Could cryptocurrencies contribute to a well-diversified portfolio for European investors?

An in-depth research regarding cryptocurrency expected return and the possible diversification, hedge and safe haven benefits of adding cryptocurrencies to a well-diversified portfolio.

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Abstract

Cryptocurrencies are relatively new in the world of finance and existing literature is limited. Therefore, research in this area is challenging though relevant and recent. The aim of this study is to investigate whether cryptocurrencies could contribute to a well-diversified portfolio for European investors. In order to efficiently answer this question, possible diversification, hedge and safe haven characteristics are examined. Furthermore, an appropriate expected return estimate is researched by finding an expected return which justifies 5% allocation to cryptocurrencies in a well-diversified portfolio. For this study correlations are examined as well as their 30-day moving correlations. Subsequently, mean-variance analysis gives a representation of the portfolio frontiers, followed by volatility target analysis and the implementation of the Black-Litterman model. We find that cryptocurrencies have extreme historical return and volatility properties and they are uncorrelated with equity asset classes and have a very low correlation with bonds. Therefore, we conclude that cryptocurrencies serve as diversifier for a well-diversified portfolio and possibly as hedge against equity. When volatility is high, cryptocurrencies appear to be more correlated with other assets which excludes the possibility of safe haven characteristics. Finally, we find that an expected return higher than the range of 11.44% to 17.27% would justify a 5% allocation in cryptocurrencies for a globally diversified European investor. By including a small proportion of cryptocurrencies to the portfolio the overall Sharpe ratio increases.

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1 Introduction

The concept of cryptocurrencies is relatively new in the world of finance and therefore there is a limited availability of literature. The first financial studies, mostly concerning Bitcoin only, date from late 2013. Over the years the number of financial publications has increased strongly. The increasing popularity of the subjects Bitcoin, cryptocurrency and Ethereum, measured by search engine results, is visually displayed in figure 1 and figure 2 in the appendix. Preis et al. (2010) and Choi & Varian (2012) investigate the use of Google Trends and mention that the search engine results represent general trends in the real population. The figures show that the first period with large interest in Bitcoin is clearly visible from late 2013 up to early 2014. Figure 2 even displays an absolute peak in news results recorded in Bitcoin's history. Besides the peak in searches in 2013 and 2014, the graphs evidently indicate an enormous expansion for searches in all three search terms in 2017. Bitcoin is the most searched variable and appears to be the most well-known search term worldwide. This is confirmed by the cryptocurrency market capitalization, in which Bitcoin is undeniably market leader. The increasing popularity and limited previous scientific research cause cryptocurrency to be an engaging subject for further research.

This study aims to answer the question whether cryptocurrencies could contribute to a well-diversified portfolio for European investors. Therefore, diversification and hedge possibilities are examined, which are essential characteristics for alternative assets in order to add value to the original portfolio. To conclude if cryptocurrencies could increase diversification in a portfolio, it is essential to investigate the correlation between cryptocurrencies and the assets in that portfolio. According to Baur & Lucey (2010) in their study for the hedging capabilities of Gold, an asset can be classified as a diversifier if it has a weak positive correlation with other assets in average. However, if the asset is uncorrelated or preferably has a negative correlation with another asset, it can be titled as a hedge possibility. Baur & Lucey (2010) also mention that if an asset is negatively correlated with another asset class in times of market tumult, it can be regarded as a safe haven. Intuitively, when an asset decreases in value in times of crisis and another asset at the same time increases in value, the second asset serves as a safe haven. In this study the correlations between cryptocurrencies and other traditional assets are investigated. Existing studies contradict each other in the case of the possible usefulness of cryptocurrencies in a portfolio. Various studies argue that cryptocurrencies do offer diversification or hedge capacities. Dyhrberg (2016) states that the Financial Times Stock Exchange Index and the US dollar can be hedged by Bitcoin. Chuen et al. (2017) conclude that cryptocurrencies provide diversification benefits due to low correlations with other assets. In a study in Asian stocks, Bouri et al. (2016) state that Bitcoin can serve as an effective diversifier, however, it does not seem to be a good hedge instrument against the Asian stock market. Though cryptocurrencies might improve a portfolio in a manner of increased diversification, other studies imply that the negative consequences should not be underestimated. Osterrieder et al. (2017) state that cryptocurrencies possess risk characteristics that exceed risks of traditional assets and implementing these in a portfolio may lead to negative results. Subsequently, in order to answer the research question it is important to find a suitable figure for expected returns of cryptocurrencies. The Black-Litterman model is very useful for this issue and it provides a clear insight of the addition of cryptocurrencies to a well-diversified portfolio.

Firstly, cryptocurrency as a concept is explained as well as the cryptocurrency market. It is important to know how the currencies have been established and how they work in order to understand the valuation and differences between several cryptocurrencies. The market description is accompanied with general statistics regarding the individual cryptocurrencies and the total market. The literature review contains a thorough analysis of advantages and disadvantages opposed to fiat currencies with the application of a SWOT-analysis. In order to understand the returns, it is essential to know what the underlying value drivers are, as is elucidated in the valuation chapter.

Subsequently, the methods which are applied are discussed followed by the data description. Next, the descriptive statistics of cryptocurrencies as well as traditional assets are discussed. In this chapter emphasis lies on risk-return properties and correlations to interpret possibilities for diversification and hedging. Further portfolio characteristics and cryptocurrency contributions are examined through constructing mean-variance analysis, volatility target frontiers and lastly by implementing the Black-Litterman model. Finally, the results are summarized in the conclusion, followed by limitations and possibilities for further research.

2 Literature review

2.1 Cryptocurrency

Since the early 1990s, when internet became increasingly important in banking, the majority of large banks have attempted to create a properly working digital cash system (Stalder, 2002). Various digital cash systems have been created, however, by the year 2000 the usage of these digital systems remained underused (Van Hove, 2000). The most well-known and widely used digital cash system is PayPal, which is founded in 1998 and serves as an intermediate party in online transactions between two other parties. Even though these online money transfers are based on digital technology, the actual payment is executed in fiat money. This is not the case for cryptocurrencies, since these are standalone currencies invented as a substitute for fiat money. There is no standard definition for the word cryptocurrency, though Chohan (2017) describes it efficiently as “a cryptocurrency can be thought of as a digital asset that is constructed to function as a medium of exchange, premised on the technology of cryptography, to secure the transactional flow, as well as to control the creation of additional units of the currency.” The first currency to use the technology of cryptography, and therefore the first cryptocurrency, has been Bitcoin (Nakamoto, 2008).

In 2009, under the pseudonym Satoshi Nakamoto, a computer programmer or a group of programmers released the software on which Bitcoin is based. The main characteristic that makes the crypto-technology unique is decentralization; there is no central authority, financial institution or service intermediate needed for the system to work. A transaction is not supervised or validated by an authority and goes directly from one party to another. The major challenge that had to be overcome was the double-spending problem, meaning a party could fraudulently use a quantity of Bitcoins twice while only compensating for one unit of the same quantity. Fiat money does not have this problem since money is either transferred physically and therefore only spendable once or is transferred and authenticated by a central financial institution. Bitcoin’s programmer(s) proposed a solution based on a proof-of-work concept using a peer-to-peer network (Nakamoto, 2008). The usage of a peer-to-peer network is essential in order to remain decentralized, since it does not require a central server. In a peer-to-peer network, individual nodes are connected directly to each other and share resources (e.g., information) without using a central server (Schollmeier, 2001). Every node, also called peer, in the network is equally privileged and devotes a share of their resources (e.g., processing power) to the network. By collaborating, peers create a server network without a physical central server. The proof-of-work concept is a complex system based on cryptographic technology which ensures that double-spending is prevented. Simplified, participants in the peer-to-peer network using the Bitcoin software have to validate a transaction between two parties in the network. The underlying technology, the blockchain, is a public file that records all the transactions. When a transaction is executed and validated by certain nodes in the network, they will add the transaction to the blockchain file and distribute the new version to the network. At average, every ten minutes a block will be added to the blockchain. A block is a record of all transactions that have been completed in the preceding ten minutes. The blockchain is actually a chain built from proof of all the transactions which are completed in the history of the blockchain. Calculating a new block and valuating transactions require a large amount of computer power and storage, which is shared by the peers in the network. Peers provide a service to the network, entitled as mining which is rewarded by receiving Bitcoins. Hayes (2015) describes mining as a reward for handling and verifying payments by contributing their computing power to the network. Subsequently he says mining is competitive, since one with more computational power or with greater efficiency has a better chance of success than another with less. Every newly added block in the blockchain is rewarded to one peer who has successfully found the new block code. At the moment the reward for every new block is 12.5 coins plus additional transaction fees. Every 210,000 blocks the reward will be halved, with the next drop in reward expected in June 2020 (Bitcoinblockhalf, 2017) to 6.25 Bitcoins. At the point of Bitcoin's release, the supply curve was already determined. The production is limited to 21 million units of Bitcoin and the supply curve has a logarithmic function which is shown in figure 3 in the appendix. According to Antonopoulos (2017), the declining supply function is meant to simulate the supply of precious metals. The current increase in supply results in a yearly inflation of 4.04%. The majority of cryptocurrencies are technically nearly the same as Bitcoin, with small alterations in the code which include different levels of privacy, anonymity or utility. Litecoin is regarded as a clone of Bitcoin, merely providing faster transactions and a different mining algorithm whereas Ripple focuses on transaction utility and less on speculation. Dash is also comparable with Bitcoin, with an added level of privacy for the users (The Merkle, 2017). Ethereum uses a comparable blockchain technology as invented by Satoshi Nakamoto, with minor changes. However, the application of the cryptocurrency is totally different than Bitcoin, since Ethereum is not invented as to serve replacement for fiat money. Ethereum has added the option to write certain programming codes on the blockchain, which are called smart contracts. These smart contracts provide programmers a new set of opportunities. It is possible to create several financial instruments (i.e., options, swaps, forwards, futures and insurances) through Ethereum. Therefore, Ethereum is very appealing for banks and other financial institutions. In February Fortune (2017) announced that "Thirty big banks, tech giants, and other organizations—including J.P. Morgan Chase, Microsoft, and Intel—are uniting to build business-ready versions of the software behind

Ethereum." These developments have contributed to global awareness of cryptocurrencies.

2.2 Cryptocurrency market

Besides these five major cryptocurrencies, there is a multitude of other cryptocurrencies. Coinmarketcap (2017) has a list of over one thousand cryptocurrencies. However the number of individual cryptocurrencies is extensive, the market capitalization of the large majority is negligible. As is displayed in table 1 the market capitalization of the five largest currencies accumulates to more than 75% of the total market. The total market value as of September 3, 2017 was over 166 billion dollars. Bitcoin and Ethereum clearly dominate the market with relative market capitalizations respectively 46% and 20%. Since the establishment of Bitcoin in 2009, it has always been market leader with capitalization levels constantly exceeding 80%. Up and until early 2017 Bitcoin has remained unthreatened, however, in this period Ethereum and Ripple started gaining power in the cryptocurrency market at the cost of Bitcoin (figure 4). Due to increasing values of these two currencies, Ethereum and Ripple had capitalization levels of respectively 30% and 11%, leaving Bitcoin at an all-time low of 37% in June 2017. After this steep decline, Bitcoin regathered momentum and remained stable at around 45%. Ripple appears to have lost the largest part of its market power, whereas Ripple was at its peak in May with a capitalization of 25%. Ever since the peak moment, Ripple has shown a decreasing trend with a current market capitalization of 5.3%. Likewise, Ethereum has also seen a drop in relative market power. However the decline Ethereum has experienced was less dramatic and appears to remain steady at around 20%. In summary, Bitcoin is the leader in the cryptocurrency market, however on the other hand, its dominance is not as solid as it has been for many years. Other entrants have gained market power and might threaten Bitcoin's position in the future.

Perhaps more interesting is the overall position of cryptocurrency in the global capital market. The capitalization with respect to the global market should be sufficient to absorb a meaningful fraction of the investors' portfolios. If large investment funds decide to invest marginal proportions of their wealth in cryptocurrencies, would there be sufficient market capital to absorb these investments? Therefore it is important to compare the cryptocurrency market with other assets. As stated before, the total cryptocurrency market capitalization amounted 166 billion dollars. When compared to public listed corporations (Forbes, 2017), this value is comparable with companies such as Toyota, Intel, Citigroup and IBM with market values in billions respectively \$172, \$170, \$164 and \$162. McDonald's (\$106 billion), BP (\$115 billion) and Unilever (\$144 billion) are examples of firms with lower market values, whereas the largest firm is Apple with a market value of \$752 billion. Stated as a proportion of gold, the total value of the cryptocurrencies combined is approximately 2%. According to the World Gold Council and Thomson Reuters, there is a total mined supply near 187,200 tons of gold, accumulating to a total value over 7.5 trillion dollars. Even though cryptocurrency value might seem small compared to other assets, it is not insignificant and even amounts more than a large number of listed multinational companies. If the market value of cryptocurrencies would be regarded as a public company it would be listed as the 40th largest in the world. More interestingly than the absolute value is the striking increase in value. In one year time measured at the first of September 2016 and 2017, the value surged from $11.4 billion to $178.8 billion, corresponding to an increase of 1468%. The cryptocurrency's market value is graphically presented in figure 5 in the appendix. The main factor which forced this extreme increase is a rise in prices of cryptocurrencies, since we know the supply of individual cryptocurrencies is limited by its mining quantity and the market value is a function of price and quantity.

Cryptocurrencies are exchanged by several online traders like Bitfinex, GDAX, Bithumb, Kraken etcetera. For investors it is relatively easy to trade cryptocurrencies, as online trading platforms only require investors to create an account and transfer money to their digital wallet. With the money in a wallet, cryptocurrencies can be purchased. Furthermore, cryptocurrencies can be traded for other cryptocurrencies directly or can be withdrawn to money in the wallet and subsequently transferred back to their bank account. These online traders are focused on trading only, where cryptocurrencies are regarded as assets or trackers for the value of underlying cryptocurrencies. However, Bitcoin and several other cryptocurrencies were invented as a substitute for fiat money. The question arises if cryptocurrencies are used by customers to buy goods in their daily life or mainly as an investment. Bitcoin is worldwide the major accepted cryptocurrency. That is to say, if a seller accepts a cryptocurrency as a payment method it will very likely be Bitcoin. There are some retailers and services which accept Bitcoin as payment, such as Amazon, Overstock, Expedia, Microsoft (Windows store and Xbox) and Dell. Furthermore a large amount of online services can be paid with by Bitcoin. Additionally, a growing number of cities worldwide are promoting the acceptance of Bitcoin payments in actual stores. With the use of an application on a telephone, tablet or computer device, payments can be done in restaurants, cafés and stores. An advantage is that Bitcoins are dividable up to a one hundred millionth (0.00000001 Bitcoin), meaning that low value products can be purchased even if the price of Bitcoin is high. Also the provided liquidity and investment opportunities are regarded to be sufficient (Burniske & White, 2016). Even though the acceptance for cryptocurrency as a payment method is increasing, it is still low and far away from mass acceptance. Even though these digital currencies are gaining popularity and their liquidity has been increasing ever since their existence, it is not likely that these digital currencies will replace fiat money in the near future (DeVries, 2016). Zhao (2015) argues that the cryptocurrency technology still needs a lot of improvements before it can compete with fiat money as a source of payment. Therefore, Glaser et al. (2014) address the question whether an increase in market capitalization is due to interest in these currencies as alternative payment method or as an investment vehicle. They conclude that "new users tend to trade Bitcoin on a speculative investment intention basis and have low intention to rely on the underlying network as means for paying goods or services" (Glaser et al., 2014). Also, according to Yermack (2013) Bitcoin appears to behave more like a speculative investment than a currency. This conclusion is subsequently confirmed by a study from Baur et al. (2015), in which transaction data of Bitcoin accounts have been analyzed. Burniske & White (2016) explain that Bitcoin and other cryptocurrencies exhibit characteristics of a unique asset class, meeting the bar of 'investability'.

2.3 Valuation

As many of these mentioned studies conclude, cryptocurrency are considered more as an asset than a currency. As with other assets, studies have been performed to determine the value drivers for cryptocurrencies. However, in contrast to more traditional assets, in the case of cryptocurrencies the literature is less extensive. The reason for the scarcity in literature is mainly that the concept of cryptocurrencies only exists for a small amount of years and is not yet regarded as an investable asset by the majority of investors. Therefore the need for scientific research in this area has been relatively low. Despite the limited availability, there are some contributive articles regarding cryptocurrencies' value.

