-French three-factor model the breakpoint between small and big stocks is the median value of the market capitalization of the stocks included. Due to the difference in market structure of cryptocurrencies, with Bitcoin representing 64.66% of the total market capitalization in the data set, different breakpoints were analyzed to observe which one is more appropriate. Should the breakpoint be based on median value, as seen in size division five, this becomes very skewed with the big portfolio representing 99.36% of the total market capitalization in the data set. A further description of the size divisions tested, is presented in Table 1.

Table 1: Five Different Size Divisions Used in Thesis

Division Name	Breakpoint*	Assets in Small Portfolio	Assets in Big Portfolio	Share of Total Market Cap for Big
SMB1	$50 000 000 000	43	1	64.66%
SMB2	$10 000 000 000	41	3	90.50%
SMB3	$1 000 000 000	39	5	94.68%
SMB4	$350 000 000	34	10	97.54%
SMB5	$90 000 000	22	22	99.36%

*If below breakpoint, included in small portfolio. If above breakpoint, included in big portfolio.

5.1.2. Value

The original Fama-French method of classifying stocks as either value, neutral or growth, is not a possible method to use for cryptocurrencies, since they do not have a book value. Therefore, an adjusted version of the value factor was created.

A common ratio to measure performance on cryptocurrencies is the *network value-to-transaction volume ratio* (NVT). The ratio is calculated using the market capitalization divided by the transaction volume, and functions in this thesis as a proxy of the original HML factor in the model. The market capitalization of each cryptocurrency is calculated by multiplying the current price with its circulating supply. The transaction volume is the daily value in USD of the cryptocurrency being traded at any given date.

The reason for choosing this ratio is based on the earlier stated objective of cryptocurrencies' ability to transfer digital value. Assuming that an adequate proxy of the value factor is how efficiently one can make a transaction with the cryptocurrency. A low number signifies that the cryptocurrency is efficient at transferring digital value, hence, classified as a value asset. A high number signifies that the cryptocurrency is not efficient at transferring digital value, hence, classified as growth asset.

Another way to look at it is that a higher transaction volume compared to market capitalization indicates that there is a relatively large amount of transactions currently being traded in the world. These are therefore classified as value cryptocurrencies because they are more established and frequently used. The assets with a lower transaction volume compared to market capitalization are classified as growth cryptocurrencies because they are not as established and not as frequently used. This is the division of value and growth cryptocurrencies that will be used throughout the thesis.

5.1.3. Portfolio construction

The cryptocurrencies are divided into two size groups: big and small, with the different size divisions. Each size group is then divided into three groups based on their NVT ratio: value, neutral, and growth, where the breakpoints are the 30th and 70th percentiles. Contrary to the original HML factor, where value stocks take on high numbers and growth stocks take on low numbers, in this model it is the opposite. The *value cryptocurrencies* take on a low number and the *growth cryptocurrencies* take on a high number. For this reason, low-minus-high (LMH) is used to represent the value factor, although the usage is the same as with the original Fama-French factor.

Once the division regarding size and value is made, the cryptocurrencies are divided into six portfolios: small growth, small neutral, small value, big growth, big neutral and big value, as presented in Table 2.

Table 2: Fama-French portfolio construction

70th Market Cap/Volume percentile	Small Value	Big Value
	Small Neutral	Big Neutral
30th Market Cap/Volume percentile	Small Growth	Big Growth

In Table 3, descriptive statistics of the average daily returns on the portfolios with different size divisions are presented. These are the portfolios created to generate the factors used for the regressions. The portfolios with 0.00% average daily return do not consist of any cryptocurrencies, and are just empty portfolios, as can be seen more clearly in Table 4. The portfolio within each size division with the largest average daily return varies from portfolio to portfolio. However, we can see that the portfolios consisting of large neutral, in general, exhibits the highest average daily return. In the traditional Fama-French three-factor model, the small-cap value stocks are the stocks that consistently do best. Considering our different factor construction, it is not surprising that these descriptive statistics differ from those of the original model.

Table 3: Average Daily Return on Portfolios Formed on Size and NVT Ratio; Cryptocurrencies Sorted by Market Cap (Down) and then NVT Ratio (Across): Jan 2, 2017 to Feb 24, 2019

	NVT Ratio Portfolios			
SMB1	All	Value (Low)	Neutral	Growth (High)
All	0.23%	0.21%	0.28%	0.34%
Small	0.29%	0.25%	0.28%	0.34%
Large	0.17%	0.17%	0.00%	0.00%

	NVT Ratio Portfolios			
SMB4	All	Value (Low)	Neutral	Growth (High)
All	0.31%	0.25%	0.36%	0.33%
Small	0.28%	0.26%	0.23%	0.34%
Large	0.35%	0.23%	0.49%	0.32%

	NVT Ratio Portfolios			
SMB2	All	Value (Low)	Neutral	Growth (High)
All	0.33%	0.25%	0.38%	0.34%
Small	0.28%	0.24%	0.26%	0.34%
Large	0.38%	0.26%	0.49%	0,00%

	NVT Ratio Portfolios			
SMB5	All	Value (Low)	Neutral	Growth (High)
All	0.31%	0.27%	0.28%	0.37%
Small	0.28%	0.32%	0.22%	0.29%
Large	0.34%	0.23%	0.34%	0.45%

	NVT Ratio Portfolios			
SMB3	All	Value (Low)	Neutral	Growth (High)
All	0.32%	0.26%	0.36%	0.34%
Small	0.28%	0.24%	0.25%	0.34%
Large	0.37%	0.27%	0.47%	0.00%

In Table 4, the number of cryptocurrencies in each portfolio formed on size and NVT ratio is presented. What is interesting to notice, which was highlighted in the size section, is the few number of big currencies compared to small currencies. Furthermore, some portfolios are lacking cryptocurrencies and some have a lot more included cryptocurrencies than others.

