Investing in the cryptocurrency market

Analyzing the diversification effects of cryptocurrencies in a well-diversified portfolio

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Abstract

In our paper we explore the effects of investing in cryptocurrencies, which currently compose an underdeveloped financial market. In line with previous research, we find solid improvements of an investor's portfolio when adding Bitcoin to a well-diversified portfolio. We furthermore show that later generations of cryptocurrencies Stellar Lumen and Litecoin provide solid improvements when included within an investor's portfolio. Similar diversification effects for cryptocurrencies like Monero and Ripple are found. By using a Mean-Variance analysis in combination with Monte Carlo methods, we reveal the added value of investing in the cryptocurrency market.

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1. Introduction

Cryptocurrencies are an extremely volatile asset. The year 2018 started off with enormous growth of the cryptocurrencies market, while already in February 2018, the price of cryptocurrencies sharply declined again. Within these two months, the price of bitcoin fell down from 17,100$ to 6,100$: a stunning decline of 64 %[1]. As Bitcoin is the leader of the cryptocurrency market, the entire market shrunk in value by over 400 million dollars. Whereas some experts labeled this phenomenon "a correction", others quickly compared it with economic events like the dot-com bubble. So far, volatility has proven to be the cause for this decrease, as it represented these fluctuations. And evidence with regard to the dot-com bubble remains only qualitative (Yermack, 2015).

As cryptocurrencies are progressively gaining attention worldwide (Frisby, 2014; Vigna & Casey, 2016), their markets became more accessible to small-time investors. Therefore, expectations are that the market will grow more efficient and become intertwined with the current monetary system over the course of the upcoming years (Urquhart, 2016). The relatively high volatility mainly attracts individual investors, yet large-company presence within the market has flourished. So far, mostly because of the promising block chain technology, as Don Tapscott[2] said: "Data is becoming a new asset class – One that may trump previous asset classes"[3] . The block chain technology[4] is the underlying technological foundation of cryptocurrencies. As a result, companies like ABN AMRO, AVEX and Money Forward also started cooperating with existing currencies on the cryptocurrency market[5].

The rise of cryptocurrencies and the coupled increase in accessibility to their corresponding markets leads to the question if the cryptocurrencies can be regarded as a financial asset. Beside the bitcoin being popular for speculators, it is especially wanted as a diversifier in an investor's portfolio (Lee, Guo & Wang, 2018). According to current literature, cryptocurrencies could probably even be of more added value when used as a diversifier in a well-diversified portfolio[6] (Kajtazi & Moro, 2018). Instead of looking at cryptocurrencies other than Bitcoin , academics mainly focuses on the diversification effects of Bitcoin (Lee, Guo & Wang, 2018). The relatively high volatility and corresponding high returns of cryptocurrencies do not go unnoticed, but also lead to skepticism among investors. Still, this skepticism is unwarranted as

[1] https://coinmarketcap.com/
[2] Don Tapscott is one of the world's leading authorities in technology and Business.
[3] https://www.forbes.com/sites/perianneboring/2016/10/06/top-25-quotes-from-don-tapscott-and-alex-tapscotts-blockchain-revolution/#2f00bfa2164a
[4] Further explained in Appendix F
[5] https://btcdirect.eu/nl-nl/blog/abn-amro-franx-ripple/
https://bitcoinmagazine.nl/2018/05/zes-beursgenoteerde-bedrijven-in-japan-stappen-in-crypto/
[6] A well-diversified portfolio is a portfolio that's invested in many different types of financial assets, causing unsystematic risk to be diversified out of the portfolio

arguments for bubble formation are backed up by qualitative evidence instead of quantitative data (Yermack, 2015).

Evidence indicating that Bitcoin serves as a good diversifier was already found some time ago (Eisl, Gasser & Weinmayer, 2015). Yet, as mentioned before, research on other cryptocurrencies remains scarce, probably due to the fact that Bitcoin significantly dominates the market (Bouri, Azzi & Dyhrberg, 2016). This creates a gap in academic literature when it comes to diversification effects and cryptocurrencies. This is somewhat of an anomaly, as there are enough competitors of the Bitcoin. Looking at the practical implementation of cryptocurrencies in our current monetary system, Ripple or Litecoin would be a much better alternative than Bitcoin. Which could be explained by the decrease of Bitcoins dominance on the market. Which gives room for competitors like Ripple and Litecoin to further develop.[7]

For investors, it is important to know if an investment is safe and if their portfolio is optimal. Since evidence for Bitcoin with regard to diversification effects is abundant, there is a need for research focused on other cryptocurrencies. Luckily, this has not been completely absent. Brauneis and Mestel (2018) created an index, composed of different cryptocurrencies,showing that investors with a stake in cryptocurrencies achieve a more optimal portfolio and a higher return to risk ratio. By using a mean-variance framework (Markowitz, 1952), they've shown that the set of 'low'-risk cryptocurrencies increases investments opportunities. Research about the isolated effect of cryptocurrencies other than the bitcoin, in an already well-diversified portfolio, however, is missing in current scientific literature[8].

[7] Appendix A

[8] For readers who are not familiar with cryptocurrencies, an explanation is provided in appendix F.

2. Literature

It seems that the cryptocurrency market becomes more and more integrated in academic literature. Obtained diversification results are supportive of the introduction of cryptocurrencies into the asset management (Krueckeberg & Scholz, 2018), and it seems that investment strategies which incorporate cryptocurrencies are generally outperforming the traditional strategies, based solely on stocks, bonds, and cash. (Anyfantaki & Topaloglou, 2018). The decentralized cryptocurrency protocols, for example, seems to be able to mitigate risk in comparison to the existing protocols (Narayanan et al., 2016). Opportunities for cryptocurrencies have grown as the volume has increased significantly in recent years (White, 2015).

Nowadays, Bitcoin is used as a financial asset, with well-established positive diversification effects in optimal portfolios (Belousova & Dorfleitner, 2012). Due to the high average return and low correlation with other financial assets, it proves to be an alternative investment for traditional investors (Guesmi et al., 2018). Still, Bitcoins transaction fees are high and the transaction time remains long compared to other cryptocurrencies. Because the underling block chain technology can be further improved by new cryptocurrencies (Árnason, 2015), it is important to investigate the added investment value of the potential competitors of bitcoin like Ripple, Litecoin or Ethereum[9].

In general, cryptocurrencies have three important characteristics that make them interesting for investors. First of all, with regard to the traditional monetary market, cryptocurrencies can serve as a vehicle currency (White, 2015). Secondly, they can shape future markets with their advanced block chain technology. Look at the financial services market for example (Fanning & Centers, 2016), a market in which is argued that cryptocurrencies are able to make information process more secure, less fraudulent and easier to control (Fanning & Centers, 2016). Last and most important, cryptocurrencies seem to be uncorrelated with traditional assets and even with each other, meaning that they could be efficiently used by investors for diversification purposes, as efficient diversification can be achieved by investing in a broad spectrum of weakly correlated or uncorrelated assets (Bodie, Kane & Markus, 2014; Trimborn, Mingyang & Härdle, 2017).

The results of investing in cryptocurrencies with regard to historical price data seem very robust when using different methods. For example, in a mean-variance framework, an index consisting of the 500 largest cryptocurrencies in the market shows characteristics with higher average returns and lower correlation compared to traditional portfolio's (Brauneis & Mestel, 2018). Furthermore, the mean-Cvar

[9] http://fortune.com/2017/12/04/bitcoin-ethereum-cryptocurrency-blockchain/

analysis also shows that cryptocurrencies lead to a better-diversified portfolio with a higher Sharpe ratio[10] (Lee, Guo & Wang, 2018). At last, significant results were also found when using a so-called "Quantitative approach to tactical asset allocation", showing that the traditional investor's portfolio is outperformed by portfolios with a higher allocation of Bitcoin. (Costanza, 2018).

From 2015 to today, the market of cryptocurrencies has grown by over 10,000% in volume ($)[11]. Cryptocurrencies contain an extreme level of volatility, probably the result of a still underdeveloped and relatively undiscovered market. Therefore, we should take the possibility of bubble formation into account when performing any analysis (Su et al., 2018), not only looking at the time frame of the price inflation in this market (2017), but also at the price deflation (2018). Otherwise, results could be overestimated when only looking at the rapid price increases (Frunza & Guégan, 2018).

Not all literature is positive on cryptocurrencies. Corbet et al. (2018) conducted a literature review on the empirical studies with regard to cryptocurrencies and argued that the price appreciation over the last 8 years had led to bubble formation. Due to the immaturity of the exchange rate system and the extinction of regulatory oversight, the perception of the role of cryptocurrencies as a credible and trustworthy financial asset is influenced by factual research on these topics. Supported by Cheah and Fry (2015), the Bitcoin in special seems to be a speculative bubble with a fundamental value of zero. However, only qualitative evidence for Bitcoin was found to support this statement (Yermack, 2015).

So far, cryptocurrencies in general remain unregulated. As White (2015) advised, they would have to remain unregulated in order to enhance development and further encourage innovation. If governments aspire to regulate cryptocurrencies in the near future is unknown, but the corresponding political climate should also be taken into account when investing in cryptocurrencies. On the legal side, it seems that new cryptocurrencies are not protected by the authorities. This leads to uncertainty for investors and creators of new cryptocurrencies during an early investment period (Witteveen, 2018). Since the cryptocurrency market is still developing, the goals of regulation might create a safer environment for investing. By introducing regulation, pricing the cryptocurrencies as a financial asset also becomes more appropriate. Therefore the asset becomes more like other financial assets, like Stocks and bonds for example. For now, cryptocurrency prices are only driven by the demand and supply model (Sontakke & Ghaisas, 2017). With central banks and national banks opening up for cryptocurrencies and block chain technology, the digitalization of monetary systems worldwide could be accepted by institutions in the future (Vaz & Brown,

[10] The Sharpe ratio is the average return without the risk free rate divided by the volatility.
[11] https://coinmarketcap.com/

2018)). The dynamics and potential make it an interesting market for investors, even for the more passive traders (Heston, 2018).

So far, most of the literature on cryptocurrencies consider Bitcoin the leading investment opportunity within the cryptocurrency market. Most of the existing literature provides results by using price information of Bitcoin. However, research towards other cryptocurrencies remains scarce. This gap shows that research to other cryptocurrencies is needed to further enrich the diversity of the literature into the cryptocurrency market.