For the majority of assets it is clear what the main determinant for underlying value is. Intuitively, for tangible assets the underlying value is the intrinsic value of the asset itself. For intangible assets the intrinsic value is more challenging to determine (Hubbard, 2014) and the valuation is often sensitive for errors (García-Ayuso, 2003). Equity is valuated by the market value of the underlying company, which in its turn is more complicated to estimate. However, scientific literature in this case is extensive. Valuing cryptocurrencies is a relatively new subject to which an increasing number of studies is dedicated. The underlying intrinsic value is very hard to determine, since the cryptocurrencies are based on a computer programming code. Yermack (2013) argues that cryptocurrencies' intrinsic value is equal to zero and its ultimate value depends on its usefulness as a currency in the consumer economy. Also Hanley (2013) has the opinion that the value of Bitcoin is only its pure market value without fundamental support. Other studies do point out there is indeed an intrinsic value. Various, diverging explanations for value determinants are given in different recent studies, ranging from purely technical aspects to more abstract factors. Hayes (2015) contradicts Yermack (2013) and argues that the main value driver for cryptocurrencies is the cost of production. That is, if mining a cryptocurrency is less costly, the price of the currency will be lower. Important factors which decrease mining costs are hardware energy efficiency, lower worldwide electricity prices and lower mining difficulty which means less computer capacity is needed. These are the results of a cross sectional empirical study regarding 66 different cryptocurrencies. The large number of currencies used in the study may have contaminated the data, since the majority of these currencies are not relevant. The average market capitalization among cryptocurrencies for 64 of 66 of these currencies was around 0.1% and a large proportion of them will not have existed for the entire time span of the data. Another comment would be that the denoted base price is BTC (Bitcoin), hence Bitcoin is always worth one in the data and other cryptocurrencies are a fraction of BTC. Bitcoin is highly volatile (Osterrieder et al., (2017) and Osterrieder, (2016)) and therefore might be unsuitable as standard price denotation. Bouoiyour and Selmi (2014) and Polasik et al. (2014) regress Bitcoin's market price against Google searches as a proxy for popularity in a period of time. They conclude that higher popularity increases the price, due to higher demand while supply is given. Garcia et al. (2014) also include social media and Kristoufek (2013) includes Wikipedia searches and find comparable results. Wang and Vergne (2017) also researched the relation between cryptocurrency prices and media activity. Subsequently, they added a proxy for innovation potential. The conclusion of the study is that innovation potential is the main value driver for cryptocurrency returns. By intuition, innovation potential or future potential plays an important role in cryptocurrencies' value. This entails that if one or more individual cryptocurrencies or the blockchain technology as a whole succeeds to be globally adopted by the majority of consumers, financial institutions, governments, etc., the day to day use of these currencies will increase immensely. When the demand grows and supply remains limited, the price obviously will tend to rise as well. On the contrary, if cryptocurrencies fail to be adopted by the market, the value will eventually decline towards zero. As it is with other assets, cryptocurrencies' value certainly depends on many variables, both technical and abstract factors influence its price. In recent literature there is no absolute consensus, however, it seems the majority of recent studies claims that future potential, measured through media and innovation potential is the largest contributor to cryptocurrency value. Therefore it is important to know what factors can make the technology successful or not.

2.4 SWOT analysis

By using the SWOT analysis, the future potential of cryptocurrencies is analyzed. The original SWOT framework was initially described by Learned et al. (1969) and is a traditional, simple and clear method to understand competitive advantages or disadvantages. The SWOT framework takes a look at the importance of both internal and external factors. By this method, cryptocurrencies are questioned by the hand of its strengths, weaknesses, opportunities and threats. The latter two explain both positive and negative external factors and emphasis on the future, where the first two focus on internal factors.

2.4.1 Strengths

Cryptocurrencies have some advantages over fiat money, where decentralization is the main interest for users. Decentralization in the cryptocurrency market means that there is no authority behind the transactions, due to the peer-to-peer network. Since there is no third party involved and transactions are encrypted, user anonymity is guaranteed. Banks, governments or other financial intermediaries cannot interfere or control transmission of money or information. For users, another advantage in practice is that there is no sales tax added onto purchases neither is capital gain taxed when holding cryptocurrencies as an investment. More precisely, cryptocurrencies are subject to taxation as stated by the law of many countries, however due to anonymity of the owners this rarely happens. Although this might be an advantage for users who look to avoid tax payments, it is questionable if this is socially desirable. The exclusion of intermediary parties in transactions means there is a higher efficiency and transaction costs are very low compared to traditional payment methods (Kim, 2017). Additionally, there are no extra transaction costs for international payments since the network is globally active and not bound by country borders. Therefore there is no need to exchange currencies, since the value of a certain cryptocurrency is exactly the same at any place globally at a given point in time. Since cryptocurrencies are decentralized and transactions are confirmed by a large network of computers worldwide, trading is not limited to opening hours of an exchange or dealer. In contrast to for example stocks, cryptocurrencies can be traded every single minute of the year.

2.4.2 Weaknesses

Needless to say, cryptocurrencies are still in their infancy and face many weaknesses. However liquidity and adoption of cryptocurrencies worldwide as payment method are increasing, the number of businesses using cryptocurrencies is still relatively small. To function as a currency, the statistical properties of Bitcoin and other cryptocurrencies are far from favorable, large price fluctuations and volatility (Osterrieder, 2016) are a risk for holders of the currency. In general, financial innovations are likely to exhibit bubble-like features (Frehen et al., 2013). More specifically, Grinberg (2011) argues that cryptocurrencies are susceptible to speculative bubbles. As a result of tax evasion possibilities and anonymity, Bitcoin and other cryptocurrencies are massively used as payments in the criminal environment and widely used as money laundering technique (Christin, 2013). Multiple hacks have proven that the blockchain technology is still vulnerable, the most well-known is the DAO/Ethereum hack. The DAO (Decentralized Autonomous Organization) was a venture capital fund cryptocurrency, running on the Ethereum blockchain with the purpose to provide a decentralized business model for enterprises. Initially, the investor sentiment was positive and prices increased, mainly Ethereum profited. However, roughly one month later hackers found a vulnerability in the DAO code and over $50 million was stolen. On this day, the price of Ethereum dropped with 26% and the other cryptocurrencies saw a decline varying from 11.5% to 18%. A couple of months later, the DAO was de-listed from all cryptocurrency trading platforms. Furthermore, cryptocurrencies face technological issues of which the scalability problem is the largest. The problem is caused by a limited size of every block in the blockchain while the number of transactions in the network continues to rise above the capacity. Consequently, the time for a transaction to be completed and verified increases and so do the accompanying transaction costs.

2.4.3 Opportunities

The main opportunities for cryptocurrencies lie in the fact that there is a lot of interest in the further development of usage by financial institutions. Multiple central banks are experimenting with cryptocurrencies. CADcoin has been used in simulations performed by the Bank of Canada, in Ecuador (Dinero electrónico) it is already possible to pay governmental bills with the central bank's digital currency (Bech and Garratt, 2017). Also, a large collaboration 'Enterprise Ethereum Alliance', has been formed to develop possible implementations of Ethereum's blockchain into financial institutions. The alliance is formed by over 150 companies of which Microsoft, Samsung, Master Card, Deloitte, ING, J.P. Morgan, UBS and Santander Bank are examples of well-known participants. Furthermore, many other banks and financial or technological firms have joined the collaboration. This certainly does not guarantee future success, however, it does demonstrate that there is great interest in the technology. Even though popularity is rising, it is not likely that Bitcoin or other cryptocurrencies will ever replace fiat money entirely, but it is possible that they co-exist next to each other (Zhao, 2015).

2.4.4 Threats

While there are good opportunities for cryptocurrencies and its technology to succeed in the future, threats cannot be underestimated. Firstly, practical issues arise when electricity or internet network failures occur since the technology is entirely dependent on digital connections. If a cryptocurrency would become a major adopted payment method, electricity failure will result in serious problems, possibly paralyzing the economy temporarily. Furthermore, cryptocurrencies are exposed to hackers. In the brief history, Bitcoin and Ethereum, the two largest cryptocurrencies have experienced numerous attacks (Atzei et al. (2017), Hileman (2016)). For cryptocurrencies individually, other new entrants in the market are threatening (Hileman, 2016), as we have seen in the case of Bitcoin and its 50% drop in market dominance (figure 4). Furthermore, a so-called hard fork may threaten the continuation of cryptocurrencies. Briefly explained, a hard fork arises when a radical change is made to the blockchain protocol which leads to a divergence of the chain. The blockchain is then split into two chains, of which one will probably cease to exist. This eventually results in value loss for the cryptocurrency. Both Bitcoin and Ethereum have experienced hard forks in which the prices dropped. In some cases, the two blockchains that split both remain active. For example, Bitcoin Cash resulted from a hard fork of Bitcoin at the end of July 2017 and is currently still active. More harmful for the cryptocurrency market as a whole would be the development of a new technology which would replace the entire market. Besides the technological risk, individual cryptocurrencies and the blockchain technology face political and legal risk. Political decisions can seriously harm the future potential. In Bangladesh, Bolivia, Ecuador and Kyrgyzstan, Bitcoin is officially illegal. Recently, the Central Bank of China has banned Bitcoin and other cryptocurrencies, making China's share of global bitcoin-trading drop from more than 90% to just about 10% (The Economist, 2017). If, for example, the USA would decide to declare cryptocurrencies illegal, the consequences would be devastating. However China's incentives are based on communistic principles, other countries may have different incentives to restrict cryptocurrencies. Likely reasons would be high criminal involvement and money laundering as mentioned before. Also the fact that authorities do not have any insight in transactions will contribute to a negative view from governments. Subsequently, the possibility for tax evasion might be an incentive for policymakers to counteract.

3 Method

3.1 Diversifier, hedge and safe haven

The main research question of this study is if cryptocurrencies could contribute to a well-diversified portfolio for European investors. In order to sufficiently answer this question, we need to specify what contribution to a well-diversified portfolio means. Firstly, a portfolio is generally regarded superior to another when it has a higher return. However, this may be misleading since risk plays an important role when rating a portfolio. More precisely, a portfolio is improved when its relative risk-return performance has increased. Therefore, we can state that cryptocurrencies contribute to a well-diversified portfolio if the risk-return tradeoff, or Sharpe ratio, increases when cryptocurrencies are added. One aspect which generally increases the risk-return ratio of a portfolio is diversification (Sharpe (1992) and French (1991)), since it reduces overall risk of the portfolio. Diversification is especially effective if the cryptocurrencies serve as a hedge or safe haven against assets in the portfolio. By investigating the correlation coefficients among these assets as well as their 30-day moving average correlations, the question whether cryptocurrencies can function as diversifier or hedge. Subsequently, the relation between volatility and correlation is regarded through 30-day moving graphs to find possible safe haven characteristics of cryptocurrencies.

3.2 Mean-variance analysis

In order to get an idea of the difference in portfolio characteristics between the standard non-cryptocurrency portfolio and the portfolio with addition of cryptocurrencies, both portfolio frontiers are constructed by mean-variance analysis according to the modern portfolio theory as introduced by Markowitz (1952). By minimizing the variance of a portfolio for certain targets of return through changing the weights of the assets in the portfolio, a frontier is created which shows the optimal portfolio choices for a given set of assets. The weights of the portfolios are restricted to a total of 1, hence a portfolio is in essence the sum of all invested assets and therefore always 1. This is done for two different portfolios of which one does not allocate cryptocurrencies and the other does. These are plotted in a single graph which visualizes the differences between the two portfolio options. The matrix notation of the mean-variance analysis is given as stated on the next page.

$$\min_{w} \text{ var}\left(r_p\right)$$

$$s.t.\ \ E\left(r_p\right) = \text{target return}$$

$$w'\iota = \sum_{i=1}^{\mathrm{K}} w_i = 1$$

The mean-variance frontiers give an intuitive graphical presentation of the of the risk-return tradeoffs. However, this method is very sensitive to expected returns, which in this case are based on historical data. Meanwhile, we know that cryptocurrencies possess extreme historical return values which strongly influence the mean-variance analysis. As discussed in the valuation chapter, cryptocurrency value arises from future potential. In the SWOT analysis it becomes clear that future success of the cryptocurrencies is possible, however many threats make this chance very fragile. For this reason it is improper to use historical returns as expected future returns. This brings up the question how to determine appropriate expected returns? The Capital Asset Pricing Model (CAPM), introduced by among others Sharpe (1964) is a model which states that the price of an asset can be calculated by multiplying its beta with the market excess return and subsequently adding the risk free rate. The beta is the asset's expected return sensitivity to the expected market returns and is calculated by dividing the covariance of the asset's return with the market's return by the market variance. However, since cryptocurrency value and thus expected return is only dependent on future potential and other internal specifics, the covariance of cryptocurrency returns with the market is theoretically zero. Then the cryptocurrency expected return is equal to the risk free rate, which is also close to zero. Therefore, the CAPM is in this case not a suitable instrument to calculate expected returns for cryptocurrencies. Furthermore, Mehta & Afzelius (2017) argue that the CAPM does not accurately predict expected returns in the case of Bitcoin and other cryptocurrencies, since their extremely volatile nature. Correspondingly, other expected return estimation models such as Fama and French, Sharpe-Lintner-Black (SLB) and Arbitrage Pricing Theory (APT) rely on several beta coefficients (Black, 1993). The Fama and French model is not suitable for cryptocurrency expected returns since it is an extension of the CAPM model with added size factors for stocks. The SLB method does not work either, because it assumes only beta matters in explaining expected returns (Black, 1993). The APT model assumes that the expected return can be predicted through the sensitivity of an asset to certain macroeconomic factors, which then is multiplied by its risk premium. Once again, cryptocurrency returns do not depend on external market factors and thus this model is not useful in explaining expected returns. The only macroeconomic factor which would make sense is global electricity costs, however finding a corresponding risk premium is tough. Moreover, we have discussed that electricity costs are not the main value drivers for cryptocurrencies. Numerous other models exist for estimating future returns, though we may conclude that cryptocurrencies have such specific and deviant value determinants that their expected returns are very hard to estimate by an existing model, mainly due to the currencies' unknown future potential. Due to the uncertain future and considering historical volatilities, it is highly probable that cryptocurrencies remain extremely risky in the future. Therefore the expectation is that future volatilities can be approximated by the dataset.

3.3 Volatility target optimization

Hence, while not having a suitable model for estimating expected returns it is necessary to come up with a method that does make sense for well-diversified investors. More accurately, we want to find an expected return for cryptocurrencies that justifies a certain position in this asset class. With the result of these findings we can interpret the probability of these expected returns. When an extremely high expected return is required for the justification of a small position in cryptocurrencies, it is more likely that the real returns fail to meet the expectation. Furthermore, for investors who want to invest in cryptocurrencies, the required expected returns are better when they are low. Hence, if future returns of cryptocurrencies turn out to be disappointing, the consequences will be less dramatic when the accounted expected returns are already lower. The first method to estimate required returns is to create a volatility target frontier, which is comparable to mean-variance analysis. Instead of minimizing risk for a given return, the volatility target frontier is drawn by maximizing the return of a portfolio for certain volatility levels by changing the weights of the individual assets, while keeping the sum of the weights equal to 1. The matrix notation of the problem that has to be solved is as follows.

$$\max_{w} E\left(r_p\right)$$

$$s.t.\ \ \mathrm{vol}\left(r_p\right) <= \text{target volatility}$$

$$w'\iota = \sum_{i=1}^{\mathrm{K}} w_i = 1$$

When solving this problem for a variety of target volatilities, every solution is a point on the volatility target frontier. The frontier is plotted in a graph with on the x-axis the standard deviation of the portfolio points and on the y-axis the accompanying return. Combining all the solutions results in a line which is the frontier. The second step of finding a required expected return for a certain position in the cryptocurrency portfolio is to minimize the expected return of the cryptocurrency portfolio for a certain volatility target by changing the weights of all other assets. The weight in the cryptocurrency portfolio is set as a fixed number corresponding with the preferences of the investor. In order to insure that the frontier does not change, the target volatilities still have to correspond with the same expected portfolio returns. To solve this, the expected return of the cryptocurrency portfolio is a function the desired corresponding expected return.

$$E(r_{P_{Cryptocurrency}}) = \frac{E(r_p) - \sum_{i=2}^{K} w_i \, E(r_i)}{w_{P_{Cryptocurrency}}}$$

In this manner the volatility target frontier remains the same, while finding the minimal required expected return for the cryptocurrency portfolio to justify a given weight in the total portfolio. Even though the method is straightforward and intuitively reasonable, there are major issues. Most importantly, this method involves altering the expected return of the cryptocurrency asset class while leaving the expected returns for the other assets classes unchanged. In a simplified world where assets are unrelated and perfectly uncorrelated, there would be no problem. However, in the real world assets do influence one another and thus, on average, a higher expected return for one asset means a higher expected return for another asset with positive correlation and lower expected returns for assets with a negative correlation. Furthermore, changing the expected return of the cryptocurrency portfolio, and consequently all other assets as well, would directly affect the volatility target frontier. As a result the solution for the required expected cryptocurrency return needs to be solved again, in its turn altering the expected return which then again affects the volatility target portfolio, as in a vicious circle. For this reason, this method is not a clean solution and neither suitable to draw conclusions. However, the results may be useful to compare with the results of the Black-Litterman model and should be within reasonable range of each other.