Table 4: Number of Cryptocurrencies in Each Portfolio Formed on Size and NVT Ratio; Cryptocurrencies Sorted by Market Cap (Down) and then NVT Ratio (Across): Jan 2, 2017 to Feb 24, 2019

	NVT Ratio Portfolios			
SMB1	All	Value (Low)	Neutral	Growth (High)
All	44	13	18	13
Small	43	12	18	13
Large	1	1	0	0

	NVT Ratio Portfolios			
SMB2	All	Value (Low)	Neutral	Growth (High)
All	44	13	18	13
Small	41	11	17	13
Large	3	2	1	0

	NVT Ratio Portfolios			
SMB3	All	Value (Low)	Neutral	Growth (High)
All	44	13	18	13
Small	39	10	16	13
Large	5	3	2	0

	NVT Ratio Portfolios			
SMB4	All	Value (Low)	Neutral	Growth (High)
All	44	13	18	13
Small	34	7	15	12
Large	10	6	3	1

	NVT Ratio Portfolios			
SMB5	All	Value (Low)	Neutral	Growth (High)
All	44	13	18	13
Small	22	3	10	9
Large	22	10	8	4

5.1.4. Momentum

The momentum factor is calculated by taking the average return on the cryptocurrencies from the prior 2-12 month period and creating six portfolios based on their performance and size (Kenneth R. French, 2019). The cryptocurrencies are sorted on their past performance and divided into the three groups: high, medium, and low, where the breakpoints are the 30th and 70th percentiles.

5.1.5. Calculating factors

The equally-weighted daily returns are calculated for each of the portfolios for the time period 02/01/2017 to 24/02/2019. The average daily return of the SMB factor is calculated by taking the average return on the three small portfolios and subtracting the average return on the three big portfolios:

$$SMB = \frac{Small\,Value + Small\,Neutral + Small\,Growth}{3} - \frac{Big\,Value + Big\,Neutral + Big\,Growth}{3}$$

The average daily return on the LMH factor is calculated by taking the average return on the two value portfolios and subtracting the average return on the two growth portfolios:

$$LMH = \frac{Small\,Value + Big\,Value}{2} - \frac{Small\,Growth + Big\,Growth}{2}$$

Since the market risk for stocks is different from the one for cryptocurrencies, a cryptocurrency index (CRIX) has been used as a proxy of the daily market return. For this research, excess return has not been used, partly because of the short time-period studied, but also due to the fact that cryptocurrencies are not subordinated any central authority or affected by interest rates. Therefore, it makes more sense to use the absolute returns for this model.

The momentum factor, which is then added to the model, is calculated by taking the average return on the two portfolios with the highest return during the previous 2-12 months and subtracting the average return on the two portfolios with the lowest return:

$$MOM = \frac{Small\,High + Big\,High}{2} - \frac{Small\,Low + Big\,Low}{2}$$

5.2. Regressions

To study the different explanatory power of CAPM, Fama-French three-factor model and Carhart four-factor model, ordinary least-squares (OLS) time-series regressions have been carried out. The reason behind the choice of regression is based on Fama and French's motivation in their paper "Common Risk Factors in the Returns on Stocks and Bonds" from 1993. Firstly, they claim that a time-series regression is a suitable method when studying asset pricing because of the way it gives direct evidence on sensitivity to common risk factors in returns, especially through the slopes and R-squared values. Secondly, the results provide a simple metric and formal test of how the different factors capture the cross-section of average returns.

For all regressions the dependent variables are the daily returns on the 44 studied cryptocurrencies. The independent variable for CAPM is the market return, proxied with CRIX. For the Fama-French three-factor model CRIX, the size factor (SMB) and the value factor (LMH) are the independent variables. For the last regression with the Carhart four-factor model the independent variables are CRIX, SMB, LMH and the momentum factor (MOM). Below the regression equations for each of the different tested models are presented:

First regression (CAPM):

$$R_{it} = \beta_1 CRIX_t + \varepsilon_{it}$$

Second regression (Fama-French three-factor model):

$$R_{it} = \beta_1 CRIX_t + \beta_2 SMB_t + \beta_3 LMH_t + \varepsilon_{it}$$

Third regression (Carhart four-factor model):

$$R_{it} + \beta_1 CRIX_t + \beta_2 SMB_t + \beta_3 LMH_t + \beta_4 MOM_t + \varepsilon_{it}$$

The regressions are tested for each of the individual cryptocurrencies for the different models and independent variables. The same process is repeated for all the five size constructions, and the results are then summarized. In total, 660 time-series regressions have been carried out.

Since this thesis is using time-series regressions, we want to test for heteroskedasticity and serial correlation. The former represents if the variance of the error terms differs and is tested with the Breusch-Pagan/Cook-Weisberg test for heteroscedasticity, while the latter represents how independent the error terms are from each other and is tested with the Breusch-Godfrey test for serial correlation (Wooldridge, 2012).

6. Empirical results

6.1. Main findings

The adjusted R-squared values obtained from the OLS regressions are, and will be throughout the thesis, presented as an average of the included cryptocurrencies. The results, as displayed in Table 5, indicate that adding more factors to the model increase the explanatory power and are thus in line with the two hypotheses of the thesis. However, these values need to be examined somewhat carefully. Of the 44 cryptocurrencies included in the data set, the tested factors are not significant for all cryptocurrencies, as seen in Table 6, and which will be discussed further in coming sections. As a consequence of this, the hypotheses can be confirmed for a majority of the cryptocurrencies, but not for all of them.