3. Theory

Modern portfolio theory presents a comprehensive outline of portfolio construction. Investors decide what they want to in- or exclude in their portfolio (Shipway, 2009), and by using a mean-variance analysis, the optimal weights for each asset can be determined. In this manner, a well-diversified optimal portfolio is created, with the weight of each asset defined by the risk and return. Existing literature is positive on the added value of cryptocurrencies in an investor's portfolio, since cryptocurrencies can be used as viable diversification tools when a mean-variance framework is used (Brauneis & Mestel, 2018).

3.1 Markowitz-mean variance portfolio theory

Markowitz (1952) enriched economic literature with his mean-variance analysis. By using this analysis, it is possible to mathematically analyze the effectivity of an investor's portfolio. Maximizing the risk versus return ratio, an optimally diversified portfolio can be constructed, measured by, for example, the Sharpe ratio or Sortino ratio. For the purposes of this research, the Sharpe ratio is enough. By using mean-variance analysis, investors were able to create a portfolio according to their risk appetite. Markowitz's theory - has been developed further by, among others, James Tobin and Bill Sharpe. Eventually, the efficient frontier is used to create the famous CAPM model (Sharpe, 1964).

Fifty years, later the diversification method is still outperforming numerous other models. Ironically, these models are created to reduce estimation errors. The Bayesian diffuse-prior or Bayes-Stein model are prime examples. (DeMiguel, Garlappi & Uppal, 2007). Further, when equally weighting assets in a portfolio, the portfolio typically has a higher out of sample Sharpe ratio. This can then be controlled through mean-variance analysis when the Sharpe Ratio is maximized (DeMiguel, Garlappi & Uppal, 2005). In general, the mean-variance theory assumes that less standard deviation is preferred to more, and higher returns are preferred to less.

3.2 Efficient frontier & Portfolio optimization

Due to simplicity, the mean-variance analysis is often used to determine weights to assets in a well-diversified portfolio. In order to study the diversification effects, a tool to determine weights of the assets is needed. Markowitz (1952) created the mean-variance analysis as a mean for investors to make more efficient investment choices. With this method the risk of a financial asset is weighted against the expected returns. And by calculating the most optimal position in an investor's portfolio, the efficient frontier is created[12]. On the X-axis, you find the standard deviation (risk). And on the Y axis, you find the Expected return. This efficient frontier represents a position in which you are not able to have a higher expected

[12] Appendix B

return for that particular level of standard deviation. Logically, when a portfolio is closer to the efficient frontier, the performance of a portfolio is deemed better. When a portfolio would be on the left side of this frontier, this portfolio is regarded as a more optimal.

Research towards the diversification effects of cryptocurrencies is often done using the mean-variance approach (Eisl, Gasser & Weinmayer, 2015; Wu, Pandey & DBA, 2014). Yet, a problem with the mean-variance framework is found in the distribution of asset returns. The mean-variance framework assumes that the asset returns are normally distributed. Luckily, this is a problem that can be avoided when doing robustness checks (Eisl, Gasser & Weinmayer, 2015). The mean-variance analysis only looks at the mean and variance by determining the behavior of an investor. However, the variables with regard to the investors risk preference go beyond return and variance (Xoing & Idzorek, 2010). Xiong & Idzorek (2010) show that other factors which impact portfolio characteristics (risk appetite) are critical. But, the inclusion of these factors doesn't actually lead to a better estimate (DeMiguel, Garlappi & Uppal, 2007). Therefore, researchers often still plea for the simplistic approach of a mean-variance analysis.

A optimal diversified portfolio is a theoretical realization in which investors will gain the maximum profit compared to the amount of risk they take. We know that by adding more different financial assets in an investor's portfolio, the Sharpe ratio will be higher (Belousova, J., & Dorfleitner, G, 2012). For example, stocks with high standard deviation show a negative correlation between higher returns and standard deviation (Chen, Chung, Ho, 2011). Characteristics which are also present at cryptocurrencies.

So far, there is enough evidence that combinations of different financial assets will result in a lower total risk level than a single financial asset can achieve (Belousova, J., & Dorfleitner, G, 2012). However, diversification only works for lowering an assets unique portfolio risk. Unique portfolio risk, is the risk associated to the loss with a specific portfolio. Which can be reduced by diversifying the portfolio, thus adding more different financial assets. The market risk, which is included in the portfolio, cannot be diversified away by adding more, or new types of assets[13]. By adding new asset, the market portfolio might be changed, and in general a "New" type of asset decreases the total risk Belousova, J., & Dorfleitner, G, 2012). This lower benchmark of market risk is reflected by the risk-free rate. A portfolio with assets from different markets provides a well-diversified portfolio. In combination with the mean-variance analysis, an investor can then compose the optimal well-diversified portfolio.

[13] Appendix C

3.3 Monte Carlo Simulation

The Monte Carlo simulation is a widely used technique in probabilistic analysis (Mahadevan, 1997). By using a computerized mathematical analysis, you aim to reduce estimation risk. The analyses present numerous outcomes which, in our case, could have occurred if time would be reverted and another random draw was taken.

A Monte Carlo simulation can be carried out using the expected mean return and standard deviation of earlier price changes. By simulating new prices with regard to certain characteristics of historical results, one can investigate to what extent the research is reliable. In an optimal portfolio setting, the portfolio simulates a random sample to estimate new prices. With these prices, new optimal portfolios can be estimated. When plotting these portfolios, it becomes clear if the original estimate is comparable to the simulated optimal portfolio's.

With regard to Monte Carlo and optimal portfolio theory, Jorion (1992) created a framework to minimize this estimation risk. The estimation should be conducted with no short sales since short sales would only be usable when the simulations are tested for true mean-variance efficiency.

3.4 Hypothesis

Our research is unique in that it looks at four major cryptocurrencies besides Bitcoin. Furthermore, we create a mixed portfolio of these cryptocurrencies to increase the potential for finding an even more efficient portfolio. We aim to see if these currencies are first of all used in an optimal portfolio. Secondly, we aim to control whether these currencies can alter the risk-return profile of an already well-diversified portfolio. These goals are reflected by our research question:

- What is the role of cryptocurrencies with regard to diversification and how does this alter a portfolio's risk to return ratio?

The hypotheses are set according to the underlying theory. Our first hypothesis originates from the least variance analysis. By looking at the expected return range of our basis portfolios, we estimate portfolios with minimum variance when including a cryptocurrency. The effects will be visible when drawing the efficient frontier: when the efficient frontier of the portfolio with the cryptocurrency is higher, the efficient frontier will exceed the basic frontier. This is the case when the line is left of the basic efficient frontier. When we find evidence for our first hypothesis, we can assume that the cryptocurrency should be added in the least variance portfolio for every investor.

H1: The efficient frontier for the portfolio with the cryptocurrency is more efficient than the frontier of the portfolio without cryptocurrency.

By using a spanning test, we can control for diversification effect of a certain cryptocurrency (Brière, Oosterlinck, & Szafarz, 2015. For our second hypothesis, we will therefore look at the Sharpe ratio when adding cryptocurrencies in a well-diversified portfolio. We do so because the optimal portfolio is presented when the Sharpe ratio is maximized (Wu, Pandey & DBA, 2014).

H2: The inclusion of cryptocurrency X[14] in an already well-diversified portfolio leads to a higher Sharpe ratio.

We will use constraints in creating different portfolio's. We use 3 of these portfolios to see if our results are robust to restrictions. These 3 are presented by an equally weighted portfolio (Rantanen, 2015), a minimum variance portfolio (Markowitz, 1952) and a portfolio with and without a short sale constraint (Asquith et al., 2005).

H3: The addition of cryptocurrency X[10] in a well-diversified portfolio offers significant diversification benefits when controlling for different portfolios.

At last, we will conduct a Monte Carlo simulation to simulate portfolios with the same basic characteristics as the ones before. The means and (co)the variances of stocks are estimated from historical data, and they could contain estimation error. By using a Monte Carlo simulation we would like to assess the impact of estimation error. We make a big assumption here that 20 times is "Numerous". A point which will be further addressed in the discussion part.

H4: The results are robust when prices are simulated numerous times.

We will use these hypotheses for the portfolios with the addition of single cryptocurrencies and the mixed portfolio. As said before, it is expected that the results for the mixed portfolio are higher for the least variance and optimal portfolio. This assumption is motivated by the empirical observation that cryptocurrencies seem uncorrelated with each other (Trimborn, Mingyang & Härdle, 2017).

[14] X stands for a certain cryptocurrency. This will be Bitcoin, Stellar Lumen, Ripple, Litecoin or Monero in our research.

4 Methodology

4.1 Research Framework

k stands for the amount of assets and N stands for the weeks for which we have data. The analysis will be conducted with $k = 11$ for the basic portfolio, $k = 12$ for single cryptocurrency effects and $k = 16$ for the mixed portfolio. We use 189 weeks of data, thus $N = 189$. With the least variance portfolio, we utilize the Markowitz least variance framework that minimizes the standard deviation. For the true optimal portfolio, we maximize the Sharpe ratio (Jorion, 1992).

Our research framework exists of 2 parts: the mean-variance analysis and a Monte Carlo simulation. Note that it is never entirely possible to eliminate the risk by diversification alone (Markowitz, 1952). Also, the investment in more assets does not necessarily decrease this risk. Since each market is influenced by changes in a different proportion, or maybe not at all (Belousova & Dorfleitner, 2012).

First, to design the efficient frontier we need a formula to capture the expected return of all of the N weekly returns. These returns are used to calculate the portfolio's expected return.[15]

(1) $\mu = \mathbb{E}[r] = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_N \end{bmatrix}.$

(2) $\mathbb{E}[r_p] = w_1 \mathbb{E}[r_1] + \cdots + w_N \mathbb{E}[r_N].$

We need to calculate the covariance matrix, which is used to create the least variance or optimal portfolio. Since we have many risky assets in our portfolio's, this is expressed by:

(3) $\Sigma = \mathrm{var}[r] = \begin{bmatrix} \mathrm{var}(r_1) & \mathrm{cov}(r_1, r_2) & \cdots & \mathrm{cov}(r_1, r_N) \\ \mathrm{cov}(r_2, r_1) & \mathrm{cov}(r_2, r_2) & \cdots & \mathrm{cov}(r_2, r_N) \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{cov}(r_N, r_1) & \mathrm{cov}(r_N, r_2) & \cdots & \mathrm{var}(r_N) \end{bmatrix}, \ \sigma_p^2 = w' \, \Sigma$

The portfolio's standard deviation is determined by the weights and the number of assets in the least variance or optimal portfolio.