3.4 Black-Litterman

The Black-Litterman model is developed by Robert Litterman and Fisher Black and is very useful for portfolio management. Many investment firms use the Black-Litterman model or a model derived from it to create their portfolios. Briefly explained, the model uses the market equilibrium weights as starting point. These weights result in a corresponding implied expected returns for these assets. Subsequently, the model lets an investor’s opinion about one or more assets’ expected returns influence the asset allocation, deviating from the global market equilibrium. Both the Black-Litterman model and the volatility target analysis use implied returns derived from global market weights. However, the Black-Litterman model uses a variance-covariance matrix to determine if an asset’s return is influenced by a change in another asset. This is a solution for the problem stated in the volatility target analysis. The Black-Litterman model assumes that the global market weights are an equilibrium in which the average consensus of all investors worldwide is represented. From these weights, the market implied expected returns can be calculated with the following formula.

$$\mu^e = \gamma \Sigma w^*$$

Essentially, the expected return vector (μ^e) is derived by multiplying the global investor's risk aversion (γ) level by the variance-covariance matrix (Σ) and the market equilibrium weights (w^*). These implied expected returns are the market equilibrium, however an investor's opinion about one or more asset classes' expected returns can be different from the equilibrium. When this is the case, this opinion can be expressed in a view, either relative or absolute. This view then is processed in the Black-Litterman model, eventually leading to different weights in the assets for which a view is expressed. Relative views are expressed when the investor has the opinion that a certain asset will outperform another asset by a given percentage. In this study we solely use one absolute view to determine the cryptocurrency required return. An absolute view states that an asset's return will be a given percentage, obviously deviating from the equilibrium. The Black-Litterman returns are derived by the following equation.

$$E(R) = v_1 R_e^{eq} + v_2 Q$$

This mathematical expression splits expected return up into two parts, of which the first expresses the excess return in market equilibrium (R_e^{eq}) and the second part is the view (Q) of the investor. Both parts are multiplied by certain weights, depending on their corresponding noise around information. The weights are slightly differently calculated. The first weight (v_1) is mainly dependent on the precision of the equilibrium returns, also called Tau (τ). The smaller the number for Tau, the more market equilibrium weights are an accurate source of information for expected returns in the model. The second weight (v_2) represents the confidence and noise around the view of the investor, where Omega (Ω) is the confidence matrix. The two weights are expressed as follows.

$$v_1 = \bar{\Sigma}^{-1} [(\tau\Sigma)^{-1}]$$
$$v_2 = \bar{\Sigma}^{-1} [P^T \Omega^{-1}]$$

$$\bar{\Sigma} = (\tau\Sigma)^{-1} + (P^T \Omega^{-1} P)$$

When deriving these formulas, we find that if Tau (τ) is 0, all weight would be on reverse engineered returns. A small number for Omega (Ω) means that confidence in the view is high. If it would be zero, all weight would be on the return expressed in the view. Intuitively, if Tau (τ) is relatively small and Omega

(Ω) is relatively large, the Black-Litterman returns will be close to the equilibrium and vice versa. In the case of cryptocurrencies, the equilibrium expected returns are probably not an accurate source of information, since the market weight of cryptocurrencies is approximately 0% and the currencies have extreme statistical properties. Therefore, Tau (τ) should not have a small number. However, for all other assets, equilibrium expected returns may be correctly estimated by the global market weights. For these reasons Tau (τ) could be set at 0.15, which is in the normal bounds of 0.05 to 0.15. For robustness, also other figures for Tau are tested. Because future potential of cryptocurrencies is very uncertain, the absolute view on the cryptocurrency return estimate comes with a moderate level of uncertainty. In the calculations of the Black-Litterman model, we let the standard error of the view be dependent on the magnitude of the view. Sensibly, when an investor's opinion deviates much from the equilibrium, there is a larger chance that the view might be wrong.

When the Black-Litterman model is set up, we subsequently have to find a suitable view to justify a certain allocation in the cryptocurrency portfolio. An allocation of 5% seems suitable, since larger numbers would too heavily overweigh this asset in the portfolio. In order to find substantial results, the intended allocation should not be too small either, since the margin of error would then be relatively large. Hence, for solving the problem in the Black-Litterman model, a value for the absolute view (Q) has to be found which makes the model allocate 5% into the cryptocurrency portfolio.

Both the volatility target analysis and the Black-Litterman model use the variance-covariance matrix to calculate portfolio risk, expressed as volatility. The return of each portfolio is the sum of the multiplications of the weights of the assets and their corresponding returns.

4 Data

4.1 Sources

In general, two different sources have been used to retrieve data. At first, for the traditional assets, DataStream provided daily price data. Cryptocurrency price data is widely available on the internet. Many websites show charts with price data for multiple cryptocurrencies, however, it is not usual that this historical data is available to download. Since Bitcoin is the most common currency, data is more common to find. Conversely, for other cryptocurrency it is harder to find data. Fortunately, CryptoCompare (2017) provides price charts for all available cryptocurrencies. From these charts daily data can be downloaded including price, trading volume and more. Daily price data for the five largest cryptocurrencies according to their market capitalization has been retrieved from CryptoCompare. From the price data, daily returns are calculated. All data is downloaded in euros.

Cryptocurrencies are traded 7 days per week, since transactions are not limited by financial institutions or regulations. Exchanges trading these currencies also trade on Saturday and Sunday. The majority of traditional assets are traded on workdays when exchanges are open. This would result in a disparity of datasets, which is undesirable. In order to correctly compare the two datasets, the returns for cryptocurrencies are calculated by workday prices. In order to do so, the prices for cryptocurrency weekend data have been eliminated and only workdays remain which subsequently result in workday returns. This results in slightly higher return variances on Mondays for cryptocurrencies. The total dataset consists of over two years of daily workday data, starting from August 10th 2015 and ending on September 1st 2017, resulting in a time series of 540 days.

4.2 Portfolio

When investigating if cryptocurrencies contribute to a diversified portfolio, it is first of all important to have a base portfolio to compare with. A portfolio is a group of financial assets in which a certain investor has invested. Investments in assets can either be positively or negatively weighted, the latter generally referred to as short selling. The average investor will likely have positions in equity, bonds and cash equivalents and other traditional assets such as real estate and commodities. The exposure to certain assets differs per investor and is mainly dependent on the accompanying risk aversion which this investor has. Every asset has different return and risk properties, where in general equity tends to have a higher return and higher volatility then bonds (Fama and French, 1993). Since it can be challenging or impossible for investors, in particular those with a relative low portfolio value and investable wealth, to gain positions in some assets, trackers and ETF's are good options to have exposure to these assets. When, for example, an investor with limited investable wealth aspires to have a small position in real estate, buying a property is either impossible or the position is disproportionate towards rest of the portfolio. In this case a solution would be investing in a real estate tracker. A tracker, or tracker fund attempts to replicate the performance of a market index by investing in a representative pool of assets or securities. An ETF serves the same purpose, however these funds are traded comparable to stocks. Investing in ETF's and trackers does not require large amounts of money, the transaction costs are relatively low and they generally offer good diversification. Therefore, these investment vehicles are suitable for investors to replicate exposure to certain asset classes or even subsets of these classes. In the case of this study, trackers and ETF's serve as a proxy for a certain asset class and its specific market. As these traded funds replicate the market accurately by holding a large number of different positions, they are suitable tools to create a diversified portfolio. The base portfolio will consist of an equity component, a bonds component and four other traditional assets. The weights of the assets in the portfolio mimic the global market weights which are computed by several research institutes or studies. The market weights in this study represent an average of three researches done by Robeco (Doeswijk et al. (2014)), SAALT (Sichert & Meyer-Cirkel (2016)) and AON Hewitt (2016). The resulting weights of the base portfolio are presented in table 2 in the appendix. Since this study emphasizes on European investors, some asset classes are represented by the European equivalent. The real estate assets class for example focuses mainly on European real estate. Additionally, the corporate bond asset class is a European oriented ETF as well. The commodity prices are retrieved from European indices and the risk free rate is the European risk free rate, as provided by the European Central Bank. Likewise, the data is retrieved in euros to replicate currency exposure of European investors.

4.3 Assets

The assets which the base portfolio is composed of are stated below, starting with the equity component, followed by the bonds component and other traditional assets. Lastly, the cryptocurrencies which have been used are described.

4.3.1 Equities

MSCI World – MSCI is an American provider of several indexes. The MSCI World index is composed of 2,400 constituents, 11 sectors, and is the industry's accepted gauge of global stock market activity. The index contains equity returns in developed markets and can be regarded as a benchmark for global stock funds.

MSCI Emerging (MSCI Emrg) – The MSCI Emerging market tracker is a good approximation of emerging market stock funds.

Proshares Global Listed Private Equity (PrivEq) – This ETF is created by Proshares and replicates the global private equity market.

4.3.2 Bonds

US Benchmark 10 years Govt bonds Index (Bonds US) – United States government bonds with a maturity of 10 years.

D Benchmark 10 years Govt bonds Index (Bonds GER) – German government bonds with a maturity of 10 years.

iShares iBoxx Investment Grade Corporate Bond ETF (Bonds Corp) – ETF (Exchange traded fund) for European corporate bonds with an investment grade risk.

iShares Global Inflation Linked Govt Bond UCITS ETF (TIPS) – ETF (Exchange traded fund) for global inflation linked government bonds. Inflation linked bonds are valuable for portfolios since they are a hedge for inflation risk.

4.3.3 Other traditional assets

MSCI Europe Real Estate (RealEst) – Real estate tracker mainly focusing on European real estate.

HFRX Global Index ETF (HedgeF) – Hedge Fund global ETF (Exchange traded fund), in this study interchangeably mentioned as hedge fund or absolute return fund.

Boerse STU Gold ETC (Gold) – Gold price tracker traded on Boerse Stuttgart stock exchange.

Crude Oil BFO M1 Europe FOB (Oil) – Oil price tracker for European Brent oil.

4.3.4 Cryptocurrencies

The dataset consists of the five largest cryptocurrencies, selected by relative market capitalization; Bitcoin (BTC), Ethereum (ETH), Dash (DSH), Ripple (RPL) and Litecoin (LTC).

Cryptocurrency Portfolio ($P_{Cryptocurrency}$) – The cryptocurrency portfolio. This is a portfolio which is constructed by combining the five previously mentioned cryptocurrencies by their relative market weights at the end of the time series of the dataset, namely September 1st 2017. The accompanying weights are 59.66% for Bitcoin, 27.76% for Ethereum, 7.53% for Ripple, 2.87% for Litecoin and 2.18% for Dash.

5 Descriptive statistics

As many studies have demonstrated, cryptocurrencies show statistical properties which are different from traditional asset classes (Osterrieder, 2017). In order to perform a study regarding the usefulness of cryptocurrencies in a diversified portfolio, it is essential to understand the basic descriptive statistical properties.

5.1 Risk and return properties

Cryptocurrencies tend to have extremely high returns which correspond with great levels of risk, with non-normal and heavy-tailed distributions due to high kurtosis values (Osterrieder et al., 2016). These extreme values are also found in the dataset of this study. Figure 8 shows the density plot of a traditional asset, German bonds. In this graph a normal density line is plotted. When compared to figure 9, which displays Bitcoin's density plot, the German bonds approximate normality much more than Bitcoin. Additionally, the kurtosis value of German bonds is 2.8, which is lower than Bitcoin's value of 5.1. Other cryptocurrencies have even higher values ranging up to 47 for Ethereum. These findings are in line with the other studies, concluding that cryptocurrencies have non-normal distributions with high kurtosis values.

In table 3 the yearly return and risk characteristics are presented through the average return, volatility and Sharpe-ratio supplemented with highest and lowest values for daily returns in the dataset. When looking at the numbers in the table, it is clear that cryptocurrencies are nowhere near other asset classes in the sense of return and risk. The return coefficients of the cryptocurrencies vary from 280.7% for Bitcoin to 924.3% for Ethereum, where the returns for traditional assets vary from -2.2% to 10.1% for respectively hedge funds and private equity. Similarly, the minimum and maximum daily returns of the cryptocurrencies are more extreme than those of the other asset classes. The cryptocurrency portfolio has had a maximum daily return of 18.5% and the largest loss on one day was -17.6%. Individual cryptocurrencies show even more extreme results with the greatest daily negative return of -35.3% and a rise of 75.8% in one day. The highest return and loss on a day for traditional assets are respectively 9.0% and -7.6%. The immense gap between the two classes is a result of extreme values for cryptocurrencies, since the other assets have relatively normal return values. The traditional assets show returns which would be expectable for these classes. The MSCI World return is 4.6%, which is close to the average 5.5% equity premium from 1900 to 2003 (Estrada, 2013). Emerging markets tend to have higher returns than developed markets, since they are still in a growing equity position (Bekaert & Harvey, 2014). However, for expected returns this is not structurally the case, since the potential high growth is already incorporated in the equity prices. Still the dataset shows that emerging markets have outperformed developed markets. Bonds are typically regarded less risky than equity, which is also reflected in the volatility in this dataset. The volatility for equity classes is around 15% to 18%, whereas bonds start at 2.2% for corporate bonds. The United States government bonds have been more risky than German government bonds, while at the same time the average return is lower. These inequalities originate from differences in monetary policy between these countries, hence the United States started raising the interest rates since last year and the Eurozone still keeps them low. The inflation linked bonds (TIPS) have an even higher volatility, which is caused by an additional inflation risk. Notable is the negative return on oil, especially given its high volatility. This is caused by a decline in oil prices from 2014 through 2015, due to oversupply by the OPEC countries. Also hedge funds seem to have underperformed in the time span of the dataset. On the other hand, private equity has outperformed listed equity funds and has the highest return of all traditional assets. In table 3 the corresponding Sharpe ratios are given. The Sharpe ratio is a measure of risk-return performance. It is the average excess return earned per unit of volatility (Sharpe, 1994), where a high Sharpe ratio implies that an asset has a relative high return compared to the risk it is exposed to. It is calculated by dividing excess return by volatility. In this study, the risk free rate is zero since the yield on AAA-rated government bonds is approximately zero in the Eurozone. The European Central Bank states that a 7 year bond yields 0%, while a 5 year bond has a negative yield of 0.335% and a 10 year bond has a positive yield of 0.420%. For investors, a horizon of 5 to 10 years is common, which in this case results in a 0% risk free rate. This means that returns are by definition excess returns and therefore the Sharpe ratio is calculated by dividing returns by volatility. For the traditional assets, corporate bonds have the best risk-return performance, followed by private equity, German government bonds and emerging market equity. Since some assets have negative historical returns and volatility is always positive, also negative Sharpe ratios occur. This is undesirable for investors since they are exposed to risk and they are negatively rewarded for this risk. When comparing negative Sharpe ratios, one should keep in mind that a lower ratio is not inferior to a less negative number. Oil, for example, has a lower return and higher volatility than TIPS and therefore should have a lower Sharpe ratio, however the ratio for TIPS (-0.06) is lower than the ratio for Oil (-0.03).

As mentioned before, cryptocurrencies' returns are extremely high. If a traditional asset class would have a yearly return of e.g. 20% for the past two years it would be considered as very high. Returns above 100% are rare, but occur for single stocks. However, it is exceptional for an entire asset class to have these extreme returns for two consecutive years. Ethereum, the youngest cryptocurrency in the dataset, has had the largest increase, but also has the highest volatility. Bitcoin is clearly the least risky cryptocurrency with a volatility of 63.2%, which still is almost twice as high as the most risky traditional asset in the dataset. Evidently, all the cryptocurrencies in the dataset are subject to extreme volatility levels. This suits with the large number of threats which cryptocurrencies are opposed to, as mentioned in the SWOT analysis. The compensation or risk premium which investors have received for bearing this risk in the past years is tremendous. Therefore the Sharpe ratios outperform traditional asset classes, whereas the lowest cryptocurrency Sharpe ratio is more than 10 times higher than the ratio for developed equity markets. This emphasizes the extreme statistical properties that the cryptocurrencies entail. Since cryptocurrencies have non-normal distributions with high kurtosis values, the Sharpe ratio coefficients should be interpreted with caution. The Sharpe ratio becomes inaccurate if it is used for assets with non-normal distributions with a high degree of kurtosis (Gregoriou et al., 2003). Therefore, the results can only be used for comparing cryptocurrencies individually. Litecoin and Ripple have low Sharpe ratios with respect to other cryptocurrencies. Dash has the highest ratio, followed by Ethereum and Bitcoin. When looking at the cryptocurrency portfolio, one can see that the Sharpe ratio is higher than all individual currencies, except for Dash which only makes up for 2.18% of the total portfolio weights. This means that the cryptocurrency portfolio benefits from diversification among cryptocurrencies, as a result of low or imperfect correlations. Figure 6 graphically displays the 30-day moving volatility of the cryptocurrency portfolio and gives a representation of the risk over time. It is clear that periods of high volatility are clustered and alternated by periods with lower levels of risk. If compared to the 30-day average daily returns of the cryptocurrency portfolio in Figure 7, volatility does not have a direct relation outside the fact that returns move more extremely, both negative and positive.

