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Should well-diversified portfolios contain cryptocurrencies?

A quantitative analysis based on portfolio performance measures

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Abstract

In this thesis we study whether cryptocurrencies should be included in a well-diversified portfolio or not. Moreover, we try to determine if the capital asset pricing model holds for cryptocurrencies, like other investments assets. We conclude that cryptocurrencies should be a part of a well-diversified portfolio. We make this conclusion based on the results from a selection of the most used financial performance metrics. We also conclude that the capital asset pricing model holds for cryptocurrencies. The data period we have looked at spans from 2010 and to the end of 2017, which is a relatively short time period and therefore a limitation in this study. Our results show that cryptocurrencies have been an excellent investment opportunity in the time period of our research. Outperforming the traditional assets, cryptocurrencies provides a better return considering the risk, either the systematic, unsystematic or whole risk.

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Preface

This master thesis concludes our financial studies in Business and Administration at Oslo Business School, Oslo Metropolitan University. As far as we know, this will be the first thesis on cryptocurrencies at Oslo Business School.

We would first and foremost like to thank our supervisor Daniel Spiro for all his help and advice. His knowledge, encouragement and valuable academic support and feedback has been crucial. Furthermore, we would like to express our gratitude to Sturla Fjesme and Per Arne Tufte for valuable insights in various topics.

We believe that cryptocurrencies are here to stay and therefore should be researched further and we want to contribute to that research field. Hopefully our research will intrigue other parties and future students to research the subject even further. We also hope that our thesis will increase the knowledge of others.

This process has been challenging and time consuming, especially handling the vast amount of data in R-Studio and interpret it. Although being difficult, it has been a learning process and we have gained a lot of knowledge and experience in both the topic and data processing.

Oslo Business School, May 2018

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1 Introduction

1.1 Motivation:

After meeting up and deciding to work together, finding the topic was easy as we both wanted to write about cryptocurrency. Both of us have experience with trading cryptocurrencies in the past and we were therefore eager to gain more information and knowledge on the subject. It is also a hot topic in finance, but which seems to have received only meager attention in the academic literature in comparison to other financial concepts.

When looking into what had already been written on the subject, we were unable to find any other master theses from Oslo Metropolitan University although we found some dissertations from other educational institutions. As we searched online we found it to be scarce with information about portfolios and cryptocurrencies and noticed that there were few well-diversified portfolios that contain cryptocurrencies. The latter stands in sharp contrast to our understanding of a well-diversified portfolio. As we understand it, a well-diversified portfolio should contain every type of assets.

The field of cryptocurrency is being researched thoroughly; the main focus is on the technology, which are blockchain, mining algorithms, security issues and proofing. These are terms that we will explain later. But in regard to finance and cryptocurrencies, the main fields are on the currency, money laundering and other legal matters.

Considered an asset by many, we find a gap in the literature where finance literature explains that well-diversified portfolios should contain every kind of asset, why do many portfolios exclude cryptocurrencies? A statement from Jamie Dimon, CEO of JPMorgan Chase & Co, one of the largest investment banks in the world, further increases the gap (La Monica 2017).

Some researchers have tried to explore this topic, but as they only use one cryptocurrency in their study (Bitcoin) we believe that it does not do well in explaining the diversification effects and the returns by adding them to a portfolio. We therefore consider adding more cryptocurrencies to the portfolio to provide a better answer.

1.2 Research question:

From the given motivation we obtain the following main research question:

- Should well-diversified portfolios contain cryptocurrencies?

Furthermore, as we test out our main research question we also want to test one of the most influential contributions to financial literature, we therefore derive to the following question:

- Does the Capital Asset Pricing Model framework hold for cryptocurrencies?

1.3 Structure of thesis

In chapter 2 we present a literature review on the topic and general information about cryptocurrencies. In chapter 3 we present the methodology of our research. In chapter 4 we look at the data we use in our research. Chapter 5 presents our empirical results, and in chapter 6 we draw a conclusion from our results.

2 Cryptocurrencies: Literature review and general information

2.1 Literature review

As Bitcoin and other cryptocurrencies have become increasingly popular in the finance world, so has research papers, articles and books about the topic become too. At first, there were more papers on the underlying technology, the blockchain ledger, starting with Satoshi Nakamoto's paper "Bitcoin: A Peer-to-Peer Electronic Cash System", which we both have previously read. After the "explosion" of cryptocurrencies, several other papers have appeared from the creators of cryptocurrencies, called "whitepapers". Whitepapers are, in this topic, "a persuasive, authoritative, in-depth report on a specific topic that presents a problem and provides a solution" writes Lindsay Kolowich from Hubspot (Kolowich 2018). These papers have become the way to sell and/or make your cryptocurrency public. It has even been created a database where all the whitepapers are available to the public (Whitepaperdatabase n.d.).

With the increasing popularity, the general media has started to write more about cryptocurrencies, typically stories of average-Joe becoming a multimillionaire in a matter of few years. Being a currency, cryptocurrencies like Bitcoin have become prone to speculative investment and economists have tried to research the phenomenon, even from large institutional entity such as European Central Bank (ECB). In "Virtual currency schemes – a further analysis", ECB concludes that cryptocurrencies are not to be categorized as currency (European Central Bank 2015). Other institutions that contributes to the literature are Financial Crimes Enforcement Network (FinCen) (Financial Crimes Enforcement Network 2013), Internal Revenue Service (IRS) (Internal Revenue Service 2014) and International Monetary Fund (IMF) (Adriano and Monroe 2016). These articles have a more regulatory character.

An article we found while researching the topic which was both interesting and relevant to our research question is "Virtual Currency, Tangible Return: Portfolio Diversification with Bitcoin" by Briére, M., Oosterlinck, K., and Szafarz, A. (2015), which looks at how well Bitcoin can improve on an already diversified portfolio. Their study shows that it dramatically improves the risk-return trade-off by including even a small portion of Bitcoin. To analyze the portfolio performance, they use some of the same performance measures as us, but we include more measures and two additional cryptocurrencies. In that way we can paint a better picture of the situation and strengthen the evidence for drawing a conclusion about cryptocurrencies in general.

"Caveat Emptor: Does Bitcoin Improve Portfolio Diversification?" by Eisl, Gasser & Weinmayer (2015), investigates the same questions as Brière et al. (2015), but differs in that they adopt the conditional value-at-risk (CVaR) framework rather than the Markowitz mean-variance framework. They argue that this framework as it is better suited for non-normal distributed returns. Another difference is that Eisl et al. (2015) uses a backtesting technique rather than a one-point reference as used by Brière et al. (2015).

The foundation of this paper builds on the works of great contribution to the finance world. Although worked on independently, Treynor, Sharpe, Lintner and Mossin developed what was later to be known as the capital asset pricing model (CAPM). Their papers were based on Markowitz mean-variance theory, and thus assume normal distribution on asset returns. Even though it has become a victim to much criticism, it has passed the test of time, as it is still one of the most used models in finance.

To help us understand the performance measures used in portfolio performance, we utilize the performance measures used in a previous class, "Financial Markets". The article "Metoder for evaluering av aktiv fondsforvaltning" by B. Espen Eckbo and Bernt Arne Ødegaard from

2015 was introduced to us in class as the factors used in the article are “standard measures”. This is also evident in actual portfolios, such as on funds to be bought on Nordnet.no and the Norwegian Sovereign Wealth Fund, where they quote some of these measures. These performance measures were also used in the articles from both Eisl et al. and Brière et al. In addition to the paper from Eckbo and Ødegaard, we had to delve deeper into portfolio performance to gain further understanding on the subject. Familiar papers from Jack L. Treynor "How to Rate Management of Investment Funds" from 1965, William F. Sharpe “Mutual fund performance” from 1966 and Michael C. Jensen “The Performance of Mutual Funds in the Period 1945-1964” to name some articles that was read to obtain additional awareness on the subject. Moreover, we had to read newer articles and papers on portfolio performance measures we previously have not used. The Sortino measure was introduced to us in Brière et al. and was a measure we never used in our classes. The measure was presented in Sortino and Price article "Performance measurement in a downside risk framework" from 1994. Another article we used was “A Universal Performance Measure” by Con Keating and William F. Shadwick. This relatively new article, from 2002, proposes a new “universal” portfolio measure, called Omega ratio, which we found both interesting and relevant to our research.

As of 01.03.2018 there is now about 42.800 articles, books and Internet sites on Google Scholar on “cryptocurrency” and “Bitcoin”.

2.2 Cryptocurrency

Like many inventions, cryptocurrency was also built on previous inventions. Its name derives from two words, namely cryptography and currency. Cryptography can be described as “the practice and study in techniques for secure communication, more generally cryptography is about constructing and analyzing protocols that prevent third parties from reading private messages” (Bellare and Rogaway 2001). The Oxford English Dictionary defines the word currency as “a system of money in general use in a particular country” (Oxford Dictionary n.d.).

One can say the phenomenon of cryptocurrency all began with a movement called Cypherpunks, which was founded in 1992. This group was anxious and concerned about the loss of privacy and individual empowerment as the world got more and more connected. As stated in the “Cypherpunks manifesto”, which gave birth to this movement: “We must defend our privacy if we expect to have any” (Hughes 1993).

Guided by this view, they set out to create tools to allow people to maintain their anonymity. One of the group´s first and most important idea was to create a digital currency (Hughes 1993). Although several types of cryptocurrencies or electronic cash systems came on the Cypherpunks forums, none of them came close to being put into life as David Chum´s eCash which through the company DigiCash almost went mainstream in 1990. This electronic cash system emerged when the computer revolution began; he first mentions this in his paper “Blind Signatures for Untraceable Payments” in 1982 (Chum 1982). The internet was not as big as today, but the enterprise network was getting big as businesses were beginning to lay out both internal and external interlinking cables (Casey and Vigna 2016). David Chum and his eCash foresaw a new way of transferring value - governments, central banks and commercial banks saw its potential. While constructed in a similar way as Bitcoin, the anonymity of eCash was asymmetrical by protecting only the identity of the payer, not the payee. This is fundamentally different from the anonymity structure of Bitcoin, which protects both. But as quickly as it had grown, eCash fell apart. Without a functioning banking system behind it, the company DigiCash did not stand a chance. As we see with the cryptocurrencies floating around today, the banks and financial institutions saw some of eCash´s features as a threat to the system they prospered from (Casey and Vigna 2016).

But what interested the financial institutions was efficient ways to run e-commerce, so in 1998 the now famous Elon Musk launched PayPal (PayPal n.d.). This company allowed people to create accounts online and add digital dollars that could be sent to other users allowing for a new kind of marketplace, which later would be a part of eBay. This service could not do what eCash could, but it did not need to as banks and financial institutions only wanted the existing form of payment to be transferred online.

2.2.1 Bitcoin

Casey and Vigna (2016) describe in their book “The Age of Cryptocurrency” a good example of the general consensus of the days after the September 15 collapse of Lehman Brothers. They write that the then co-CEO of a large asset manager company called Pacific Investment Management Co. rang to his wife telling her to withdraw as much money as she could. Because she did not understand why, the co-CEO told his wife that there was a chance that the U.S. banks would not open the next day. This lack of trust in both the financial system and government is what triggered Satoshi Nakamoto, the creator of Bitcoin, to work on an alternative currency. In his first forum post February 11, 2009, Satoshi writes: *"The root problem with conventional currency is all the trust that's required to make it work. The central bank must be trusted not to debase the currency, but the history of fiat currencies is full of breaches of that trust. Banks must be trusted to hold our money and transfer it electronically, but they lend it out in waves of credit bubbles with barely a fraction in reserve. We have to trust them with our privacy, trust them not to let identity thieves drain our accounts. Their massive overhead costs make micropayments impossible."* (Nakamoto 2009b).

The reason for Satoshi Nakamoto's focus on trust lies in infamous incidents from the past. Consider for example the Weimar republic formed after the First World War following the collapse of the German Empire as a consequence of being on the losing side. Newly formed, the republic was in debt due to required repayments to the victors. Inflation skyrocketed where the root of the problem came from the war (Boesler 2013). The government then printed more money, and hyperinflation was a fact (Research Online n.d.).
Even though the hyperinflation of the Weimar Republic is one of the most famous, the Hungarian Pengö was the worst of its kind. After losing the First World War, the Austro-Hungarian Empire was divided and broken up (Taylor 2014). First, they replaced the old currency Kronen with the new Pengö: the new nation lacked the proper government structure and therefore printed Kronen to fill the budget (Taylor 2014). After the Second World War, the Pengö money supply quickly rose. There has been reports that prices rose by 150 000% each day at the height of the inflation (Taylor 2014). The Pengö was later replaced by the Forint and the new currency helped to stabilize the Hungarian economy.

Other incidents have occurred in recent years. The Bank of Cyprus took money from its own citizens when the Cyprus bailout happened by imposing a 30% tax on deposit accounts larger than 100.000 € were taxed 30% (Amos, et al. 2013). Money was seized from own citizens to cover bank losses (Ewing 2015).

These and other incidents such as that of Zimbabwe, Greece and Iceland show that Satoshi Nakamoto's concerns were rooted in historical events.

To create Bitcoin, Satoshi had to solve two problems. The first problem was to create value in the Bitcoins. Satoshi solved this by fiddling with the supply-and-demand dynamics of Bitcoin. This was done by figuring out the time schedule for future releases of coins. He programmed an algorithm so that a diminishing release of a finite supply of coins created a sense of scarcity, which built a base of support for Bitcoin's price that would incentivize miners to keep working with it (Casey and Vigna 2016). The release of coins would be halved every four years, starting with 50 coins per block in 2008 to 0 in 2140. The max supply of Bitcoin was set to 21 million Bitcoin (Bitcoin n.d.).

His second problem was that because there was no central authority, i.e. decentralization, he had to figure out how to get everyone to cooperate in the network and stop people from gaming the system. The solution consisted in two parts. One main component was the blockchain ledger, which was first conceptualized by Satoshi. This system was programmed so that every transaction was arranged chronologically in an array of blocks. The miners then verified their contents by comparing the new block with historical blocks. Once verified and approved they moved to next block, sealing the previous block (Nakamoto 2009a). The blockchain revolution solved the problem all previous cryptocurrencies had, namely double spending - that no coins could be spent two times by the same person.

The other component was to create a mining reward algorithm, creating incentives for people in the network to commit both electricity and computing power, making it possible to maintain the blockchain ledger (Popper 2015). All of this laid the foundation for a decentralized mechanism of trust.

2.2.2 Altcoins

After the success of Bitcoin, several new types of cryptocurrencies came into existence. Some popular examples are Ethereum, Ripple, IOTA and Litecoin. The name altcoin comes from alternative coin because they are alternatives to Bitcoin. Although most altcoins offer no improvement or are any different from Bitcoin, there are some altcoins that are significantly distinctive from Bitcoin. The altcoins can differ in a range of ways. They can differ in their economic model, how the coins are distributed or their proofing system. Other ways they can be diverse is their mining algorithm, more or less private or in which programming language they are programmed with (Bitcoin Magazine n.d.). This is done because the creator or creators thinks that what they have done is a better solution to what already exist. However, a problem is that these promises to a better solution are often just that, promises. And because they regularly are small, with considerably fewer people in their network the altcoins are more volatile. On top of this there are also several altcoins that are outright scams, which can reduce the credibility of altcoins or even Bitcoin itself (Jenkinson 2018).

2.2.3 Litecoin

One of the most successful altcoins is Litecoin, introduced in 2011, by a former Google employee, Charles Lee, as an open source project (McMillan 2013). This project was a source fork from the Bitcoin source code, meaning that it uses the source code of Bitcoin but changed it so that it can be seen as a whole different type of cryptocurrency. One major difference from Bitcoin is the process speed of a block, whereas Bitcoin processes a block in 10 minutes Litecoin only uses 2,5 minutes (Litecoin 2018). Litecoin also uses a different type of algorithm as proof-of-work called “scrypt”, the main difference being that scrypt is simpler and therefore easier to solve so it uses less energy. Another contrast is also that the maximum supply of Litecoin is 84 million coins (Coindesk 2014).

2.2.4 Ethereum

Ethereum was launched 30th July 2015 and is also considered an altcoin. First introduced by Vitalik Buterin, a former programmer of Bitcoin Magazine, in 2013. A crowdsale took place between July and August 2014 (Buterin 2014). Buyers could then buy 2000 ETH (Ethereum tokens) for 1 BTC (Bitcoin). Unlike Litecoin, Ethereum builds upon an entire new source code and does not build on the original Bitcoin code. A major difference between Bitcoin and Ethereum is that Ethereum blocks are processed in 14-15 seconds, which is vastly faster than Bitcoin (10 minutes) (Madeira 2018a). Another difference is that while Bitcoin uses full proof-of-work mechanism when mining, Ethereum uses a hybrid between proof-of-stake and proof-of-work but strives for full proof-of stake (Harm, Obregon and Stubbendick 2016).

Ethereum also uses another kind of costing the transaction: while Bitcoin uses a fee to the miners based on the block size, Ethereum uses “gas” (Madeira 2018a). Ethereum “gas” is calculated on the complexity of the block being mined. We will not go further in on this topic as it is far more technical than needed. But because of this technology, pooling of computing power is highly discouraged.

2.3 Cryptocurrency, is it money?

For the purpose of this dissertation we have to classify cryptocurrency as either asset or currency. Both FinCen and ECB write that cryptocurrency or virtual currency is not regarded as money or currencies as defined in economic literature (European Central Bank 2015; Financial Crimes Enforcement Network 2013). ECB argues “virtual currency is not money or currency from a legal perspective” (European Central Bank 2015) while FinCen on the other hand writes, “that it operates like a currency in some environments but does not have all the attributes of real currencies” (Financial Crimes Enforcement Network 2013).

Against this conclusion, The Economist (2015) write in “Bitcoin: the magic of mining” that Bitcoin nonetheless have three qualities as currency: hard to earn, limited in supply and easy to verify, but also comment that stability is a major issue.

On the other hand, Glaser, Zimmermann, Haferkorn, Weber and Siering (2014) classifies it as an investment asset for two reasons. First, the way new investors acquiring Bitcoins and store their investment in a wallet for speculation purposes. Secondly, because the Bitcoin price reacts to news events related to itself. Other governmental institutions such as Commodity and Futures Trading Commission and IRS have classified Bitcoin as either a commodity or asset (Commodity Futures Trading Commission 2015; Internal Revenue Service 2014).

John Carrick has written a paper where he analyzes Bitcoin and researches if Bitcoin could be a complement to emerging markets currencies. He concludes that although being highly volatile, the rise of value may add some balance to the emerging market currencies (Carrick 2016).

These reasons and the above conclusion that it is not a currency suffices, for the purposes of this dissertation, we choose to classify Bitcoin and altcoins as investments assets.

2.4 Risk when investing in cryptocurrencies

Kiran and Stannett (2014) present a number of risks regarding investing in Bitcoin. We choose to mention those risks that have the highest relevance for our study. First there is a high risk of bubble formation from two different feedback loops, being word of mouth and growth of the user base. They find that the bubble factor poses a high risk to the value of Bitcoins. Second there is the risk of regulation, for example exchanging Bitcoin can be banned in the investors' country of residence. This also poses a high risk to the value of Bitcoins. Thirdly, there is a high risk of severe deflation because of the strictly limited number of Bitcoins that can cause bubble formation. Fourthly, this also poses a high risk to the value of Bitcoins. There are also high risks of volatility that can cause high risks to the value of Bitcoins. Fifthly, there is also risks of hostile attacks towards the Bitcoin ecosystems, which if successful can cause high risk to the Bitcoin price. Finally, there is also risk of fraud, not to the Bitcoin price, but the risk that the investor can trade with fraudulent counterparties.