The adjusted R-squared value of the first regression, using just CRIX, yields an explanatory value of 7.7% at a significance level of 0.1% for all five size divisions. When adding the SMB and the LMH factor the explanatory value increases most for SMB1, SMB2 and SMB3 with an adjusted R-squared value of 43.2%, 33.9% and 35.5% respectively. SMB4 and SMB5 both accumulate very low adjusted R-squared values in comparison, confirming that dividing up portfolios by median market capitalization value as is done in the ordinary Fama-French three-factor model, is not suitable for cryptocurrencies.

CRIX loses its relevance and is not significant for 32, 12 and 14 of the 44 currencies for SMB1, SMB2 and SMB3 respectively for the Fama-French three-factor model. This is also true when adding the MOM factor, where the number of cryptocurrencies not significant with CRIX rises even further to 33, 36 and 36. Which is almost all the cryptocurrencies included in the data set.

Table 5: Average Adjusted R-Squared Values from OLS Regressions

	1 Factor	3 Factors	4 Factors
SMB1	0.077	0.432	0.451
SMB2	0.077	0.339	0.428
SMB3	0.077	0.355	0.439
SMB4	0.077	0.126	0.154
SMB5	0.077	0.119	0.148

Average adjusted R-squared values for each size division from the OLS regressions with 1, 3 and 4 factors.

Table 6: Number of Cryptocurrencies and Significance Levels from OLS Regressions

1 Factor

		Not significant	p<0.05	p<0.01	p<0.001
CRIX	SMB1	0	0	0	44
	SMB2	0	0	0	44
	SMB3	0	0	0	44
	SMB4	0	0	0	44
	SMB5	0	0	0	44

3 Factors

		Not significant	p<0.05	p<0.01	p<0.001
CRIX	SMB1	34	2	6	2
	SMB2	12	9	12	11
	SMB3	14	8	10	12
	SMB4	0	0	0	44
	SMB5	0	0	0	44
SMB	SMB1	0	0	0	44
	SMB2	0	0	0	44
	SMB3	0	0	0	44
	SMB4	5	1	4	34
	SMB5	11	4	3	26
LMH	SMB1	11	5	4	24
	SMB2	4	1	2	37
	SMB3	4	1	0	39
	SMB4	10	3	8	23
	SMB5	11	5	6	22

4 Factors

		Not significant	p<0.05	p<0.01	p<0.001
CRIX	SMB1	33	8	2	1
	SMB2	36	4	3	1
	SMB3	36	5	2	1
	SMB4	0	0	0	44
	SMB5	0	0	0	44
SMB	SMB1	0	0	0	44
	SMB2	0	0	0	44
	SMB3	1	0	0	43
	SMB4	5	1	4	34
	SMB5	11	3	4	26
LMH	SMB1	10	0	2	32
	SMB2	7	1	3	33
	SMB3	6	1	1	36
	SMB4	9	4	7	24
	SMB5	12	2	5	25
MOM	SMB1	15	1	5	23
	SMB2	0	0	3	41
	SMB3	0	2	1	41
	SMB4	9	8	6	21
	SMB5	9	6	6	23

The numbers in the table indicate the number of cryptocurrencies within each size division and their associated significance level. They all sum up to 44, which is the total number of assets included in the data set. P indicates which p-value the cryptocurrencies exhibit.

Considering the three different regressions that have been carried out for each size division, roughly 80% of the cryptocurrencies that are not significant for SMB2 and SMB3 are not significant with CRIX. Considering this, SMB, LMH and MOM are still significant for the greater part of the included assets.

Looking at Table 6 one can see that the SMB factor is significant at 0.1% for SMB1, SMB2 and SMB3 but slightly less significant for SMB4 and SMB5 when applying the Fama-French three-factor model. This might be the case because in the three former size divisions we include assets that are more equal in market capitalization than in the latter size divisions. The LMH factor is significant at a 5% level for 40 of 44 currencies for SMB2 and SMB3. When adding the MOM factor, the SMB factor is approximately on the same significance level as before, whereas the LMH factor loses slightly in the number of cryptocurrencies it was earlier significant for. However, the MOM factor is significant at a 5% level for all assets included in SMB2 and SMB3.

6.2. Statistical tests

6.2.1. Test for heteroskedasticity

An assumption of the OLS regression is that the error terms have the same variance. When this assumption does not hold, the regression is subjected to heteroskedasticity. This itself does not cause bias or inconsistency to the OLS estimators, but can invalidate the standard errors, as well as the t-statistics and F-statistics. Even though serial correlation, that will be discussed in the next section, is a more pressing issue for time-series regression than heteroscedasticity, it is useful to test for and correct heteroskedasticity (Wooldridge, 2012). In Table 7 the Breusch-Pagan/Cook-Weisberg test for heteroskedasticity is presented. For SMB1, SMB2 and, SMB3 the cryptocurrencies are almost all heteroskedastic. For SMB4 and SMB5 the results are pretty evenly spread between existing heteroskedasticity and non-existent. Since the cryptocurrencies in general are mainly heteroskedastic this is a problem that needs to be corrected for.

Table 7: Breusch-Pagan/Cook-Weisberg Test for Heteroskedasticity

	Heteroskedasticity	Homoskedasticity
SMB1	40	4
SMB2	39	5
SMB3	40	4
SMB4	24	20
SMB5	29	15

The numbers in the table indicate the number of cryptocurrencies within each size division and whether they are subjected to heteroskedasticity or not. They all sum up to 44, which is the total number of assets included in the data set.