5.2 Correlations

5.2.1 Correlations over the whole time span

When looking at the correlations between cryptocurrencies individually (table 4), one can directly see that all the correlations are positive. This entails that when a cryptocurrency increases in price, in general all cryptocurrencies will increase in price. Bitcoin and Litecoin seem to have the highest correlation, which confirms the statement that Litecoin is a replication (page 4) of Bitcoin, with small alterations. Bitcoin has the lowest correlation with Ripple and Ethereum, which also is explainable since the latter two have different objectives. Bitcoin, Litecoin and Dash are developed to function as a real currency, whereas Ethereum and Ripple are not. When comparing cryptocurrencies to other assets, it is noticeable that the correlations are on average slightly positive or slightly negative. The highest correlation is between Dash and MSCI World, the lowest is between Ethereum and private equity. The low numbers for the correlations imply that the traditional assets and cryptocurrencies do not have large influence on each other's price movements. This is a positive signal for diversification in a portfolio. It is clear that Ethereum is mostly negatively correlated with other assets. All assets are negatively correlated with Ethereum, except for the four bond categories. In general, the magnitude of the correlation coefficients between cryptocurrencies and the other assets are considerably low. The highest positive correlation coefficient is 0.110 for the assets Bitcoin and inflation linked bonds (TIPS), where the most negative correlation is between Ethereum and private equity with a correlation of -0.099. These numbers are marginal when compared with other correlation coefficients. In contrast to cryptocurrencies, the MSCI World tracker has a positive correlation with the real estate tracker of 0.844. The cryptocurrencies are on average slightly positively correlated with other assets with the exception of Ethereum which has a negative mean correlation. When comparing the cryptocurrency portfolio with other assets, similar results occur. Sensibly, the correlations with individual cryptocurrencies are highly positive, since the portfolio consists of these assets. The highest correlations pertain Bitcoin and Ethereum, which is caused by the higher weights of these currencies in the portfolio, compared to the other three cryptocurrencies. The correlations with non-cryptocurrency assets are again very low, where the highest correlation is 0.129 regarding US government bonds. Also German government bonds and inflation linked bonds have a relatively high correlation compared to other assets. On average, the correlation with the four bond assets is positive (0.090) and the equity and commodity assets are negatively correlated (-0.007). The cryptocurrency portfolio and equity classes are uncorrelated in this dataset, while bonds seem to have a very low positive correlation. Therefore, it appears that the cryptocurrency portfolio behaves more like a bond than an equity asset. However, the coefficients are of such low magnitude that this statement is not significant.

5.2.2 Moving correlations

Correlations are important statistics to learn about the relation between returns of the assets and the cryptocurrency portfolio. The correlations mentioned before are average correlations over the whole time span. However, like returns, correlations may vary over time and therefore it might be more insightful to have a look at moving correlations. These moving correlations give an understanding about how the correlation is for a certain period and how they change over time. The figures 10 up and until 20 show all the moving correlations between individual traditional asset classes and the cryptocurrency portfolio.

Additionally, figure 21 represents the average of all the individual moving correlations. The moving correlations are computed over a period of 30 days. Firstly, generally looking at the moving correlations, it can be concluded that all assets have moments on which they positively correlate with the cryptocurrency portfolio as well as moments on which they negatively correlate with the cryptocurrency portfolio. The average moving correlations in figure 21 begin with positive numbers and decline towards the beginning of 2016, where they eventually end up as negative. By March 2016 the correlation rises towards a peak and immediately decline again to the ultimate low point. Only a couple of months later the highest correlational point is reached and one month later it drops again. This period, roughly from May to September 2016, seems to have the most variation in correlation. From here there is one more period with a positive average correlation, after which the correlation remains close to zero. The period with high correlations halfway through 2016 also shows high volatilities, as can be seen in figure 6. In this period some important events happened in the blockchain world which probably have caused these concurrences. It started with the creation of DAO in May 2016, where the volatility and correlation started to increase. When the DOA hack occurred and DOA was de-listed from the exchanges, the price levels stabilized. This resulted in a drop in volatility as well as average moving correlation. All individual assets show a comparable pattern in correlation with the cryptocurrency portfolio, with a strong increase in May 2016 and a resolute decrease just before September 2016. The only exceptions are gold and hedge funds, which experienced a drop in correlation in May and again in September. More strikingly is the difference in the hedge fund moving correlation and the volatility of the cryptocurrency portfolio. At the moment when all other assets see a decrease in correlation before September 2016, hedge funds' correlation increases. Then, when volatility increases again at the beginning of 2017, the moving correlation drops to negative numbers. The impression thus arises that hedge funds' correlations and the cryptocurrency portfolio volatility move in opposite direction. An explanation may be that hedge funds are discouraged to have positions is cryptocurrencies in times of high volatility. Hedge fund managers have targets for achieving returns while maintaining acceptable levels of risk. Cryptocurrencies are extremely risky, especially in periods with high volatility which may discourage hedge fund managers to have exposure to these risky assets.

Comparing the 30-day moving volatility with the moving correlations, it is noticeable that volatility does appear to have an effect on correlations. Interestingly, the strongest similarity appears to be the German government bonds. Also other bond assets seem to have comparable graphs. This matches with the correlation coefficients over the whole time span of the dataset in which the bond asset classes have the highest correlation with the cryptocurrency portfolio. To a lesser extent, also equity classes show similar graphs. The assets gold and hedge funds are the most deviant from the other moving correlations. In summary, correlations between the cryptocurrency portfolio and traditional assets are considerably low and vary over time with coefficients both positive and negative. Many assets' correlations move in a similar manner and follow cryptocurrency volatility, implying that the main driver in correlation movement is the cryptocurrency portfolio.

6 Results

6.1 Diversifier, hedge and safe haven

As discussed in the general statistics, correlations between cryptocurrencies and traditional asset classes are relatively low. None of the assets have substantial correlations with either individual cryptocurrencies or the cryptocurrency portfolio. An ideal hedge would mean that the cryptocurrency portfolio is significantly negatively correlated with at least one other asset class in the portfolio. Since correlations are not distinctively negative, the hedge capabilities of cryptocurrencies in the diversified traditional portfolio are not ideal. Only hedge funds, private equity and oil show negative correlation coefficients with the cryptocurrency portfolio, however the coefficients are too low to assume the assets to be negatively correlated. Though less strong than a negative correlation, a hedge also exists when two assets are uncorrelated. The correlations between the cryptocurrency portfolio and the other assets are not significantly different from zero. Therefore, we can state that the cryptocurrency portfolio, for this dataset and time frame, would have provided against the base portfolio. The cryptocurrencies have the highest correlation with bonds. Luckily, the positive correlation coefficients with the bond like assets are of such a low magnitude that the cryptocurrency portfolio can certainly serve as diversifier for this asset class. Therefore, we can conclude that the cryptocurrency portfolio could certainly serve as a diversifier and additionally might have hedging characteristics for a diversified, traditional portfolio. In times of turmoil in the cryptocurrency market, the cryptocurrency portfolio on average tends to have higher correlations with the other assets. This contradicts the possibility of safe haven benefits for cryptocurrencies in the base portfolio. Once again, only hedge funds might have these characteristics due to managers avoiding high levels of risk which cryptocurrencies possess. Therefore, the combination of the five largest cryptocurrencies does not entail safe haven characteristics, at least for 10 out of 11 assets in the dataset. Correlations between individual cryptocurrencies demonstrate that investors should preferably invest in a cryptocurrency portfolio rather than in one individual cryptocurrency, since a portfolio benefits from diversification among cryptocurrencies.

6.2 Mean-variance analysis

The mean-variance analysis consists of two portfolios. One portfolio only contains traditional assets, where the other portfolio also allocates weight to cryptocurrencies. In both portfolios short selling is limited to 5%, since larger numbers can be hard to acquire in real life, particularly if the investor has a significant investable wealth. Moreover it is not desirable for investors to have large negative positions as this can make a portfolio more risky. However, when applied correctly, limited levels of short selling can significantly improve risk-return ratios of a portfolio. Therefore, a limit of 5% is chosen. In figure 22 the mean-variance frontiers are presented. The traditional assets are also displayed, whereas cryptocurrencies lay outside the plotted are due to high volatility and returns. Noticeable is that the frontier of the portfolio with cryptocurrency allocation has higher returns than the portfolio without cryptocurrencies. For moderate levels of risk in the portfolio, only 2% to 4% is allocated to cryptocurrencies. In the minimum-variance portfolio, the allocation is -0.03%. This means that the allocation of a small amount of cryptocurrencies results in considerably higher returns for a given amount of risk. Moreover, the portfolio with cryptocurrencies has a lower minimum-variance point than the traditional portfolio, where the daily volatilities are respectively 0.118% and 0.133%. Even though these results appear very positive towards cryptocurrencies, these finding should be interpreted with caution. Since the mean-variance analysis is very sensitive to expected returns and underlying data are historical data, this does not give a reliable view of the future. The fact that cryptocurrencies' returns have exceeded a manifold of 100% in the past years is heavily influencing the frontier. However, these frontiers give a good representation of historical events.

6.3 Volatility target optimization

As discussed in in the method chapter, no decisive conclusions can be drawn from the volatility target optimization, however findings may still be insightful. Firstly, in order to find market equilibrium implied returns which are used for the Black-Litterman model as well, we need to set the global risk aversion level. Existing literature is indecisive about a proper risk aversion level for the average global investor. However, we can estimate the risk aversion level by setting it in such a manner that the equity risk premium in the dataset equals the average equity risk premium in the global market. Also the exact equity risk premium is not the same in every study. For example, Damodaran (2011) argues the equity risk premium is around 6% to 6.5%, while Dimson et al. (2003) state the global equity risk premium is only 3.5%. Generally, it is said that the average global equity premium is around 5%. Setting the risk aversion level to 3.96 results in a global equity risk premium of 5%. When looking at other numbers in table 2, the implied returns do make sense. Emerging market equity has an implied return of 5.07% which is slightly higher than the developed global equity. The bond assets have a return much lower than the equity classes, as is also discussed in the descriptive statistics. Logically, TIPS do have a higher return than the other bonds, since it is exposed to and compensated for inflation risk. Cryptocurrencies have a total market value of approximately zero, hence the implied return is very low, namely 1.29%. Table 5 shows the weights of every asset in the possible portfolio options and the corresponding return and volatility. The return of a portfolio is maximized for the stated volatility by changing the weights of the individual assets. As in the mean-variance analysis, short selling is limited to 5%. The minimum risk portfolio has a volatility of 1.91% with a corresponding return of 0.17%. When increasing the risk of the portfolios, one can see that the return also increases as is graphically presented in figure 23. When reaching higher levels of risk, as volatility goes above 20%, the relative rate at which return increases declines. Both low volatility and high volatility points on the graph contain a curved line, whereas approximately from 5% volatility to 20% volatility the line is rather linear. As a result of the limitation on short selling, the frontier is curved at both ends. If there would be no limit on negative position, the frontier would be more linear and higher values for return and risk would be achievable. As presented in the table, the highest level of risk while still maximizing return and satisfying constraints is 25.79% with a return of 6.65%. Here, all assets have a negative position to the maximum of 5% and are used to finance a position of 155% in emerging equity funds. No point on the original frontier has a positive weight in the cryptocurrency portfolio, which is rational since it has a very low return and a very high volatility.

Subsequently, when further solving the problem, the initial implied return for the cryptocurrency portfolio is replaced by the formula to ensure that the points on the frontier remain unchanged. Then we try to find the minimum required expected return for the cryptocurrency portfolio to justify a 5% allocation for multiple volatility targets. The results are displayed in figure 24, which can be interpreted as follows. On the x-axis the target volatility is given. The y-axis represents the required expected return for the 5% cryptocurrency portfolio which results in the same return for the original portfolio on the frontier. Consequently, the point on the frontier remains the same while the allocation to cryptocurrencies has increased to 5%. The original volatility target portfolio of 10% has a return of 3.42% as stated in table 5 with an allocation of 0% in the cryptocurrencies. When you would increase this allocation to 5% and require to have the same portfolio return of 3.42% for 10% volatility, the return of the cryptocurrency portfolio should be 5.63%. Similarly, for the target portfolio with 7.5% volatility and 2.56% return, the required expected return for cryptocurrencies is 7.35%, whereas the target portfolio of 5% results in a cryptocurrency return of 12.11%. From figure 24 it becomes clear that for lower levels of volatility targets, the required cryptocurrency return increases exponentially. Intuitively, the target portfolio has a position of 5% in the highly risky cryptocurrencies and in order to accomplish low targets of volatility, relatively large allocations to low risk assets are required. However, these assets with low risk also have low returns. Hence, in order to reach the same return as the original target portfolio, a higher expected return for the cryptocurrency portfolio is required. Even though this method might not be an academically clean option and no clear conclusion can be drawn, we do see that the required expected returns for cryptocurrencies are not shockingly high. One could say that for a moderately risky portfolio with 7.5% volatility, a required return on cryptocurrencies of 7.35% is considerably low, especially when compared to the equity risk premium of 5%. Realizing that cryptocurrencies are extremely volatile, risk is efficiently diversified away in the total portfolio this, since correlations with all other assets are very low.

6.4 Black-Litterman

The implied returns for the Black-Litterman model are the same as for the volatility target analysis, because we use the same equilibrium market weights and the same global investor risk aversion level. Since the implied equilibrium returns are known, the next step is to express a view which results in a 5% allocation in the cryptocurrency portfolio. To solve this, we only express one absolute view regarding the return on the cryptocurrency portfolio. The accuracy of the equilibrium as a source of information, also known as Tau (τ), is set to 0.15 as discussed before. The confidence in the view is expressed as a function of the view itself. More precisely, the standard error of the view is 0.25 multiplied by the magnitude of the view. Omega (Ω) is the square of the standard error and thus varies with the expressed view. We know that the Black-Litterman model is very useful since it adjusts expected returns of assets if a view is expressed. The correlations with other assets determine the new expected returns by using a variance-covariance matrix. These new returns, the Black-Litterman expected returns, determine the weights in the portfolio by reverse engineering. Now we need to find such a view for the cryptocurrency portfolio to justify the position of 5% in cryptocurrencies. If we, for example, implement a view resulting from the volatility target portfolio of 7.5% volatility, the cryptocurrency portfolio return would be 7.35%. When implementing this view, the Black-Litterman allocation in the cryptocurrency portfolio is 3%. This entails that this result from the volatility target analysis is estimated too low. When we solve the Black-Litterman model with an allocation of 5% in the cryptocurrency portfolio, the expressed view is that cryptocurrencies will have an expected return of 11.44%. Hence, if an investor has the opinion that cryptocurrency prices will increase by at least 11.44%, it would be justified to have a 5% position in the cryptocurrency portfolio. In table 6 the Black-Litterman solution for a view of 11.44% in the cryptocurrency portfolio is given. Firstly, the implied equilibrium returns for the assets are displayed in the left column, followed by the historical returns which have been calculated over the time period of the dataset. These historical returns are not related to any aspect of the model, the only purpose is to compare them with the results. Then we see the Black-Litterman expected returns, which is the solution of the equation in the method chapter, and consist of two portions. Both initial implied returns and the view are incorporated in these returns. For a

5% allocation in cryptocurrencies, the Black-Litterman expected return of the cryptocurrency portfolio is 11.33%. Hence, if the view is completely certain, the required expressed view should be 11.33%. Clearly, the view has a substantial influence on the Black-Litterman returns since the return is nearly equal to the view. This is because the confidence in the view is not very low and Tau (τ) has a large number. Later on, we test for robustness by varying these numbers. When looking at the difference between the implied returns and the Black-Litterman returns, clearly some assets have relatively increased a lot more than other assets. Obviously, the cryptocurrency portfolio has increased the most since the view was expressed regarding this asset. Both developed global equity and emerging market equity have only increased slightly with respectively 1.2% and 0.3%. Then the bond assets show the largest relative improvement of returns, where German government bonds have increased the most of all assets by 19.9%. This was expectable since this asset class showed a relatively high correlation with the cryptocurrencies. US government bonds and TIPS have increased with 9.3% and 6.0% respectively. Oil, hedge funds and private equity have a lower expected return than in the equilibrium, since they are negatively correlated with the cryptocurrency portfolio and the expressed view. This proves that the Black-Litterman model does indeed take into account that a change in return of one asset affects the returns of other assets as a result of their respective correlation. Subsequently, in table 6 we find the reverse engineered weights corresponding to the implied returns, the historical returns and the Black-Litterman returns. In the last column the Black-Litterman results are translated to a portfolio without a position in the risk free rate. Since the risk free rate is approximately zero, it does make sense to have a short position as borrowing does not bear costs. However, borrowing 5% in the risk free rate and investing this in highly risky cryptocurrencies may not be wise. Moreover, the global investment in the risk free rate adds up to zero since one party borrows to another, which results in a negative and positive investment of the same amount, hence the sum is zero. Therefore, the Black-Litterman portfolio is also stated as a portfolio with 100% allocation in risky assets and 0% in the risk free rate. If an investor would prefer to have either a negative or positive position in the risk free rate, this naturally is possible. The implied weights are exactly the same as the market equilibrium weights, since the implied equilibrium returns are essentially reversed without being altered. The second weights column shows what occurs when the historical returns are reversed to portfolio weights by the Black-Litterman model. Hence, there are many assets with large negative weights, which is impossible in the real world. The negative weight in German government bonds would mean that on average, investors borrow 674% of their portfolio value from the German government and invest this in risky assets. Additionally, an equilibrium weight of more than 100% is impossible since this would imply that more than all investable wealth in the world would be invested in that asset. Even if an individual investor would try to replicate such a portfolio, it could not be achieved. Furthermore, the statistical properties of this portfolio show that it is highly unrealistic. On the other hand, the Black-Litterman weights do give a realistic set of asset weights to invest in. As a result of the absolute view, the only change in weights is realized in the cryptocurrency portfolio which increased from 0% to 5%. This is financed by borrowing 5% of the portfolio value against the risk free rate. A relative view between two assets would only influence their weights, while the weight of other assets and the risk free rate remain unchanged. Therefore this Black-Litterman portfolio result is called a self-financing portfolio. When solving the model to a portfolio with a total of 100% weights the weight in the risk free rate is zero. To compensate, mainly the weight in corporate bonds is reduced, since this asset class has the return and risk properties which lie closes to that of the risk free rate. We can conclude that the position gain in the cryptocurrency portfolio weights is at the expense of the position in corporate bonds. This results in a portfolio that is underweighted in this asset and has a high position in cryptocurrencies compared to the equilibrium portfolio. The expected portfolio returns of the Black-Litterman results have increased significantly, from 2.95% to 3.58% corresponding to an increase of 21%. On the other hand, also volatility has increased as well, hence at a lower rate namely 10%. Therefore, the Sharpe ratio of the portfolio has increased with 10%, which is beneficial for investors. The difference between the two Black-Litterman portfolios is negligible.