Also, there is the risk that cryptocurrencies will not be used as currencies in the future, leaving them with a low or zero value. This risk is very hard to measure, as it is hard to know what will happen in the future, but it is easy to think that this can also pose a high risk to the value of cryptocurrencies. Among factors that influence this is the possibility that central banks might establish their own cryptocurrencies with prices connected to the "normal" currencies. Another factor is the risk that only some of the more than thousand cryptocurrencies will be used in the future, and investors who invest in the cryptocurrencies that end up not being used will be left with worthless investments. This risk can be made smaller by diversifying between many cryptocurrencies, but with the number of cryptocurrencies exceeding 1500, investing in all of them might be challenging, but investing in hundreds of them might be possible for a single investor.

To sum up the risks associated with investing in cryptocurrencies, investors face severely high risks, many of them not risks associated with other investments assets, leaving cryptocurrencies as maybe the most risky investment opportunity.

2.5 Pros and cons with cryptocurrency

We would like to start this section with the pros of cryptocurrency. These points that we mention are what we and several other influential actors regard as positive attributes with cryptocurrencies.

2.5.1 *Pros*

Anonymity is maybe one of cryptocurrencies strongest selling point. As written in the section about cryptocurrency this was one of the first ideas of the Cypherpunks. With digital transferring today, be that either by traditional banks or PayPal or similar systems, the financial institutions have a record of who transferred what to whom since the bank account holder must provide the bank with a document identifying him or her. So, if Peter sends money to Susan, there is a record showing this and other relevant information about them. Although earlier Bitcoin were completely anonymous, newer and current wallet and exchanges such as Coinbase.com and Bitfinex.com requires, due to regulations in their countries of operation, account holders have to verify themselves by sending photos of a document, such as passport or driver's license and a photo of their face (Coinbase n.d.). While arguing for anonymity, researchers have shown that the possibility to de-anonymize implies that the system does not provide real anonymity (Möser 2013).

A point to mention is that the website blockchain.info offers information about every single transaction made. One can search for address, block or hash and the information will range from the balance of the address to every transaction made from and to the address.

Sending money is easy and not expensive in developed countries, but it can be very expensive in developing countries. While most people in developed countries have a bank account, this is not the case in developing countries where one of the most common reasons for not having a bank account is the paperwork (The Economist 2012). As there are several cryptocurrency-exchanges and wallets that do not require any form of identification it can be easy for these people to create an account to help them store value. Smartphones has become more and more frequent in the emerging world; it can help people store, maintain or even speculate with cryptocurrencies (Poushter 2016).

Hyperinflation in Venezuela is a good example of how cryptocurrency can be an alternative for its citizens that do not longer have faith in its own country's currency. With the economic crisis that is occurring there now (Biller 2018) people are searching for alternative ways of storing their values and making money. As reported by Chun 2017 Venezuelans have started to lend their computing power to mine Bitcoin after the socialist regime of President Maduro made electricity practically free. A person with several Bitcoin miners could have earned up to 500 dollars per month by doing this, which at the state the country was in, is a lot of money. This was from September of 2017 (Chun 2017).

Although cryptocurrency is helping individuals in Venezuela, this may create more instability and higher inflation for the country. If citizens have access to other currencies and cryptocurrencies and choose to use them rather than the country's own currency, it will create less trust and more fear that other may not accept the country's currency. Cryptocurrencies may be a positive mechanism for individuals but may be a negative on aggregate.

As earlier mentioned, Bitcoin is a decentralized currency. This means that there is no central control or management controlling the currency. There are no policies made by management that everyone has to follow, holders of the currency will be safe from destructive politics. Although mentioned above that top exchanges and wallets require identification, which may indicate some form of centralization, not all do.

2.5.2 Cons

Researchers at Cornell University find that over 50% of the mining power in the two biggest cryptocurrencies, Bitcoin and Ethereum are concentrated in eight and five mining pools respectively (Basu, et al. 2018). They conclude that both Bitcoin and Ethereum have a fairly centralized mining process. This indicates that although initially Satoshi Nakamoto made the Bitcoin in a way that every user was a part of a network, some people found a way to pool up their computing power in order to win the next block. When so few control so much, it can be an indication that maybe Bitcoin and Ethereum are not as decentralized as we first thought.

Volatility can be seen as a positive mechanism when dealing with investments instruments, we see volatility as a negative feature because a currency needs stability to be useful. Since the price of Bitcoin is purely driven by supply and demand its volatility has been relatively high and may be a factor that made cryptocurrencies as famous as they are today. Mark T. Williams from Boston University writes that the volatility of Bitcoin was in 2010-2014 seven times greater than gold, eight times greater than S&P 500 and 18 times greater than the U.S. Dollar (Williams 2014). These numbers are very high and are dangerous for a currency. Another explanation for this instability in terms of price is the predetermined number of coins that reduces its flexibility (Iwamura, et al. 2014). Others explain the volatility as being a startup syndrome for these new currencies as we slowly but surely are about to learn its usefulness and potential (Lee 2013). A comparison is made between a startup company and this so called “startup currency”. Furthermore, claiming that as we learn more and more about cryptocurrencies the volatility will decline.

This high volatility also has made some people describe the Bitcoin mania as a bubble, associating it with the tulip mania or south sea bubble (Adkisson 2018). Although volatility can be fun and something risk-seeking investors try to look for, it is not a good selling point for something that tries to be a currency. National Bank of Belgium argues that a stable currency is a currency that successfully performs because its purchasing power is stable (National Bank of Belgium 2013). A consumer would not use his currency to purchase an item if he did not know what it would cost tomorrow.

In addition to the volatility of cryptocurrencies, there is also the issue that they are associated with criminality and terrorist activities. With the introduction of Bitcoin came one of its first uses, which was an anonymous website where one could buy and sell illegal goods and services, Silk Road (Panda 2018). Soon other websites tried to do the same (Popper and Ruiz 2017), but all were shut down by law enforcement and the owner of Silk Road was even sentenced to life in jail (U.S. Attorney’s Office Southern District of New York 2015)

New York University has written a report where they show that terrorists use cryptocurrencies as a mean to store value and payment (Goldman, et al. 2017), although they get mostly of their funding through traditional means (Panda 2018). There has even been reported of transferal of Bitcoin to the so-called Islamic State as a mean of funding (Bernstein 2017).

2.6 How to establish a new currency

Satoshi Nakamoto sought after a currency to remove the third-party trust system. As it is now, when you pay for a cup of coffee you pay electronically via your banking institution and where this third-party is managing the transaction and thus getting paid for it. He also writes in his paper that this creates a world where small casual transactions are almost impossible (Nakamoto 2009a). What he proposed was a system where the trust would go from the third-party to a cryptographic proof. Trust in mathematics or numbers and not in people.

“It is relatively easy to set up a currency” says Chris Sunderland, the creator of the Bristol Pound, he continues with “It’s much more difficult to sustain it” (Campbell 2015).
Bristol Pound was created, like Bitcoin, because of the financial crisis of 2008. The currency is in use by over 2000 individuals and independent businesses (Bristol Pound n.d.). A difference is though that the Bristol Pound is backed up by the Sterling Pound (Harvey 2012). To create a currency, it requires a fancy logo, name and programming skill / printing press, the latter depending on whether one is creating a currency or cryptocurrency. In addition, one must sell the idea and explain why the currency is superior to others. A step that has to be taken when developing a currency is choosing how to base the currency. Chris Campbell from Laissez Faire argues that there are three foundations on which to base a currency: fiat, valued or backed (Campbell 2015). Furthermore, European Central Bank writes that a currency needs to have three main attributes to be a currency: being a mean of exchange, being a unit of account and being a store of value (European Central Bank 2015). These are traits that cryptocurrencies technically have. Furthermore, The Economist writes that: “Bitcoin have three useful qualities in a currency: they are hard to earn, limited in supply and easy to verify.” (The Economist 2015).

Cryptocurrencies uses the technology to remove the base of trust, whereas hard currencies are legal tender in its country and therefore backed up by its own country (Investopedia n.d.). This is something that cryptocurrency to this date does not have, although Venezuela has released its own cryptocurrency “Petro” but has lately been regarded as scam (Laya 2018). Petro is backed by Venezuelan oil-reserves.

Economist Nick Blanchard uses another commodity as an example, in the future maybe water is scarce, and one can create a currency backed up by water reserves (Campbell 2015). Ultimately, currencies work because there is a mutual trust that both parties agrees to accept it as an exchange for goods and services. Blanchard says: “Currency loses all its value when people no longer want it in exchange for what you want." (Campbell 2015).

Ithaca HOURs was created in 1991 to be a non-asset backed currency in Ithaca, New York (Glover n.d.). This currency is still operating and is backed up by an IOU, meaning that one receives it for doing work and one can use it to buy goods and services in that particular town (Thompson 2011).

Even though there has been a decline in usage of the Ithaca HOURs (Khromov 2011), it is still a good example that currencies do not need to be backed up by a valuable asset; there is mutual trust in the community that the currency is accepted.

Therefore, as cryptocurrencies usually are not backed by a physical asset, they have to be built upon an algorithm to remove the trust factor which normal currencies have. Derek Thompson writes, “Money is all about trust. It's doesn't particularly matter whether your currency is backed by something concrete (like gold), something specific (like hours of labor) or something invisible (like a government's promise to accept that money as payment for taxes). What matters is that people agree to accept it in exchange for goods and services.” (Thompson 2011).

What we remain with is how to attract people to use your currency and prove that your currency is superior to others. What cryptocurrency have that the normal currencies do not is its technology, which is the blockchain technology.

Derek Thompson continues with saying that creators of currencies face a chicken-egg problem. What he means is that on the one hand, to help facilitate the growth of a currency to the people, you have to sign up retailers. But on the other hand, to make the currency popular among retailers you have to get users (Thompson 2011).

How to establish a currency and getting the trust needed to sustain is a very hard question to answer, and we will not delve deeper into this topic in this thesis.

2.7 How many cryptocurrencies is too many?

There are no theoretical limits to how many cryptocurrencies there could be. This is because cryptocurrencies are based on computer codes, often open source, which means that they can, as previously mentioned, be copied. But realistically, there will be a limit to the number of cryptocurrencies, as not all cryptocurrencies can co-exist. Much like in the business world, there are competitors, but there were also competitors that no longer exist. An example is Nokia and Blackberry in the cellular phone industry, where they were the biggest but failed to maintain their positions (Mehta 2016).

Similar to the mobile phone example, the three different competitors Apple, Samsung and Nokia were based on much of the same technology, the mobile phone with applications, Wi-Fi, text messages and so forth. But what differentiated them from each other was the operating system. Apple have iOS, Samsung uses android and Nokia had Symbian and some models had Windows Mobile (Bouwman, et al. 2014; Mehta 2016). What ultimately killed Nokia's operating system and therefore also the company was the mistake of not incorporating applications as good as their competitors (Bouwman, et al. 2014; Mehta, 2016).

When the "crypto" dust has settled, perhaps we will see the same situation for cryptocurrencies? As cryptocurrencies ultimately do the same thing, maybe the technology, idea or people behind the different currencies are the factors that make or break them?

2.8 Forks

A fork, when talking about cryptocurrencies, is where a path divides into two separate paths. When this happen, the community splits into what they believe is the better option or path to follow. Sometimes, the fork manages to resolve the problem on its own, and nothing drastic happens. But other times there is a deep split in the community where the result becomes a whole new cryptocurrency (Castor 2017).

Due to the way the distributed ledger functions, there will be a fork every time two miners find a block at the same time, but this will solve itself when the next block added will close the fork. This happen because there will not be any reward for the miners who continue on the shortest chain. Ethereum has managed to solve this problem with its GHOST-protocol (Madeira 2018c), and rewards these so called "orphan" blocks to some degree (Madeira 2018b).

Normally forks are categorized into hard-forks and soft-forks. Hard forks generally come from a new rule set in the network, which makes the old version incompatible with the new. An example of this type of fork can be when the block size changes to a bigger size. This will split the cryptocurrency community as some will stick to the old set of rules, while other will venture with the new rules. Consequences of these hard forks include the creation of other cryptocurrencies, like the split between Bitcoin (BTC) and Bitcoin Cash (BCH), and Ethereum (ETH) and Ethereum Classic (ETC) (Larson 2017; Rizzo 2016)

In contrast, soft forks are backwards compatible. This means that the participants can continue to contribute their computing power and validating and verifying transactions without having to upgrade their protocol. When the majority chooses to use this option, the minority will be more and more incentivized to upgrade, as they will have reduced functionalities (Master the Crypto 2018).

2.9 Proof-of-work vs proof-of-stake

In a “proof-of-work” system players use computing power to validate transactions and earn “mining rewards” and “transaction fees.” If one use computing power to earn rewards one is called a “miner.” Miners compete to solve “block-problems”, the miner who first solves the problem is rewarded with the mining rewards and the transaction fees. The miner who has the most computing power will solve blocks more often than miners with less computing power (Rosic 2017).

In a “proof-of stake” system players earn rewards and/or transaction fees, hereafter called “rewards.” The players compete to create new blocks by staking their wealth. Players on average earn rewards corresponding to the size of their stake. A player with a 10% stake in the network will on average earn 10% of all rewards. Proof-of-stake systems can be much more cost effective than proof-of-work systems as they don't rely on computing power, and therefore uses much less electricity (Rosic 2017).

2.10 How to store and transfer cryptocurrency

There are two different ways to store cryptocurrency, though they build on the same principle, namely that everything is based on a string, your address. The object or purpose of the wallet is to hold one’s private keys, and it’s therefore crucial to maintain and be careful with it so that one does not lose one’s assets.

The first way is to store it on an exchange. Traders mostly use this method, since there is a transaction fee for sending cryptocurrencies and making a transaction every time you want to exchange can make the speculations less profitable (World Crypto Index n.d.).
The other way is to store cryptocurrencies in a wallet. The wallet can be either a physical object like a piece of paper or a software application on a computer or mobile phone (Coindesk 2018). There are two types of storage methods. The first is cold storage. Cold storage means that the wallet is not connected to the Internet and is used for storing the assets.

Hot storage are wallets that are connected to the Internet for the purpose of spending or exchanging / speculating (T. K. Sharma 2017).

Cryptocurrency functions like any other currency in the way that when two parties agree to buy/sell a certain item, the selling party sends his or her currency. The only difference is that with normal currency, you need bank account number or Swift (Society for Worldwide Interbank Financial Telecommunication) / IBAN (International Bank Account Number) but with cryptocurrency you need the receiver's public address. This address is called public because it can be seen on the blockchain ledger and used to send and receive cryptocurrency. The address acts like an account number, where the addresses are the holders of the amount of Bitcoin. The buyer then enters the address and the amount agreed upon in his or her wallet and press send. As soon as the person hits send, the recipient can see it on the blockchain. In order to be a confirmed transaction, it will have to be validated on the following blocks, this can take from one minute up to one hour depending on which cryptocurrency is being transferred.

There are two types of addresses or keys, where the public key is the unique key known to the public. The private key is the cryptographic code you need to spend your cryptocurrency. If someone get access to your private key, they can steal your cryptocurrency (Bitcoin Wiki 2017). Most wallet-services store your private key for you, either on your computer or in a centralized database, so that you only have to remember your personal password. Some services also have two-factor authentication for increased security. Private keys can also be stored offline, on for example a piece of paper or something more durable like a Cryptosteel (Cryptosteel n.d.).

3 Methodology

In this section we will review the various methods to evaluate funds, indices, currencies and cryptocurrencies and provide good reasons to why we choose the methods. Moreover, we will try to show weaknesses and strength we find with all of the performance measures. The majority of the formulas come from lectures from previous classes. We view cryptocurrencies as one package, but we look at the three cryptocurrencies we research differently. Most of the performance measures in this research are related to the Capital Asset Pricing Model.

3.1 Annualized returns

We choose to calculate the average returns by two methods. The first method is the arithmetic average, which is the simplest form. This is done by adding all the returns and divides that number with the number of observations. By doing this, one assumes that every observation is independent from the next (Gallant 2018); therefore, the arithmetic provides an unbiased estimate of the expected future return (Bodie, et al. 2014). This is not always true in the world of finance, although being very useful, returns often are connected with each other, the geometric mean solves the problem that the arithmetic has.

The geometric mean is useful in finding the average in economic figures and it has therefore a wide range of applications in business and economics (Lind, Marchal and Mason 2002). First one has to add "1" to every number, to eliminate the problem with negative returns, as all the data values must be positive to determine the geometric mean (Lind, et al. 2002). Then we multiply them together and square that number with the number of observations.

By looking at the formula in Lind et al. and the fact that one cannot use negative numbers we derive to this formula:

Equation 1: Geometric Mean (Lind, et al. 2002)

$$Mean_G = \sqrt[n]{((1 + a_1) \cdot (1 + a_2) \cdot (1 + a_2) \cdot \ldots \cdot (1 + a_n)}$$

3.2 Capital Asset Pricing Model (CAPM)

The Capital asset Pricing Model is a well-known model used to theoretically determine the required rate of return for an asset, developed independently by Treynor, Sharpe, Lintner and Mossin during the 1960s (Bodie, et al. 2014). It is a mean-variance model that uses the beta to measure the market risk of an individual asset. We want to check if the CAPM holds for cryptocurrencies, we also want to check if including cryptocurrencies in a well-diversified portfolio offer either higher expected return or lower risk. Also, we want to see if the risk-free rate of return applies to cryptocurrencies. One of the main advantages of the model is that it is easy to understand and fairly straightforward to implement and it is about expected return, not risk (Grinold and Kahn 2000).

The CAPM standardizes the risk yield from an asset by dividing the covariance of each asset with the market portfolio by the variance of the market portfolio; this yields a risk measure called beta. Defined by Berk and DeMarzo as "the expected % change in its return given a 1% change in the return of the market" (Berk and DeMarzo 2014).

The beta of the market is 1, assets with more systematic risk than the market has a beta higher than 1 and assets with less risk has a beta lower than 1. The beta symbolizes the systematic risk, meaning the risk cannot be diversified or removed. The beta is a risk factor that cannot predict future behavior. If an asset has a beta of 2, it does not mean that it is twice as volatile as the market indefinitely or in the future. A positive beta show that the asset is expected to move with the market, while a negative beta means that the asset is expected to move opposite of the market. If a beta is zero, this means that the asset will stay the same.

Equation 2: Beta, using correlation (Berk and DeMarzo 2014, 389)

$$\beta_i = \frac{SD(R_i) \cdot Corr(R_i, R_{Mkt})}{SD(R_{Mkt})}$$

Where; β_i is the beta of the asset

$SD(R_i)$ is the standard deviation of the asset

$Corr(R_i, R_{Mkt})$ is the correlation between the asset and the benchmark

$SD(R_{Mkt})$ is the standard deviation of the benchmark

Equation 3: Beta, using covariance (Berk and DeMarzo 2014, 389)

$$\beta_i = \frac{Cov(R_i, R_{Mkt})}{Var(R_{Mkt})}$$

Where; β_i is the beta of the asset

$Cov(R_i, R_{Mkt})$ is the covariance between the asset and the benchmark

$Var(R_{Mkt})$ is the variance of the benchmark

Although Eugene Fama and Kenneth French critiques the CAPM in their 1996 paper "The CAPM is Wanted, Dead or Alive", blaming the *beta* for its flaws writing that it "does not suffice to explain expected return" (Fama and French 1996, 1955).