(4) $\sigma_p^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \mathrm{cov}(r_1, r_j).$

(5) $\sigma_p^2 = \frac{1}{N} \sigma^2.$

[15] The book of Cuthbertson & Nitzsche (2004) is used for the mathematical explanation.

With the covariance matrix, the expected returns and standard deviation of each asset, we can calculate the portfolio risk and return characteristics. These mentioned portfolio's will be further explained in section 4.2. This process leads to the mean variance-frontier[16]. By looking at the efficient frontier, every portfolio above the minimum variance frontier or below the efficient line is not optimal. By minimizing the standard deviation, the minimum variance frontier is created. And by maximizing the risk to return ratio the efficient frontier is created.

Second, we will execute optimization techniques for different portfolio characteristics by using the mean-variance analysis as explained above. Lastly, we will conduct a Monte Carlo simulation to control if our results are robust to simulated portfolio's or not.

To do the simulation we follow these steps (Jorion, 1992):

1. First estimate the expected returns, variances and covariance's for the k assets. Do so by using n-observations and suppose they are "True data".
2. Use the following model to forecast asset returns: $R_t = \mu + \varepsilon_t$
3. Use a simulation method on the true values to estimate normally distributed random returns. Do so by using the risk and return characteristics of the true data.
4. Simulate the returns for each asset and for each point in time by using the formula from step 2.
5. Create covariance matrices to simulate optimal portfolios by maximizing the Sharpe ratio.
6. Repeat step 2 to 5 numerous times.
7. Estimate the returns and (co)variances using the simulated stock returns. Find the efficient frontier with those returns and (co)variances. Make a scatter plot with these portfolio's for risk and return characteristics.

Besides the scatter plot, the distribution figure shows the weights attributed to the cryptocurrency for each simulated portfolio. By comparing the Sharpe ratio of the benchmark with the ratio of the original portfolio, we can see whether the original portfolio significantly exceeds the one of the benchmark or not. To statistically compare these means we conduct a one sample T-test. If the one exceeds the other, it is unlikely that the benchmark is efficient. Since we use a research time frame of 187 weeks, we have taken the arithmetic mean for the simulation. Since the arithmetic mean is on average higher than the geometric mean, we expect to better capture the estimation risk in this way. Since we do not use data from a long time period, this is a suitable choice (Jacquier, Kane & Marcus, 2003).

[16] Appendix D

4.2 Portfolio construction

The simulated portfolios are constrained by different characteristics. These portfolios are created to see if our results are robust for a change in characteristics. In each portfolio, the sum of investments has to sum up to 100%. Only portfolio 2 and 3 will control for short sale constraints. In line with Jorion (1992), we expect that short selling will lead to more imprecisely measured optimal portfolios. This is caused by the underlying relation between estimation error and unrestricted optimization. When we allow portfolios for short selling, we do expect a higher risk to return ratio, as an investor can use all of the assets in his portfolio creation, also the ones with a negative return. By using short selling an investor can always create a portfolio with higher returns for the same level of risk (Aitken et al., 1998; Asquith et al., 2005). [17]

The basic portfolio in our research will be used as a mean of comparison for each of these portfolio's. The basic portfolio is the portfolio without any cryptocurrency.

Portfolio 1, Equally weighted assets.

Portfolio weights are determined by dividing 100% by the number of assets. In turn, this means that each asset will have equal weight. DeMiguel et al. (2009) shows that this diversification strategy performed well against the mean-variance optimization. With this strategy we expect that a portfolio with a cryptocurrency provides a higher mean return and also a higher Sharpe ratio (Rantanen, 2015).

Portfolio 2, Constraint by asset with the lowest standard deviation (Looking at the basic portfolio).

This structure will additionally control for diversification effects and is constrained by the standard deviation of the asset which has the lowest in the basic portfolio. We expect that through diversification, some of the risk that is inherent to the cryptocurrency (unique risk) can be diversified away. Of course, this only happens when assets are not highly correlated (Sharpe, 1964). We aim to achieve a higher return when investing in a certain cryptocurrency with the same or lower standard deviation than the asset with the lowest standard deviation in the basic portfolio. In this portfolio the return is maximized.

[17] The rate of a 10-year U.S. treasury bond is used as risk-free rate.

Portfolio 3, Constraint by the asset with the highest return (Looking at the basic portfolio)

In line with Markowitz (1952), we create the least variance portfolio. This portfolio is constrained by the asset of the basic portfolio with the highest weekly return. We expect that the addition of cryptocurrencies will lead to a lower standard deviation. In this portfolio construction, we aim to further decrease the standard deviation and see if we are able to maintain the same return as the highest single asset/index in the portfolio. In this case, the standard deviation of the portfolio is minimized. The least variance basic portfolio is not considered, since we've already controlled for this in hypothesis 1.

Portfolio 4, Maximum sharpe ratio.

This portfolio maximizes the risk to return ratio. Since it has no weight constraints besides the 100%, it should yield the highest risk to return ratio of all the portfolios. That is, compared to the no short sale portfolios. When short sale would be allowed, the investment proportions would become unrealistic. This portfolio is also a good robustness check to see if the other portfolio calculations are valid (Eisl, Gasser & Weinmayer, 2015).

4.3 Data

Table 1 represents information about the indexes, price information, and information sources. To control for diversification effects of other cryptocurrencies, we have chosen four competitors of Bitcoin. The selection was made based on complete price information for the time period and the underlying correlation. Stellar Lumens and Ripple are relatively uncorrelated with the bitcoin, Litecoin and Monero are relatively highly correlated with the Bitcoin. Correlations are significant when we look at the P-values [18].

Asset	Asset class	Source
Bitcoin (BTC) Prices	Virtual currency	Coinmarketcap
Stellar Lumen (XLM) Prices	Virtual currency	Coinmarketcap
Ripple (XRP) Prices	Virtual currency	Coinmarketcap
Litecoin (LTC) Prices	Virtual currency	Coinmarketcap
Monero (XMR) Prices	Virtual currency	Coinmarketcap
MSCI World Index (MSC)	Equity	MSCI
MSCI Em. Markets Index (EMS)	Equity	MSCI
MSCI Frontier Markets Index (FMM)	Equity	MSCI
MSCI EAFE Index (MM)	Currency	MSCI
World Commodity Index	Commodities	Thomas Reuters Eikon
PIMCO Invest. Grade Corp. Bond Index ETF	Fixed-Income	Thomas Reuters Eikon
iShares iBoxx $ High Yield Corp. Bond ETF	Fixed-Income	Thomas Reuters Eikon
iShares TIPS bond ETF	Fixed-Income	Thomas Reuters Eikon
FTSE EPRA/NAREIT Global REIT's Index	Real-estate	Thomas Reuters Eikon
Red Rocks Cap. Global Listed Priv. Equity Index	Private Equity	Thomas Reuters Eikon
Global Hedge Funds Index	Alternative	Thomas Reuters Eikon

Table 1, Asset overview

Besides that, the motivation for choosing these currencies is supported by existing literature. With Ripple and Litecoin being two major competitors of Bitcoin that are forcing the price of Bitcoins down and competing for market share (Cheah & Fry, 2015). Monero is the number one currency with regard to privacy[19]. Due to its relatively low price it will have a lot of growth potential during the growing

[18] Appendix E/E'

[19] https://getmonero.org/

popularization of cryptocurrencies (Sovbetov, 2018). At last, we look at Stellar Lumens, a currency which uses Bitcoins and Ripples protocols, yet with higher transaction speed and reduced transaction fees. Making it an important competitor in the cryptocurrency market (Lee, Guo & Wang, 2018).

Since Bitcoin is still the leading currency on the market, we do the same research for Bitcoin to check if earlier research can be consistently confirmed. We use daily price information spanning from the 4th of August, 2013 to the 1st of March, 2018. Naturally, we incorporate only trading days in the analysis and thus exclude weekends. We end up with 189 weeks of complete price information for every financial asset.

With regard to the other asset classes, the selection made is in line with the work of Eisl, Gasser & Weinmayer (2015). To further improve upon the analysis, we have added the Private equity index. The next assets are needed to create a well-diversified portfolio (Eisl, Gasser & Weinmayer,2015): Currencies, Fixed-income assets, equity, real estate and alternative investment opportunities. We have used less fixed income asset class indexes due to the inconclusive observations. The gaps in the data could lead to unreliable return and risk ratios.

With the data, we will estimate the geometric weekly return and standard deviation. With the excess returns, we create covariance matrices to determine the portfolio weightings. In table 2, we present the summary statistics for our data. We use weekly data which is in line with earlier research (Eisl, Gasser & Weinmayer, 2015; Brière, Oosterlinck & Szafarz, 2015).

Table 1, Summary statistics (Weekly).

Asset	Return	Stdev	Risk/return
BTC	1,41%	11,24%	0,13
XLM	2,67%	41,50%	0,06
XRP	2,68%	33,65%	0,08
LTC	1,61%	22,17%	0,07
XMR	2,53%	21,75%	0,12
MSC	0,12%	1,67%	0,07
EMS	0,06%	2,41%	0,03
FMM	-0,05%	1,50%	-0,03
Commodity	-0,28%	3,33%	-0,08
Corpbond	-0,01%	0,60%	-0,02
HighYieldCorp	-0,04%	0,93%	-0,04
IsharesTips	0,01%	0,57%	0,02
HedgeFunds	0,02%	0,55%	0,04
MM	0,05%	1,96%	0,02
PrivateEquity	0,19%	2,06%	0,09
RealEstate	0,01%	1,77%	0,00

We expect that the cryptocurrencies are uncorrelated with other financial assets, as predicted by previous research (Trimborn, Mingyang & Härdle, 2017). Table 3 is in major lines supporting this statement. Bitcoin is uncorrelated with all of the shown assets, except the money market. For Stellar Lumen, Ripple and Litecoin we find no correlation with the other assets at all. And Monero is correlated with 4 of the assets. The impact of the correlation of Monero with other financial assets will be accounted for in chapter 5.