6.2.2. Test for serial correlation

When the error terms in the OLS regressions are serially correlated the regression is no longer the best linear unbiased estimator, as presented by the Gauss–Markov theorem, meaning that the OLS is no longer a minimum-variance estimator (Wooldridge, 2012). Serial correlation invalidates the usual OLS standard errors and test statistics, and thereby it is important to test and correct for this problem in the model. When performing the Breusch-Godfrey test for serial correlation for the five size divisions with one, seven and 30 lags, existing serial correlation is detected for all size divisions, as seen in Table 8. For SMB1, SMB2 and SMB3, the number of cryptocurrencies subjected to serial correlation is roughly half, as described earlier, this will have negative effect upon the results. Consequently, it is important to take this into account and correct for.

Table 8: Breusch-Godfrey Test for Serial Correlation with 1, 7 and 30 Lags

	Lags 1		Lags 7		Lags 30	
	Serial correlation	No serial correlation	Serial correlation	No serial correlation	Serial correlation	No serial correlation
SMB1	19	25	22	22	27	17
SMB2	20	24	22	22	27	17
SMB3	19	25	18	26	24	20
SMB4	39	5	38	6	31	13
SMB5	36	8	36	8	29	15

The numbers in the table indicate the number of cryptocurrencies included in the data set. For the assets in the left box, the null hypothesis of no serial correlation can be rejected at a 5% significance level, meaning there exist serial correlation. For the assets in the right box, the alternative hypothesis of no serial correlation is accepted.

6.3. Modifying the regression model

As presented in section 6.1, CRIX as an independent variable, is neither able to explain much of the change in return on cryptocurrencies nor significant for the majority of the included assets. To improve the model, a new modified regression will be analyzed where CRIX is omitted. When running OLS regressions with just SMB, LMH, and MOM factors the adjusted R-squared is not that much different from the previous model when CRIX was included, as can be seen in Table 9. This further strengthens the decision of omitting the market risk factor.

In addition to this, SMB4 and SMB5 have been excluded since these size divisions generate the lowest adjusted R-squared, and thus, have the weakest explanatory power of the five size divisions. Furthermore, they also exhibit serial correlation for a vast majority of the tested cryptocurrencies, indicating that they are not useful for finding the best predictive model. Focus has thus been on SMB1, SMB2 and SMB3 when improving the model.

Table 9: Average Adjusted R-squared Values from OLS Regressions when Omitting CRIX

	2 Factors	3 Factors
SMB1	0.430 (0.432)	0.450 (0.451)
SMB2	0.331 (0.339)	0.427 (0.428)
SMB3	0.348 (0.355)	0.437 (0.439)

Numbers in parentheses indicate average adjusted R-squared value in original OLS regression when CRIX was not omitted.

6.4. OLS regression with Newey-West standard errors

A way to correct for the problems presented in the tests above is to use a model that generates robust standard errors for heteroskedasticity and serial correlation. The framework developed by Newey and West (1987) has been used on the OLS regression to correct for heteroskedasticity and serial correlation in the model. According to the rule-of-thumb, as presented by Jeffrey Wooldridge in *Introductory Econometrics* (2012), it is suitable to use a maximum lag of four for quarterly data and twelve for monthly data. Following this trend, it would mean a lag of 365 for daily data, something not quite possible. Hence, a maximum lag of 30 has been chosen to represent the previous month.

The number of significant cryptocurrencies and their associated p-values are presented in Table 10.

Table 10: Significance Level from OLS Regression with Newey-West Standard Errors when Omitting CRIX

		2 Factors						3 Factors			
		Not significant	$p<0.05$	$p<0.01$	$p<0.001$			Not significant	$p<0.05$	$p<0.01$	$p<0.001$
	SMB1	0	0	0	44		SMB1	0	0	0	44
SMB	SMB2	1	2	3	38	SMB	SMB2	0	0	0	44
	SMB3	3	1	1	39		SMB3	1	1	1	41
	SMB1	15	3	3	23		SMB1	13	5	5	21
LMH	SMB2	5	1	2	36	LMH	SMB2	10	6	2	26
	SMB3	4	0	1	39		SMB3	9	4	1	30
							SMB1	17	7	7	13
						MOM	SMB2	1	3	2	38
							SMB3	2	2	1	39

The numbers in the table indicate the number of cryptocurrencies within each size division and their associated significance level. They all sum up to 44, which is the total number of assets included in the data set. P indicates which p-value the cryptocurrencies exhibit.

Comparing the three size divisions it is easy to conclude that the first size division exhibits a greater part of cryptocurrencies that are not significant. For the second and third size division, the number of cryptocurrencies that are not significant are quite similar. Using the new modified Fama-French model, the third size division explains 34.8% of the change in return for 37 of 44 cryptocurrencies at a significance level of 5%. When adding the momentum factor the model explains 43.7% for 32 of 44 cryptocurrencies at a significance level of 5% for the modified Carhart model.

6.5. Comparing results with original Fama-French model

Applying the Fama-French factors based on U.S. stocks (Kenneth R. French, 2019) on the 44 cryptocurrencies included in the data set, results in very low adjusted R-squared values, as presented in Table 11. For all models tested, the values are close to zero and differs a lot from the obtained result when constructing factors based on cryptocurrency data.