Equation 4: Capital Asset Pricing Model (Fjesme 2017)

$$E(r_i) = r_f + \beta_i[E(r_m) - r_f]$$

Where; $E(r_i)$ is the expected rate of return of the asset

r_f is the risk free-rate

β_i is the beta for the asset

$E(r_m)$ is the expected return of the benchmark market

One of the problems with using the CAPM is that cryptocurrencies have a very low correlation with other assets (R. Sharma 2018), which leads to low beta values and lower expected return. Jurek And Stafford (2015) support this view, they find that expected return for alternative investments can dramatically exceed those suggested by traditional models, affecting the attractiveness of these investments (Jurek and Stafford 2015). Jurek and Stafford (2015) investigated hedge funds alternative investments, but we believe their findings also fit cryptocurrencies.

3.2.1 Capital Asset Pricing Model Assumptions

Three main assumptions underlie the CAPM, which are (Berk and DeMarzo 2014, 379-380):

1. Investors can buy and sell all securities at competitive market prices (without incurring taxes or transactions costs) and can borrow and lend at the risk-free interest rate.

2. Investors hold only efficient portfolios of traded securities – portfolios that yield the maximum expected return for a given level of volatility.
3. Investors have homogeneous expectations regard the volatilities, correlations, and expected returns of securities

3.2.2 Market risk premium

One of the parameters for the CAPM model is the "equity market risk premium". Calculated by subtracting the risk-free rate from the expected return of the market portfolio (Bodie, et al. 2014). Often it is chosen to only use one number, but this factor may differ from country to country, so for this thesis we choose two different approaches. The first approach is the use of the return of the MSCI World Price Index as the expected return of the market portfolio.

The other approach was to use one selected number for the equity market risk premium. Since it may differ from region to region or country to country, we chose the number from what we already have used in previous evaluation classes. This number is set to 5,5% annual rate. KPMG argues for a market risk premium of 5,5 % in December 2017 (Baardwijk, et al. 2018), while Duff and Phelps recommend lowering the equity market risk premium to 5% for US (Grabowski, et al. 2017b). We also used Damodaran's equity risk premium by country and regions to determine what number to set, which he set for implied premium to be 5,07 % (Damodaran 2018). We chose 5,5% since we think it reflects best the market risk seeing that most of the indices and funds are set in the US, and the currencies are between the US Dollar and the given currency.

3.3 Jensen's Alpha:

Jensen's model is based on the individual works of Sharpe, Lintner and Treynor and thus have the same assumptions as mentioned in the CAPM section (Jensen 1967). In Jensen's original paper he writes that "a central problem in finance has been to evaluate the performance of risky assets" (Jensen 1967) and with this paper he derives with a risk-adjusted measure. As the CAPM finds the expected return of an asset, Jensen's Alpha is a measurement to see if the assets return is greater or lesser than what was expected by the CAPM. It was first used to test mutual fund from 1945 to 1964 but has later been adapted to other types of funds, portfolios, strategies and assets.

As a performance metric it shows the average return on the portfolio over and above that predicted by the CAPM, given the portfolio's beta and the average market return (Bodie, et al. 2014). If one gets a positive alpha, the manager's selection of stocks, bonds, assets or strategy has delivered a superior risk-adjusted return. But still, it is the beta that decides which one to go through. As with two portfolios with same alpha, a manager will choose the one with lowest beta since it would give same return for lower risk.

We choose to use this portfolio measure as it builds further on the CAPM, which is a central work in finance, and to our thesis. This will strengthen our findings as they are related and together build a strong foundation on which to get an understanding on the portfolios strengths and weaknesses. Furthermore, the Jensen's alpha is a relative good and easy way to evaluate a portfolio performance. It is easy to understand if a portfolio is good or bad by looking at if it gives higher or lower rates of return than what was expected. Even non-finance people can relate to this measure, as it is easy to interpret.
Some major weakness to this measure is that it depends on the beta, which is not a very good explanation for risk. As explained in the CAPM section, beta only shows the systematic risk and not showing how the risk is distributed, i.e. skewness or kurtosis. Furthermore, it required a benchmark, known as the market that has to be picked. This can lead to a selection bias, where one selects a benchmark that suits the manager.

Equation 5: Jensen's Alpha (Fjesme 2017)

$$\alpha_p = \overline{r_p} - [\overline{r_f} + \beta_p(\overline{E(r_m)} - \overline{r_f})]$$

Where; α is the excess return over the CAPM

$\overline{r_p}$ is the average rate of return of the asset

$\bar{r}_f$ is the risk-free rate

β_p is the beta for the asset

$\overline{E(r_m)}$ is the average expected return of the benchmark market

We choose to set the market risk premium as the MSCI World Price Index for the Jensen's alpha. One last remark is that the Jensen's alpha should not be mistaken for just alpha.

3.4 Treynor ratio:

Jack Treynor introduced his Treynor ratio in 1965, one year before the Sharpe ratio as we will discuss later in the thesis. This ratio considers the systematic risk of the portfolio and therefore is categorized as a risk to volatility ratio. Since it uses the beta, measure for systematic risk, the Treynor ratio uses the sensitivity of the investment to the market as the factor (denominator). As this portfolio measure does not include any added value gained from active management, it can only be a selection or ranking criteria (Investopedia n.d.). Where the higher ratio shows that the investment added in the portfolio has added value in relation to its risk, and lower ratio indicates that the investment has performed worse than the risk-free instrument.

Like the Jensen's alpha and CAPM, this relies on the beta and is therefore limited in explaining the risk, as written above. In addition, as the beta is calculated based on historical prices, both Jensen´s alpha and Treynor ratio both are used to analyze past performance (Kidd 2011b). One limitation with the beta is that if you have negative returns and negative beta you might end up with a positive Treynor ratio, which can be misleading. Another limitation with the beta is that when the beta is close to zero, you might end up with a high Treynor ratio. The Treynor ratio is also reliant on the benchmark, so the selection bias will also be a weakness here. A major limitation to this measurement is that Treynor is only applicable to a well-diversified portfolio. An advantage with this measure is that since it uses the non-diversifiable risk, i.e. beta, it can be a good measure for when adding an asset to an already diversified portfolio (Investopedia n.d.).

We chose to use this measurement as it builds on the CAPM since it uses the beta. Together with other measurements, this measure will give us a good clue on whether adding cryptocurrency to the portfolio adds value. Last point for choosing this specific measurement is that it is a good tool when looking at well-diversified portfolios, as we have.

Equation 6: Treynor Ratio (Fjesme 2017)

$$TM = \frac{(\overline{r_p} - \overline{r_f})}{\beta_p}$$

Where; $\overline{r_p}$ is the average rate of return of the asset

$\overline{r_f}$ is the average risk-free rate

β_p is the beta for the asset

3.5 Information ratio:

The use of the information ratio is to check if a manager has beaten the benchmark by a lot in a few months or a little every month. A high ratio means that the manager is consistent at doing so. The information ratio is calculated by estimating the alpha and checks it against the "tracking error". The tracking error is defined as the "standard deviation of the excess return" (Eckbo and Ødegaard 2015). The tracking error is a measure of risk in an investment portfolio that is due to active management decision. It can also be seen as a measure to how well the manager follows the index. The "inventors" of the information ratio writes in their book that it "is a ratio of (annualized) residual return to (annualized) residual risk". Furthermore, "an information ratio of 0,5 is good and a ratio of 1 is exceptionally good" (Grinold and Kahn 2000).

As explained above, this portfolio measure is used to examine how well the managers beat the benchmark index, but the measure cannot explain how this was achieved (Kidd 2011a). With this measurement it can be hard to explain whether the manager beat the market by skill or sheer luck. Furthermore, it cannot clarify whether this was due to a single extreme event or many small events. We see this as a negative property with this performance measure. Another disadvantage with the information ratio is the same as the other abovementioned measurements, that it requires a benchmark. As this can be selected, it can be chosen to maximize the measurement. An advantage with this portfolio measure is that it is one of the most used one (Eckbo and Ødegaard 2015), which means that it is more recognizable and easy to interpret and comparable with other information ratios in other portfolios.

We chose this measurement as it was recommended to us by Associate Professor Sturla Fjesme, from the article "Metoder for evaluering av aktiv fondsforvaltning" by Espen Eckbo and Bernt Arne Ødegaard from 2005. This measurement is also used in several other portfolios, as it is one of the most used measurements to measure portfolio performance.

Equation 7: Information Ratio (Fjesme 2017)

$$IR_p = \frac{E(r_p - r_i)}{\sigma(r_p - r_i)}$$

Where; $E(r_p - r_i)$ is the expected return over the benchmark return

$\sigma(r_p - r_i)$ is the standard deviation of the expected excess return over the benchmark, also called "tracking error"

3.6 Sharpe ratio:

The Sharpe ratio was first introduced a year after Treynor ratio, in 1966, by Nobel laureate William F. Sharpe. The ratio was originally developed as a single-period forecasting tool, trying to predict future performance. Since then it has seen to revisions, the last being in 1994. The major change done is that it changed from expected returns to actual returns, meaning that it is no longer a forecasting tool. The Sharpe ratio can be defined as the risk premium divided by the standard deviation of the excess return (Bodie, et al. 2014). This ratio was initially called reward-to-volatility ratio (Sharpe 1966). This measure looks very similar to the Treynor measure, but it uses all the risk, not only the non-diversifiable risk (Beta), measured by the standard deviation. The Sharpe ratio tells an investor what portion of a portfolio's performance is associated with the risk taken. This means that it shows how much an investor is compensated for investing in a risky asset versus a risk-free asset (risk-free rate). Although this measure is widely used when evaluating the performance of investments managers (Bodie, et al 2014; Kidd 2011a), it has some drawbacks. Its largest flaw is that it treats volatility as risk, meaning that volatility is bad. Signifying that it penalizes the downside deviation equal to the upside deviation (Kidd 2011a). Furthermore, since it is based on the Markowitz mean-variance theory (Sharpe 1966), the ratio presumes normal distribution on the variance. So as for the same as we write in the CAPM section, the skewness and kurtosis of the distribution is not taken into account. Moreover, the measure is dimensionless. This means that it cannot provide evidence in how well a portfolio with 0,5 Sharpe ratio is better than a portfolio with -0,2, other than that the first portfolio is superior.

An advantage with the Sharpe ratio is that it is a well-known performance measure, so when explaining to investors and managers the ratio you have, they will know if it is better or worse.

We choose to use this measurement, as it is the most used measure to evaluate portfolio performance. Although Fjesme writes in his lecture notes that the Sharpe should be used when a portfolio is not well-diversified and Treynor should be use and when a portfolio is diversified, we choose to use this measurement regardless, as it is one of the most used and used in the papers we use as inspiration to this thesis.

Equation 8: Sharpe Ratio (Fjesme 2017)

$$SI = \frac{(\overline{r_p} - \overline{r_f})}{\sigma_p}$$

Where; $\overline{r_p}$ is the average rate of return of the asset

$\overline{r_f}$ is the risk free rate

σ_p is the standard deviation of the asset

3.7 Omega ratio:

This portfolio measure is a relative new one, introduced in 2002 by Con Keating and William F. Shadwick, it is very similar to the Sharpe ratio. The difference starts where the Omega ratio looks at the entire distribution, thereby considering the kurtosis and skewness as we discussed is one of the Sharpe ratio´s weakness. This is very important when the returns are asymmetrical, which is often the case with alternative investments (Breaking Down Finance n.d.)

The Omega ratio is measured by setting a specified return level, called Level and solving it by looking at two integrals (Keating and Shadwick 2002). The integral below the specified return level measures the “weight” of the losses and the integral above measures the gains. Therefore, the Omega ratio is the ratio of upside returns relative to the downside returns.

One of the Omega ratio main advantages is that because it uses the integral it takes into consideration the entire distribution of returns. This means that it uses the actual distribution rather than the theoretical normal distribution. Another advantage with this ratio is that it was constructed for alternative investments, such as hedge funds (Keating and Shadwick 2002). This is appropriate for our thesis as our aim is to change or switch the alternative investment in a diversified portfolio. The last advantage is that instead of using a benchmark, which can in some instances be wrong, with the Omega ratio you set a given threshold or level. This can be a good thing for either the manager or the investor who is thinking about the portfolio.

We choose to use this variable as we feel that it may contribute to a better understanding of the performance of the portfolio. Not only because the Omega ratio takes into account the entire distribution, but also because it is better suited for alternative investments such as cryptocurrencies.

Equation 9: Omega Ratio (Keating and Shadwick 2002)

$$\Omega(r) = \frac{\int_r^b [1 - F(X)]dx}{\int_a^r [F(X)]dx}$$

3.8 Sortino ratio:

The Sortino ratio is a variation of the Sharpe ratio, but differs where the Sharpe ratio looks at all the volatility. The Sortino ratio looks only on the downside volatility (Hoffman and Rollinger 2013). As we wrote earlier, the investor/manager only cares about the downside volatility, as that is where she or he loses money. That is a major disadvantage about the Sharpe ratio, and something that the Sortino tries to compensate for. Furthermore, the ratio does not assume normal distribution on the return and is therefore suited for alternative assets such as cryptocurrencies (Edwards 2016). The Sortino ratio was developed by Frank A. Sortino in the early 80´s and can be easily understood as the required rate of return less the MAR, this is then divided by target downside deviation (Hoffman and Rollinger 2013), which is somewhat similar to the Omega ratio. Just like with all other ratios we choose, the higher the number the better it is with the Sortino ratio.

An advantage with the Sortino ratio is like we wrote above that it only takes into account the downside risk, and such does not penalize for both the upside and the downside volatility like the Sharpe ratio. This is important because we only care about the downside risk when investing. In particular when two strategies or assets gives the same Sharpe ratio, the Sortino could give a better explanation. In addition, when setting a minimum acceptable return, you only care about the returns that do not beat the MAR and therefore only they should be relevant. Furthermore, Ashraf Chaudhry and Helen L. Johnson show in their paper "The Efficacy of the Sortino Ratio and Other Benchmarked Performance Measures Under Skewed Return Distributions" that Sortino ratio achieves higher power if the distribution is skewed (Chaudhry and Johnson 2007). A disadvantage with the Sortino ratio is that it uses historical data, and as discussed above, if something has happened before does not mean it will happen again.

We chose this portfolio measure as it is used in the article that is considered as the main inspiration to this thesis. By using the ratio, we can compare our findings to those in the article "Virtual currencies, Tangible return: Portfolio Diversification with Bitcoin". Another reason is that it is better for assets where the returns are not normal distributed, as we think cryptocurrency is.

Equation 10: Sortino Ratio (Hoffman and Rollinger 2013)

$$SR = \frac{(R - T)}{TDD}$$

Where; R is the expected return

T is the target or MAR

TDD is target downside deviation.

3.9 Honorable mentions

We started the thesis with over twelve portfolio performance measures we wanted to test but felt that it was too many. After a conversation with our advisor Daniel Spiro, we came to a conclusion together to use fewer measures. After browsing through several other papers about portfolio performance we chose to use six measurements as we felt that they together would paint a better picture of how better or worse cryptocurrency would contribute to a well-diversified portfolio.

Although we picked the above-mentioned performance measures, we delved into many other measurements. Some of the were Calmar ratio, Fama-French 3 factor and Carhart 4 factor, APT, Sterling ratio and Modigliani-Modigliani (M-squared). The ones we actually chose were chosen because they we think they are better suited for our needs, as cryptocurrency behave somewhat different from stocks, bonds and equity stocks.

Other factors that we took into consideration when choosing factors was recommendations from Associate Professor Sturla Fjesme. We used his lecture notes from previous classes as well as an article he advocated which was Eckbo and Ødegaard from 2005. Another reason for using the factor we chose was because previous paper on the same topic had these factors, so we thought it would be a good idea to use same variables to which we could compare results.

3.10 Weaknesses and limitations

A weakness with the thesis is that even though there are a lot of empirical and theoretical articles about the performance measures in the finance literature, there is not as much on cryptocurrencies. This means that much of our sources, except a few articles, which we have mentioned in the literature review, are not scientifically the best sources. This is mainly because cryptocurrency is a relatively new concept in the finance literature, and therefore not as well researched as other subjects. But as we have competence in both finance and cryptocurrencies, from our educational program and private trading, we are confident that our sources are reliable.

Another weakness is that both Litecoin and Ethereum have few observations, with respectively 219 and 126 logged observations. While Bitcoin and the traditional assets have 390 and 417 logged observations respectively. Because of the short dataperiod it may lead to extreme values in some of the measures. With the reduced dataperiod, the extreme values will have much more impact on the statistics. Having so few observations limits our results, as it only shows how well cryptocurrencies have performed in comparison to traditional assets only in the short time period. We suggest that other research should be done in the future to see if it will show the same results then.

We base our research on only three different cryptocurrencies. This was done because of survivability of the cryptocurrencies, as not many have survived since the establishment of Bitcoin. At the beginning of the thesis we wanted to test ten different cryptocurrencies, but as we researched further we saw that few which was on the top in 2013 was still on top in 2017, making them not viable to test in 2017. The top 10 changed from year to year, while only Bitcoin and Litecoin remained on the list. We therefore choose to limit our dataset to have Bitcoin, Litecoin and Ethereum as they had a lot of transactions and price data; even though Ethereum came in 2015 it has been on the top 10 since its release.

Another limitation we had is to look at cryptocurrencies as an investment asset and not currency. While we have already written why we have choose to do so, we want to mention this as a limitation. Had we looked on cryptocurrencies as a normal currency, maybe the conclusion would have been different, given the stability and legislations made.

4 Data

As we use the article by Brière et al. as our basis, we choose to use as much of the same data as them as we could. The funds and prices on precious metal, currency and other commodities were selected from the article as far as we could, but some funds/indices were restricted on Thomson Reuter DataStream for us, and therefore we had to find similar funds. The funds, commodities and currencies chosen was (underlined and cursive are those which Brière et al. also used):

- Thomson Reuters Global Emerging Markets Index
- *<u>HFRX Global Hedge Fund CAD Index</u>*
- MSCI International World Real Estate Price Index USD Realtime
- MSCI International World Price Index USD Realtime
- Thomson Reuters Global Developed Index
- *<u>ICE Brent Crude Electronic Energy Future Continuation 1</u>*
- S&P Global Developed Sovereign Bond Index
- *<u>FTSE EPRA/NAREIT Global Index</u>*
- Thomson Reuters SGX Corporate Bonds 3+ Years Index
- PowerShares Emerging Markets Sovereign Debt ETF

- SPDR Citi Int. Govt. Inflation-Protected Bond ETF
- *US Dollar / Japanese Yen FX Spot Rate*
- *Euro / US Dollar FX Spot Rate*
- UK Pound / US Dollar FX Spot Rate
- *Gold / US Dollar FX Spot Rate*

The fund and indices we chose which was similar to those used in the article by Brière et al. was chosen on being the same type, e.g.; Barclays Global Inflation World was used in the article as World inflation linked bond, whereas we chose SPDR Citi Int. Govt. Inflation-Protected Bond ETF.