	RBTC	RXLM	RXRP	RLTC	RXMR	RMSCeq	REMSeq	RFMMSeq	RWorldCom	RCorpBondFI	RHighYieldCorpFI	RIsharesTipsbond	Rhedge	RMM	RPrivEq	RRealEst
RBTC	1															
RXLM	,264**	1														
RXRP	0,113	,526**	1													
RLTC	,350**	,196**	,563**	1												
RXMR	,400**	0,130	0,087	,250**	1											
RMSCeq	0,001	0,058	0,038	-0,025	0,076	1										
REMSeq	-0,025	0,068	0,050	-0,058	,144*	,804**	1									
RFMMSeq	,154*	0,050	0,051	0,054	,223**	,476**	,514**	1								
RWorldCom	-0,038	0,055	0,011	0,000	0,047	,473**	,518**	,409**	1							
RCorpBondFI	0,060	0,050	0,071	0,049	,199**	0,117	,322**	0,107	0,058	1						
RHighYieldCorpFI	-0,034	0,096	0,017	-0,012	0,111	,678**	,643**	,336**	,576**	,358**	1					
RIsharesTipsbond	0,023	0,001	0,044	0,083	,153*	-0,009	,254**	0,042	0,097	,759**	,173*	1				
Rhedge	0,017	0,093	0,056	-0,017	,144*	,862**	,721**	,502**	,450**	0,135	,652**	-0,003	1			
RMM	-0,069	0,039	0,024	-0,072	0,049	,906**	,813**	,463**	,506**	0,129	,621**	0,050	,742**	1		
RPrivEq	-0,069	0,032	0,028	-0,080	0,076	,901**	,785**	,456**	,516**	0,073	,656**	-0,022	,802**	,901**	1	
RRealEst	0,002	-0,009	-0,002	-0,010	0,110	,590**	,577**	,203**	,218**	,545**	,491**	,491**	,443**	,522**	,464**	1

Table 2, Correlation matrix.

5 Results

For hypothesis 2 and 3, each graph will be compared with the results of the basic portfolio. Therefore, table 4 below presents the results for the basic portfolio. We will test the hypothesis per currency in separate chapters. To retrieve these results, the solver function of Excel is used. The basic portfolio exists out of all the asset indexes except for cryptocurrencies. And with regard to our fourth hypothesis, we define the optimal portfolio by maximizing the Sharpe ratio (Jorion, 1992).

	Portfolio 1	Portfolio 2		Portfolio 3		Portfolio 4
Constraint variable	None	$\sigma_p \leq$	No shortsale	μ_p = Highest E[r]	No shortsale	None
Value of constraint	-	0,550%		0,188%		-
Variables	Weights					
MSC	9,1%	66,6%	0,0%	77,8%	0,0%	0,0%
EMS	9,1%	-1,6%	0,0%	-1,9%	0,0%	0,0%
FMM	9,1%	-6,9%	0,0%	-8,0%	0,0%	0,0%
Commodity	9,1%	-7,0%	0,0%	-8,1%	0,0%	0,0%
Corpbond	9,1%	-6,9%	0,0%	-8,1%	0,0%	0,0%
Highyield	9,1%	-29,0%	0,0%	-33,9%	0,0%	0,0%
Isharestips	9,1%	71,5%	60,3%	83,5%	0,0%	46,4%
Hedge	9,1%	-63,8%	22,4%	-74,5%	0,0%	0,0%
MM	9,1%	-45,8%	0,0%	-53,5%	0,0%	0,0%
PrivateEq	9,1%	39,3%	16,3%	45,9%	95,8%	45,5%
Realest	9,1%	-19,9%	0,0%	-23,3%	0,0%	0,0%
Combined	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%
M_p	0,008%	0,161%	0,043%	0,188%	0,181%	0,092%
Σ_p	1,187%	0,550%	0,550%	0,643%	1,969%	0,966%
risk/return	0,007	0,293	0,079	0,293	0,092	0,095

Table 3, Portfolio results basic portfolio

In table 4 we see the 0,550% as constraint for the 2nd portfolio. This represents the standard deviation of The Hedge Funds index, which is the asset with the lowest standard deviation in the basic portfolio. The 0,188% is the constraint of the 3rd portfolio. Which presents the return of the Private equity index. This is the asset in the basic portfolio with the highest return.

5.2 Bitcoin

The addition of bitcoin in the least variance framework is presented in figure 1. Since the efficient frontier of a portfolio with bitcoin is left of the portfolio without bitcoin for every point, we find support for our first hypothesis. This means that Bitcoin will be used in an investor's portfolio.

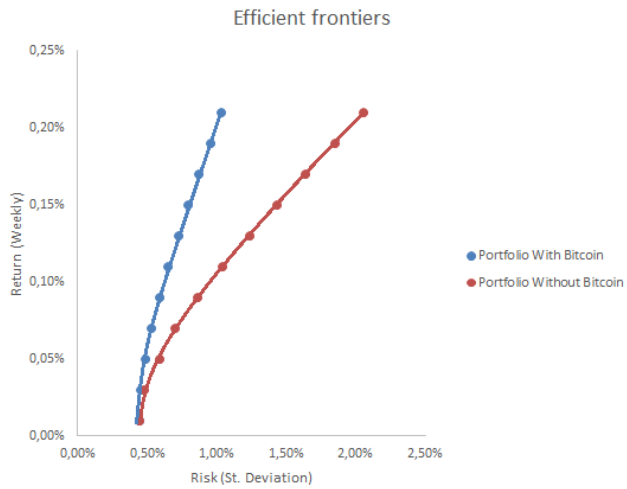

Figure 1, Efficient frontier Bitcoin versus no bitcoin

Secondly, portfolio 4 in table 5 shows a Sharpe ratio of 0,162, which is higher than 0,095 of the basic portfolio. Therefore we accept our second hypothesis. Meaning that the addition of Bitcoin leads to a better Sharpe ratio. In the extent of our first hypothesis, we see that 2,9% of the weight in the least variance portfolio is attributed to the Bitcoin. Increasing the Sharpe ratio from 0,079 to 0,125.

	Portfolio 1	Portfolio 2		Portfolio 3		Portfolio 4
Constraint variable	None	σ_p <=	No shortsale	μ_p = Highest E[r]	No shortsale	None
Value of constraint	-	0,550%		0,188%		-
	Weights					
BTC	8,3%	2,0%	2,9%	2,2%	8,1%	11,6%
MSC	8,3%	53,5%	0,0%	57,4%	0,0%	0,0%
EMS	8,3%	-0,9%	0,0%	-0,9%	0,0%	0,0%
FMM	8,3%	-9,6%	0,0%	-10,4%	0,0%	0,0%
Commodity	8,3%	-6,3%	0,0%	-6,8%	0,0%	0,0%
Corpbond	8,3%	-11,2%	0,0%	-12,1%	0,0%	0,0%
Highyield	8,3%	-24,7%	0,0%	-26,6%	0,0%	0,0%
Isharestips	8,3%	65,6%	51,8%	70,4%	56,2%	40,0%
Hedge	8,3%	-56,4%	37,9%	-60,6%	0,0%	0,0%
MM	8,3%	-38,3%	0,0%	-41,2%	0,0%	0,0%
PrivateEq	8,3%	38,3%	7,4%	41,2%	35,8%	48,4%
Realest	8,3%	-17,3%	0,0%	-18,6%	0,0%	0,0%
Combined	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%
M_p	0,125%	0,175%	0,069%	0,188%	0,188%	0,260%
Σ_p	1,424%	0,550%	0,550%	0,591%	1,171%	1,599%
risk/return	0,087	0,319	0,125	0,319	0,161	0,162

Table 5, Portfolio returns portfolio with Bitcoin.

Thirdly, we see that every portfolio uses a weight in Bitcoin. This means that Bitcoin offers diversification effects for every portfolio we use. We see that the results are robust for equal weighting, with and without short sale constraints, and when maximizing the Sharpe ratio. Therefore we accept our third hypothesis that the addition of Bitcoin leads to diversification benefits in every portfolio.

Fourthly, figure 2 show that Bitcoin has an average weight of 27,15% in an optimal portfolio. The scatter plot in figure 2 shows that the data normally distributed.

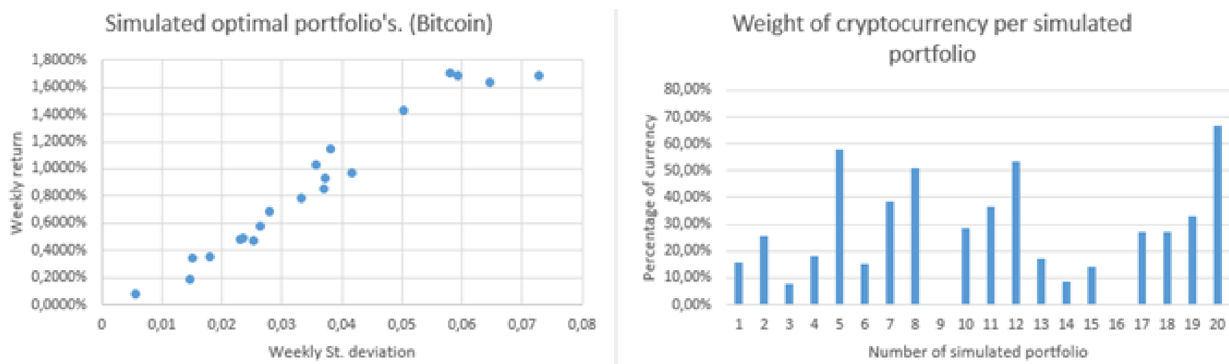

Figure 2, Simulation of portfolio's weights and risk to return ratio. With Bitcoin.

At last, when we statistically control for the difference between the simulated portfolios and the original portfolio in table 6 we find a value of 0,084. Since p > 0,05 we fail to reject our null hypothesis[20]. Meaning that there is no significant difference between the mean of the simulated portfolios and the original portfolio. We therefore accept our fourth hypothesis that our simulations are robust when prices are simulated numerous times.

Original &. Estimated portfolio	Mean Return	St. Deviation	Risk/return ratio
Original Portfolio	0,39%	0,018	0,214
Estimated Benchmark	0,88%	0,035	0,233
One-Sample T-test	t- value	Significance (95%)	Mean Difference
BTC portfolio	1,821	0,084	0,019

Table 4, Original portfolio compared to estimated benchmark. With Bitcoin.