In order to check for robustness, the same calculations have been performed with different values for Tau (τ) and Omega (Ω). When setting Tau to the lowest reasonable level 0.05, the required expected return for the cryptocurrency portfolio increases from 11.44% to 11.64%. Therefore we can state that the accuracy of the equilibrium returns in this case does not have a large effect on the model. This makes sense, since cryptocurrencies' expected return cannot be efficiently retrieved from the market equilibrium. When the standard error of the view is doubled to 0.5 times the view, the required rate of return is 11.79%. If the standard error is set to the same value as the view, the required cryptocurrency return is 13.88%. The change in implied return is now larger than when altering the level for Tau, meaning that the uncertainty around the view is a more important factor than equilibrium returns in the case of cryptocurrencies. When simultaneously lowering Tau and increasing the uncertainty of the view, these effects strengthen each other. If Tau is 0.05 and the standard error is a function of 1 times the view, the required return is 17.27%. Besides Tau and Omega, the variance-covariance matrix (VCV) is an important factor when constructing the Black-Litterman model. For this reason, we test the robustness of the variance-covariance matrix by using different sample lengths. When the VCV is calculated over a period of 1 year instead of the full length of the dataset, the required rate of return for the cryptocurrency portfolio to justify a 5% allocation decreases to 10.60%. When calculated over periods of 1.5 and 0.5 years, the VCV gives similar results, respectively 10.27% and 10.41%. Therefore, the results from the Black-Litterman model with a VCV-matrix estimated over the entire time span of the dataset are the most conservative, since a higher required view is safer from the investor's point of view. For this reason, the minimum required view is 11.44% to 17.27% depending on the level of certainty of the view and the equilibrium market returns. Even though these returns are considerably high for traditional assets, they are much lower than the historical returns of cryptocurrencies. If cryptocurrencies would have a higher correlation with the other assets, the required rate of return consequently would be much higher as well. Diversification is the most important factor for the justification of cryptocurrencies in a well-diversified portfolio.

7 Conclusion

7.1 Discussion

Cryptocurrencies are new in the world of finance and have impressed with extremely high returns over the past few years. The underlying technology of cryptography is an innovation which may entail a great potential for the future and therefore many large financial firms are investigating the possibility of implementing the technology in their business model. On the other hand, a large number of threats to the individual cryptocurrencies and the technology as a whole make their future uncertain. The underlying value of these currencies is mainly determined by their future potential. Bitcoin is the market leader among cryptocurrencies, however new entrants have gained relative market power, of which Ethereum is the largest competitor.

Cryptocurrencies have statistical properties which are incomparable with other, more traditional assets. Both return and risk have been extremely high in the past couple of years. Even though cryptocurrencies are extremely risky, investors could benefit from diversification and hedge possibilities by adding a small proportion of these currencies to their portfolios. The cryptocurrency portfolio used in this study, constructed through relative market weights, could be used as a hedge against equity asset classes. Also bond asset classes have significantly low correlations with the cryptocurrencies, although slightly higher than other assets. Therefore, we can conclude that cryptocurrencies certainly serve as a diversifier, even for already diversified portfolios. Evidence is too fragile to conclude that cryptocurrencies can be regarded as a hedge. In times of high volatility, cryptocurrencies tend to have a higher correlations with other assets and thus unsuitable as a safe haven. Subsequently, using the Black-Litterman model, volatility target analysis and mean-variance frontiers, findings show that expected returns for the cryptocurrency portfolio do not have to be extremely high to justify a modest allocation of 5% in cryptocurrencies. Furthermore, the Black-Litterman model shows that the Sharpe ratio of the equilibrium portfolio will increase by adding cryptocurrencies as an asset class. The model implies that it would make sense for investors to invest in this new asset class if they are convinced that the yearly return on cryptocurrencies will exceed the range of 11.44% to 17.27%. When tested for robustness, uncertainty around the view has larger influence on the results than the trust in information from equilibrium returns. Regardless from the view, if the real return on cryptocurrencies would turn out to be 11.33% and the other assets behave exactly the same in the future, a 5% allocation in the cryptocurrency portfolio is justified. Compared to the historical returns, these required returns are relatively low and reasonable.

Given these points, it can be concluded that European investors could increase the risk-return tradeoff of their well-diversified portfolio by allocating a small proportion of their wealth to cryptocurrencies if they expect that cryptocurrencies will increase more than the required return. Even though returns have been extremely high in the past, this asset class should be handled with caution, since uncertainty about the future is large.

7.2 Limitations

Since cryptocurrencies are relatively new, existing literature is scarce. This causes this topic to be challenging as a fact that there is not a large fundamental base to build on, scientifically. However, fortunately cryptocurrencies are becoming more widely known and the available literature is increasingly growing. As a result it can be challenging to gather scientific resources as evidence.

Preferably, the length of the dataset would have been larger. However, because Ethereum is now the second largest cryptocurrency and it only exists for two years, the maximum time span is used. Future studies with larger datasets might provide more robust results. This study emphasizes on European investors, additional research may focus more on investors in different regions. Expectedly, the results will be comparable since cryptocurrencies are hardly correlated with other assets or markets.

The mean-variance analysis is heavily dependent on expected returns, which are hard to estimate. Since the mean-variance is built up by historical data, it does not give a reliable view on the future. Moreover the volatility target analysis is a simple method to find a required rate of return to justify an allocation in the cryptocurrency portfolio, however the method is not clean and unreliable. Therefore, the Black-Litterman method is much more reliable and accurate. Even though the Black-Litterman is a very decent method, future studies could use more elaborate methods to investigate portfolio allocation possibilities for cryptocurrencies. Additionally, the results from the Black-Litterman model are sensitive to different levels of cryptocurrency allocation, further research in this area may result in interesting findings. Cryptocurrencies have non-normal distributions. If they develop towards more normal distributions is the future, regression analysis may be a suitable extension to scientific research.

Furthermore, the results show that the market weighted cryptocurrency portfolio diversifies risk away in the case of cryptocurrencies. An idea for additional research may be to find an ideal cryptocurrency portfolio which has the highest Sharpe ratio. Considering the extreme volatile properties of cryptocurrencies it may also be useful to find a cryptocurrency portfolio with the lowest risk.

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Appendices

Figures

Figure 1

Graph displaying worldwide Google searches for the subjects Bitcoin, Ethereum and cryptocurrency. The graph contains data from January 2011 until September 2017. Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. Source: Google Trends (www.google.nl/trends).

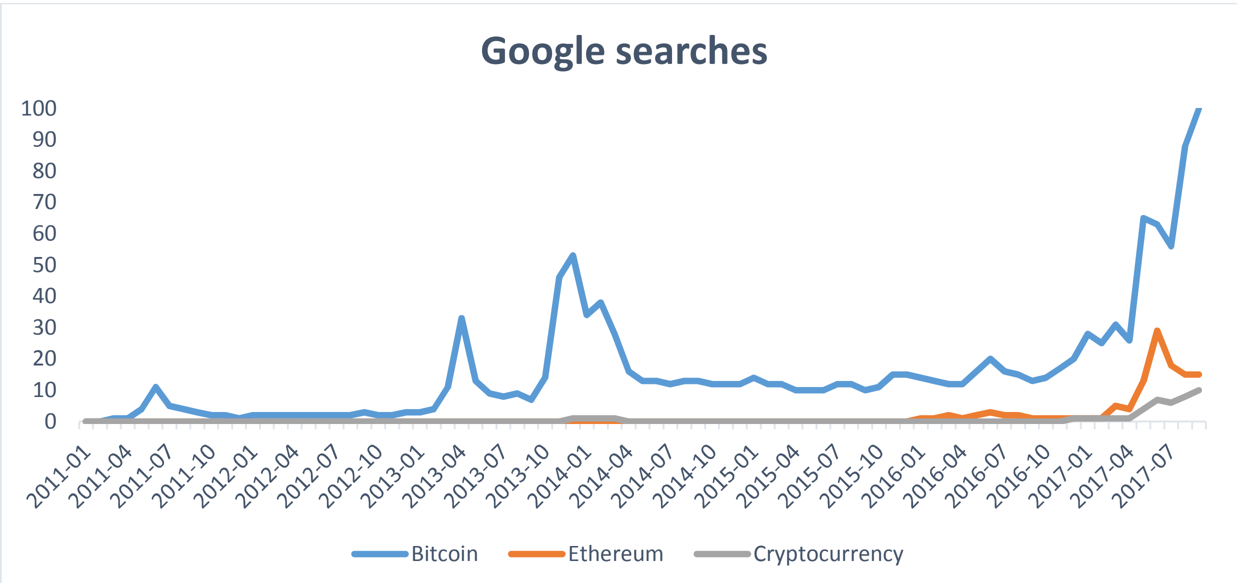


Figure 2

Graph displaying worldwide Google news results for the subjects Bitcoin, Ethereum and cryptocurrency. The graph contains data from January 2011 until September 2017. Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. Source: Google Trends (www.google.nl/trends).

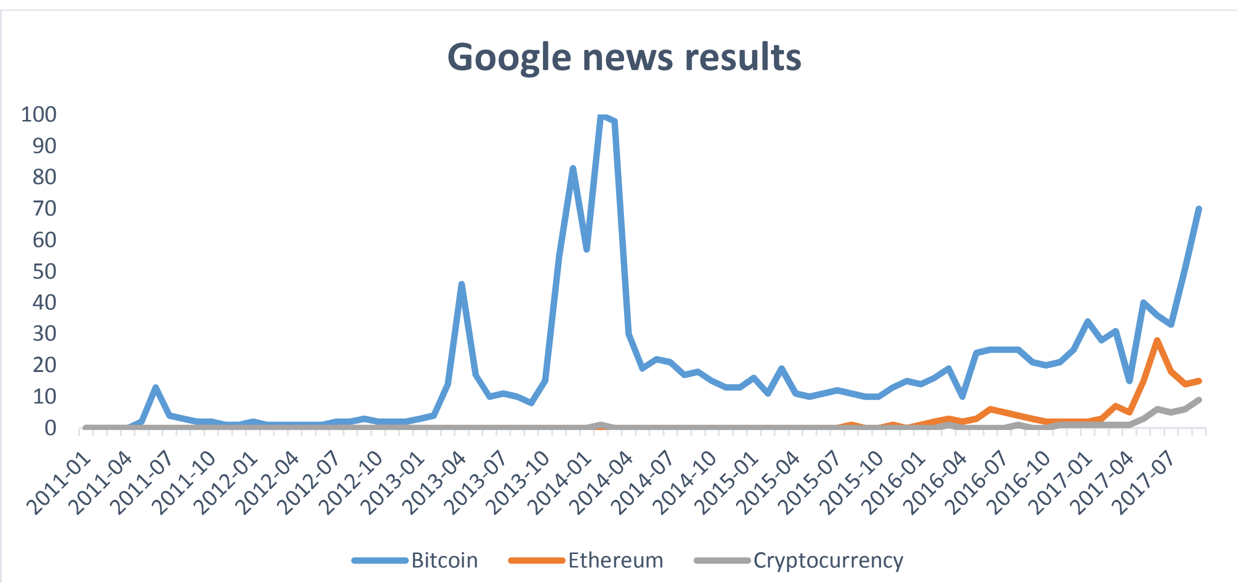


Figure 3

Total expected Bitcoin supply curve over time. Supply is predetermined and limited to 21 million units. Coinivore (2017).

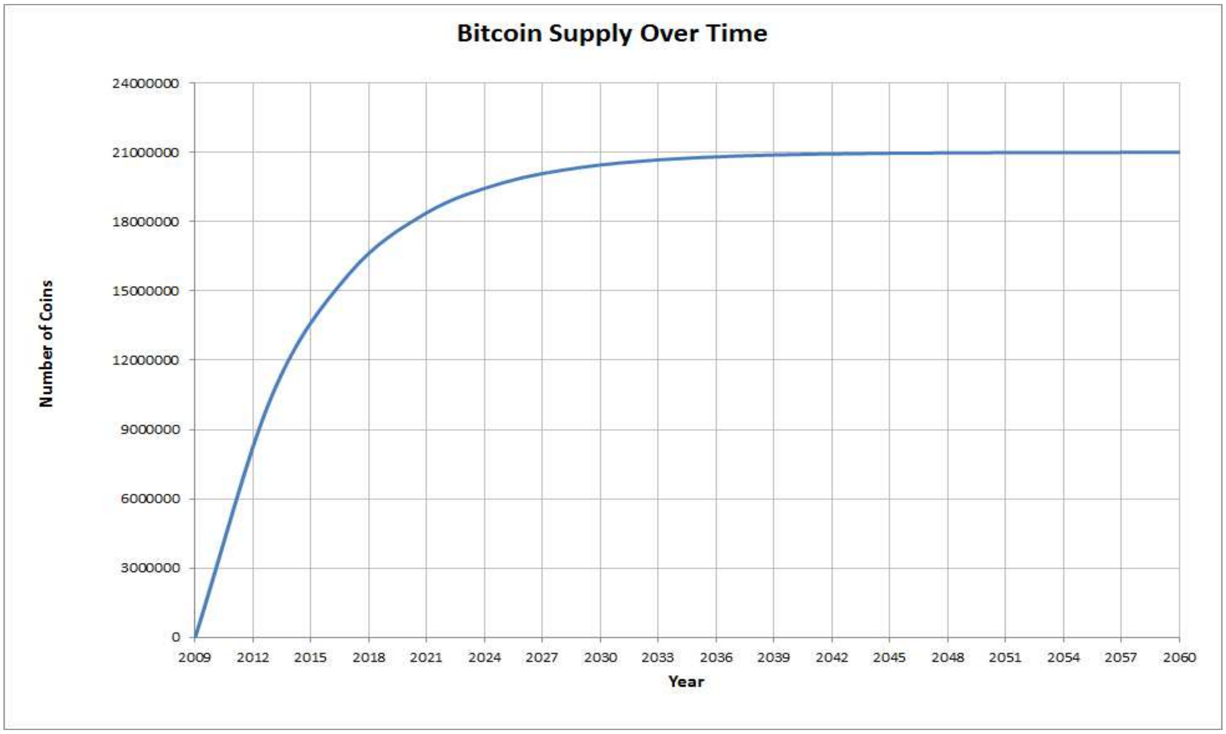


Figure 4

Relative market capitalization (dominance) in the cryptocurrency market in the period of September 2013 to September 2017. CoinMarketCap (2017).

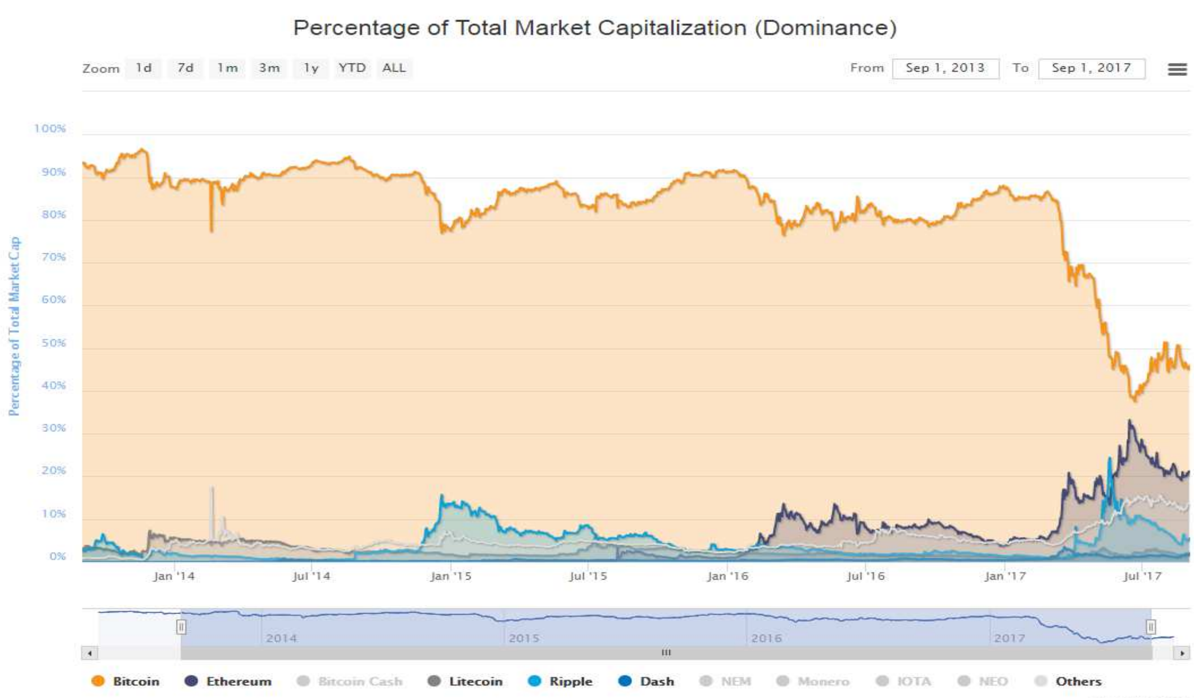


Figure 5

Total cryptocurrency market capitalization in US dollars in the period of September 2013 to October 2017. CoinMarketCap (2017).