4.1 Dataset

We collected 418 (417 logged) weekly observations for the indices mentioned above. We choose to collect weekly data, for two reasons. Firstly, cryptocurrencies do not have the same limitations as stock and bond markets. Trades happen even on weekends, public holidays and holidays. That means using daily data would have provided data for Saturday and Sunday, which we then had to trim out. Using weekly data also made it possible to "trim" out observations on holidays and other days where there was no trade, as they are incorporated in a weekly observation. Secondly, we were recommended by former Associate Professor Helge Nordahl to use weekly data in a previous class, Evaluation. His arguments were that daily data swing too much, and monthly does not capture patterns that well. On this basis we chose to use weekly data for the entire dataset.

The data on Bitcoin was picked from July 2010 to December of 2017. That gave us 391 (390 logged) observations on Bitcoin. Although introduced earlier we chose to use Yahoo Finance historical data, which dates back to July 2010. We first looked into just using one single exchange, namely Bitstamp (Bitcoincharts 2018), but data from that exchange was only from September 2011. We could have used data from closed down exchanges such as Mt. Gox and then adding the data from the largest exchange after the crash, but we felt as it could have corrupted the dataset, as it would come from two independent sources. Yahoo Finance was consequently chosen due to that it uses www.cryptocompare.com as source for its data. Cryptocompare uses data from several exchanges and therefore provide better data than from one single exchange.

We would like to mention that Brière et al. uses www.blockchain.com as source for data on Bitcoin price and was a site we looked upon when searching for data, but we find it that Yahoo Finance provided better data.

Litecoin and Ethereum were introduced much later than Bitcoin and we therefore have 220 (219 logged) and 127 (126 logged) observations respectively. Litecoin was introduced in October 2011, but our first observation in the dataset was on 18.10.2013. We choose to use Yahoo Finance for our source for price on Litecoin as well. Ethereum was the last of the cryptocurrencies used in this thesis to be introduced and we therefore only have 126 observations, spanning from 31.07.2015 to December 2017. Same procedures were used to gather the data on Ethereum as with Bitcoin and Litecoin.

One thing we had to do was to convert the dates from the Yahoo Finance dataset for Bitcoin, Litecoin and Ethereum. This was done because the data from Thomson Reuters DataStream comes with the weekly exchange date from Friday, while Yahoo Finance provides an exchange date from weekly prices from the following Monday. We solved this problem by setting the cryptocurrency close date one week earlier. That means that the open data from Monday on Yahoo Finance was set as close date for the previous week.

The dataset we gathered from the different funds, indices, commodities and cryptocurrencies was then put in a new dataset containing only the close data from them. We use Microsoft Excel as a platform to contain the data. To calculate the values we needed for our thesis, we use the software called R-Studio. This is an open source software created to be an IDE (Integrated Development environment), and it is said to be a very good and powerful statistical program (Amirtha 2014; Quora 2015). This was the program we were thought on our master's program. Packages most used were Performance Analytics, Quantmod, fBasics, DescTools and tseries.

As our dataset contains the price data of assets which start at different points in time, it proved to be difficult using several packages in the statistical program R-Studio, as several of the functions had difficulties when comparing two vectors when one of the vector had NA's (no observations) in them. We searched the Internet and asked several of our fellow students and even staff from the school but was unable to find a good solution to which we could continue to use all of the functions in the Performance Analytics package. This meant that we used both Microsoft Excel and R-Studio to gather our results. R was used for the descriptive statistics and correlation matrix, as the packages for these functions are good at handling NA's. Furthermore, R was used for the more advanced performance measures as they proved to be difficult to program in Microsoft Excel.

4.2 Risk-free interest rate

We use a normalized risk-free return of 3,5%, which is Duff & Phelps recommendation, based on real interest rates and long term-growth estimates (Grabowski, et al. 2017a). We choose to a US risk free rate since the assets in our study are valued in US Dollars.

4.3 The benchmark, MSCI World Price Index

To calculate some of our performance measurements we have to select an index to which we can benchmark the selected cryptocurrencies. This benchmark would act as the market, to see if the cryptocurrencies could beat the market. First index that came to mind was the Standard and Poor's 500. This index was ruled out, although one of the most used index (Investopedia n.d.), we felt that it did not suit our needs as it contains only stocks from the largest 500 companies, by market capitalization, in the US.

As we had previously used MSCI World Price Index in other classes, we looked at this index again. MSCI World Price Index contains more than 1600 securities from 23 developed countries in the world (MSCI n.d.). These factors made the MSCI World Price Index far more suitable for our thesis than the S&P 500. Ryan Barnes (2018) argues for the MSCI when selecting an international benchmark (Barnes 2018). Since cryptocurrencies are not restricted to one single country, we feel that using an international index is the better choice.

4.4 Volatility

When dealing with stocks, indices, bonds, options or even cryptocurrency one has to take into account the volatility. Volatility is defined on Investopedia as "The statistical dispersion of returns for a given security or market index" (Investopedia n.d.). Can also be described as the uncertainty or risk of changes in the security. Volatility is often measured as standard deviation or variance between the returns from the same security or the market index. For stocks, beta is mostly used, which we discussed earlier in the thesis. The volatility only tells you how much an asset can move, but not if it will increase or decrease.

The same mechanism works for cryptocurrencies. When news about legal restrictions in countries comes out, more often than not the prices on cryptocurrencies does tend to decrease (Kuznetsov 2018). The large increase in the late 2017 was enabled by the increase participations of new market participants and the media had an article every other day about how much the cryptocurrency prices had increased. This also led to increased attention from regulators, which lead to several bans and new laws (Kuznetsov 2018; Pauw 2018).

In an article by Jonathan Barker (2017), he explains the seven factors to what determines the volatility of Bitcoin. The article mentions that the bad press about Bitcoin and its services, such as exchanges, and how the security breaches have influenced the price of Bitcoin in a negative way (Barker 2017).

Business Insider have written an article based on a study where they show a 91% correlation between the Google searches and the price of Bitcoin (Edwards 2017). Search term “bitcoin” was the second most searched regarding news (Google n.d.), showing what a popularity gain it had. The study did not however show if the searches was predicting or trailing the prices.

We have in our research used the volatility, measured in standard deviation, in many of our performance measures, and also looked and the standard deviation as a factor on its own.

5 Empirical results

5.1 Descriptive statistics

We will in this section present a table containing the variable number (vars), number of observations (n), mean, standard deviation (sd), median, trimmed mean (trimmed), median absolute deviation (mad), maximum observation (max), minimum observation (min), range of values (range), skewness (skew), kurtosis (kurt) and standard error (se). Most results in this section are derived from R-Studio, but we use Microsoft Excel to create tables and figures.

Table 1: Descriptive statistics

asset	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Thomson.Reuters.Global.Emerging.Markets.Inde	1	417	0,00028	0,02023	0,00004	0,00083	0,01802	-0,07807	0,07276	0,15084	-0,32229	1,53322	0,00099
HFRX.Global.Hedge.Fund.CAD.Index	2	417	-0,00014	0,01431	0,00091	0,00040	0,01320	-0,06304	0,03870	0,10175	-0,55025	1,19252	0,00070
MSCI.International.World.Real.Estate.Price.Inde	3	417	0,00112	0,02001	0,00243	0,00183	0,01693	-0,09733	0,06678	0,16411	-0,58802	2,42971	0,00098
MSCI.International.World.Price.Index.USD.Realt	4	417	0,00141	0,01940	0,00251	0,00224	0,01353	-0,08966	0,07865	0,16831	-0,66672	2,88632	0,00095
Thomson.Reuters.Global.Developed.Index	5	417	0,00124	0,01935	0,00241	0,00210	0,01327	-0,09101	0,07844	0,16945	-0,68820	3,03141	0,00095
ICE.Brent.Crude.Electronic.Energy.Future.Contir	6	417	-0,00037	0,03947	0,00072	0,00048	0,02931	-0,14781	0,14223	0,29004	-0,33847	1,54446	0,00193
S.P.Global.Developed.Sovereign.Bond.Index	7	417	0,00011	0,00321	0,00022	0,00027	0,00302	-0,01335	0,00926	0,02261	-0,58012	1,15432	0,00016
FTSE.EPRA.NAREIT.Global.Index	8	417	0,00098	0,02118	0,00210	0,00171	0,01808	-0,09304	0,07203	0,16507	-0,61830	2,42822	0,00104
Thomson.Reuters.SGX.Corporate.Bonds.3..Years	9	417	0,00087	0,00922	0,00117	0,00097	0,00850	-0,04295	0,03188	0,07483	-0,27378	1,40842	0,00045
PowerShares.Emerging.Markets.Sovereign.Debt	10	417	0,00035	0,01110	0,00105	0,00083	0,00910	-0,07897	0,03527	0,11424	-1,31608	7,48365	0,00054
SPDR.Citi.Intl.Govt.Inflation.Protected.Bond.ETF	11	417	0,00007	0,01214	0,00035	0,00056	0,01081	-0,05263	0,03428	0,08691	-0,57324	1,56049	0,00059
US.Dollar.Japanese.Yen.FX.Spot.Rate	12	417	0,00051	0,01364	0,00016	0,00053	0,01211	-0,04840	0,04564	0,09404	-0,01683	0,66258	0,00067
Euro.US.Dollar.FX.Spot.Rate	13	417	-0,00046	0,01363	-0,00007	-0,00009	0,01262	-0,04613	0,03816	0,08429	-0,28640	0,46037	0,00067
UK.Pound.Sterling.US.Dollar.FX.Spot.Rate	14	417	-0,00043	0,01191	-0,00070	-0,00009	0,01211	-0,05633	0,02779	0,08412	-0,40597	0,69613	0,00058
Gold.US.Dollar.FX.Spot.Rate	15	417	0,00035	0,02261	0,00092	0,00080	0,02047	-0,08842	0,07463	0,16305	-0,27936	1,02588	0,00111
BTC.USD.rate	16	390	0,03115	0,16406	0,01946	0,02726	0,09277	-0,78847	0,68361	1,47208	0,17292	4,40674	0,00831
LTC.USD.rate	17	219	0,02057	0,19242	0,00517	0,00570	0,09135	-0,54103	1,26130	1,80233	2,06469	10,30911	0,01300
ETH.USD.rate	18	126	0,05426	0,19513	0,02662	0,04178	0,13649	-0,42496	0,61510	1,04007	0,55467	0,67354	0,01738

The first thing worth mentioning while looking at the descriptive statistics is that the cryptocurrencies have relative high mean in comparison to the other assets, Ethereum having the highest weekly mean return of 5,43% while US Dollar spot rate has the lowest -0,046%. As the package Psych containing the descriptive statistics function “Describe” does not specify if it uses arithmetic or geometric mean, we calculate this by using other functions. As such, we will not explain the means any further in this section. The cryptocurrencies also show the highest standard deviation and standard error. The high standard deviation shows that the cryptocurrencies have the highest volatility of all the asset in our research. This means that the returns for the cryptocurrencies disperse heavily from the mean, which can be clearly seen by the minimum and maximum observations.

The min and max in the descriptive statistics shows the minimum weekly return and maximum weekly return that has occurred in the observations we have. Oil, depicted as ICE Brent Crude, has a max of 14,22% and a min of approximately the same (14,78%), which is the highest of the traditional assets. This may be explained by the recent event such as the “Arab-spring” because OPEC countries set oil production and some of them were involved in the “Arab-spring” (Darbouche and Fattouh 2011). They write in their paper that although the oil markets show great resilience, the events in the MENA (Middle East and North Africa) region contributed to higher prices and volatility (Darbouche and Fattouh 2011). Whether or not other macroeconomic factors where to contribute to this min / max movement is another discussion.

Likewise, cryptocurrencies do also have a high minimum and maximum. Highest minimum comes from Bitcoin with -78,85%, whereas the maximum in that period was 126,13% from Litecoin. The minimum and maximum from our descriptive statistics exhibits same patterns as those from Brière et al. and Eisl et al., meaning that there is a huge gap from the highest peak to the lowest bottom.

5.2 Skewness and kurtosis

Last point of interest in the descriptive statistics is skewness and kurtosis. Skewness is a measure to see if a distribution lacks symmetry (Dunlop and Tamhame 2000). From previous classes we have learned that if a distribution is symmetric the skewness will be 0, while a positive skewed allocates more weight to values above the mean, and vice versa, negative skewed allocates more weight below the mean. When asked of an acceptable range, Associate

Professor Per Arne Tufte provided us with a website quoting empirical articles showing an acceptable range for skewness is ±2 (Aslam 2014). This then disproves our previous belief that cryptocurrencies are not normally distributed. Litecoin is the only one of the cryptocurrencies that shows skewness above the acceptable range, 2,065, meaning it is positively skewed to the right.

We were not able to access the empirical articles provided by Associate Professor Per Arne Tufte as they were not available for us, and we therefore felt more secure to follow what we have learned in previous classes. This means that our results show that no asset in the research is normally distributed.

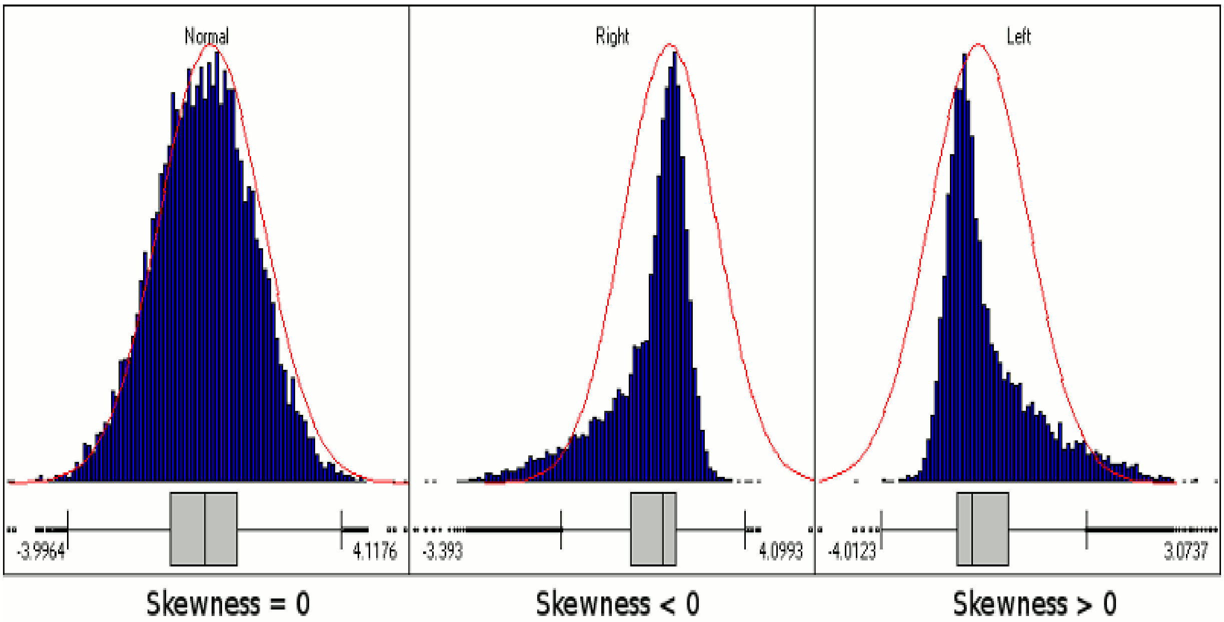


Figure 1: Skewness, from https://develve.net/skewness

Kurtosis show how the tails heaviness, or how the amount of the probability is distributed to the tails (Dunlop and Tamhame 2000). Textbooks implicate that kurtosis beyond 3 gives heavier tails, while less than 3 gives a lighter tail, which means that a kurtosis of 3 show normal tails and therefore normal distributed.

In our descriptive statistics there are four accounts of kurtosis excess of 3. These observations are Thomson Reuter Global Developed Index (3,03), Powershares Emerging Markets Sovereign Debt ETF (7,48), Bitcoin (4,40) and Litecoin (10,31).

The rest of the assets show a kurtosis less than 3, meaning that the distribution allocates more weight around the mean.

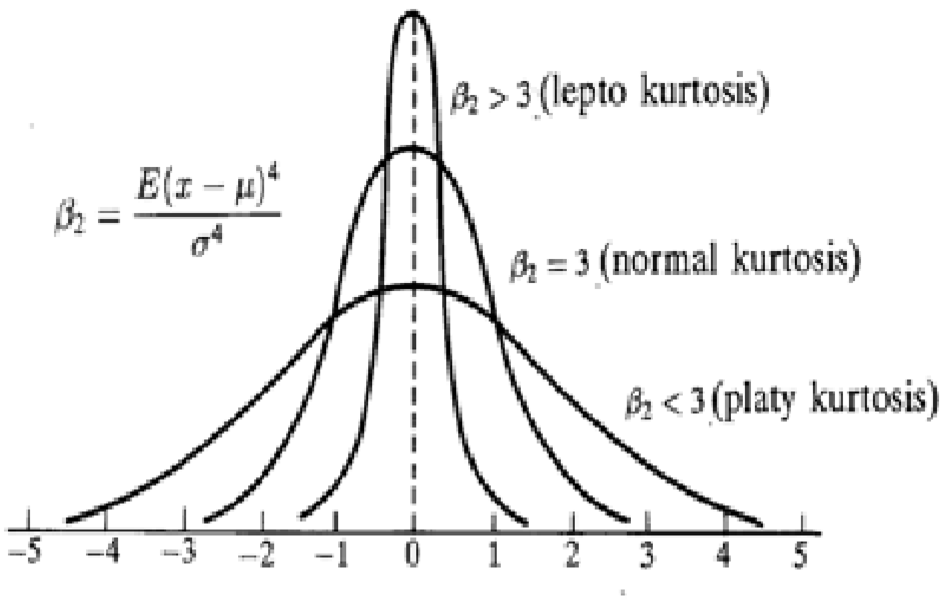


Figure 2: Kurtosis (Kothandaraman 2013)

Provided with these results we perform a test on the skewness and kurtosis, which is done by setting the skewness or kurtosis as the numerator and dividing it by (6/n) and (24/n) respectively, where n represents the number of observations. Given the results, if the test statistics are in range of -1,96 and 1,96 we keep the null hypothesis that the distribution is normally distributed.

We create the following table with skewness, kurtosis and t-test results for both:

Table 2: T-test skewness and kurtosis

Asset	Skewness	T-test Skewness	Kurtosis	T-test Kurtosis
Thomson.Reuters.Global.Emerging.Markets.Index	-0,32345117	-2,6965043	1,5550363	-6,0230897
HFRX.Global.Hedge.Fund.CAD.Index	-0,55223616	-4,6038084	1,2126974	-7,4500722
MSCI.International.World.Real.Estate.Price.Index.USD.Realtime	-0,590142	-4,9198167	2,4558415	-2,2682337
MSCI.International.World.Price.Index.USD.Realtime	-0,66912062	-5,5782351	2,914657	-0,3557381
Thomson.Reuters.Global.Developed.Index	-0,69068447	-5,7580057	3,0604452	0,2519559
ICE.Brent.Crude.Electronic.Energy.Future.Continuation.1	-0,33968923	-2,8318756	1,5663377	-5,9759818
S.P.Global.Developed.Sovereign.Bond.Index	-0,58221158	-4,8537035	1,1743172	-7,6100541
FTSE.EPRA.NAREIT.Global.Index	-0,62052677	-5,1731244	2,4543464	-2,274466
Thomson.Reuters.SGX.Corporate.Bonds.3..Years.Index	-0,27477216	-2,2906837	1,429637	-6,5457959
PowerShares.Emerging.Markets.Sovereign.Debt.ETF	-1,32082381	-11,0112669	7,5341112	18,8996855
SPDR.Citi.Intl.Govt.Inflation.Protected.Bond.ETF	-0,57530993	-4,7961668	1,5824403	-5,908861
US.Dollar.Japanese.Yen.FX.Spot.Rate	-0,01689241	-0,1408264	0,680205	-9,6696779
Euro.US.Dollar.FX.Spot.Rate	-0,28743688	-2,3962652	0,4770274	-10,5165897
UK.Pound.Sterling.US.Dollar.FX.Spot.Rate	-0,40743119	-3,3966177	0,7139238	-9,5291267
Gold.US.Dollar.FX.Spot.Rate	-0,28037066	-2,3373565	1,0452567	-8,1480211
BTC.USD.rate	0,17358297	1,4471033	4,4448703	6,0227007
LTC.USD.rate	2,07891073	17,3311844	10,4314924	30,9769351
ETH.USD.rate	0,56134294	4,6797286	0,7325565	-9,4514594

5.3 Jarque-Bera Test

To further improve upon our results, we perform a Jarque-Bera test. This test is a goodness-of-fit test to check whether the distribution follows a normal distribution. The Jarque-Bera relies on two descriptive measures, skewness and kurtosis.