[20] Appendix G shows that simulated portfolios for Bitcoin are normally distributed.

5.2 Stellar Lumen

The addition of Stellar Lumen in the least variance framework is presented in figure 3. Since the efficient frontier of a portfolio with Stellar Lumen is left of the portfolio without Stellar Lumen for every point, we find support for our first hypothesis. Meaning that Stellar Lumen will be used in an investor's portfolio.

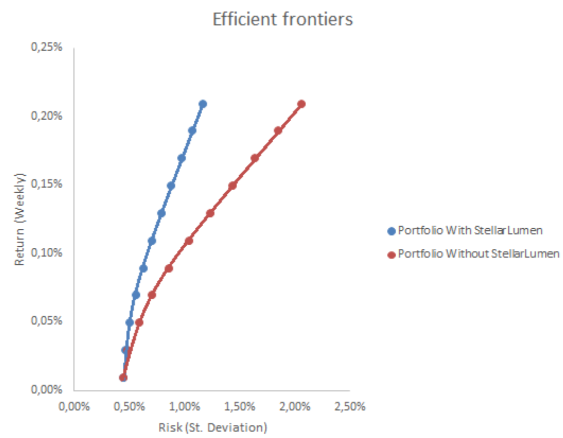

Figure 3, Efficient frontier Stellar Lumen versus no Stellar Lumen

Secondly, portfolio 4 in table 7 shows a Sharpe ratio of 0,113. This is higher than the 0,095 ratio of the basic portfolio. Therefore, we accept our second hypothesis. Meaning that the addition of Stellar Lumen indeed leads to a better Sharpe ratio. In the extent of hypothesis 1 we see that 0,5% of the weight in a least variance portfolio is attributed to Stellar Lumen. Which leads to a 0,01 increase in the Sharpe ratio from 0,079 to 0,089.

	Portfolio 1	Portfolio 2		Portfolio 3		Portfolio 4
Constraint variable	None	σ_p <=	No shortsale	μ_p = Highest E[r]	No shortsale	None
Value of constraint	-	0,550%		0,188%		-
	Weights					
XLM	8,3%	0,3%	0,5%	0,4%	2,3%	1,6%
MSC	8,3%	63,5%	0,0%	71,8%	0,0%	0,0%
EMS	8,3%	-2,0%	0,0%	-2,3%	0,0%	0,0%
FMM	8,3%	-6,5%	0,0%	-7,4%	0,0%	0,0%
Commodity	8,3%	-6,8%	0,0%	-7,7%	0,0%	0,0%
Corpbond	8,3%	-8,8%	0,0%	-10,0%	0,0%	0,0%
Highyield	8,3%	-29,2%	0,0%	-33,0%	0,0%	0,0%
Isharestips	8,3%	70,0%	58,7%	79,2%	32,5%	50,1%
Hedge	8,3%	-64,6%	28,8%	-73,0%	0,0%	0,0%
MM	8,3%	-44,3%	0,0%	-50,0%	0,0%	0,0%
PrivateEq	8,3%	39,4%	12,1%	44,5%	65,2%	48,2%
Realest	8,3%	-18,2%	0,0%	-20,5%	0,0%	0,0%
Combined	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%
Mp	0,230%	0,167%	0,049%	0,188%	0,188%	0,141%
Σp	3,695%	0,550%	0,550%	0,622%	1,677%	1,245%
risk/return	0,062	0,303	0,089	0,303	0,112	0,113

Table 7, Portfolio returns portfolio with Stellar Lumen.

Thirdly, we see that every portfolio uses a weight in Stellar Lumen. This means that Stellar Lumen offers diversification effects in every setting we investigate. We see that the results are robust for equal weighting, with and without short sale constraints, and for maximizing the Sharpe ratio. Therefore, we accept our third hypothesis that the addition of Stellar Lumen leads to diversification benefits in every portfolio

Fourthly, figure 4 shows that Stellar Lumen has an average weight of 8,42% in an optimal portfolio. The scatter plot in figure 4 shows that our simulated data could have some dispersion on the lower bound.

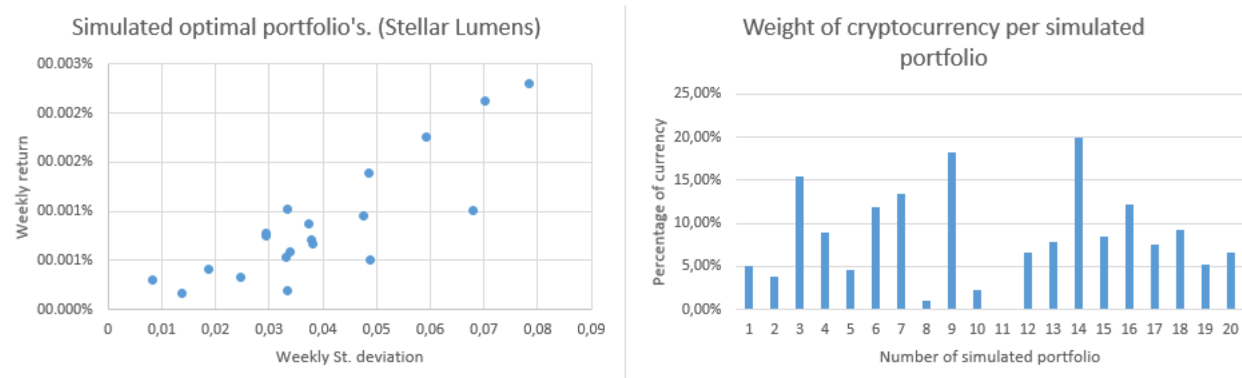

Figure 4, Simulation of portfolio's weights and risk to return ratio. With Stellar Lumen.

At last, when we statistically control for the difference between the simulated portfolios and the original portfolio in table 8, we find a p-value of 0,108. Since $p > 0,05$ we fail to reject our null hypothesis[21]. Meaning that there is no significant difference between the mean of the simulated portfolios and the original portfolio. Therefore, we accept our fourth hypothesis that our simulations are robust when prices are simulated numerous times.

Original &. Estimated portfolio	Mean Return	St. Deviation	Risk/return ratio
Original Portfolio	0,33%	0,018	0,183
Estimated Benchmark	3,96%	0,04	0,213
One-Sample T-test	t- value	Significance (95%)	Mean Difference
XLM portfolio	1,686	0,108	0,0303

Table 8, Original portfolio compared to estimated benchmark. With Stellar Lumen.

[21] Appendix G shows that simulated portfolios for Stellar Lumens are normally distributed.

5.3 Ripple

The addition of Ripple in the least variance framework is presented in figure 5. Since the efficient frontier of a portfolio with Ripple is left of the portfolio without Ripple for every point, we find support for our first hypothesis. This means that Ripple is used in an investor's portfolio.

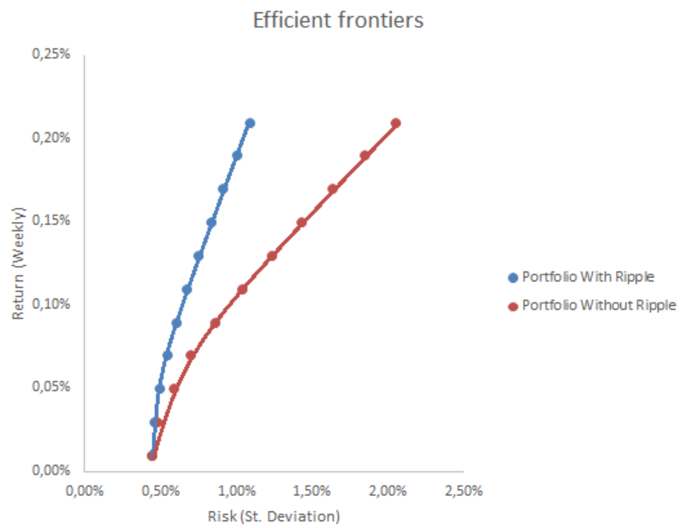

Figure 5, Efficient frontier Ripple versus no Ripple

Secondly, portfolio 4 in table 9 shows a Sharpe ratio of 0,122. This is higher than the 0,095 ratio of the basic portfolio. Therefore we accept our second hypothesis. This means that the addition of Ripple indeed leads to a better Sharpe ratio. In the extent of hypothesis 1, we see that 0,7% of the weight in the least variance portfolio is attributed to Ripple. Which leads to a 0,015 increase in the Sharpe ratio from 0,079 to 0,094.

	Portfolio 1	Portfolio 2		Portfolio 3		Portfolio 4
Constraint variable	None	σp <=	No shortsale	μp = Highest E[r]	No shortsale	None
Value of constraint	-	0,550%		0,188%		-
	Weights					
XRP	8,3%	0,4%	0,7%	0,4%	2,9%	2,6%
MSC	8,3%	63,4%	0,0%	72,3%	0,0%	0,0%
EMS	8,3%	-1,0%	0,0%	-2,0%	0,0%	0,0%
FMM	8,3%	-7,0%	0,0%	-7,8%	0,0%	0,0%
Commodity	8,3%	-6,8%	0,0%	-7,7%	0,0%	0,0%
Corpbond	8,3%	-9,3%	0,0%	-10,7%	0,0%	0,0%
Highyield	8,3%	-27,3%	0,0%	-31,0%	0,0%	0,0%
Isharestips	8,3%	68,5%	55,6%	78,8%	41,4%	46,4%
Hedge	8,3%	-63,6%	33,4%	-71,7%	0,0%	0,0%
MM	8,3%	-44,4%	0,0%	-50,3%	0,0%	0,0%
PrivateEq	8,3%	38,2%	10,4%	43,7%	55,7%	51,0%
Realest	8,3%	-18,5%	0,0%	-21,0%	0,0%	0,0%
Combined	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%
Mp	0,230%	0,165%	0,052%	0,188%	0,188%	0,173%
Σp	3,053%	0,550%	0,550%	0,627%	1,550%	1,419%
risk/return	0,075	0,301	0,094	0,301	0,122	0,122

Table 9, Portfolio returns portfolio with Ripple.