Table 11: Using Factors from Kenneth R. French's Website and Applying Them on Cryptocurrencies

Models	1 Factor	3 Factors	4 Factors
Average Adjusted R-Squared	-0.001	0.003	0.002

The independent variables constructed based on U.S. stocks compared to the independent variables created in this thesis display low correlation among each other, ranging from 0.101 to -0.058, as presented in Table 12. The SMB factor for U.S. stocks exhibits the highest correlation with the three factors constructed for SMB1, SMB2 and SMB3.

Table 12: Correlation Between Fama-French Independent Variables and Independent Variables for Cryptocurrencies

		Stocks			
		Rm-Rf	SMB	HML	MOM
Stocks	Rm-Rf				
	SMB	-0.252			
	HML	-0.107	0.129		
	MOM	-0.364	0.294	0.037	
	CRIX	0.025	0.029	0.003	-0.010
SMB1	SMB	0.020	0.080	0.023	0.016
	LMH	0.026	0.084	0.031	-0.002
	MOM	-0.002	0.069	0.035	0.049
SMB2	SMB	0.000	0.033	-0.004	0.014
	LMH	0.031	0.099	0.027	-0.010
	MOM	0.010	0.068	0.042	0.039
SMB3	SMB	0.001	0.068	0.030	0.008
	LMH	0.035	0.068	0.023	-0.012
	MOM	0.008	0.068	0.021	0.045
SMB4	SMB	-0.026	0.068	0.063	0.028
	LMH	-0.001	0.068	0.050	0.010
	MOM	-0.001	0.068	0.016	0.031
SMB5	SMB	-0.058	0.068	-0.008	-0.019
	LMH	-0.007	0.068	-0.004	-0.024
	MOM	-0.033	0.068	0.003	0.037

7. Interpretation and implications

The results show that the size, value and momentum factor all contribute to explain the change in return on cryptocurrencies, with varying degrees of significance levels, while the market factor does not. Size is significant for all cryptocurrencies within SMB1 and SMB2 and for 43 of 44 cryptocurrencies for SMB3 when applying the modified Carhart model, indicating the importance of the market capitalization when determining the returns.

As can be seen in Table 3 in section 5.1.3, the big portfolios outperform the small ones in four of five size divisions. This is contradictory to the original Fama-French three-factor model, where the small-cap stocks tend to outperform the large-cap stocks (Fama & French, 1992). Looking at the individual average return on cryptocurrencies, as seen in Table A1 in appendix 11.2, one cannot notice any particular pattern of higher returns associated with either small or big cryptocurrencies. One explanation for this could be the previously discussed volatility and spread of daily returns, which makes the average less representable of the cryptocurrencies' actual performance.

The value factor is significant for 31 of 44 for SMB1, 34 of 44 for SMB2 and 35 of 44 for SMB3 when applying the modified Carhart model. This indicates that the NVT ratio, used as a proxy for value, and the division into growth and value cryptocurrencies are applicable and generate significant results.

As discussed, the overall market seems to have less importance in explaining the change in return. As presented in Table 6, very few cryptocurrencies have a high significance level with CRIX for the Carhart four-factor model, with Bitcoin being the only asset with a significance level of 0.1%. One possible reason for this could be that CRIX is being calculated on the market value of 55 cryptocurrencies with the largest ones representing a huge part of the total. Thereby, Bitcoin plays a great part in the index, and together with a few of the other large cryptocurrencies basically constitute the entire index. This could be one of the reasons why CRIX does not explain the change in return for the majority of the altcoins.

After determining that CRIX is not adding much explanatory value to the models, omitting the independent variable from the Fama-French three-factor model and Carhart four-factor model generate significant results for more of the studied cryptocurrencies without significantly affecting the adjusted R-squared values. Thereby, this adjustment in total strengthens the model and provides some interesting insights. Considering asset pricing models of stocks, the market factor by itself explains up to 70% of the change in return. For cryptocurrencies, when only taking the market factor into account, it explains 7.7% of the change in return, a much lower number than for stocks. When adding more factors, CRIX loses its significance and seems to be irrelevant. The fact that omitting the market factor improves the explanatory power, is somewhat surprising, but highlights the difficulties with finding an appropriate market proxy for cryptocurrencies. One could argue that this is due to the market structure itself and the immature characteristics of it. Another reason for why the market factor is not significant could be that CRIX is not a good proxy for the actual market. An alternative could be to use a price-weighted approach instead of weighing the index by market capitalization, a topic that is beyond the scope of this thesis but certainly an interesting aspect for further research.

Another interesting finding from the research is when comparing the original Fama-French factors with the returns on cryptocurrencies. As can be seen from the results, the factors based on stocks are not able to explain the change in return. One would expect that using factors based on stocks would not generate a perfect result, but the fact that they produce an adjusted R-squared of as low as 0% is telling. This adds some validity to the widely spread opinion that cryptocurrencies is a special asset class that operates without strong connection to other assets, as was discussed in section 3.2. Thereby, the results suggest that to truly understand why cryptocurrencies behave like they do, one cannot look at the stock market, instead one should look directly on the asset pricing of cryptocurrencies.

Further evidence that support this are the results from directly comparing the constructed factors based on cryptocurrency returns to the factors based on stock returns. Weak correlation can be observed, which strengthens the interpretation that the cryptocurrency market, as well as the individual cryptocurrencies, operates fairly independently from the stock market.

Lastly, comparing the results of this thesis to previous research, similar findings have been reached. The model of this thesis explains a similar adjusted R-squared value of 35% for the three-factor model as Stoffels (2017). This adds support to the findings that size and NVT ratio are important factors that help determine change in return on cryptocurrencies, even though they are not significant for all. What is different from previous is that, taking the momentum factor into consideration, the model explains more than previously concluded.