Equation 11: Jarque-Bera Test (Carlson, et al. 2013)

$$JB = N\left[\left(\frac{S(r)}{6}\right)^2 + \left(\frac{K(r)-3}{24}\right)^2\right]$$

Where; S(r) is the skewness of the time series

K(r)-3 is the kurtosis of the time series

N is the number of observations

As the test is sensitive to the sample size, we follow the table below provided by Carlson, Newbold, and Thorne which comes from the original paper from Jarque and Bera (Carlson, et al. 2013):

Table 3: Jarque-Bera test statistics

N	10%	5%	N	10%	5%
20	2,13	3,26	200	3,48	4,43
30	2,49	3,71	250	3,54	4,51
40	2,70	3,99	300	3,68	4,60
50	2,90	4,26	400	3,76	4,74
75	3,09	4,27	500	3,91	4,82
100	3,14	4,29	800	4,32	5,46
125	3,31	4,34	Infinite	4,61	5,99
150	3,43	4,39			

Table was recreated from the table in the book by Carlson et al. 2013.

The null hypothesis is rejected if the Jarque-Bera test statistics exceed the appropriate value given in the table above.

For the sample size of the funds, bonds, indices, commodities and Bitcoin we choose the number 4,74 which is the significance point for 5% confidence interval given a sample size of 400. For the two other cryptocurrencies we choose differently. Litecoin has 219 observations, and therefore we set it to 4,43, which is the significance point for a sample size of 200. While we set the number 4,34 for Ethereum as it has 126 observations. The test was done in R-Studio and was sub sequentially processed in Microsoft Excel to produce the table below.

Table 4: Jarque-Bera test results

Thomson.Reuters.Global.Emerging.Mar	HFRX.Global.Hedge.Fund.CAD.Index	MSCI.International.World.Real.Estate.F
Test Results:	Test Results:	Test Results:
STATISTIC:	STATISTIC:	STATISTIC:
X-squared: 49.2863	X-squared: 46.7473	X-squared: 128.996
P VALUE:	P VALUE:	P VALUE:
Asymptotic p Value: 1.984e-11	Asymptotic p Value: 7.062e-11	Asymptotic p Value: < 2.2e-16

MSCI.International.World.Price.Index.U	Thomson.Reuters.Global.Developed.In	ICE.Brent.Crude.Electronic.Energy.Futu
Test Results:	Test Results:	Test Results:
STATISTIC:	STATISTIC:	STATISTIC:
X-squared: 178.7212	X-squared: 195.8945	X-squared: 50.6476
P VALUE:	P VALUE:	P VALUE:
Asymptotic p Value: < 2.2e-16	Asymptotic p Value: < 2.2e-16	Asymptotic p Value: 1.005e-11

S.P.Global.Developed.Sovereign.Bond.I	FTSE.EPRA.NAREIT.Global.Index	Thomson.Reuters.SGX.Corporate.Bonds
Test Results:	Test Results:	Test Results:
STATISTIC:	STATISTIC:	STATISTIC:
X-squared: 47.5189	X-squared: 131.425	X-squared: 40.7593
P VALUE:	P VALUE:	P VALUE:
Asymptotic p Value: 4.802e-11	Asymptotic p Value: < 2.2e-16	Asymptotic p Value: 1.41e-09

PowerShares.Emerging.Markets.Sovere	SPDR.Citi.Intl.Govt.Inflation.Protected.	US.Dollar.Japanese.Yen.FX.Spot.Rate
Test Results:	Test Results:	Test Results:
STATISTIC:	STATISTIC:	STATISTIC:
X-squared: 1107.5022	X-squared: 66.5123	X-squared: 8.0589
P VALUE:	P VALUE:	P VALUE:
Asymptotic p Value: < 2.2e-16	Asymptotic p Value: 3.553e-15	Asymptotic p Value: 0.01778

Euro.US.Dollar.FX.Spot.Rate	UK.Pound.Sterling.US.Dollar.FX.Spot.Ra	Gold.US.Dollar.FX.Spot.Rate
Test Results:	Test Results:	Test Results:
STATISTIC:	STATISTIC:	STATISTIC:
X-squared: 9.6959	X-squared: 20.3928	X-squared: 24.4465
P VALUE:	P VALUE:	P VALUE:
Asymptotic p Value: 0.007845	Asymptotic p Value: 3.73e-05	Asymptotic p Value: 4.915e-06

BTC.USD.rate	LTC.USD.rate	ETH.USD.rate
Test Results:	Test Results:	Test Results:
STATISTIC:	STATISTIC:	STATISTIC:
X-squared: 323.0077	X-squared: 1150.6946	X-squared: 9.4346
P VALUE:	P VALUE:	P VALUE:
Asymptotic p Value: < 2.2e-16	Asymptotic p Value: < 2.2e-16	Asymptotic p Value: 0.008939

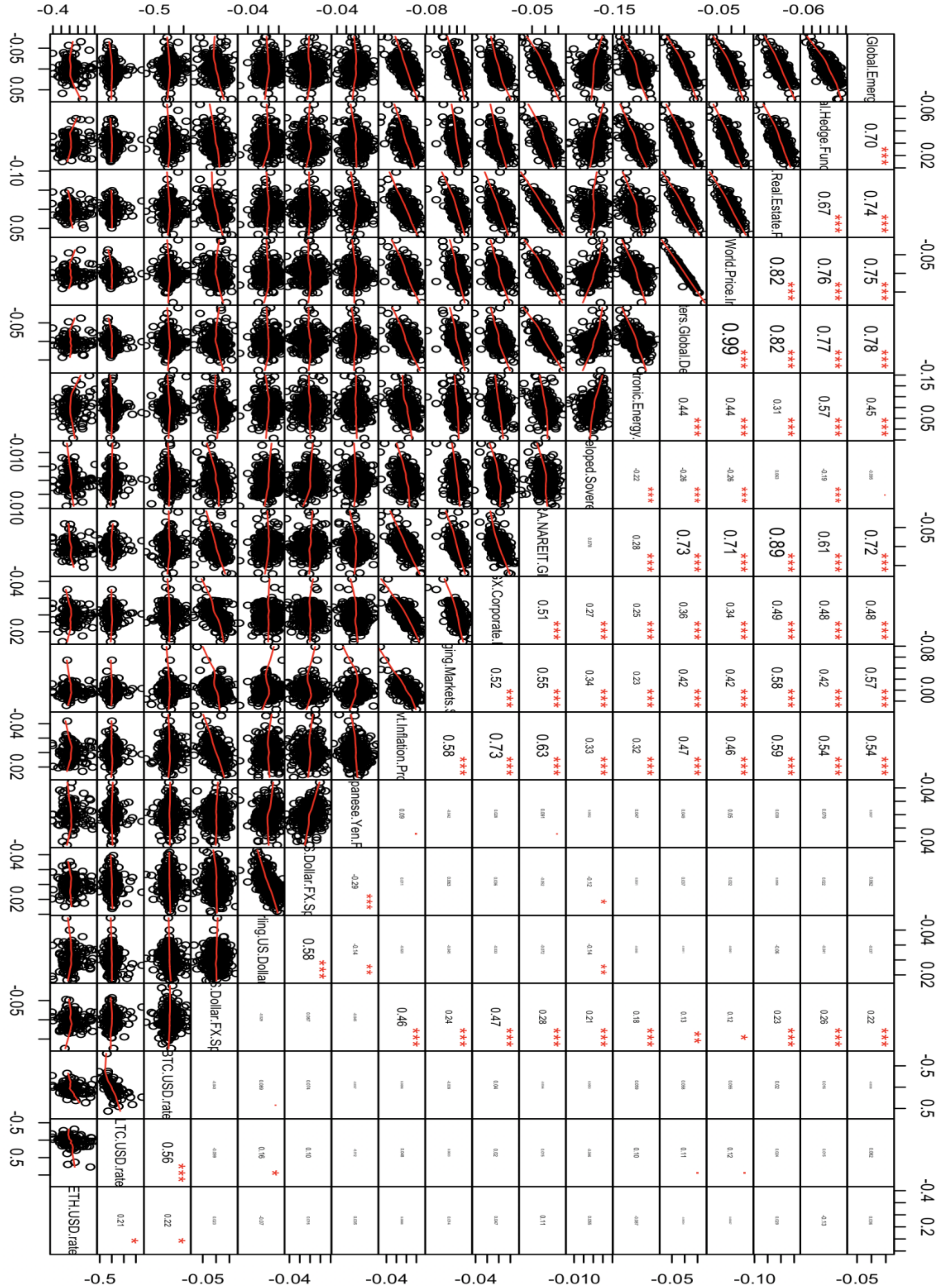
We divide the table into six by three cells to provide a better view

The test result shows us that we can reject the null hypothesis which is that the returns follow a normal distribution as all test statistics are above the numbers required given in the abovementioned table from Jarque and Bera. All results show low p-values.

Given the results in the descriptive statistics of skewness, kurtosis and Jarque-Bera test results we can conclude that none of the assets in our research follow a normal distribution.

5.4 Correlation matrix

Table 5: Correlation matrix



The stars show the significance levels for the correlation, three stars is on 99%, two stars is 95% and one star is 90%. Furthermore, the numbers under the stars is the correlation coefficient, the larger the size the greater is the correlation. In addition, the squares under the names show the distributions for each pair.

The correlation matrix shows us that cryptocurrencies have very low correlation with other assets, but some correlation with other cryptocurrencies with the 0,56 correlation between Bitcoin (BTC/USD) and Litecoin (LTC/USD) being the most noticeable. Litecoin also has some minor correlations with other assets. We can also see that most of the other assets correlates fairly well with each other, except for the normal currencies.

5.5 Annualized returns

Table 6: Annualized return

Asset	Geometric mean	Arithmetic mean
Thomson.Reuters.Global.Emerging.Markets.Index	0,004103748	0,014761454
HFRX.Global.Hedge.Fund.CAD.Index	-0,012509582	-0,007244403
MSCI.International.World.Real.Estate.Price.Index.USD.Realtime	0,049015801	0,058336006
MSCI.International.World.Price.Index.USD.Realtime	0,065483864	0,073309233
Thomson.Reuters.Global.Developed.Index	0,056331532	0,064625126
ICE.Brent.Crude.Electronic.Energy.Future.Continuation.1	-0,058265364	-0,019086688
S.P.Global.Developed.Sovereign.Bond.Index	0,005620129	0,005872144
FTSE.EPRA.NAREIT.Global.Index	0,039747371	0,050731361
Thomson.Reuters.SGX.Corporate.Bonds.3..Years.Index	0,044200972	0,045477693
PowerShares.Emerging.Markets.Sovereign.Debt.ETF	0,015074417	0,018192648
SPDR.Citi.Intl.Govt.Inflation.Protected.Bond.ETF	-0,000188187	0,003651741
US.Dollar.Japanese.Yen.FX.Spot.Rate	0,021990055	0,026580342
Euro.US.Dollar.FX.Spot.Rate	-0,028522611	-0,024097961
UK.Pound.Sterling.US.Dollar.FX.Spot.Rate	-0,025515955	-0,022149068
Gold.US.Dollar.FX.Spot.Rate	0,004709896	0,018019913
BTC.USD.rate	1,361206329	1,619969796
LTC.USD.rate	0,271189954	1,069824652
ETH.USD.rate	5,492198485	2,821516475

The table above shows that with both arithmetic and geometric average the cryptocurrencies show far superior returns than the traditional assets in our research.
The best mean for non-cryptocurrencies is the MSCI World Price Index, which again shows that it is difficult to beat the market. While the lowest results come from ICE Brent Crude, which represents oil futures, and this asset have -5,8% weekly geometric mean.

These results are in line with what we thought, have previously read and what Brière et al. and Eisl et al. find. Although we show that four assets have a negative mean return, while both Brière et al. and Eisl et al. show only one asset with negative mean return. Brière et al. does not specify whether they use geometric mean or arithmetic mean.

5.6 Capital Asset Pricing Model

Table 7: CAPM from R-Studio

Asset	Alpha	Beta	Beta+	Beta-	R-squared	Annualized Alph	Correlation	orrelation p-valu	Tracking Erro	Active Premium	nformation Rati	Treynor Ratio
Thomson.Reuters.Global.Emerging.Markets.Index	-0,001	0,786	0,6742	0,7575	0,5681	-0,049	0,7537	0	0,1004	-0,0614	-0,6112	-0,038
HFRX.Global.Hedge.Fund.CAD.Index	-0,0012	0,5606	0,5374	0,5937	0,5775	-0,0615	0,7599	0	0,091	-0,078	-0,8573	-0,0819
MSCI.International.World.Real.Estate.Price.Index.USD.Re	-0,0002	0,8451	0,8897	0,829	0,6716	-0,0089	0,8195	0	0,0855	-0,0165	-0,1927	0,016
MSCI.International.World.Price.Index.USD.Realtime	0	1	1	1	1	0	1	0	0	0	#I/T	0,0295
Thomson.Reuters.Global.Developed.Index	-0,0002	0,9872	0,9585	1,0031	0,9797	-0,0082	0,9898	0	0,02	-0,0092	-0,4582	0,0209
ICE.Brent.Crude.Electronic.Energy.Future.Continuation.1	-0,0017	0,8862	0,8283	1,2157	0,1897	-0,0843	0,4356	0	0,2567	-0,1237	-0,4821	-0,1018
S.P.Global.Developed.Sovereign.Bond.Index	-0,0005	-0,043	-0,0436	-0,0564	0,0677	-0,0265	-0,2602	0	0,1476	-0,0599	-0,4056	0,66
FTSE.EPRA.NAREIT.Global.Index	-0,0003	0,7753	0,7985	0,76	0,5042	-0,0137	0,7101	0	0,112	-0,0257	-0,2297	0,0059
Thomson.Reuters.SGX.Corporate.Bonds.3..Years.Index	0,0001	0,1595	0,2034	0,1784	0,1126	0,0049	0,3356	0	0,1332	-0,0213	-0,1598	0,0558
PowerShares.Emerging.Markets.Sovereign.Debt.ETF	-0,0005	0,2389	0,2364	0,1893	0,1743	-0,0252	0,4175	0	0,1289	-0,0504	-0,3909	-0,0806
SPDR.Citi.Intl.Govt.Inflation.Protected.Bond.ETF	-0,0008	0,289	0,267	0,2741	0,2134	-0,0412	0,462	0	0,1262	-0,0657	-0,5205	-0,1177
US.Dollar.Japanese.Yen.FX.Spot.Rate	-0,0002	0,0349	-0,1018	0,1088	0,0025	-0,0091	0,0497	0,3115	0,167	-0,0435	-0,2605	-0,3602
Euro.US.Dollar.FX.Spot.Rate	-0,0011	0,0223	-0,1177	0,0662	0,001	-0,0577	0,0317	0,5181	0,1684	-0,094	-0,5583	-2,7552
UK.Pound.Sterling.US.Dollar.FX.Spot.Rate	-0,0011	-0,0037	-0,1543	0,0273	0	-0,0549	-0,0061	0,9011	0,1646	-0,091	-0,5529	15,6182
Gold.US.Dollar.FX.Spot.Rate	-0,0004	0,1409	0,3018	-0,0883	0,0146	-0,0216	0,1209	0,0135	0,2016	-0,0608	-0,3015	-0,2079
BTC.USD.rate	0,03	0,4881	-1,1271	1,0055	0,003	3,6494	0,055	0,2784	1,1832	1,2796	1,0814	2,6247
LTC.USD.rate	0,019	1,4833	-1,0684	2,1998	0,0132	1,6655	0,1151	0,0894	1,3794	0,21	0,1522	0,1535
ETH.USD.rate	0,0536	0,0046	-1,2277	-1,2525	0	14,1018	0,0004	0,9968	1,4115	5,424	3,8428	1143,5242

Table is derived from R-Studio and copied into Microsoft Excel

Table 8: CAPM from Microsoft Excel

Asset	Beta COV/VAR	Beta KORR/STD	CAPM (MSCI)	CAPM (normal)
Thomson Reuters Global Emerging Markets Index	0,7841	0,7860	0,0672	0,0781
HFRX Global Hedge Fund CAD Index	0,5593	0,5606	0,0579	0,0658
MSCI International World Real Estate Price Index USD R	0,8431	0,8451	0,0696	0,0814
MSCI International World Price Index USD Realtime	0,9976	1,0000	0,0759	0,0899
Thomson Reuters Global Developed Index	0,9848	0,9872	0,0754	0,0892
ICE Brent Crude Electronic Energy Future Continuation	0,8840	0,8862	0,0713	0,0836
S&P Global Developed Sovereign Bond Index	-0,0429	-0,0430	0,0332	0,0326
FTSE EPRA/NAREIT Global Index	0,7734	0,7753	0,0667	0,0775
Thomson Reuters SGX Corporate Bonds 3+ Years Index	0,1592	0,1595	0,0415	0,0438
PowerShares Emerging Markets Sovereign Debt ETF	0,2383	0,2389	0,0448	0,0481
SPDR Citi Intl Govt Inflation-Protected Bond ETF	0,2883	0,2890	0,0468	0,0509
US Dollar/Japanese Yen FX Spot Rate	0,0348	0,0349	0,0364	0,0369
Euro/US Dollar FX Spot Rate	0,0222	0,0223	0,0359	0,0362
UK Pound Sterling/US Dollar FX Spot Rate	-0,0037	-0,0037	0,0348	0,0348
Gold/US Dollar FX Spot Rate	0,1405	0,1409	0,0408	0,0427
BTC/USD rate	0,4869	0,4881	0,0550	0,0618
LTC/USD rate	1,4765	1,4833	0,0955	0,1162
ETH/USD rate	0,0046	0,0046	0,0352	0,0353

Risk-free rate (weekly)	E(rm) weekly
0,000661785	0,00103016
Risk-free rate (yearly)	E(rm) yearly
0,035	0,055

Table is from our own calculations using both formulas to calculate the Beta. Notice that Performance Analytics uses the correlation divided by the standard deviation.