Thirdly, we see that every portfolio uses a weight in Ripple. This means that Ripple offers diversification effects in every setting we investigate. We see that the results are robust for equal weighting, with and without short sale constraints, and for maximizing the Sharpe ratio. Therefore we accept our third hypothesis that the addition of Ripple leads to diversification benefits in every portfolio.

Fourthly, the estimations in figure 6 show that Ripple has an average weight of 8,65% in an optimal portfolio. However, when we look at the scatter plot in figure 6, it seems that the data contains a certain degree of dispersion.

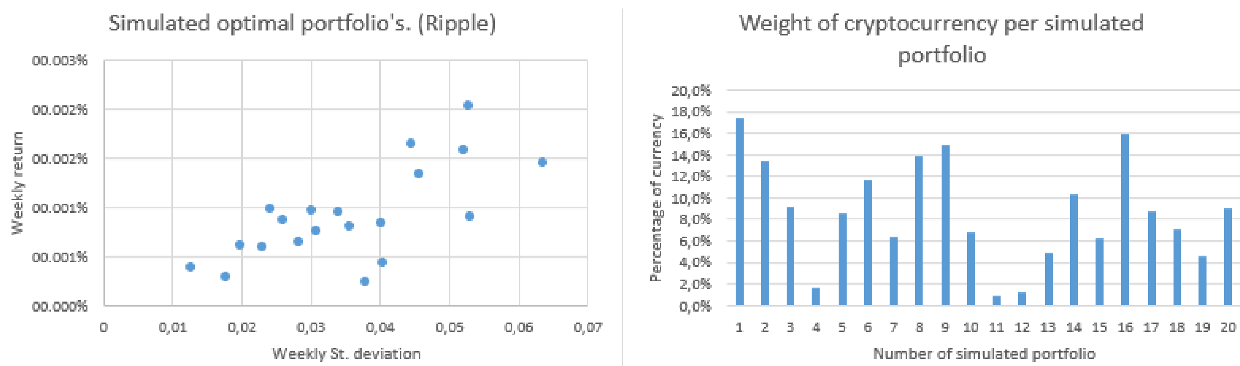

Figure 6, Simulation of portfolio’s weights and risk to return ratio. With Ripple.

At last, when we statistically control for the difference between the simulated portfolios and the original portfolio in table 10 we find a p-value of 0,011. Since $p < 0,05$ we reject our null hypothesis [22]. Accepting the alternative hypothesis, meaning that there is a significant difference between the mean of the simulated portfolios and the original portfolio. Therefore, we cannot find support for robustness of our simulations when prices are simulated numerous times, which is our fourth hypothesis.

Original &. Estimated portfolio	Mean Return	St. Deviation	Risk/return ratio
Original Portfolio	0,45%	0,022	0,205
Estimated Benchmark	3,55%	0,036	0,261
One-Sample T-test	t- value	Significance (95%)	Mean Difference
XRP portfolio	2,82	0,011	0,056

Table 10, Original portfolio compared to estimated benchmark. With Ripple.

[22] Appendix G shows that simulated portfolios for Ripple are normally distributed.

5.4 Litecoin

The addition of Litecoin in the least variance framework is presented in figure 7. Since the efficient frontier of a portfolio with Litecoin is left of the portfolio without Ripple for every point, we find support for our first hypothesis. This means that Litecoin is used in an investor's portfolio.

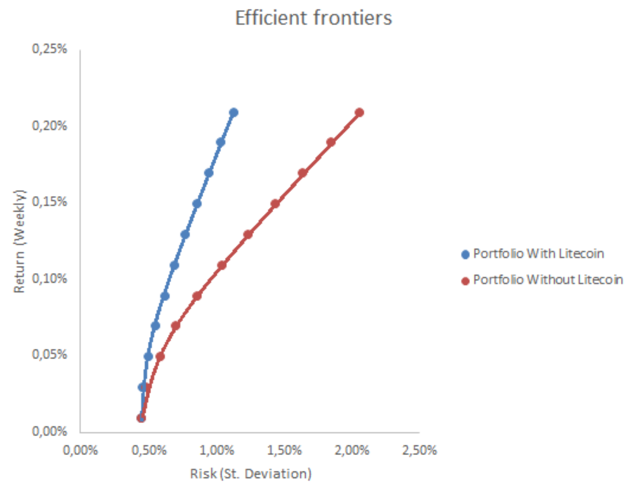

Figure 7, Efficient frontier Litecoin versus no Litecoin

Secondly, portfolio 4 in table 11 shows a Sharpe ratio of 0,115, which is higher than the 0,11 ratio of the basic portfolio. Therefore, we accept our second hypothesis, meaning that the addition of Litecoin indeed leads to a better Sharpe ratio. In the extent of hypothesis 1, we see that 0,7% of the weight in the least variance portfolio is attributed to Litecoin, leading to a 0,05 increase in the Sharpe ratio from 0,079 to 0,084.

	Portfolio 1	Portfolio 2		Portfolio 3		Portfolio 4
Constraint variable	None	σp <=	No shortsale	μp = Highest E[r]	No shortsale	None
Value of constraint	-	0,550%		0,188%		-
	Weights					
LTC	8,3%	0,6%	0,7%	0,6%	4,5%	4,1%
MSC	8,3%	60,8%	0,0%	69,1%	0,0%	0,0%
EMS	8,3%	-0,9%	0,0%	-0,7%	0,0%	0,0%
FMM	8,3%	-7,6%	0,0%	-8,7%	0,0%	0,0%
Commodity	8,3%	-6,9%	0,0%	-7,9%	0,0%	0,0%
Corpbond	8,3%	-6,5%	0,0%	-7,7%	0,0%	0,0%
Highyield	8,3%	-28,4%	0,0%	-32,3%	0,0%	0,0%
Isharestips	8,3%	65,4%	55,6%	74,4%	36,1%	40,1%
Hedge	8,3%	-60,8%	33,4%	-69,2%	0,0%	0,0%
MM	8,3%	-43,2%	0,0%	-49,3%	0,0%	0,0%
PrivateEq	8,3%	39,6%	10,4%	45,1%	59,5%	55,8%
Realest	8,3%	-18,5%	0,0%	-21,1%	0,0%	0,0%
Combined	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%
Mp	0,141%	0,165%	0,045%	0,188%	0,188%	0,177%
Σp	2,241%	0,546%	0,534%	0,623%	1,645%	1,545%
risk/return	0,063	0,303	0,084	0,303	0,115	0,115

Table 11, Portfolio returns portfolio with Litecoin.

Thirdly, we see that every portfolio uses a weight in Litecoin. Meaning that Litecoin offers diversification effects in every setting we investigate. We see that the results are robust for equal weighting with and without short sale constraints, and maximizing the Sharpe ratio. Therefore, we accept our third hypothesis: the addition of Litecoin leads to diversification benefits in every portfolio.

Fourthly, the estimations in figure 8 show that Litecoin has an average weight of 12,19% in an optimal portfolio. However, from the scatter plot in figure 8 it seems that the data contains a degree of dispersion.

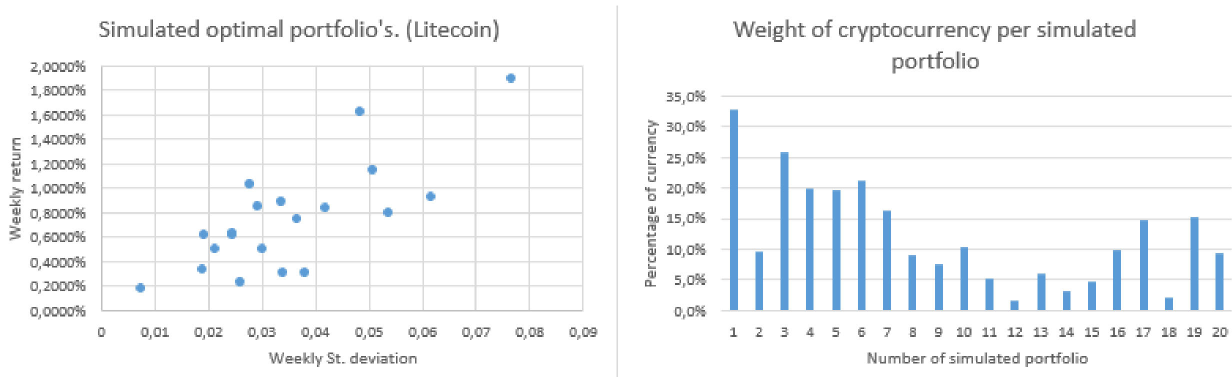

Figure 8, Simulation of portfolio's weights and risk to return ratio. With Litecoin.

At last, when we statistically control for the difference between the simulated portfolios and the original portfolio in table 12 we find a p-value of 0,219. Since p > 0,05 we fail to reject the null hypothesis[23]. Meaning that there is no significant difference between the mean of the simulated portfolios and the original portfolio. Therefore, we find support for our fourth hypothesis that our simulations are robust when prices are simulated numerous times.

Original &. Estimated portfolio	Mean Return	St. Deviation	Risk/return ratio
Original Portfolio	0,41%	0,021	0,195
Estimated Benchmark	3,52%	0,035	0,218
One-Sample T-test	t- value	Significance (95%)	Mean Difference
LTC portfolio	1,279	0,216	0,234

Table 12, Original portfolio compared to estimated benchmark. With Litecoin.

[23] Appendix G shows that simulated portfolios for Litecoin are normally distributed.

5.5 Monero

The addition of Monero in the least variance framework is presented in figure 9. Since the efficient frontier of a portfolio with Monero is left of the portfolio without Monero for every point, we find support for our first hypothesis. This means that Monero is used in an investor's portfolio.