Asplund and Ivarsson (2018) found that both the trading volume of each cryptocurrency and the total market size are important price drivers. This is in line with the findings in this thesis, indicating the importance of the size of the cryptocurrencies and transaction volume.

8. Limitations

Firstly, in the modified Fama-French and Carhart model, when using Newey-West standard errors and omitting CRIX as an independent variable, the results are still not significant for all cryptocurrencies. This is a limitation to the thesis since the model cannot explain the change in return on all cryptocurrencies included in the data set.

Secondly, the scope of included assets compared to the original models is a limitation to this study. In the original Fama-French three-factor model and Carhart four-factor model, the factors used are constructed based on the returns of hundreds of stocks and divided up by median market capitalization. This thesis is using 44 cryptocurrencies and dividing them up more unevenly. As presented in Table 4, the number of cryptocurrencies in each portfolio is not even, consisting of more cryptocurrencies in the small portfolios. This affects the factor construction, since some portfolios are not containing any cryptocurrencies, and thereby taking on a daily average return of zero. Keeping in mind that when applying the original Fama-French factors on cryptocurrencies they yield no significant values, as presented in section 6.5. For this reason, constructing factors based on cryptocurrencies and applying them on the cryptocurrency market still proves to be more accurate.

Thirdly, another limitation to our research is that the independent variables used in the thesis are constructed based on the dependent variables. For this reason, the adjusted R-squared values could possibly be inflated. To minimize this effect, regressions on each cryptocurrency individually were carried out rather than grouping them into portfolios like in the original Fama-French method, since each cryptocurrency then only is a small part of each independent variable.

9. Conclusion

In this thesis, we have studied what determines the change in return on cryptocurrencies, by applying and adjusting traditional asset pricing models. Since Bitcoin was established in 2008, there are now over 2,000 cryptocurrencies being traded worldwide with a total market cap over $240 billion. Although there exist differences in opinion whether cryptocurrencies are a speculative asset, a currency, a commodity or maybe just a hoax, it is interesting to notice that applying financial models on this untested and undeveloped financial market yields significant values.

The research question of this thesis is: what determines the change in return on cryptocurrencies. As presented in the results section and interpreted in the following section, the size factor, value factor (approximated with the NVT ratio) and the momentum factor are all important when explaining the change in return on cryptocurrencies, while the market factor have little importance in most cases.

The first hypothesis is that *the Fama-French three-factor model explains more of the change in return, on average for the 44 cryptocurrencies, than the capital asset pricing model.* Since the results indicate that CRIX, alone, explains 7.7% and the modified Fama-French model explains 34.8%. The first hypothesis can be confirmed for 37 of 44 cryptocurrencies at a significance level of 5%. The second hypothesis is that *the Carhart four-factor model explains more of the change in return, on average for the 44 cryptocurrencies, than the Fama-French three-factor model.* Since the results indicate that the modified Carhart model explains 43.7%. The second hypothesis can be confirmed for 32 of 44 cryptocurrencies at a significance level of 5%.

Another important insight that the research provides is the difficulty in finding a clear and significant proxy for the market factor of cryptocurrencies. We argue that the reason for this could be the uneven size distribution of the total market, or that the index used in our research is not reflecting the actual market in a sufficient way. This is one important difference from applying asset pricing models on stocks, where the market risk factor explains a big part of the change in return.

9.1. Suggestions for further research

Ever since Fama and French established their model in 1992, it has been tested several times and proven adequate for many stock markets. To try and do the same for a volatile, immature and unexplored asset class such as cryptocurrencies is a difficult task. Examples on how to take this research further could be to adjust the data collection of the model, to include more assets and extend the time period. Another example of how to further improve the asset pricing model could be to take other factors into account, such as media attention or internet activity. Since cryptocurrencies are a new research phenomenon within the field of finance it is important to base the research within the academic field, but not be afraid of being creative when trying to explain it.

Another possible area for further research is to study the market structure and its implication on returns, to try and find a good market proxy. As discussed, the market factor is seldom significant for the models in this thesis, and does not provide a high explanatory value. To investigate the market deeper could possibly provide even more insights in what makes up the change in return on cryptocurrencies, or at least provide deeper knowledge around the market characteristics of cryptocurrencies in general.

Lastly, the thesis sheds light on the fact that the size, value and momentum factors all explain the change in return on cryptocurrencies. However, which sub factors within these groupings that explain the change in return have not been studied in detail. For further research, focus could be on more specific factors such as which proof-of-concept is used for each cryptocurrency and whether they issue coins or tokens, and how this affects the change in return.

10. References

10.1. Literature

AMMOUS, S., 2018. *The Bitcoin Standard: The Decentralized Alternative to Central Banking.* 1st edn. Hoboken, New Jersey: John Wiley & Sons, Inc.

ASNESS, C.S., MOSKOWITZ, T.J. and PEDERSEN, L.H., 2013. Value and Momentum Everywhere. *The Journal of Finance,* 68(3), pp. 929-985.

ASPLUND, J. and IVARSSON, F., 2018. *What drives the price development of cryptocurrencies?,* University of Gothenburg.

BAUR, D.G., DIMPFL, T. and KUCK, K., 2017. *Bitcoin, Gold and the Dollar - A Replication and Extension.*

BIANCHI, D., 2017. *Cryptocurrencies As an Asset Class? An Empirical Assessment.* WBS Finance Group Research Paper.

BLACK, F., JENSEN, M.C. and SCHOLES, M., 1972. The Capital Asset Pricing Model: Some Empirical Tests. In: M.C. JENSEN, ed, *Studies in the Theory of Capital Markets.* New York: Praeger.