Table 9: Beta

Beta: MSCI.International.World.Price.Index.USD.Realtime	
Asset	*Value*
Thomson.Reuters.Global.Emerging.Markets.Index	0,78598
HFRX.Global.Hedge.Fund.CAD.Index	0,56061
MSCI.International.World.Real.Estate.Price.Index.USD.Realt	0,84512
MSCI.International.World.Price.Index.USD.Realtime	1,00000
Thomson.Reuters.Global.Developed.Index	0,98718
ICE.Brent.Crude.Electronic.Energy.Future.Continuation.1	0,88616
S.P.Global.Developed.Sovereign.Bond.Index	-0,04304
FTSE.EPRA.NAREIT.Global.Index	0,77529
Thomson.Reuters.SGX.Corporate.Bonds.3..Years.Index	0,15953
PowerShares.Emerging.Markets.Sovereign.Debt.ETF	0,23892
SPDR.Citi.Intl.Govt.Inflation.Protected.Bond.ETF	0,28904
US.Dollar.Japanese.Yen.FX.Spot.Rate	0,03493
Euro.US.Dollar.FX.Spot.Rate	0,02229
UK.Pound.Sterling.US.Dollar.FX.Spot.Rate	-0,00375
Gold.US.Dollar.FX.Spot.Rate	0,14087
BTC.USD.rate	0,48810
LTC.USD.rate	1,48328
ETH.USD.rate	0,00461

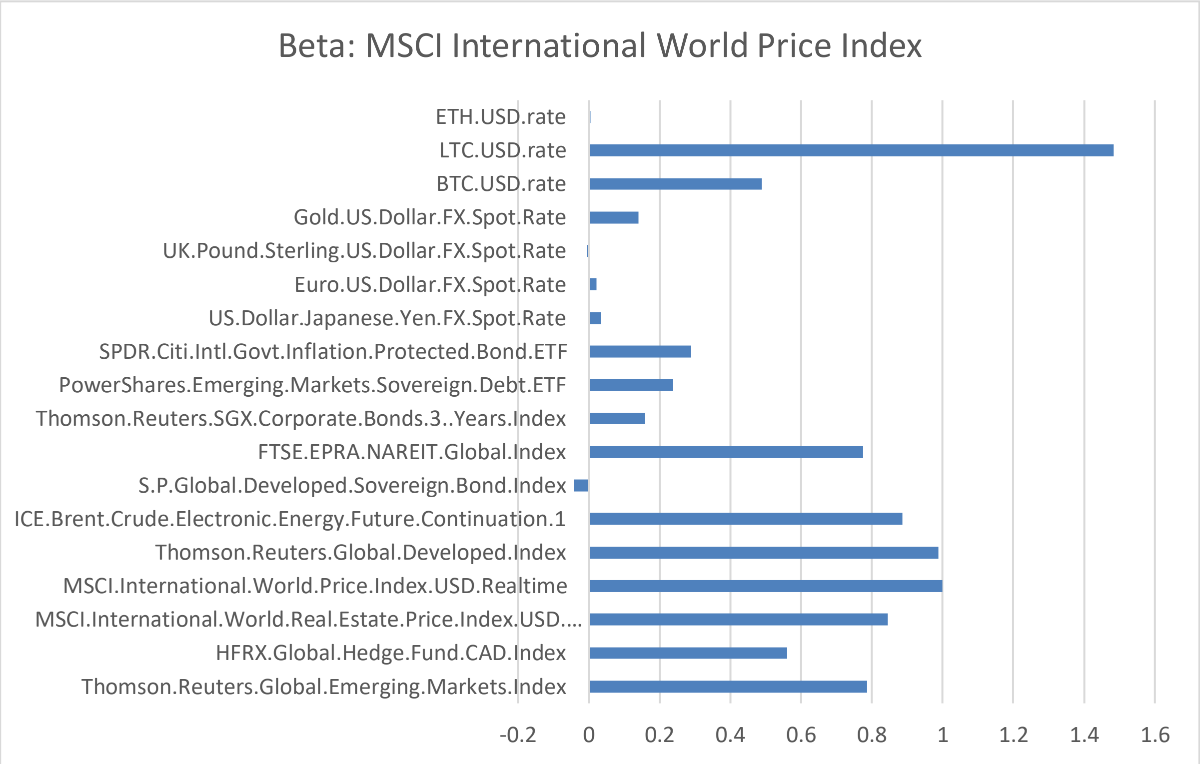


Figure 3: Beta

The CAPM results show us that Bitcoin has a beta value of 0,49 compared to the market, which in this case is the MSCI World Price Index. Litecoin has a higher beta than all of the assets, with a value of 1,48 and Ethereum has a very low beta only 0,0046. The beta-values indicate a low rate of required return for Bitcoin and Ethereum, and a higher rate of required return for Litecoin. These low betas for Bitcoin and Ethereum show us that the cryptocurrencies have a low correlation to the market (MSCI World Price Index) and therefore does not tend follow it.

We decided to calculate the betas for the assets using the two different formulas. They are closely related and therefore gives very similar results, but as you can see, using the covariance formula, it does not give 1 beta for what we have chosen as the benchmark.

As we explained in chapter 3.2 we choose to use two methods when choosing market risk premium. We decided to calculate the CAPM in both Microsoft Excel and R-Studio as Performance Analytics does not allow us to set the market risk premium we chose, and only use a vector from a dataset as benchmark. We therefore present two different CAPM results.

The market premium for CAPM (MSCI) is set to be the average rate of return for MSCI World Price Index less the risk-free rate of return. Since the MSCI World Price Index gives a lower market premium than 5,5 % used in the CAPM (Normal) these required rate of return are somewhat lower. Litecoin shows the highest expected rate of return (11,6%) of all assets in the paper, while the two other cryptocurrencies shows significantly lower rates, respectively 6% and 3,5%. The low expected return for Ethereum can be explained by the low beta value.

While some of the traditional assets outperform Bitcoin and Ethereum, nine assets fail to beat the cryptocurrencies. All returns in the table are compounded yearly.
Further we see that R-squared for all three cryptopairs is very low, indicating that the market (MSCI World Price Index) only explains very small parts or close to zero of the price variation in cryptocurrencies.

5.7 Jensen's Alpha

Table 10: Jensen's Alpha

Jensen's Alpha (Risk free = 0.000661784781395003)	
Asset	*Value*
Thomson.Reuters.Global.Emerging.Markets.Index	-0,04751
HFRX.Global.Hedge.Fund.CAD.Index	-0,04951
MSCI.International.World.Real.Estate.Price.Index.USD.Realt	-0,00643
MSCI.International.World.Price.Index.USD.Realtime	0
Thomson.Reuters.Global.Developed.Index	-0,00832
ICE.Brent.Crude.Electronic.Energy.Future.Continuation.1	-0,11637
S.P.Global.Developed.Sovereign.Bond.Index	0,007748
FTSE.EPRA.NAREIT.Global.Index	-0,01117
Thomson.Reuters.SGX.Corporate.Bonds.3..Years.Index	0,033198
PowerShares.Emerging.Markets.Sovereign.Debt.ETF	-0,00107
SPDR.Citi.Intl.Govt.Inflation.Protected.Bond.ETF	-0,01959
US.Dollar.Japanese.Yen.FX.Spot.Rate	0,019064
Euro.US.Dollar.FX.Spot.Rate	-0,03063
UK.Pound.Sterling.US.Dollar.FX.Spot.Rate	-0,02593
Gold.US.Dollar.FX.Spot.Rate	-0,00508
BTC.USD.rate	1,321015
LTC.USD.rate	0,18073
ETH.USD.rate	5,491225

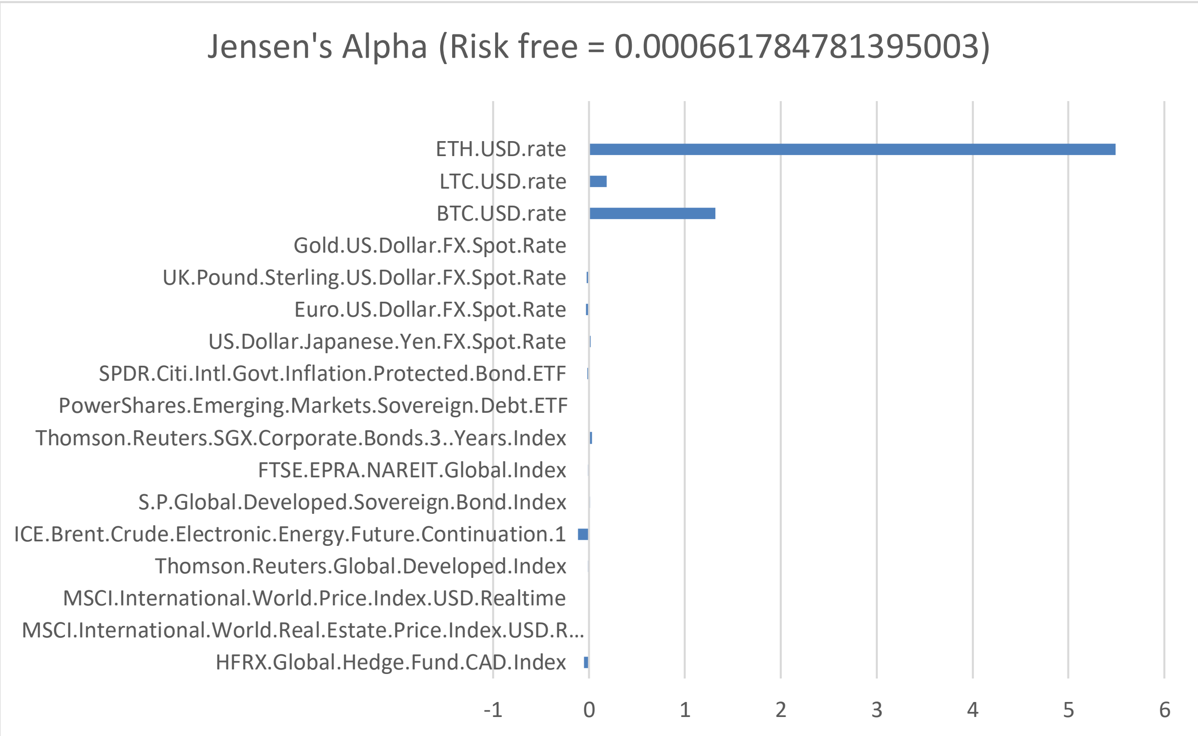


Figure 4: Jensen's Alpha

All three cryptocurrencies are showing positive results for Jensen’s Alpha. Bitcoin has a positive alpha of 132%, showing superior returns compared to the MSCI World Price Index when adjusting for risk. Further Litecoin also show a better risk-adjusted return than MSCI World index when adjusting for risk with an alpha of 18%. Ethereum has shown by far the best results when adjusting for risk with an alpha of 549% compared to the MSCI World Price Index.

All but three traditional assets show a positive Jensen’s alpha, which are the S&P Global Developed Sovereign Bond Index, Thomson Reuters SGX Corporate Bonds 3 years Index and US dollar to Japanese Yen. This show us that most of the funds, indices and currencies fail to outperform what is expected/required from them, set by the CAPM.

We choose to set the CAPM to which test the Jensen’s alpha to be the CAPM without the equity market risk premium and using the MSCI World Price Index as benchmark. This was chosen because how Performance Analytics works; we had to choose a benchmark vector to which to test the assets. It did not allow us to set a single equity market risk premium.

To sum up the results from Jensen's Alpha, cryptocurrencies have been better investments than the other assets in our study.

5.8 Treynor Ratio

Table 11: Treynor Ratio

Treynor Ratio: MSCI.International.World.Price.Index.USD.Realtime	
Asset	*Value*
Thomson.Reuters.Global.Emerging.Markets.Index	-0,03801
HFRX.Global.Hedge.Fund.CAD.Index	-0,08194
MSCI.International.World.Real.Estate.Price.Index.USD.Realt	0,016026
MSCI.International.World.Price.Index.USD.Realtime	0,029466
Thomson.Reuters.Global.Developed.Index	0,020885
ICE.Brent.Crude.Electronic.Energy.Future.Continuation.1	-0,10178
S.P.Global.Developed.Sovereign.Bond.Index	0,66
FTSE.EPRA.NAREIT.Global.Index	0,00591
Thomson.Reuters.SGX.Corporate.Bonds.3..Years.Index	0,055751
PowerShares.Emerging.Markets.Sovereign.Debt.ETF	-0,08064
SPDR.Citi.Intl.Govt.Inflation.Protected.Bond.ETF	-0,11771
US.Dollar.Japanese.Yen.FX.Spot.Rate	-0,36021
Euro.US.Dollar.FX.Spot.Rate	-2,75516
UK.Pound.Sterling.US.Dollar.FX.Spot.Rate	15,6182
Gold.US.Dollar.FX.Spot.Rate	-0,20795
BTC.USD.rate	2,624671
LTC.USD.rate	0,153523
ETH.USD.rate	1143,524

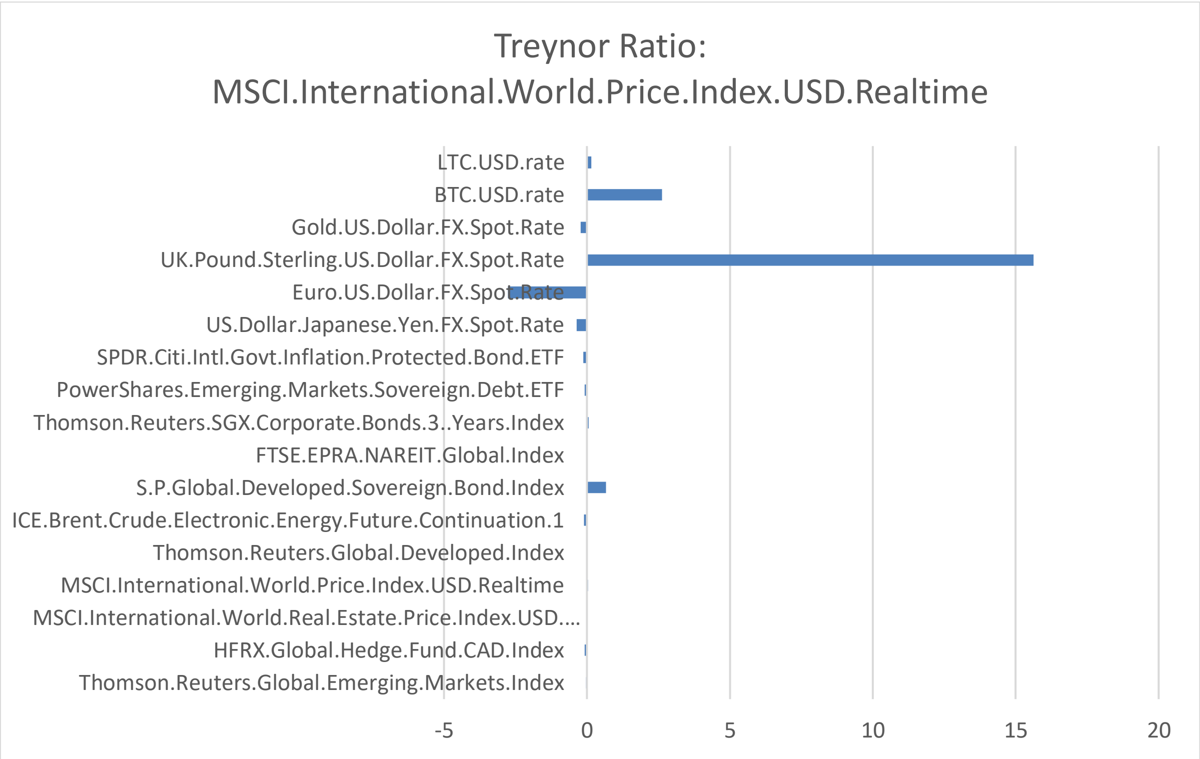


Figure 5: Treynor Ratio

The Treynor ratios provided gives us an overlook on how the assets risk adjusted return were. Since it uses the beta as a factor for systematic risk, it explains the assets sensitivity to the market. Ethereum has the absolute best Treynor ratio with 1143,52, which is very high and therefore we excluded it from the graph. This high number happens because the annual geometric average return for Ethereum is 549%, and then subtracting this large number by the small risk-free rate and then dividing it with a low beta gives us this extreme value.

One peculiar thing to notice is that UK Sterling pound to US Dollar has a Treynor of 15,62 that is much higher than the two other cryptocurrencies and is the second highest Treynor ratio in this thesis. As we research this Treynor ratio more, we see that UK Sterling pound to US Dollar has a negative annualized return, and when then divided by a low negative beta gives this high Treynor ratio for the UK Sterling pound. Another currency with an unusual Treynor ratio is the Euro to US Dollar. The ratio of -2,76 can be explained by the same reasons as those we explained for the UK Sterling pound.

Bitcoin also show a high value 2,62. Litecoin has also a positive value, but much lower than the other cryptocurrencies with 0,15. As most of the other traditional assets, except UK Sterling pound to US Dollar, shows much lower Treynor ratio, demonstrates to us that the cryptocurrencies are slightly superior.

Morningstar writes in an article that Treynor ratio is best used when comparing two assets from the same category (Morningstar 2012), so comparing the currencies and commodities with the MSCI World Price Index may not be the most correct. Because of this late finding we find it difficult to use the Treynor ratios for the currencies (Yen, GBP and EURO). We should have found a benchmark for every single fund, index, currency and commodity to make the Treynor ratio more correct. For the cryptocurrencies, as we have explained before, are more similar to stocks and therefore we regard the results as valid for them.

All in all, the Treynor Ratio indicates that cryptocurrencies are better investments in the sample period, though the results are more mixed than in the other measures since the LTC-USD has a much lower value than the other cryptocurrencies.