Figure 6

30-day moving volatility of the cryptocurrency portfolio.

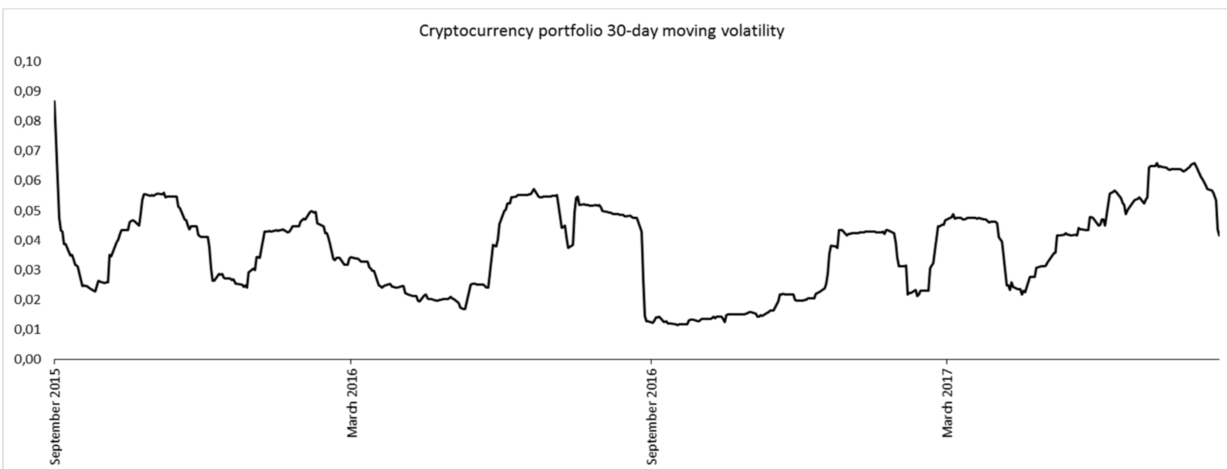


Figure 7

30-day moving average daily return of the cryptocurrency portfolio.

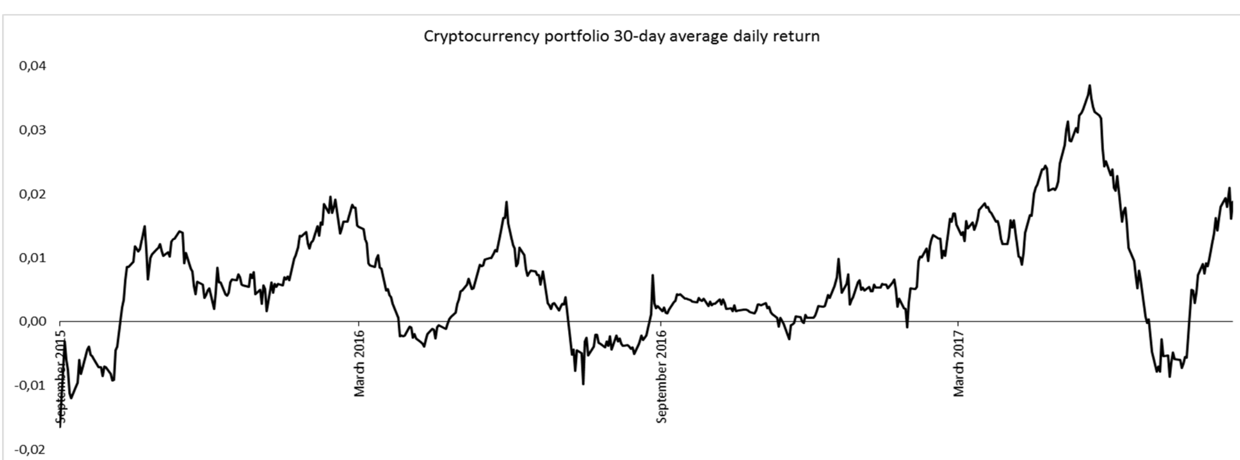


Figure 8

Density plot of German bonds returns compared to the normality curve. Kurtosis value is 2.8.

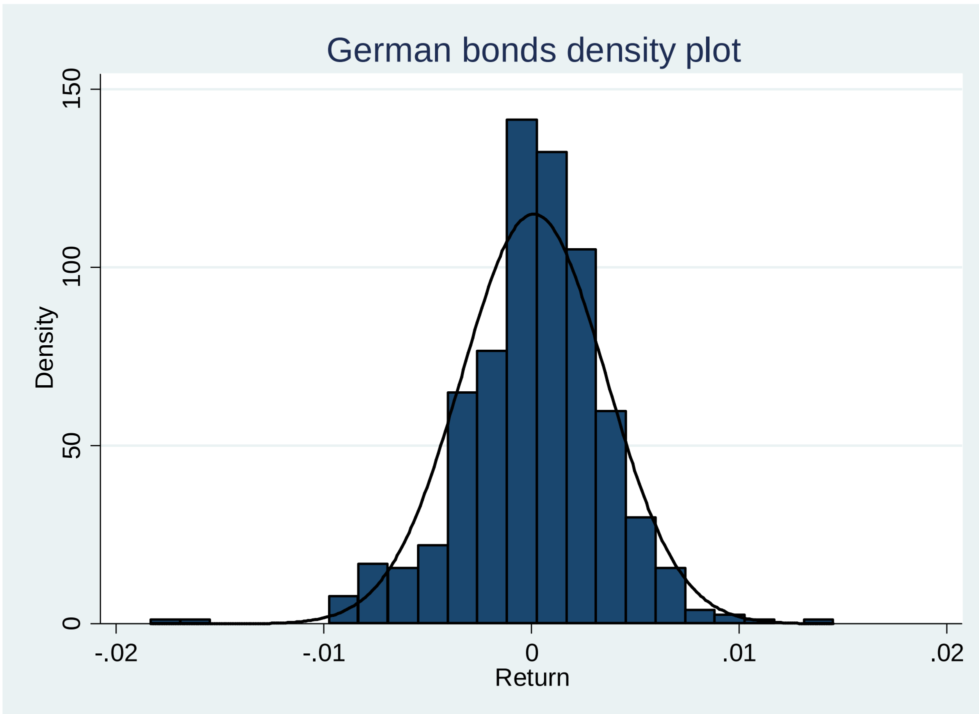


Figure 9

Density plot of German bonds returns compared to the normality curve. Kurtosis value is 5.1.

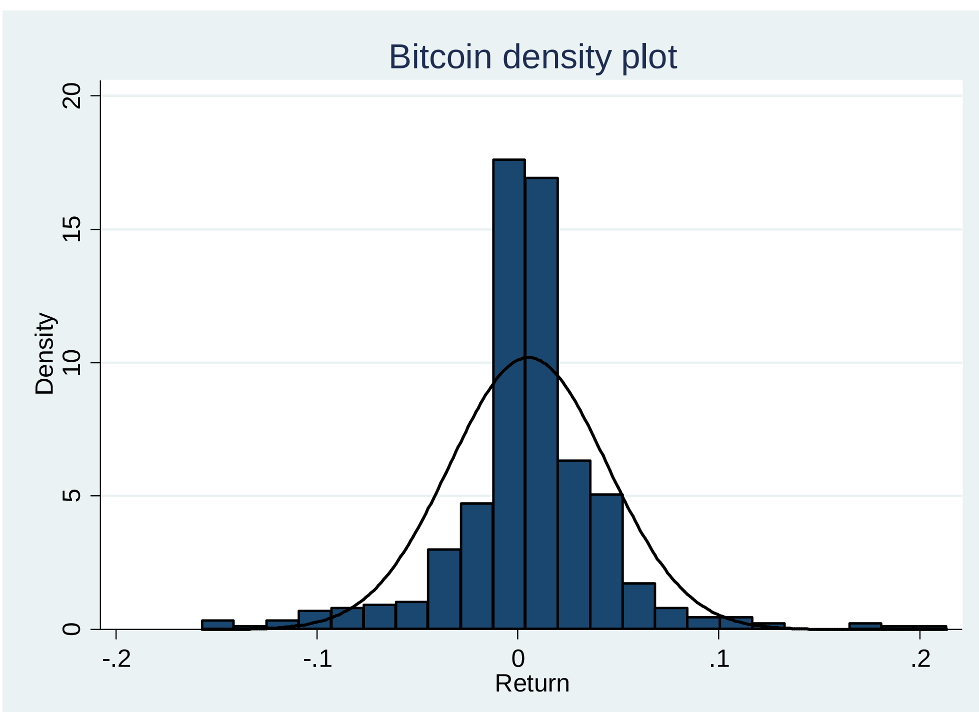


Figure 10

30-day moving correlation between MSCI World equity and the cryptocurrency portfolio.

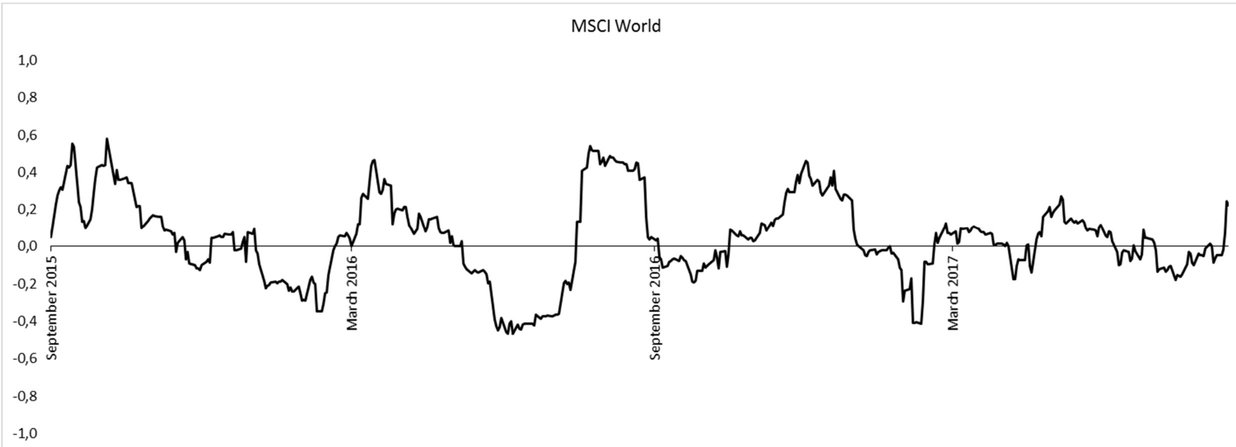


Figure 11

30-day moving correlation between MSCI Emerging equity and the cryptocurrency portfolio.

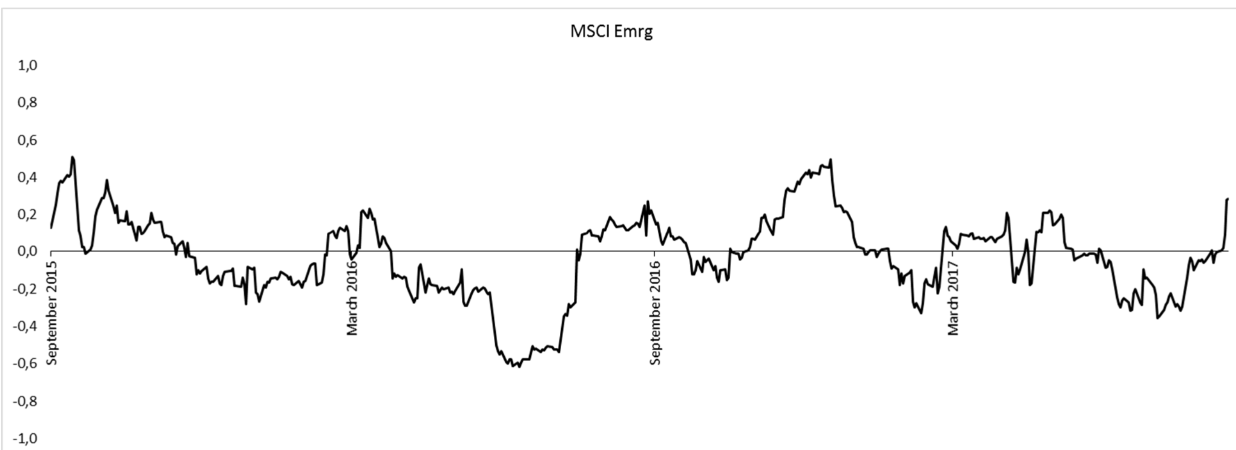


Figure 12

30-day moving correlation between European corporate bonds and the cryptocurrency portfolio.

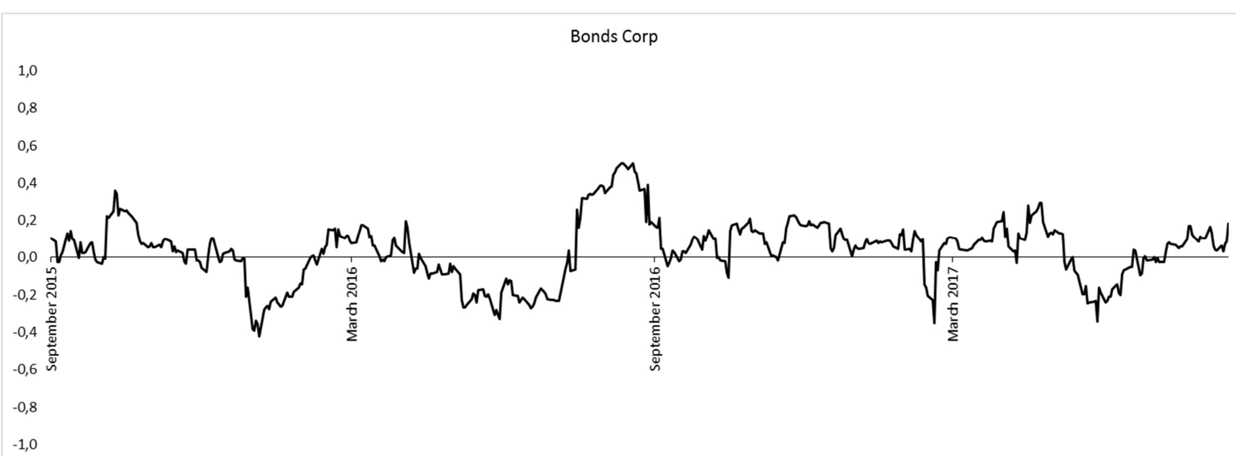


Figure 13

30-day moving correlation between German government bonds and the cryptocurrency portfolio.

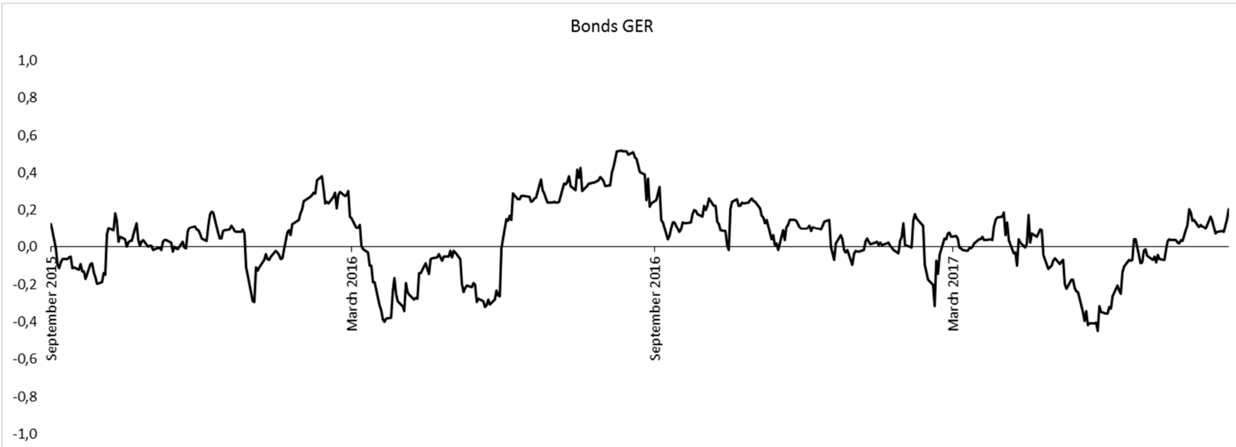


Figure 14

30-day moving correlation between United States government bonds and the cryptocurrency portfolio.