BURNISKE, C. and WHITE, A., 2017. *Bitcoin: ringing the bell for a new asset class.*

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

DANIEL, K., HIRSHLEIFER, D. and SUBRAHMANYAM, A., 1998. Investor Psychology and Security Market under- and Overreactions. *The Journal of Finance,* 53(6), pp. 1839-1885.

DE GEER, C., 2018. *Bitcoin och blockkedjan: en begriplig överblick.* 1st edn. Sweden: Ekerlids.

DYHRBERG, A.H., Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters,* 16(C), pp. 139-144.

EARLE, T.C., 2009. Trust, Confidence, and the 2008 Global Financial Crisis. *Risk Analysis,* 29(6).

FAMA, E. and FRENCH, K., 1992. The Cross-Section of Expected Stock Returns. *The Journal of Finance,* 47(2), pp. 427-465.

FAMA, E. and FRENCH, K., Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics,* 33(February, 1993), pp. 3-56.

GATES, M., 2017. *Bitcoin: Complete Guide To Bitcoin. Understand everything from getting started with bitcoin, sending and receiving bitcoin to mining bitcoin.* 2nd edn. Wise Fox Publishing.

GLASER, F., ZIMMERMANN, K., HAFERKORN, M., WEBER, M.C. and SIERING, M., 2014. *Bitcoin - Asset or Currency? Revealing Users' Hidden Intentions.* ECIS 2014 (Tel Aviv).

HARARI, Y.N., 2014. *Sapiens: A Brief History of Humankind.* 1 edn. London: Harvill Secker.

JEGADEESH, N. and TITMAN, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance,* 48(1).

KLEIN, T., HIEN, P.T. and WALTHER, T., 2018. Bitcoin Is Not the New Gold: A Comparison of Volatility, Correlation, and Portfolio Performance. *International Review of Financial Analysis,* 59, pp. 105-116.

LANSKY, J., 2018. *Possible State Approaches to Cryptocurrencies.*

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

LIU, Y. and TSYVINSKI, A., 2018. *Risks and Returns of Cryptocurrency,* Yale University.

MARKOWITZ, H., 1952. Portfolio Selection. *The Journal of Finance,* 7(1), pp. 77-91.

NAKAMOTO, S., 2008. *Bitcoin: A Peer-to-Peer Electronic Cash System.*

NEWEY, W. and WEST, K., 1987. A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica,* 55(3), pp. 703-708.

NORGREN-HANSSON, O., 2018. *Blockkedjor, bitcoin och kryptovalutor: vår tids ekonomiska revolution?* 1st edn. Sweden: Lava Förlag.

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

STOFFELS, J., 2017. *Asset Pricing of Cryptocurrencies and Momentum based Patterns,* Erasmus School of Economics.

WOOLDRIDGE, J., 2012. *Introductory Econometrics: A Modern Approach.* 5 edn.

YERMACK, D., 2013. Is Bitcoin a Real Currency? An Economic Appraisal. In: D. LEE KUO CHUEN, ed, *Handbook of Digital Currency.* Academic Press, pp. 31-43.

10.2. Electronic

CoinMarketCap. Methodology. Available: https://coinmarketcap.com/methodology/. Retrieved: Feb 25, 2019.

CoinMarketCap. Available: https://coinmarketcap.com/. Retrieved: May 15, 2019.

CRIX. Contacts. Available: https://thecrix.de/contacts. Retrieved: Apr 15, 2019.

How Bitcoin Mining Works. Available: https://www.coindesk.com/information/how-bitcoin-mining-works. Retrieved: Apr 4, 2019.

Kenneth R. French. Detail for Daily Momentum Factor (Mom). Available: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor_daily.html. Retrieved: Mar 16, 2019.

Oxford Dictionary. Available: https://en.oxforddictionaries.com/definition/cryptography. Retrieved: May 5, 2019.

What is Blockchain Technology? Available: https://www.coindesk.com/information/what-is-blockchain-technology. Retrieved: Apr 4, 2019.

10.3. Data

CoinMarketCap. Available: https://coinmarketcap.com/. Retrieved: Feb 25, 2019.

CRIX. Available: http://thecrix.de/. Retrieved: Feb 25, 2019.

Kenneth R. French. Available: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Retrieved: Apr 10, 2019.

11. Appendix

11.1. CoinMarketCap's verification process

11.1.1. Price

For market pairs, which means trading one cryptocurrency for another, the price is calculated by using the unconverted price from the individual exchange and then converting it to USD using CoinMarketCap's existing reference prices. The price for each cryptocurrency is calculated by the weighted average of the market pair prices, based on trading volume. The reason for using this weighted average is that it minimizes the generally abnormally high price fluctuations from the smaller exchanges, and thereby gives a more realistic view of the price. Prices gets manually removed when it is believed that it does not represent the free market price, for example by applying certain exchange restrictions for that particular exchange.

11.1.2. Volume

The volume is the total of all reported spot trade volumes for the cryptocurrency. For pairs, the conversion works in a similar way as with prices. In other words, using direct market data and converting it with CoinMarketCap's reference prices, to get the volume in USD.

11.1.3. Circulating supply

Circulating supply is the approximation of the number of coins circulating on the market, equivalent with the public float of traditional shares. This metric excludes coins that are locked and not publicly traded, since these will not be able to affect the market price. The amount of locked or reserved coins are gathered through direct contact with the team behind each cryptocurrency, and their blockchain and distribution table are examined. The best approximation of freely circulating supply is then determined, verified and updated in real-time.