5.9 Information ratio

Table 12: Information Ratio

Information Ratio: MSCI.International.World.Price.Index.USD.Realtime	
Asset	*Value*
Thomson.Reuters.Global.Emerging.Markets.Index	-0,61117
HFRX.Global.Hedge.Fund.CAD.Index	-0,85727
MSCI.International.World.Real.Estate.Price.Index.USD.Realt	-0,19268
MSCI.International.World.Price.Index.USD.Realtime	#I/T
Thomson.Reuters.Global.Developed.Index	-0,45816
ICE.Brent.Crude.Electronic.Energy.Future.Continuation.1	-0,48212
S.P.Global.Developed.Sovereign.Bond.Index	-0,40555
FTSE.EPRA.NAREIT.Global.Index	-0,22971
Thomson.Reuters.SGX.Corporate.Bonds.3..Years.Index	-0,15976
PowerShares.Emerging.Markets.Sovereign.Debt.ETF	-0,39094
SPDR.Citi.Intl.Govt.Inflation.Protected.Bond.ETF	-0,52053
US.Dollar.Japanese.Yen.FX.Spot.Rate	-0,26051
Euro.US.Dollar.FX.Spot.Rate	-0,55832
UK.Pound.Sterling.US.Dollar.FX.Spot.Rate	-0,55291
Gold.US.Dollar.FX.Spot.Rate	-0,30149
BTC.USD.rate	1,08109
LTC.USD.rate	0,150441
ETH.USD.rate	3,810149

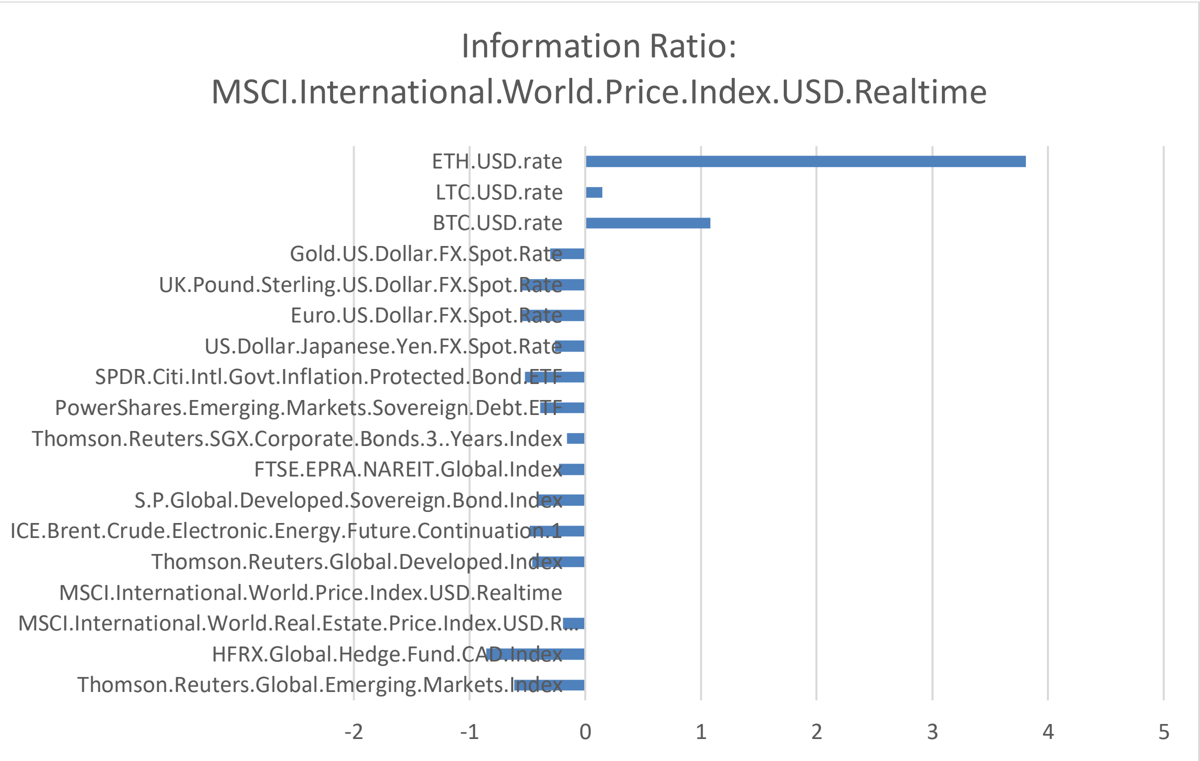


Figure 6: Information Ratio

The results from the Information Ratio measure indicate that cryptocurrencies have consistently outperformed the MSCI World Price Index return over the sample period. Ethereum has the best results with a value of 3,81, which is considered to be extremely good. Ethereum is the asset with the least observations, which of course can lead to more extreme values. Bitcoin has what we can call an exceptionally good Information ratio of 1,08 and Litecoin has a close to zero but still positive information ratio. All the other assets in the datasets has negative information ratio, indicating that it is better to invest in the benchmark, MSCI World Price Index, than other assets except cryptocurrencies.

To sum up the Information ratio, it clearly indicates that cryptocurrencies was a good investment in the sample period.

5.10 Sharpe ratio

Table 13: Sharpe Ratio

Annualized Sharpe Ratio (Rf=3.4%)	
Asset	*Value*
Thomson.Reuters.Global.Emerging.Markets.Index	-0,13472
HFRX.Global.Hedge.Fund.CAD.Index	-0,40368
MSCI.International.World.Real.Estate.Price.Index.USD.Realt	0,165829
MSCI.International.World.Price.Index.USD.Realtime	0,278054
Thomson.Reuters.Global.Developed.Index	0,216544
ICE.Brent.Crude.Electronic.Energy.Future.Continuation.1	-0,18798
S.P.Global.Developed.Sovereign.Bond.Index	-1,23327
FTSE.EPRA.NAREIT.Global.Index	0,106845
Thomson.Reuters.SGX.Corporate.Bonds.3..Years.Index	0,166399
PowerShares.Emerging.Markets.Sovereign.Debt.ETF	-0,20262
SPDR.Citi.Intl.Govt.Inflation.Protected.Bond.ETF	-0,35145
US.Dollar.Japanese.Yen.FX.Spot.Rate	-0,07964
Euro.US.Dollar.FX.Spot.Rate	-0,59552
UK.Pound.Sterling.US.Dollar.FX.Spot.Rate	-0,65875
Gold.US.Dollar.FX.Spot.Rate	-0,10055
BTC.USD.rate	1,340214
LTC.USD.rate	0,746197
ETH.USD.rate	1,980748

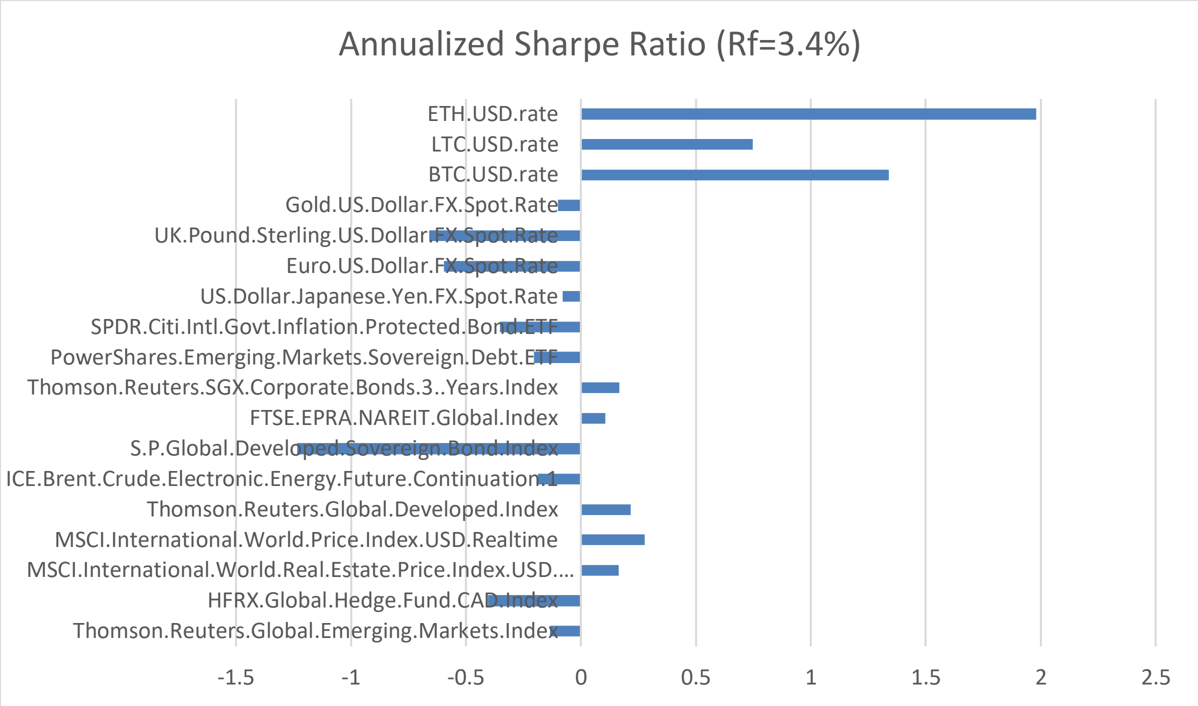


Figure 7: Sharpe Ratio

The Sharpe ratio gives us an indication on how well the asset has performed when looking at its standard deviation and the risk-free rate. We calculate this by using weekly rates and therefore by multiplying the result with the square root of 52 we get the annualized Sharpe ratio, a method proposed by Morningstar (Morningstar 2005).

First thing we can see is that the cryptocurrencies has a much higher Sharpe than any other asset in question, respectively 1,34 (Bitcoin), 0,75 (Litecoin) and 1,98 (Ethereum). The results on Bitcoin are in line with the results from Brière et al., but our results are lower (Brière et al. shows a Sharpe ratio 2,30). This may be explained by the few observations they have (only two and a half years of observations), which can have influenced their results on the standard deviation and annual mean. Nevertheless, we feel that our results reflect what we could see from the descriptive statistics.

Second element of interest is the Sharpe ratio of the S&P Global Developed Sovereign Bond Index, which is very low (-1,23). This result is far more negative than any other of our assets and that of the results in Brière et al. Lowest Sharpe ratio from Brière et al. is -0,14 which is for the EUR-USD. Again, we see that the cryptocurrencies outperform the traditional assets as they have superior Sharpe ratios.

The third component we wanted to mention is that Brière et al. show only one asset with a negative Sharpe ratio, while we show ten assets with a negative Sharpe measure. As we do not have any insights in the dataset and methodology of Brière et al., it proves to be very difficult to explain these differences.

We want to clarify that since the Sharpe ratio is dimensionless, we cannot describe how better the cryptocurrencies are than the traditional assets just that they are much higher. This makes it difficult to explain how much better the cryptocurrencies are in comparison to the traditional assets.

To sum up the results from the Sharpe Ratio, it indicates that the cryptocurrencies have been a far better investment than the other assets in the sample period.

5.11 Omega ratio

Table 14: Omega Ratio

Omega (L = 0.1%)	
Asset	*Value*
Thomson.Reuters.Global.Emerging.Markets.Index	0,862497
HFRX.Global.Hedge.Fund.CAD.Index	0,754166
MSCI.International.World.Real.Estate.Price.Index.USD.Realt	0,961786
MSCI.International.World.Price.Index.USD.Realtime	1
Thomson.Reuters.Global.Developed.Index	0,97617
ICE.Brent.Crude.Electronic.Energy.Future.Continuation.1	0,883846
S.P.Global.Developed.Sovereign.Bond.Index	0,336833
FTSE.EPRA.NAREIT.Global.Index	0,945995
Thomson.Reuters.SGX.Corporate.Bonds.3..Years.Index	0,858933
PowerShares.Emerging.Markets.Sovereign.Debt.ETF	0,76442
SPDR.Citi.Intl.Govt.Inflation.Protected.Bond.ETF	0,746132
US.Dollar.Japanese.Yen.FX.Spot.Rate	0,842295
Euro.US.Dollar.FX.Spot.Rate	0,700014
UK.Pound.Sterling.US.Dollar.FX.Spot.Rate	0,678497
Gold.US.Dollar.FX.Spot.Rate	0,884725
BTC.USD.rate	1,752526
LTC.USD.rate	1,400147
ETH.USD.rate	2,162531

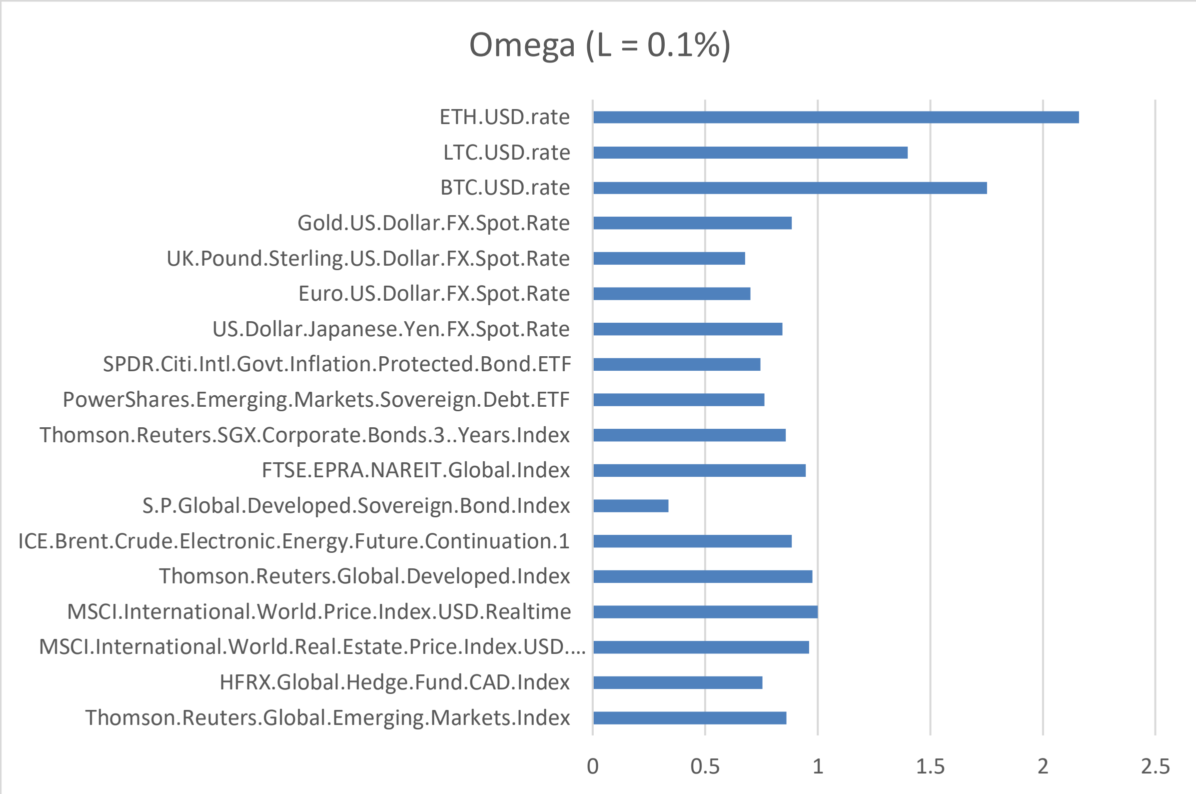


Figure 8: Omega Ratio

As we set the required level of return (L) as the weekly mean from the MSCI International World Price Index, the results show that the cryptocurrencies outperform the traditional assets as they are higher. All three cryptocurrencies have a higher than 1 Omega ratio, where Bitcoin have 1,75, Litecoin 1,4 and Ethereum 2,16.

MSCI World Price Index has, of course, 1 as it is the benchmark set. Many other traditional assets show an Omega ratio close to 1, while S&P Global Developed Sovereign Bond Index shows the lowest Omega ratio of all assets with 0,33.

The results from the Omega ratio clearly indicate that cryptocurrencies have been better investments in the sample period.

5.12 Sortino ratio

Table 15: Sortino Ratio

Sortino Ratio (MAR = 0.141%)	
Asset	*Value*
Thomson.Reuters.Global.Emerging.Markets.Index	-0,35153
HFRX.Global.Hedge.Fund.CAD.Index	-0,55977
MSCI.International.World.Real.Estate.Price.Index.USD.Realt	-0,09089
MSCI.International.World.Price.Index.USD.Realtime	#I/T
Thomson.Reuters.Global.Developed.Index	-0,05597
ICE.Brent.Crude.Electronic.Energy.Future.Continuation.1	-0,37073
S.P.Global.Developed.Sovereign.Bond.Index	-0,55508
FTSE.EPRA.NAREIT.Global.Index	-0,13232
Thomson.Reuters.SGX.Corporate.Bonds.3..Years.Index	-0,21651
PowerShares.Emerging.Markets.Sovereign.Debt.ETF	-0,39291
SPDR.Citi.Intl.Govt.Inflation.Protected.Bond.ETF	-0,49613
US.Dollar.Japanese.Yen.FX.Spot.Rate	-0,33951
Euro.US.Dollar.FX.Spot.Rate	-0,67751
UK.Pound.Sterling.US.Dollar.FX.Spot.Rate	-0,68748
Gold.US.Dollar.FX.Spot.Rate	-0,33141
BTC.USD.rate	2,144108
LTC.USD.rate	1,42521
ETH.USD.rate	3,919912

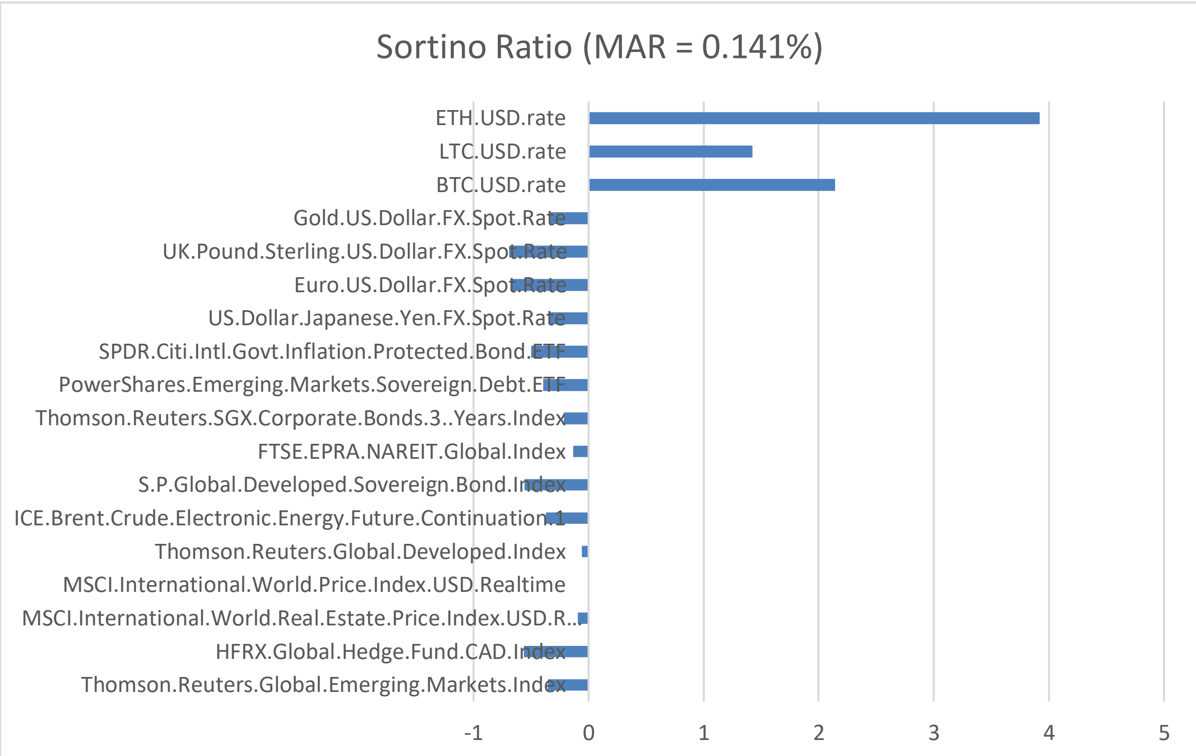


Figure 9: Sortino Ratio

As Performance Analytics package in R does not take into account scaling for our Sortino ratios, we had to do this manually. We did this by multiplying the output Sortino ratio with the square root of 52 (Harwood 2017). This works because it works in many ways as the Sharpe ratio, using the standard deviation.

The results show superior returns for cryptocurrencies. Ethereum shows a result of 3,92. Bitcoin gives a result of 2,14 and Litecoin gives a result of 1,43, indicating that they have been good investments in the period. All the other assets in our study shows results below zero. The currencies UK Sterling pound to US Dollar and EURO to US Dollar has the lowest Sortino ratio with respectively -0,69 and -0,68. S&P Global Developed Sovereign Bond index and HFRX Global Hedge Fund CAD Index, reporting a Sortino ratio of -0,56, indicating that they were a poor investment compared to the other investments in the dataset.

The results from the Sortino Ratio imply that cryptocurrencies have been better investments than the other assets in our dataset.

5.13 Historic return of cryptocurrencies

We have researched the historic return of cryptocurrencies by creating portfolios of the ten largest cryptocurrencies by market cap on the last Sunday of each year and then rebalance the portfolios on the last Sunday of each year with the cryptocurrencies that are the ten largest. By doing this we believe we are overcoming the problems with survivor bias. Over the full period the equal-weighted portfolios have had an accumulated return of 3058%, mostly driven by the enormous return of 9363% of 2017. The value-weighted portfolios have had an accumulated return of 2263% over the full period.