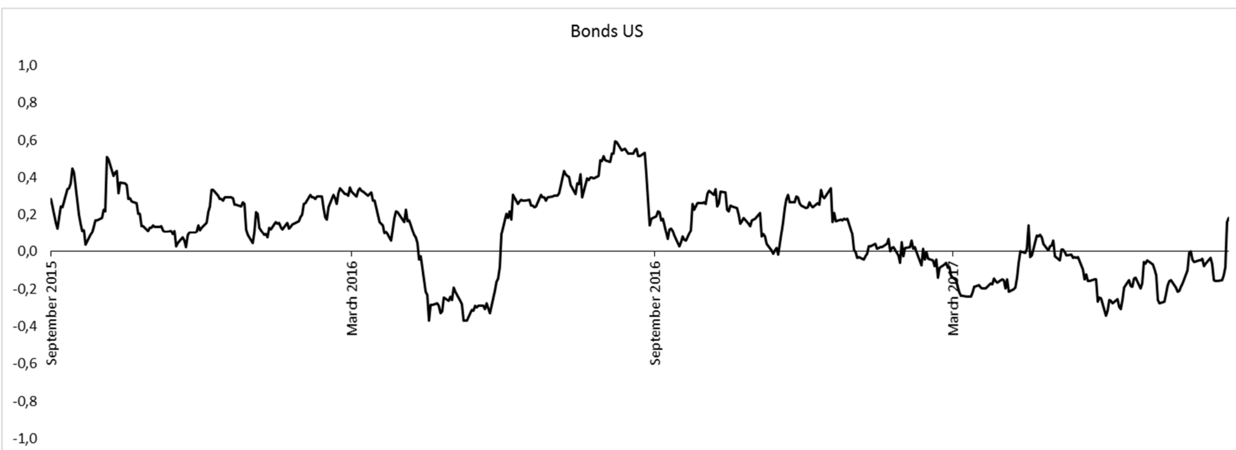


Figure 15

30-day moving correlation between TIPS (inflation linked bonds) and the cryptocurrency portfolio.

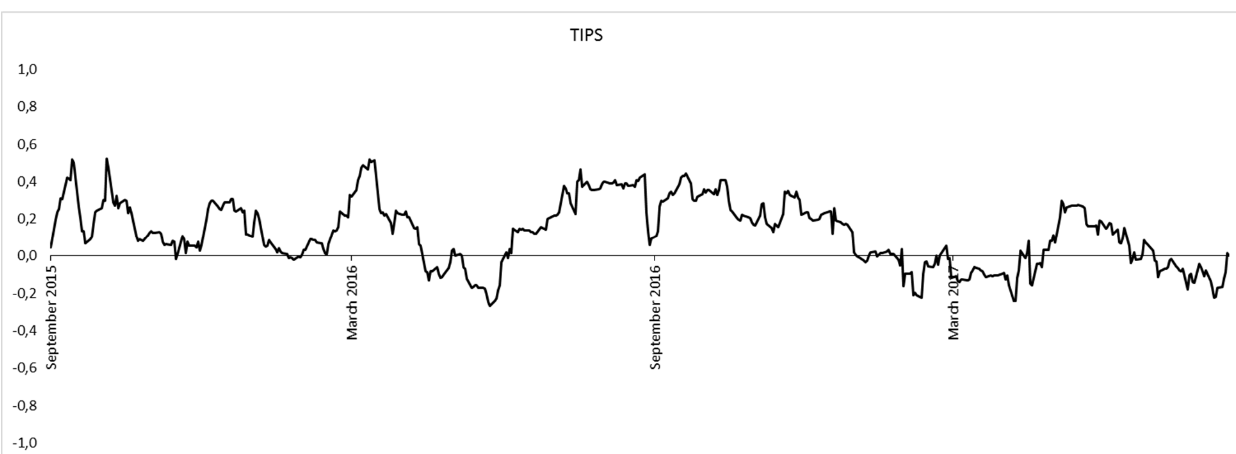


Figure 16

30-day moving correlation between Gold index and the cryptocurrency portfolio.

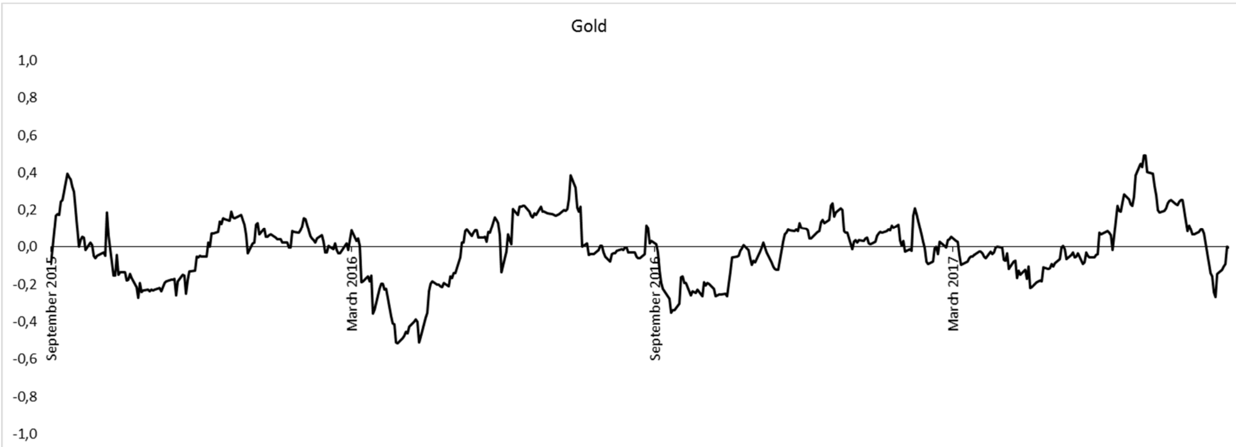


Figure 17

30-day moving correlation between Oil index and the cryptocurrency portfolio.

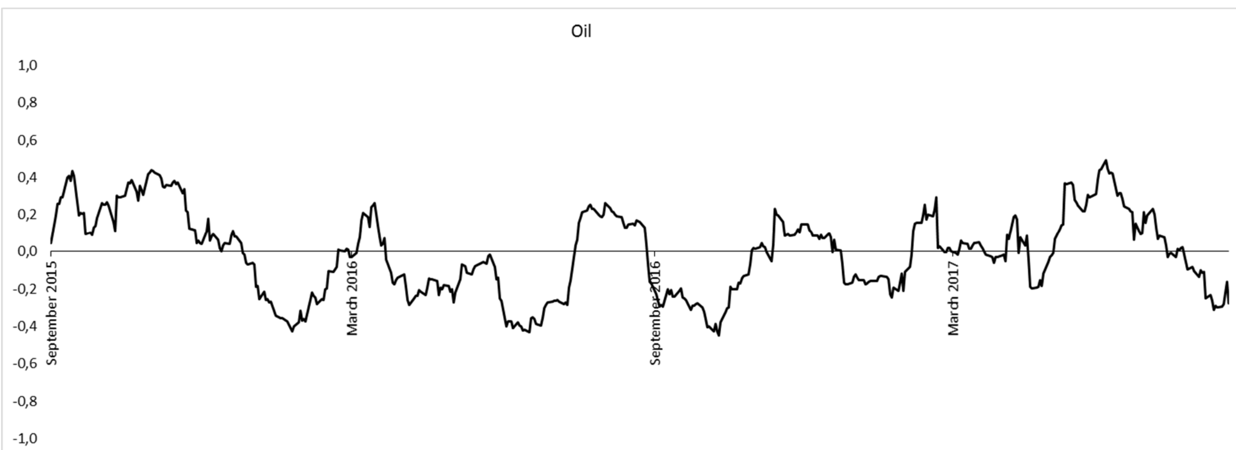


Figure 18

30-day moving correlation between Global real estate and the cryptocurrency portfolio.

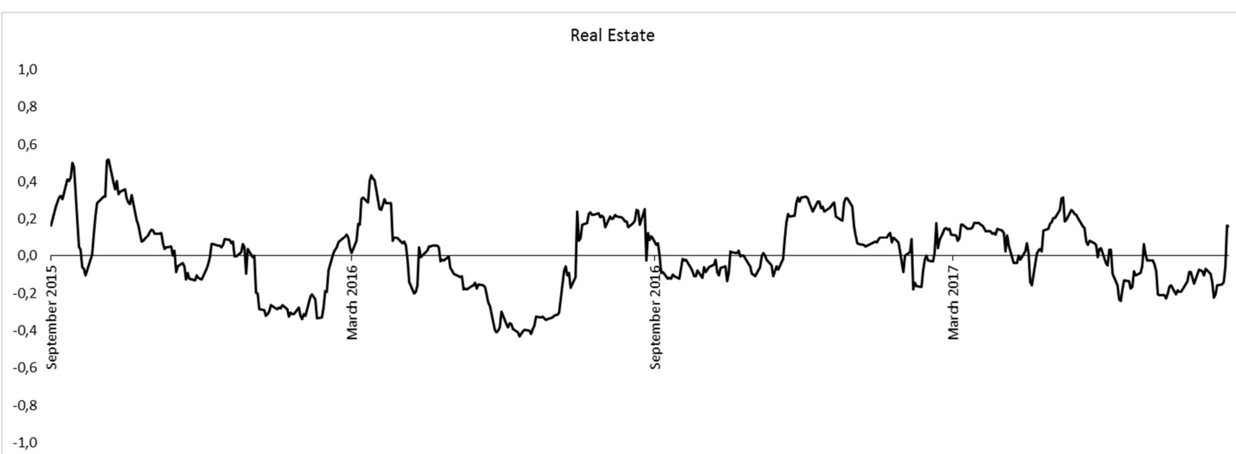


Figure 19

30-day moving correlation between Hedge funds and the cryptocurrency portfolio.

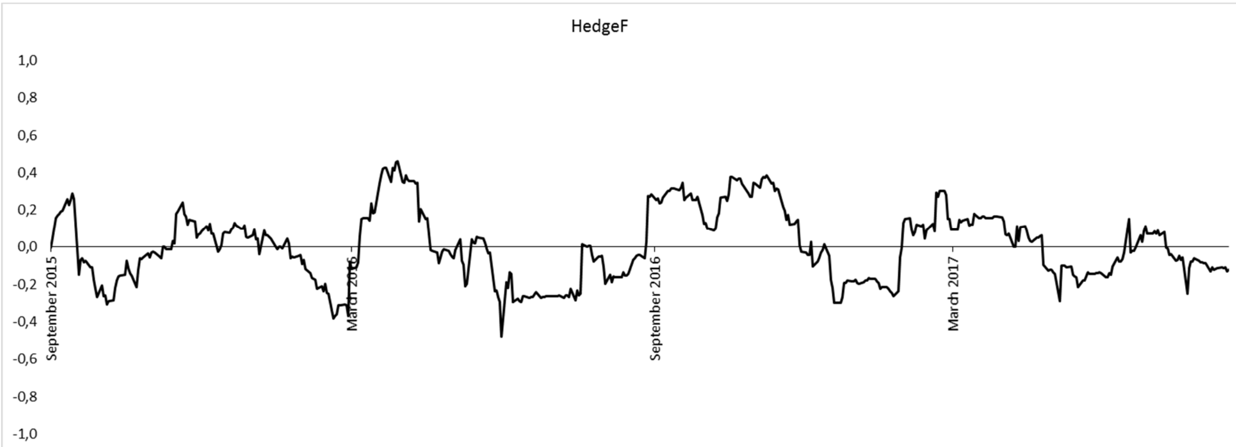


Figure 20

30-day moving correlation between Private Equity and the cryptocurrency portfolio.

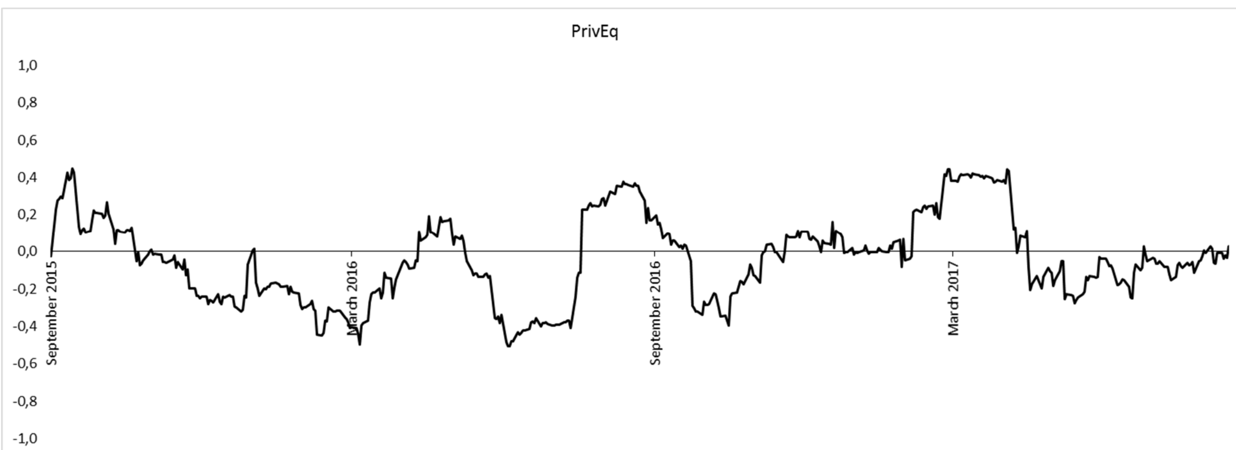


Figure 21

The average of 30-day moving correlations of 11 different assets.

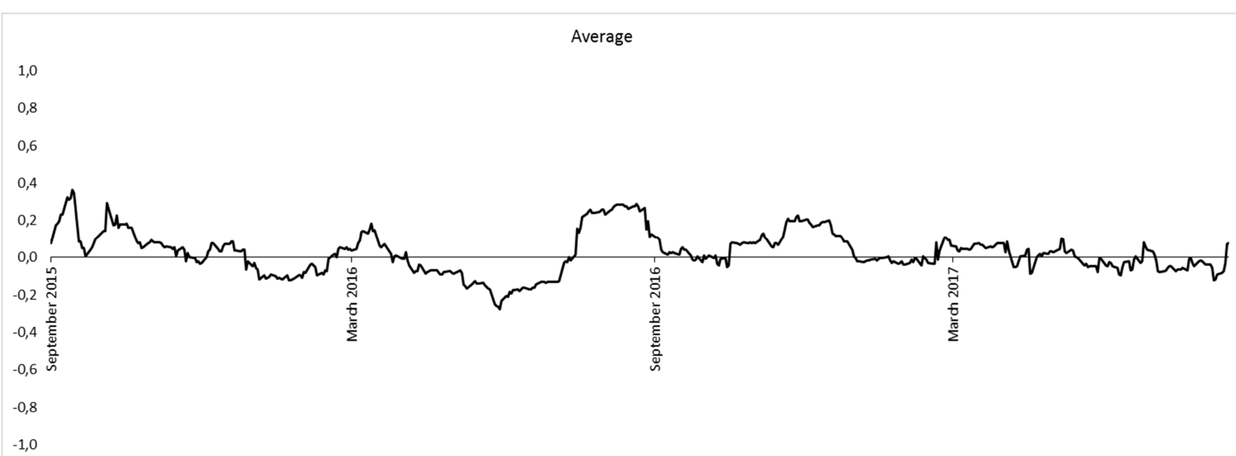


Figure 22

Mean-variance frontier with 5% short selling allowed. Two portfolios of which on contains only traditional assets and the other has an addition of cryptocurrencies.