11.1.4. Market capitalization

The market capitalization of each cryptocurrency is calculated by multiplying the current price with its circulating supply.

11.2. Descriptive statistics

Table A1: Descriptive Statistics of Dependent Variables

Name	Abbreviation	Rank Based on Market Cap	Market Cap (24/02/2019)	Market Cap in % of Total	Mean Return	Std. Dev.	Min Return	Max Return
Bitcoin	BTC	1	$ 66 897 483 404	64.66%	0.17%	4.54%	-20.75%	22.51%
Ethereum	ETH	2	$ 14 263 873 721	13.79%	0.36%	6.35%	-31.55%	29.01%
Ripple	XRP	3	$ 12 469 397 085	12.05%	0.49%	9.04%	-61.63%	102.74%
Litecoin	LTC	4	$ 2 708 358 746	2.62%	0.29%	6.89%	-39.52%	51.03%
Stellar	XLM	5	$ 1 615 486 768	1.56%	0.45%	9.54%	-36.64%	72.31%
Monero	XMR	6	$ 824 146 428	0.80%	0.16%	6.87%	-29.32%	43.03%
Dash	DASH	7	$ 705 066 679	0.68%	0.25%	6.84%	-24.32%	43.77%
NEO	NEO	8	$ 590 106 576	0.57%	0.53%	9.69%	-46.10%	80.12%
Ethereum Classic	ETC	9	$ 455 271 069	0.44%	0.14%	7.35%	-43.53%	45.77%
NEM	XEM	10	$ 386 361 143	0.37%	0.32%	8.64%	-36.15%	99.56%
Zcash	ZEC	11	$ 312 358 965	0.30%	0.01%	6.77%	-23.62%	52.82%
Waves	WAVES	12	$ 268 014 336	0.26%	0.32%	7.66%	-28.50%	38.27%
Dogecoin	DOGE	13	$ 233 678 259	0.23%	0.28%	7.82%	-49.29%	47.72%
Decred	DCR	14	$ 151 572 566	0.15%	0.45%	8.75%	-34.20%	44.11%
Augur	REP	15	$ 139 637 683	0.13%	0.15%	7.71%	-31.18%	65.35%
Lisk	LSK	16	$ 136 381 433	0.13%	0.26%	8.08%	-41.00%	47.05%
BitShares	BTS	17	$ 123 723 836	0.12%	0.31%	8.96%	-39.17%	52.00%
Bytecoin	BCN	18	$ 123 157 756	0.12%	0.31%	14.02%	-91.03%	159.78%
DigiByte	DGB	19	$ 118 259 625	0.11%	0.47%	10.66%	-36.14%	116.56%
Steem	STEEM	20	$ 95 751 936	0.09%	0.08%	9.19%	-33.17%	66.91%
Siacoin	SC	21	$ 93 457 296	0.09%	0.30%	9.57%	-44.00%	58.43%
Verge	XVG	22	$ 90 801 594	0.09%	0.72%	15.58%	-69.31%	97.33%
Stratis	STRAT	23	$ 82 435 785	0.08%	0.31%	9.21%	-34.21%	44.54%
Golem	GNT	24	$ 59 360 772	0.06%	0.23%	9.17%	-35.88%	50.69%
Factom	FCT	25	$ 56 998 072	0.06%	0.10%	8.57%	-31.86%	33.32%
MaidSafeCoin	MAID	26	$ 55 251 902	0.05%	0.03%	6.95%	-37.94%	28.50%
Ardor	ARDR	27	$ 54 104 727	0.05%	0.21%	8.30%	-32.98%	51.03%
PIVX	PIVX	28	$ 40 969 206	0.04%	0.59%	9.85%	-40.12%	54.96%
Zcoin	XZC	29	$ 36 460 612	0.04%	0.31%	9.11%	-34.08%	61.83%
MonaCoin	MONA	30	$ 32 882 202	0.03%	0.39%	9.46%	-33.89%	85.22%
DigixDAO	DGD	31	$ 30 449 321	0.03%	0.07%	8.01%	-46.02%	57.95%
Syscoin	SYS	32	$ 25 728 448	0.02%	0.21%	9.27%	-45.65%	56.53%
Nxt	NXT	33	$ 24 987 893	0.02%	0.18%	8.74%	-56.63%	47.11%
Obyte	GBYTE	34	$ 23 003 229	0.02%	0.06%	9.85%	-41.87%	61.56%
Unobtanium	UNO	35	$ 18 966 017	0.02%	0.51%	8.87%	-91.02%	60.68%
Vertcoin	VTC	36	$ 18 013 624	0.02%	0.30%	10.16%	-38.51%	65.36%
Nexus	NXS	37	$ 16 952 111	0.02%	0.30%	9.60%	-35.65%	76.64%
Blocknet	BLOCK	38	$ 15 832 287	0.02%	0.42%	10.36%	-37.22%	69.43%
Groestlcoin	GRS	39	$ 15 549 789	0.02%	0.66%	13.27%	-52.23%	90.09%
Emercoin	EMC	40	$ 12 350 436	0.01%	0.07%	9.00%	-52.52%	65.72%
Peercoin	PPC	41	$ 11 711 007	0.01%	0.08%	8.24%	-66.72%	33.10%
NavCoin	NAV	42	$ 9 893 271	0.01%	0.18%	9.47%	-34.58%	82.51%
Einsteinium	EMC2	43	$ 9 565 978	0.01%	0.47%	11.45%	-47.33%	91.21%
Clams	CLAM	44	$ 7 337 649	0.01%	0.12%	8.27%	-63.28%	49.45%

Mean return, minimum return and maximum return are all expressed on a daily basis.