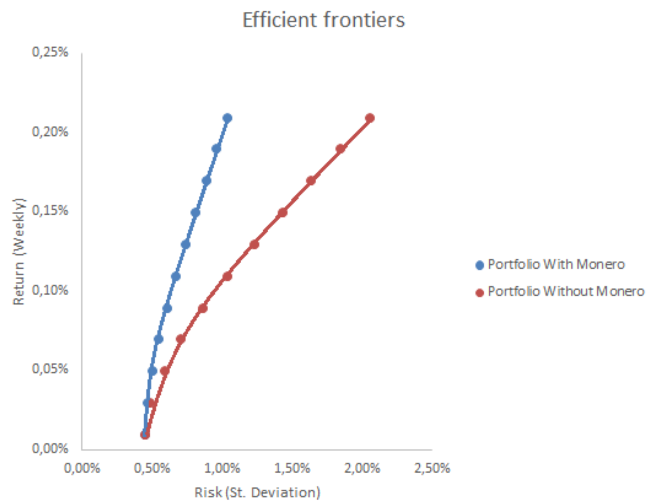

Figure 9, Efficient frontier Monero versus no Monero

Secondly, portfolio 4 in table 13 shows a Sharpe ratio of 0,143. Which is higher than 0,11 of the basic portfolio. Therefore, we accept our second hypothesis, meaning that the addition of Monero indeed leads to a better Sharpe ratio. In the extent of hypothesis one, we see that 1,1% of the weight in the least variance portfolio is attributed to Monero. Which leads to a 0,021 increase in the Sharpe ratio from 0,079 to 0,102.

	Portfolio 1	Portfolio 2		Portfolio 3		Portfolio 4
Constraint variable	None	$\sigma p <=$	No shortsale	μp = Highest E[r]	No shortsale	None
Value of constraint	-	0,550%		0,188%		-
	Weights					
XMR	8,3%	1,0%	1,1%	1,1%	4,2%	8,0%
MSC	8,3%	63,3%	0,0%	68,1%	0,0%	0,0%
EMS	8,3%	-2,2%	0,0%	-2,4%	0,0%	0,0%
FMM	8,3%	-9,6%	0,0%	-10,3%	0,0%	0,0%
Commodity	8,3%	-6,0%	0,0%	-6,5%	0,0%	0,0%
Corpbond	8,3%	-11,4%	0,0%	-12,3%	0,0%	0,0%
Highyield	8,3%	-26,9%	0,0%	-28,9%	0,0%	0,0%
Isharestips	8,3%	64,4%	51,5%	69,3%	56,4%	26,1%
Hedge	8,3%	-65,6%	40,7%	-70,6%	0,0%	0,0%
MM	8,3%	-39,9%	0,0%	-42,9%	0,0%	0,0%
PrivateEq	8,3%	35,0%	6,6%	37,7%	39,4%	65,9%
Realest	8,3%	-18,4%	0,0%	-19,8%	0,0%	0,0%
Combined	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%
Mp	0,218%	0,175%	0,056%	0,188%	0,188%	0,331%
Σp	2,241%	0,550%	0,550%	0,592%	1,340%	2,315%
risk/return	0,097	0,319	0,102	0,319	0,141	0,143

Table 13, Portfolio returns portfolio with Monero.

Thirdly, we see that every portfolio uses a weight in Monero. This means that Monero offers diversification effects in every setting we investigate. We see that the results are robust for equal weighting, with and without short sale constraints and also for the maximization of the Sharpe ratio. Therefore we accept our third hypothesis that the addition of Monero leads to diversification benefits in every portfolio.

Fourthly, the estimations in figure 10 show that Monero has an average weight of 18,14% in an optimal portfolio. However, the scatter plot in figure 8 indicates that the simulated data could contain a certain degree of dispersion.

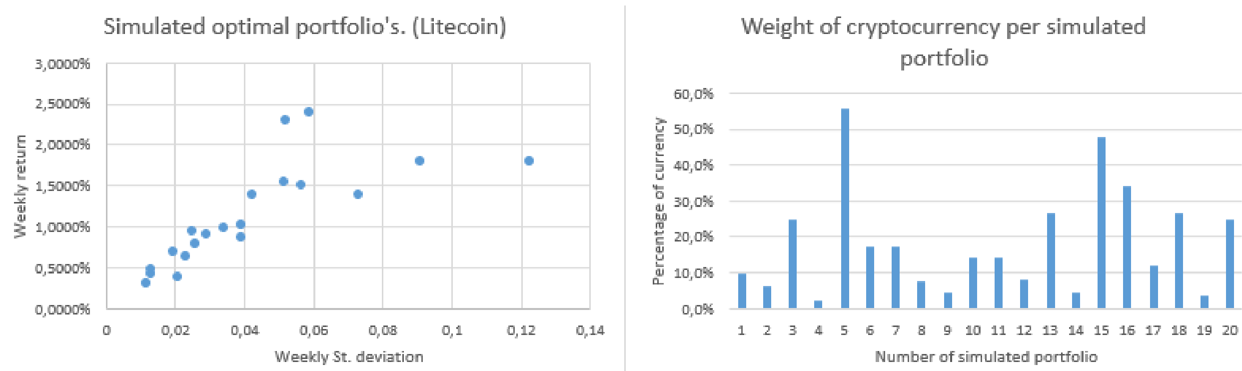

Figure 10, Simulation of portfolio’s weights and risk to return ratio. With Monero.

Lastly, when we statistically control for the difference between the simulated portfolios and the original portfolio in table 14 we find a p-value of 0,001 Since $p < 0,05$ we reject our null hypothesis [24]. Accepting our alternative hypothesis, meaning that there is a significant difference between the mean of the simulated portfolios and the original portfolio. Therefore, we find no support for our fourth hypothesis that our simulations are robust when prices are simulated numerous times.

Original &. Estimated portfolio	Mean Return	St. Deviation	Risk/return ratio
Original Portfolio	0,97%	0,044	0,223
Estimated Benchmark	4,19%	0,042	0,293
One-Sample T-test	t- value	Significance (95%)	Mean Difference
XMR portfolio	3,958	0,001	0,696

Table 14, Original portfolio compared to estimated benchmark. With Monero.

[24] Appendix G shows that simulated portfolios for Monero are normally distributed.

5.6 Mixed

The addition of all cryptocurrencies in the least variance framework is presented in figure 11. Since the efficient frontier of a portfolio with the addition of these currencies is left of the portfolio without these for every point, we find support for our first hypothesis. This means that cryptocurrencies are used in a least variance framework.

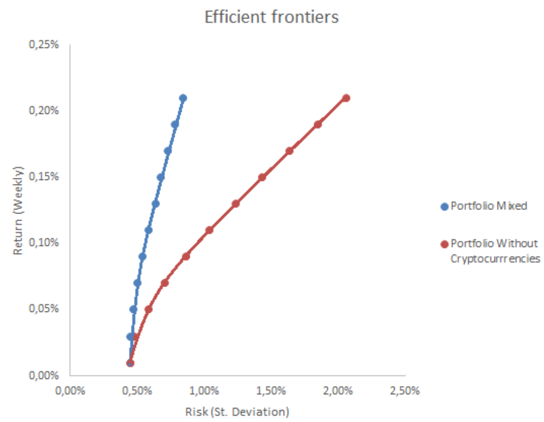

Figure 11, Efficient frontier Mixed versus no Mixed

Secondly, portfolio 4 in table 15 shows a Sharpe ratio of 0,182. Which is way higher than 0,095 of the basic portfolio. This is also higher than of the singular cryptocurrencies. Therefore, we accept our second hypothesis. Which means that the addition of all the cryptocurrencies indeed leads to a better Sharpe ratio. We see that using a mix of all the cryptocurrencies even leads to a higher Sharpe Ratio, in comparison to the addition of a single cryptocurrency.

	Portfolio 1	Portfolio 2		Portfolio 3		Portfolio 4
Constraint variable	None	σp <=	No shortsale	μp = Highest E[r]	No shortsale	None
Value of constraint	-	0,550%		0,188%		-
	Weights					
BTC	6%	1%	2%	2%	5%	11%
XLM	6%	0%	0%	0%	0%	0%
XRP	6%	0%	0%	0%	1%	2%
LTC	6%	0%	0%	0%	0%	0%
XMR	6%	0%	0%	0%	1%	4%
MSC	6%	36%	0%	47%	0%	0%
EMS	6%	-11%	0%	-12%	0%	0%
FMM	6%	-8%	0%	-10%	0%	0%
Commodity	6%	-6%	0%	-7%	0%	0%
Corpbond	6%	-4%	0%	-6%	0%	0%
Highyield	6%	-16%	0%	-21%	0%	0%
Isharestips	6%	92%	50%	106%	64%	26%
Hedge	6%	32%	42%	22%	0%	0%
MM	6%	-23%	0%	-30%	0%	0%
PrivateEq	6%	26%	5%	33%	28%	57%
Realest	6%	-20%	0%	-23%	0%	0%
Combined	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%
Mp	0,686%	0,152%	0,073%	0,188%	0,188%	0,420%
Σp	5,707%	0,550%	0,550%	0,648%	1,079%	2,307%
risk/return	0,120	0,276	0,133	0,291	0,175	0,182

Table 15, Portfolio returns Mixed portfolio.

Thirdly, we see that each portfolio has weights in 3 cryptocurrencies except the least variance portfolio. This means that our mix of cryptocurrencies offers diversification effects in almost every setting we investigate. We see that the results are robust for equal weighting, with and without short sale constraints and also for the maximization of the Sharpe ratio. Therefore we accept our third hypothesis with a side note.

Fourthly, the estimations in figure 12 show the weights of each cryptocurrency in the simulated portfolios. We find that Bitcoin has the highest average weight with a percentage of 11,36% in the true portfolio. The average weights in the mixed portfolio reflect the weights of the cryptocurrencies when looked at individually. Meaning that the average weight is the highest for Bitcoin and the lowest for Stellar Lumen.

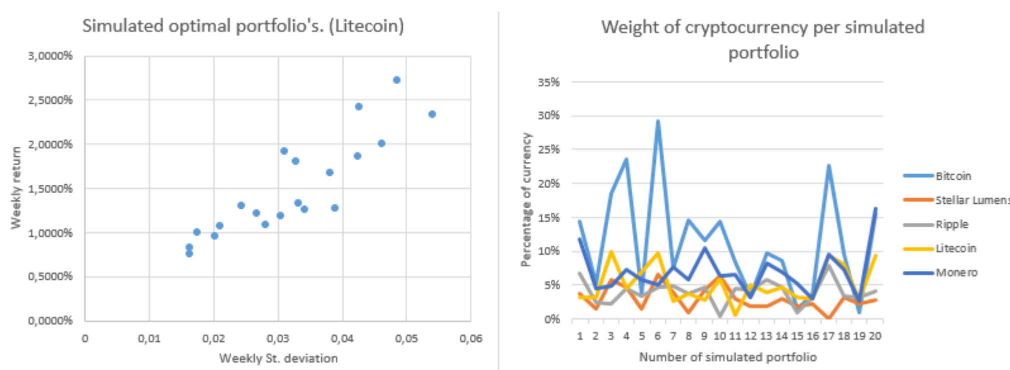

Figure 12, Simulation of portfolio's weights and risk to return ratio. With Mixed portfolio.