During the four-year period 21 different cryptocurrencies have been part of the portfolio for at least one year each, and only to cryptocurrencies have been in the portfolio the full period, namely Bitcoin and Litecoin. The data has been collected from historic snapshots on www.coinmarketcap.com/historical/. In appendix 1 you can find screenshots from the .xls file with all the numbers and data for each cryptocurrency in the portfolio.

Table 16: Historic returns

Year	Equal-weighted return	Value-weighted return
2014	**(78 %)**	**(60%)**
2015	**(45 %)**	**12 %**
2016	**183 %**	**112 %**
2017	**9363 %**	**2366 %**
2014 - 2017	**3058 %**	**2263 %**

The table shows the return from investing in the 10 largest cryptocurrencies on the last Sunday of the preceding year and holding the position until the last Sunday of the following year. The equal weighted portfolio invests 1/10 in each of the 10 largest cryptocurrencies ranked by market cap, while the value weighted portfolio invests weighted on each cryptocurrency weight of the market cap of the ten largest. The portfolios are rebalanced each year on the last Sunday since some cryptocurrencies falls out of the top 10 and some get in. Returns in ( ) and red shows a negative return.

6 Concluding remarks

In this thesis we show that the capital asset pricing model seems to hold for cryptocurrencies, like it does for the traditional assets. The alpha is much higher for the cryptocurrencies than the other assets, as it should be based on risk and return. **We therefore conclude that the capital asset pricing model does in fact hold for cryptocurrencies.** Our research also suggests that it is difficult to outperform the market, which is in line with previous financial literature. Cryptocurrencies does in fact beat the market, which again show that it is has been formidable investment in the time period.

With their low correlations, cryptocurrencies also show some safe haven attributes as they could be used as a hedge when the market is worse.

All the performance metrics in our work indicates that cryptocurrencies offer a good tradeoff between risk and return. Our paper show that cryptocurrencies outperform all traditional assets, based on the performance measures we use. Our results suggest that given systematic, unsystematic or whole risk taken into account, cryptocurrencies do provide a better return than the other assets. **Based on our research, well-diversified portfolio should contain cryptocurrencies.** We do not know how much of the portfolio should be of cryptocurrencies, as we did not research this.

This shows that although being heavily criticized by media, finance people and famous investors, it has clearly been an excellent investment opportunity up until now.

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Attachments

Historic returns 2014

Asset	29/12 2013	mcap mUSD	Vekter 29/12 2013	28/12 2014	mcap mUSD	Avkastning	Vektet avkastningsbidrag til proteføljen
Bitcoin	754,01	9268	0,887423255	320,19	4249	-0,5753505	-0,510579378
Litecoin	24,35	598	0,057259291	2,72	95	-0,8882957	-0,050863181
Peercoin	4,61	96	0,009192127	0,59	12,59	-0,8720174	-0,008015694
Namecoin	5,1	39	0,003734302	0,7155	7,45	-0,8597059	-0,003210401
Ripple	0,027209	212,7	0,020366306	0,023793	737	-0,1255467	-0,002556922
Quarkcoin	0,11	27,85	0,002666674	0,005679	1,4	-0,9483727	-0,002529001
Bitshares PTS	19,7	23,95	0,002293244	0,00709	0,443	-0,9996401	-0,002292419
Infiniecoin	0,000108	10,57	0,001012091	0,000005	0,414	-0,9537037	-0,000965235
Omni	179,29	115,92	0,011099493	3,08	1,604	-0,9828211	-0,010908817
NXT	0,052105	51,73	0,004953216	0,018032	16,71	-0,6539296	-0,003239054
Avkastning EW						-79 %	
Avkastning VW						-60 %	
Total mcap		10443,72					

Historic returns 2015

Asset	28/12 2014	mcap mUSD	Vekter 28/12 2014	27/12 2015	mcap mUSD	Avkastning	Vektet avkastningsbidrag til proteføljen
Bitcoin	316	4315	0,79753218	416,5	6251	0,31803797	0,253645519
Ripple	0,023793	737	0,13621813	0,006171	207	-0,740638	-0,100888321
Litecoin	2,74	96	0,01774347	3,43	150	0,25182482	0,004468247
Bitshares	0,016369	40,88	0,00755576	0,00335	8,496	-0,7953449	-0,006009437
Dogecoin	0,000183	17,75	0 %	0,00014	14,383	-0,2349727	-0,000770874
NXT	0,016162	16,16	0,00298682	0,006167	6,166	-0,6184259	-0,001847126
Peercoin	0,578719	12,71	0,00234916	0,408048	9,33	-0,2949117	-0,000692795
Maidsafecoin	0,04965	22,47	0,00415308	0,013993	6,33	-0,7181672	-0,002982607
Paycoin	10,74	132	0,02439728	0,038444	0,632	-0,9964205	-0,024309946
Stellar	0,005759	20,47	0,00378343	0,001691	8,179	-0,7063726	-0,002672509
Avkastning EW						-45 %	
Avkastning VW						12 %	
Total mcap		5410,44					

Historic returns 2016

Asset	27/12 2015	mcap mUSD	Vekter 27/12 2015	25/12 2016	mcap mUSD	Avkastning	Vektet avkastningsbidrag til proteføljen
Bitcoin	416,5	6251	0,928056127	878,81	14115	1,109988	1,03013116
Ripple	0,006171	207	0,030732302	0,006381	229	0,03403014	0,001045825
Litecoin	3,43	150	0,022269784	4,35	213	0,26822157	0,005973236
Ethereum	0,933542	64,491	0,009574671	7,29	635	6,80896842	0,065193632
Dash	2,69	16,378	0,002431563	9,91	69	2,68401487	0,006526353
Dogecoin	0,00014	14,38	0,00213493	0,000223	24,455	0,59285714	0,001265708
Peercoin	0,408048	9,33	0,001385181	0,233687	5,547	-0,4273051	-0,000591895
Bitshares	0,00335	8,496	0,001261361	0,004224	10,89	0,26089552	0,000329083
Maidsafecoin	0,013993	6,33	0,000939785	0,10421	47	6,44729508	0,00605907
Stellar	0,001691	8,179	0,001214297	0,002636	18,24	0,55884092	0,000678599
Avkastning EW						183 %	
Avkastning VW						112 %	
Total mcap		6735,584					

Historic returns 2017

Asset		25/12 2016	mcap mUSD		Vekter 25/12 2016		31/12 2017	mcap mUSD		Avkastning	Vektet avkastningsbidrag til proteføljen
Bitcoin		878,81	14115		0,904849397		13170	220903		13,9861745	12,65538154
Ethereum		7,29	635		0,040707004		721,66	69797		97,9931413	3,989007232
Ripple		0,006381	229		0,014680164		2,12	82199		331,236327	4,862603526
Litecoin		4,35	213		0,013654475		220	12000		49,5747126	0,676916698
Monero		9,63	131		0,008397823		338	5255		34,0986501	0,286354426
Ethereum Classic		1,1	96		0,00615413		27,14	2680		23,6727273	0,145685036
Dash		9,91	69		0,004423281		1008	7850		100,715439	0,445492666
Maidsafecoin		0,10421	47		0,003012959		0,800732	362		6,68383073	0,02013811
Augur		2,89	31,75		0,00203535		65,03	715		21,5017301	0,043763551
Nem		0,003615	32,531		0,002085417		0,9322	8389		256,869986	0,535680941
Avkastning EW										9363 %	
Avkastning VW										2366 %	
Total mcap			15599,281					410150			

Accumulated historic returns

Akkumulert avkastning i perioden 1/1 2014 - 31/12-2017 hvis man hadde rebalansert porteføljen ved starten av hvert år	
Equal weighted	3037 %
Value weighted	2262 %

R-Studio script file

```
#### Housekeeping ####
rm(list=ls())
setwd("/Users/john-johnparma/Dropbox/Skole/Skole HiOA/Masteroppgave/Dataset")


#### Libraries ####
library(quantmod)
library(dplyr)
library(stargazer)
library(readxl)
library(fBasics)
library(psych)
library(rJava)
library(xlsx)
library(spatialEco)
library(PerformanceAnalytics)
library(DescTools)
library(tseries)
library(forecast)


#### Load datafile ####
samlet_dataset_btc = read_excel("Samlet dataset.xlsx", col_names = T)


#### Make a log matrix from dataset ####
samlet_dataset_log = diff(log(as.matrix(samlet_dataset_btc[2:19])))
dates = samlet_dataset_btc[,1]
```

```
dates = dates[-1,] # Removing top row

#Chaining dates vector with logged matrix
samlet_dataset_log = cbind(dates,samlet_dataset_log)
#samlet_dataset_log[is.na(samlet_dataset_log)] <- 0 #Converting NA to 0

#Setting Exhange date as row names
samlet_dataset_log = data.frame(samlet_dataset_log[,-1], row.names =
samlet_dataset_log[,1])
samlet_dataset_log = as.xts(samlet_dataset_log)


dates = samlet_dataset_btc[,1]
col_names = colnames(samlet_dataset_log)
samlet_dataset_btc = samlet_dataset_btc[,-1]
samlet_dataset_btc = data.matrix(samlet_dataset_btc)
samlet_dataset_btc = cbind(dates,samlet_dataset_btc)
samlet_dataset_btc = data.frame(samlet_dataset_btc[,-1], row.names =
samlet_dataset_btc[,1])
samlet_dataset_btc = as.xts(samlet_dataset_btc)

#Making three different datasets
samlet_btc = samlet_dataset_log[,-17]
samlet_btc = samlet_btc[,-17]
samlet_btc = na.omit(samlet_btc)

samlet_ltc = samlet_dataset_log[,-16]
samlet_ltc = samlet_ltc[,-17]
samlet_ltc = na.omit(samlet_ltc)

samlet_eth = samlet_dataset_log[,-16]
samlet_eth = samlet_eth[,-16]
samlet_eth = na.omit(samlet_eth)

#### Make a correlation table/chart and descriptive statistics ####
correlation_log = cor(samlet_dataset_log, use = "complete.obs") #complte.obs will ignore the
NA in the dataset

chart.Correlation(samlet_dataset_log, histogram = F, pch = "+")
dev.copy(jpeg, filename = "corr.jpeg")
dev.off()

#charts.RollingPerformance(samlet_dataset_log[,16:18], Rf = rf, legend.loc = T)

#chart.TimeSeries(samlet_dataset_log, legend.loc = T, xaxis = T, yaxis = T, type = "l", main
= "Returndata", colorset = redfocus)

desc_stats = describe(samlet_dataset_log, na.rm = T)
write.xlsx(x=desc_stats, file = "desc.xlsx", col.names = T, row.names = T, showNA = T)
```

```
#desc_stats1 = table.Stats(samlet_dataset_log, ci=0.95, digits = 4)


#### Performance ratios ####
rf_w =  ((1 + 0.035)^(1/52)-1) #Normalized from the paper by Duff & Phelps
rf = 0.035

#returns = Return.calculate(samlet_dataset_btc[,1:18], method = "log")

#Skewness and Kurtosis
skewness.vector = vector(mode = "numeric")
kurtosis.vector = vector(mode = "numeric")

for(i in 1:18) {
  skew = skewness(samlet_dataset_log[,i], na.rm = T)
  skewness.vector = insert.values(skewness.vector, skew, i)
  kurt = kurtosis(samlet_dataset_log[,i], na.rm = T)
  kurtosis.vector = insert.values(kurtosis.vector, kurt, i)
}

ttest.s.vector = vector(mode = "numeric")
ttest.k.vector = vector(mode = "numeric")

ttest.k.vector = vector(mode = "numeric")
for(j in 1:18) {
  skew = skewness.vector[j]/sqrt(6/length(samlet_dataset_log[,j]))
  kurt = (kurtosis.vector[j]-3)/sqrt(24/length(samlet_dataset_log[,j]))
  ttest.s.vector = insert.values(ttest.s.vector, skew, j)
  ttest.k.vector = insert.values(ttest.k.vector, kurt, j)
}


sk_dataset = cbind(skewness.vector,ttest.s.vector,kurtosis.vector,ttest.k.vector)


#Test of normality using JB-test
normalTest(samlet_dataset_log[,18],method="jb", na.rm = T)
#Have to do this for every single one


#Autocorrelation
acfPlot(samlet_dataset_log[,1], lag.max = length(samlet_dataset_log[,1]), na.action =
na.omit)
#Have to do this for every single one

#Beta
beta.assets = CAPM.beta(samlet_dataset_log[,1:15], Rb = samlet_dataset_log[,4], Rf = rf)
BTC.USD.rate = CAPM.beta(na.omit(samlet_dataset_log[,16]), Rb = samlet_dataset_log[,4],
Rf = rf)
```

```
LTC.USD.rate = CAPM.beta(na.omit(samlet_dataset_log[,17]), Rb = samlet_dataset_log[,4],
Rf = rf)
ETH.USD.rate = CAPM.beta(na.omit(samlet_dataset_log[,18]), Rb = samlet_dataset_log[,4],
Rf = rf)
beta.assets = cbind(beta.assets,BTC.USD.rate,LTC.USD.rate,ETH.USD.rate)

#CAPM
table.assets = table.SFM(samlet_dataset_log[,1:15], Rb = samlet_dataset_log[,4], Rf = rf)
table.btc = table.SFM(na.omit(samlet_dataset_log[,16]), Rb = samlet_dataset_log[,4], Rf = rf)
table.ltc = table.SFM(na.omit(samlet_dataset_log[,17]), Rb = samlet_dataset_log[,4], Rf = rf)
table.eth = table.SFM(na.omit(samlet_dataset_log[,18]), Rb = samlet_dataset_log[,4], Rf = rf)
table.assets = cbind(table.assets,table.btc,table.ltc,table.eth)

write.xlsx(x=table.assets, file = "table.xlsx", col.names = T, row.names = T, showNA = T)

#Returns
ret.vector.geo = vector(mode = "numeric")
for(i in 1:18) {
  ret = Return.annualized(na.omit(samlet_dataset_log[,i]), scale = 52)
  ret.vector.geo = insert.values(ret.vector.geo, ret, i)
}

ret = annualReturn(na.remove(samlet_dataset_log[,18]), type = 'arithmetic')

ret.vector.ari = vector(mode = "numeric")
for(i in 1:18) {
  ret = Return.annualized(na.omit(samlet_dataset_log[,i]), scale = 52, geometric = F)
  ret.vector.ari = insert.values(ret.vector.ari, ret, i)
}

ret.vector.geo = cbind(ret.vector.geo,ret.vector.ari)


#Jensen's Alpha
jalpha.assets = CAPM.jensenAlpha(samlet_dataset_log[,1:15], Rb = samlet_dataset_log[,4],
Rf = rf)
jalpha.btc = CAPM.jensenAlpha(na.omit(samlet_dataset_log[,16]), Rb =
samlet_dataset_log[,4], Rf = rf)
jalpha.ltc = CAPM.jensenAlpha(na.omit(samlet_dataset_log[,17]), Rb =
samlet_dataset_log[,4], Rf = rf)
jalpha.eth = CAPM.jensenAlpha(na.omit(samlet_dataset_log[,18]), Rb =
samlet_dataset_log[,4], Rf = rf)
jalpha.assets = cbind(jalpha.assets,jalpha.btc,jalpha.ltc,jalpha.eth)

#Treynor' ratio
tratio.assets = TreynorRatio(samlet_dataset_log[,1:15], samlet_dataset_log[,4], Rf = rf, scale
= 52)
tratio.btc = TreynorRatio(na.omit(samlet_dataset_log[,16]), samlet_dataset_log[,4], Rf =
rf_w, scale = 52)
```

```
tratio.ltc = TreynorRatio(na.omit(samlet_dataset_log[,17]), samlet_dataset_log[,4], Rf = rf_w,
scale = 52)
tratio.eth = TreynorRatio(na.omit(samlet_dataset_log[,18]), samlet_dataset_log[,4], Rf =
rf_w, scale = 52)
tratio.assets = cbind(tratio.assets,tratio.btc,tratio.ltc,tratio.eth)

#Information ratio
infratio.test = InformationRatio(na.trim(samlet_dataset_log[,1:18]), samlet_dataset_log[,4])
infratio.assets = InformationRatio(samlet_dataset_log[,1:15], samlet_dataset_log[,4])
infratio.btc = InformationRatio(na.omit(samlet_dataset_log[,16]), samlet_dataset_log[,4])
infratio.ltc = InformationRatio(na.omit(samlet_dataset_log[,17]), samlet_dataset_log[,4])
infratio.eth = InformationRatio(na.omit(samlet_dataset_log[,18]), samlet_dataset_log[,4])
infratio.assets = cbind(infratio.assets,infratio.btc,infratio.ltc,infratio.eth)

#Sharpe ratio
sharpe.assets = SharpeRatio.annualized(samlet_dataset_log[,1:15], Rf = rf, scale = 52,
geometric = F)
sharpe.btc = SharpeRatio.annualized(na.omit(samlet_dataset_log[,16]), Rf = rf, scale = 52,
geometric = F)
sharpe.btc.t = SharpeRatio(na.omit(samlet_dataset_log[,16]), FUN = "StdDev")
sharpe.btc.t = sharpe.btc.t*sqrt(52)
sharpe.ltc = SharpeRatio.annualized(na.omit(samlet_dataset_log[,17]), Rf = rf, scale = 52,
geometric = F)
sharpe.eth = SharpeRatio.annualized(na.omit(samlet_dataset_log[,18]), Rf = rf, scale = 52,
geometric = F)
sharpe.assets = cbind(sharpe.assets,sharpe.btc,sharpe.ltc,sharpe.eth)

#Omega ratio
omega.assets = Omega(samlet_dataset_log[,1:15], L = samlet_dataset_log[,4])
omega.btc = Omega(na.omit(samlet_dataset_log[,16]), L = samlet_dataset_log[,4], na.rm = T)
omega.ltc = Omega(na.omit(samlet_dataset_log[,17]), L = samlet_dataset_log[,4], na.rm = T)
omega.eth = Omega(na.omit(samlet_dataset_log[,18]), L = samlet_dataset_log[,4], na.rm = T)
omega.assets = cbind(omega.assets,omega.btc,omega.ltc,omega.eth)

#Sortino ratio
sortino.assets = SortinoRatio(samlet_dataset_log[,1:15], MAR = samlet_dataset_log[,4])
sortino.assets = sortino.assets*sqrt(52)
sortino.btc = SortinoRatio(na.omit(samlet_dataset_log[,16]), MAR = samlet_btc[,4])
sortino.btc = sortino.btc*sqrt(52)
sortino.ltc = SortinoRatio(na.omit(samlet_dataset_log[,17]), MAR = samlet_ltc[,4])
sortino.ltc = sortino.ltc*sqrt(52)
sortino.eth = SortinoRatio(na.omit(samlet_dataset_log[,18]), MAR = samlet_eth[,4])
sortino.eth = sortino.eth*sqrt(52)
#using mean return from the market as minimum acceptable return (made into weekly return)
sortino.assets = cbind(sortino.assets,sortino.btc,sortino.ltc,sortino.eth)

#### Write everything to a matrix/excel file ####
master = matrix()
```

```
master =
rbind(beta.assets,jalpha.assets,tratio.assets,infratio.assets,sharpe.assets,omega.assets,sortino.assets)


#Write to excel file
master = as.data.frame(master, col.names = col.samlet_dataset_btc)
write.xlsx(x=master, file = "master.xlsx", row.names = T, showNA = T)
```