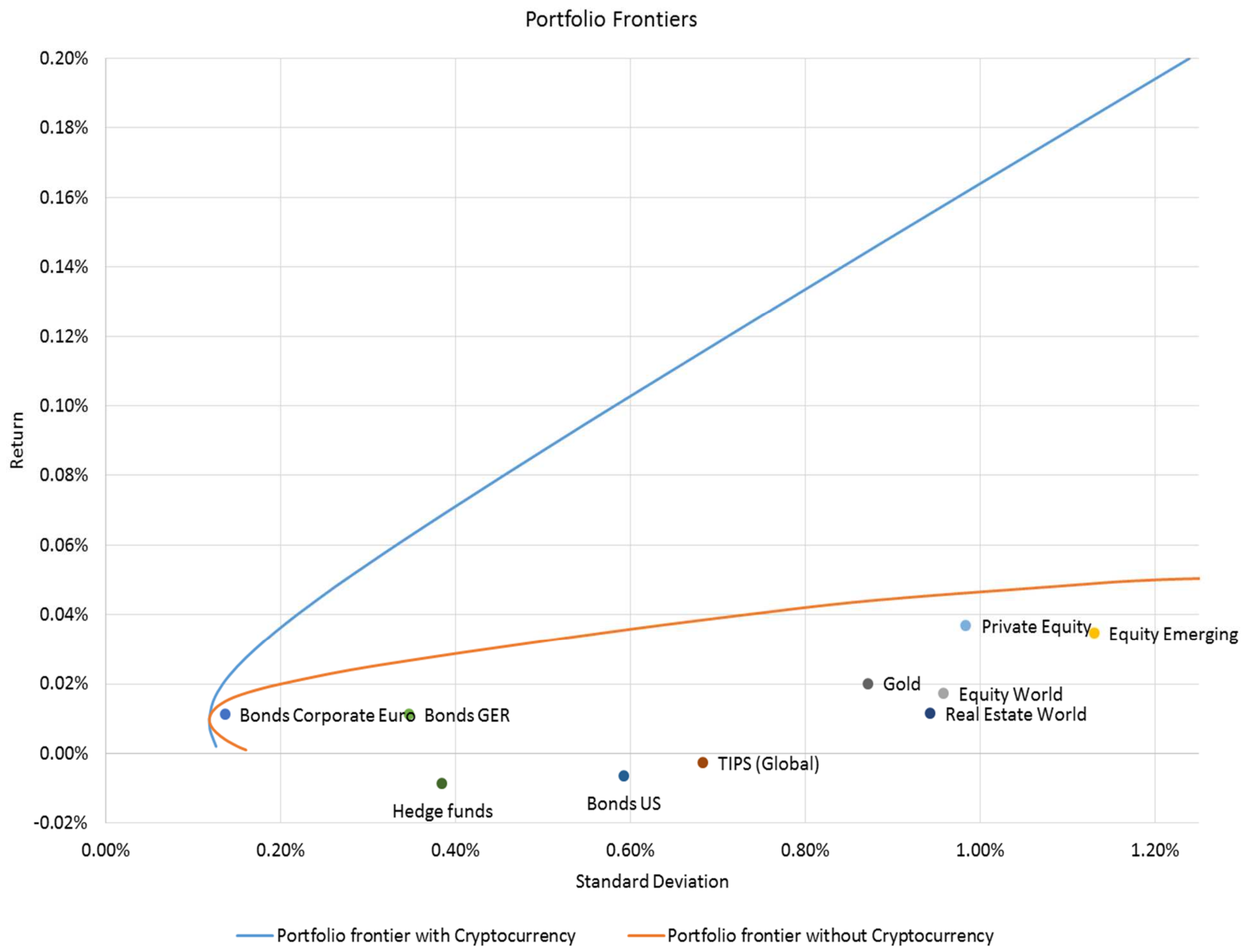


Figure 23

The volatility target frontier for portfolios consisting of traditional assets and cryptocurrencies, with the allowance of short selling limited to 5%

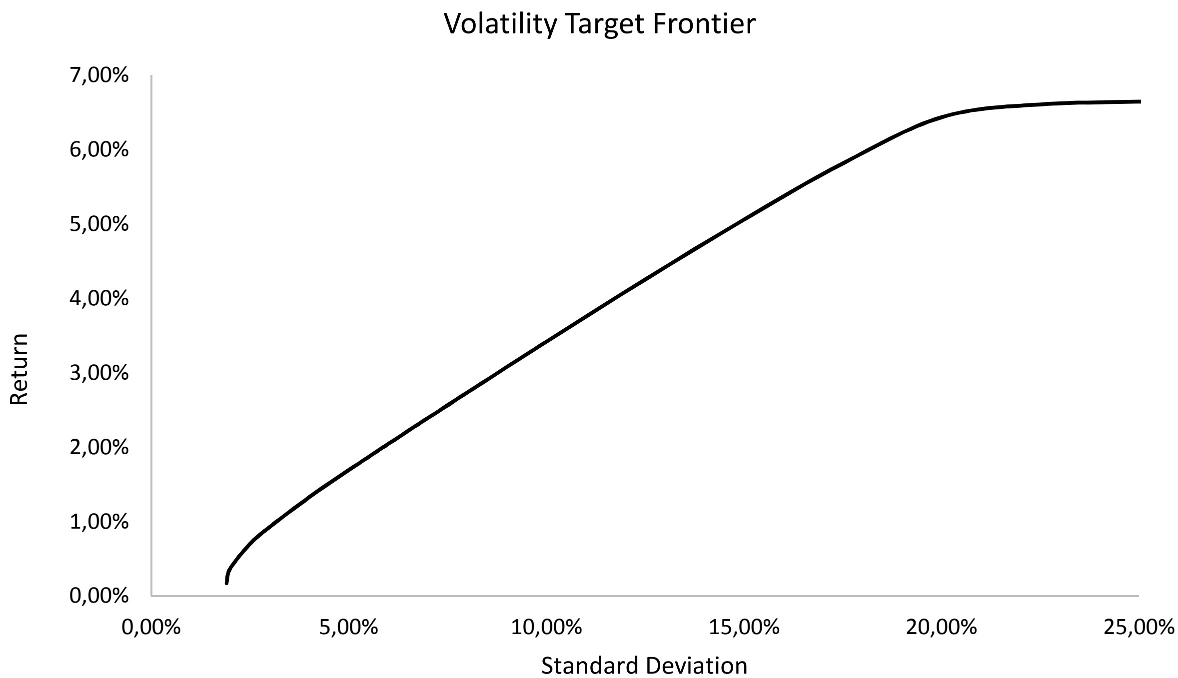
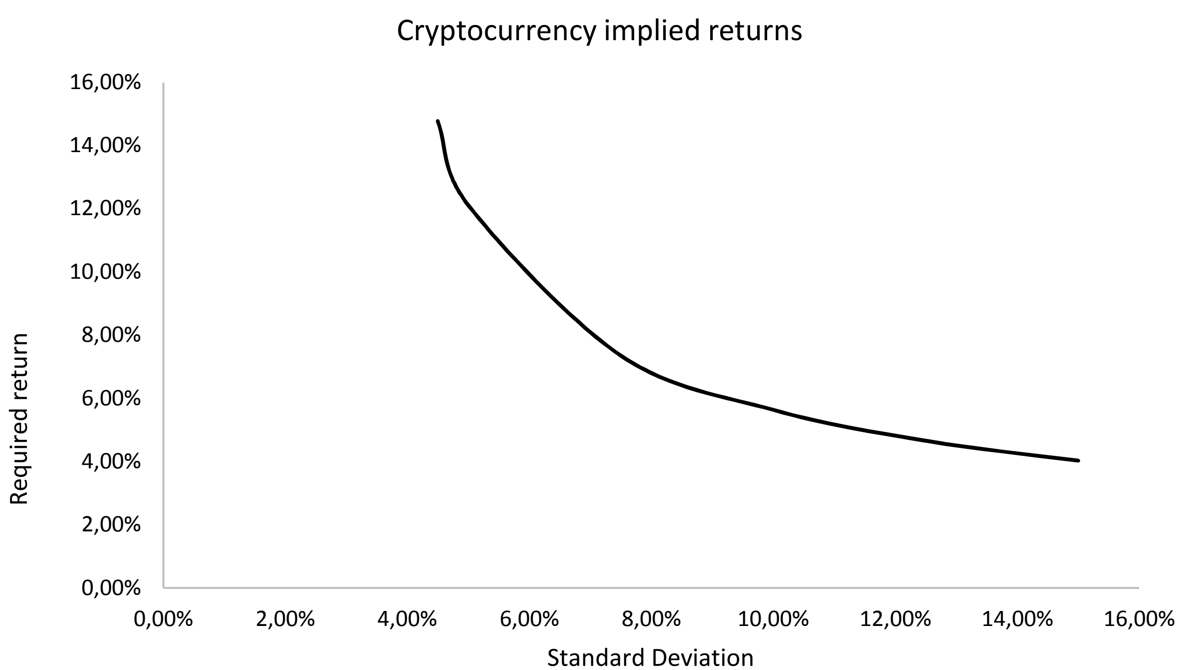


Figure 24

Implied returns for certain targets of variance for a portfolio with 5% allocation in the cryptocurrency asset class.



Tables

Table 1

Relative market capitalization of cryptocurrencies in the cryptocurrency market (data from CoinMarketCap, September 3, 2017)

	Dollars (millions)	Percentage
Total market	166,644	
Bitcoin	76,620	46.0%
Ethereum	33,307	20.0%
Dash	2,717	1.6%
Ripple	8,777	5.3%
Litecoin	4,203	2.5%
Top 5 total	125,625	75.4%

Table 2

Average market weights by total global invested capital, their yearly historical volatility and the market implied returns as discussed in the Black-Litterman model.

Asset	**Weights**	**Volatility**	**Implied returns**
MSCI World	34.6%	15.44%	0.0500
MSCI Emrg	5.6%	18.21%	0.0507
Bonds Corp	12.9%	2.20%	0.0028
Bonds GER	13.3%	5.59%	0.0031
Bonds US	17.2%	9.54%	0.0185
TIPS	2.5%	11.00%	0.0240
Gold	0.1%	14.05%	0.0049
Oil	0.1%	36.21%	0.0497
Real Estate	8.0%	15.19%	0.0473
HedgeF	2.0%	6.20%	0.0045
PrivEq	3.7%	15.84%	0.0247
$P_{cryptocurrency}$	0.0%	71.23%	0.0129

Table 3

Descriptive statistics (yearly return, yearly volatility, Sharpe ratio, daily minimum return and daily maximum return) of the cryptocurrencies and traditional assets.

	Return	Volatility	Sharpe ratio	Min	Max
$P_{cryptocurrency}$	423.2%	71.3%	5.94	-17.6%	18.5%
Bitcoin	280.7%	63.2%	4.44	-15.7%	21.3%
Ethereum	924.3%	171.7%	5.38	-35.3%	50.9%
Ripple	396.6%	123.5%	3.21	-20.9%	75.8%
Litecoin	315.9%	100.3%	3.15	-22.0%	56.3%
Dash	858.6%	100.0%	8.59	-24.9%	39.4%
MSCI World	4.6%	15.5%	0.30	-5.8%	3.8%
MSCI Emrg	9.4%	18.2%	0.52	-7.1%	3.9%
Bonds Corp	3.0%	2.2%	1.35	-0.7%	0.7%
Bonds GER	3.0%	5.6%	0.53	-1.8%	1.5%
Bonds US	-1.7%	9.5%	-0.18	-4.3%	3.9%
TIPS	-0.7%	11.0%	-0.06	-3.1%	3.2%
Gold	5.4%	14.1%	0.38	-3.3%	5.4%
Oil	-0.9%	36.2%	-0.03	-6.7%	9.0%
Real Estate	3.0%	15.2%	0.20	-6.7%	3.5%
Hedge funds	-2.2%	6.2%	-0.36	-3.3%	1.8%
Private equity	10.1%	15.9%	0.64	-7.6%	4.6%

Table 4

Correlation matrix of cryptocurrencies, the cryptocurrency portfolio and other assets with additionally a general statistics regarding the correlations between cryptocurrencies and traditional assets.

	$P_{cryptocurrency}$	Bitcoin	Ethereum	Ripple	Litecoin	Dash	MSCI World	MSCI Emerging	Bonds Corp	Bonds GER	Bonds US	TIPS	Gold	Oil	Real Estate	Hedge funds	Private equity
$P_{cryptocurrency}$	1.000																
Bitcoin	0.746	1.000															
Ethereum	0.812	0.243	1.000														
Ripple	0.255	0.194	0.013	1.000													
Litecoin	0.414	0.468	0.128	0.247	1.000												
Dash	0.396	0.319	0.258	0.105	0.251	1.000											
MSCI World	0.027	0.067	-0.033	0.058	0.058	0.124	1.000										
MSCI Emrg	0.006	0.037	-0.035	0.050	0.044	0.047	0.773	1.000									
Bonds Corp	0.060	0.031	0.047	0.092	0.024	-0.029	0.171	0.223	1.000								
Bonds GER	0.078	0.035	0.079	0.053	0.013	-0.047	-0.085	-0.054	0.809	1.000							
Bonds US	0.129	0.104	0.092	0.067	0.078	0.008	0.333	0.324	0.400	0.507	1.000						
TIPS	0.093	0.110	0.026	0.075	0.098	0.119	0.531	0.463	0.217	0.176	0.651	1.000					
Gold	0.007	0.035	-0.023	0.020	0.028	-0.002	-0.010	0.008	0.205	0.294	0.314	0.166	1.000				
Oil	-0.002	0.043	-0.040	-0.017	0.050	0.063	0.447	0.437	-0.026	-0.174	0.028	0.203	0.074	1.000			
Real Estate	0.037	0.055	-0.007	0.060	0.051	0.078	0.844	0.723	0.350	0.146	0.473	0.515	0.121	0.334	1.000		
HedgeF	-0.042	-0.013	-0.063	0.023	0.071	0.035	0.228	0.213	0.095	-0.087	-0.015	0.052	-0.038	0.152	0.169	1.000	
PrivEq	-0.079	-0.027	-0.099	-0.007	0.010	0.053	0.513	0.483	0.097	-0.202	-0.174	0.032	-0.121	0.352	0.400	0.213	1.000
Correlations compared with non-cryptocurrency assets																	
Average	0.028	0.044	-0.005	0.043	0.048	0.041											
Maximum	0.129	0.110	0.092	0.092	0.098	0.124											
Minimum	-0.079	-0.027	-0.099	-0.017	0.010	-0.047											

Table 5

Portfolio weights and returns for certain volatility targets.

	Weights												Sum of weights	Portfolio statistics	
	MSCI World	MSCI Emrg	Bonds Corp	Bonds GER	Bonds US	TIPS	Gold	Oil	RealEst.	HedgeF	PrivEq	$P_{cryptocurrency}$		Return	Volatility
$Portfolio_1$	0.035	-0.022	1.010	-0.050	-0.025	0.027	0.002	0.005	-0.050	0.070	-0.001	0.000	1	0.0017	0.0191
$Portfolio_2$	0.064	-0.015	0.960	-0.050	-0.005	0.025	0.003	0.005	-0.050	0.063	0.001	0.000	1	0.0037	0.0200
$Portfolio_3$	0.113	-0.004	0.877	-0.050	0.029	0.021	0.004	0.004	-0.050	0.051	0.006	0.000	1	0.0070	0.0250
$Portfolio_4$	0.146	0.004	0.819	-0.050	0.053	0.019	0.005	0.003	-0.050	0.043	0.009	0.000	1	0.0093	0.0300
$Portfolio_5$	0.167	0.010	0.720	-0.050	0.077	0.021	0.003	0.003	0.000	0.037	0.013	0.000	1	0.0133	0.0400
$Portfolio_6$	0.203	0.019	0.629	-0.050	0.107	0.020	0.003	0.002	0.022	0.027	0.018	0.000	1	0.0169	0.0500
$Portfolio_7$	0.241	0.028	0.524	-0.033	0.133	0.019	0.003	0.002	0.041	0.020	0.022	0.000	1	0.0204	0.0600
$Portfolio_8$	0.301	0.044	0.298	0.062	0.155	0.023	0.002	0.001	0.063	0.020	0.031	0.000	1	0.0256	0.0750
$Portfolio_9$	0.400	0.070	-0.050	0.202	0.194	0.026	-0.001	0.001	0.101	0.013	0.043	0.000	1	0.0342	0.1000
$Portfolio_{10}$	0.487	0.093	-0.050	0.070	0.255	0.007	-0.011	0.000	0.172	-0.050	0.027	0.000	1	0.0425	0.1250
$Portfolio_{11}$	0.578	0.123	-0.050	-0.050	0.270	-0.022	-0.036	-0.001	0.259	-0.050	-0.020	-0.001	1	0.0506	0.1500
$Portfolio_{12}$	0.682	0.167	-0.050	-0.050	0.090	-0.050	-0.050	-0.008	0.371	-0.050	-0.050	-0.002	1	0.0581	0.1750
$Portfolio_{13}$	0.917	0.260	-0.050	-0.050	-0.050	-0.050	-0.050	-0.027	0.238	-0.050	-0.050	-0.039	1	0.0644	0.2000
$Portfolio_{14}$	0.535	0.965	-0.050	-0.050	-0.050	-0.050	-0.050	-0.050	-0.050	-0.050	-0.050	-0.050	1	0.0661	0.2250
$Portfolio_{15}$	-0.050	1.550	-0.050	-0.050	-0.050	-0.050	-0.050	-0.050	-0.050	-0.050	-0.050	-0.050	1	0.0665	0.2579

Table 6

The Black-Litterman solution for an absolute view of 11.44% return of the cryptocurrency portfolio. Tau (τ) is 0.15 and the standard error of the view is 2.9%. Based on a VCV-matrix over the full sample length.

	Returns			**Weights**			
Asset	Implied	Historical	Black-LM	Implied	Historical	Black-LM	Constrained
MSCI World	0.0500	0.0459	0.0506	34.6%	63.8%	34.6%	34.5%
MSCI Emrg	0.0507	0.0945	0.0509	5.6%	110.4%	5.6%	5.8%
Bonds Corp	0.0028	0.0299	0.0030	12.9%	3031.7%	12.9%	6.1%
Bonds GER	0.0031	0.0297	0.0037	13.3%	-674.3%	13.3%	15.2%
Bonds US	0.0185	-0.0169	0.0202	17.2%	-299.8%	17.2%	17.0%
TIPS	0.0240	-0.0070	0.0254	2.5%	-63.8%	2.5%	2.5%
Gold	0.0049	0.0535	0.0050	0.1%	152.6%	0.1%	0.1%
Oil	0.0497	-0.0092	0.0496	0.1%	-33.1%	0.1%	0.1%
Real Estate	0.0473	0.0301	0.0481	8.0%	-174.0%	8.0%	8.2%
HedgeF	0.0045	-0.0222	0.0042	2.0%	-241.2%	2.0%	1.9%
PrivEq	0.0247	0.1008	0.0230	3.7%	96.1%	3.7%	3.7%
$P_{cryptocurrency}$	0.0129	4.2315	0.1133	0.0%	216.6%	5.0%	5.0%
			Risk free rate	0.0%	-2085.0%	-5.0%	0.0%
			Portfolio ER	0.0295	10.2427	0.0358	0.0358
			Portfolio Vol	0.0864	1.6082	0.0951	0.0950
			Sharpe ratio	0.3420	6.3689	0.3768	0.3768