Lastly, when we statistically control for the difference between the simulated portfolios and the original portfolio in table 16 we find a p-value of 0,000. Since $p < 0,05$ we reject our null hypothesis [25]. Accepting our alternative hypothesis, meaning that there is a significant difference between the mean of the simulated portfolios and the original portfolio. Therefore, we find no support for our fourth hypothesis that our simulations are robust when prices are simulated numerous times.

Original &. Estimated portfolio	Mean Return	St. Deviation	Risk/return ratio
Original Portfolio	1,28%	0,044	0,291
Estimated Benchmark	3,21%	0,032	0,471
One-Sample T-test	t- value	Significance (95%)	Mean Difference
Mixed Portfolio	10,23	0	0,18

Table 16, Original portfolio compared to estimated benchmark. Mixed.

[25] Appendix G shows that simulated portfolios for Mixed are normally distributed.

6 Conclusion

This research is unique, since it individually looks at cryptocurrencies other than Bitcoin. It better well-diversified portfolio, since we added private equity. Creating a well-diversified portfolio with more different financial assets. The time frame that is used also included the massive growth and subsequent downfall in the beginning of 2018, which promotes the validity of our results. By combining all the cryptocurrencies in a mixed portfolio, even more significant diversification effects were found. Our research is further on supported by robustness checks and a Monte Carlo study. Our evidence supports the validity of earlier findings in the literature (Kajtazi & Moro, 2018; Guesmi et al., 2018; Trimborn et al., 2017; Sontakke & Ghaisas, 2017), and provides useful insights for investors who are interested in the effects of adding in cryptocurrencies in a traditional investor's portfolio.

The goal of our paper is to analyze the consequences of investing in cryptocurrencies. We have come up with three different perspectives to analyze investments with these financial assets. and have used the efficient frontier, four constructed portfolios and a Monte Carlo simulation to conduct the study. Our results are promising and uncover opportunities for future investments.

Every cryptocurrency is used in the least variance framework, which means that we find confirmation for our first hypothesis for each individual cryptocurrency. For each, we find compelling evidence that adding them in the portfolio leads to a higher Sharpe ratio. This means that we find confirmation for our second hypothesis for each individual cryptocurrency.

Further on, every cryptocurrency offers diversification benefits in an investor's portfolio. In every portfolio that we've created, a portion of weight is acknowledged. All of the currencies are robust against the equal weighting, with and without short sale and the strategy. Leading to confirmation of our third hypothesis for all the individual cryptocurrencies.

The benchmark of our simulated portfolio's should be equal to the original portfolio (Jorion, 1992). Therefore, we find robust results for Bitcoin, Litecoin and Stellar Lumen. However, the Monte carlo simulation results for Monero and Ripple show a significant difference from the benchmark. Meaning that we only accept the fourth hypothesis for Bitcoin, Litecoin and Stellar Lumen.

When we combine the five cryptocurrencies together, the Sharpe ratio is higher than for any of the individual cryptocurrencies[26]. Furthermore, the efficient frontier is more steep to the left than any of the frontiers of the cryptocurrencies. The simulation results show that on average, Bitcoin has the main weight

[26] We define a higher Sharpe ratio as "More optimal" (Jorion, 1992).

and Stellar lumen has the least weight in a mixed portfolio. Since we find significant diversification benefits in every portfolio, we also find confirmation for the second and third hypothesis. With regard to our estimations, we find a significant difference between the mean of the estimations and the original mixed portfolio. Therefore, we are unable to find support for our fourth hypothesis.

With our research, we have revealed the investment power of cryptocurrencies. Our results are in line with the implication of investing in Bitcoin and solid new evidence is found for investing in Litecoin and Stellar Lumen. At last, we've managed to uncover and analyze the diversification effects of Monero and Ripple. This research serves as a basis for the analyses of diversification effects with regard to cryptocurrencies. Investors are less familiar with the cryptocurrency market than with other well-established financial markets. Therefore, we hope these results can give them a clear view when willing to invest in this emerging market.

7 Discussion

The analysis provides useful insights with regard to the investment in cryptocurrencies. Of course, results are always susceptible to errors and footnotes have to be made. A critical reflection is therefore needed to stimulate further research. During our research, similar research was conducted with regard to the diversification effects of cryptocurrencies. The results were in line with our research. However, researchers choose to derive the Mean-Cvar analyses from the original Mean-var to investigate diversification effect. It seems that the Mean-Cvar analysis is often used to reduce the chance on big losses[27] in a portfolio (Kajtazi & Moro, 2018). It is interesting to see the difference in outcome when using another approach. As we have seen in our literature section, different methods presented the same general results. In our case, both studies found the same confirmation that cryptocurrencies enhance diversification benefits and lead to a higher Sharpe ratio and a lower risk profile of the portfolio. Tail risk however requires further investigation.

We used Excel for our analyses. In comparison to other statistical programs, like STATA, Excel has less capacity to do a lot of simulations at once. Our Monte Carlo simulations were time consuming since the portfolios had to be estimated manually. For future research, it is of added value that the simulation analysis is done in a statistical program like SPSS or STATA. A Monte Carlo simulation is normally done for a higher amount of times. And therefore, our results should be interpreted with caution.

The cryptocurrency market is not as well established in as other financial markets like the stock market. In the last years, numerous platforms emerged in which you can invest. But, it can still be challenging to invest in certain cryptocurrencies. Therefore, future research should use a variable to take extra transaction costs into account. It is hard to measure the accessibility of a market, but it would eventually improve the validity of the research in this field.

So far, historical research uses short sale constraints as a robustness check. But in practice, it is only possible to short sell on the cryptocurrency market since the end of 2017. Since the short sale wasn't possible before that period, it could have had an effect on the effectivity of using the short sale constraint as a robustness check.

[27] Defined by "Tail risk".

With this research, the basis with regard to the diversification effects of cryptocurrencies is set. But, future research should critically reflect on the possibility to use the Mean-var of Mean-Cvar analysis, extent its robustness checks or not, and use a suitable statistical program to conduct a larger Monte Carlo simulation. The cryptocurrency market is rapidly developing, and so is the literature in this field. Therefore, ideas for future research in this topic are presented.

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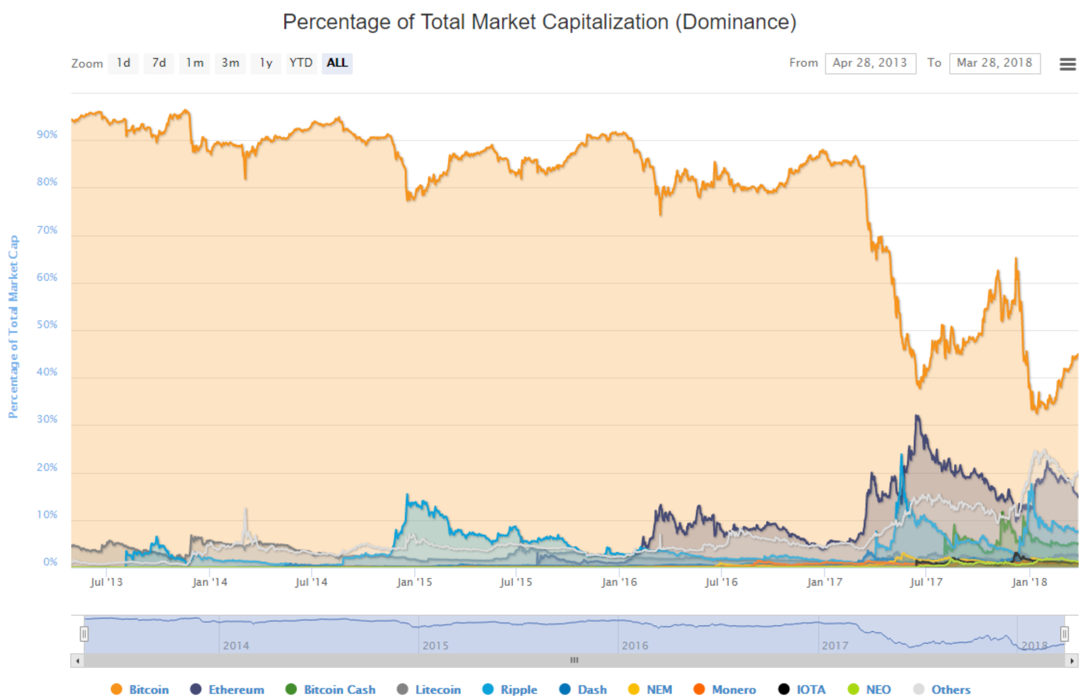
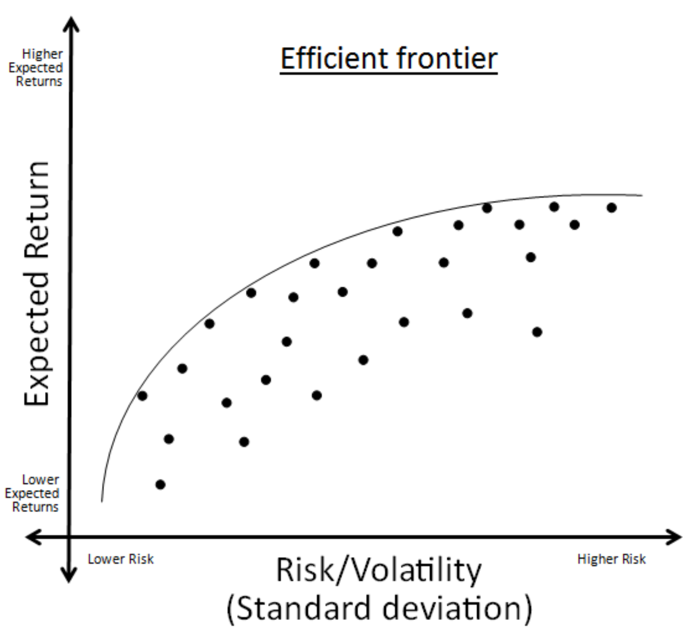
9 Appendix

Appendix A, Bitcoin domination, Cryptocurrency market



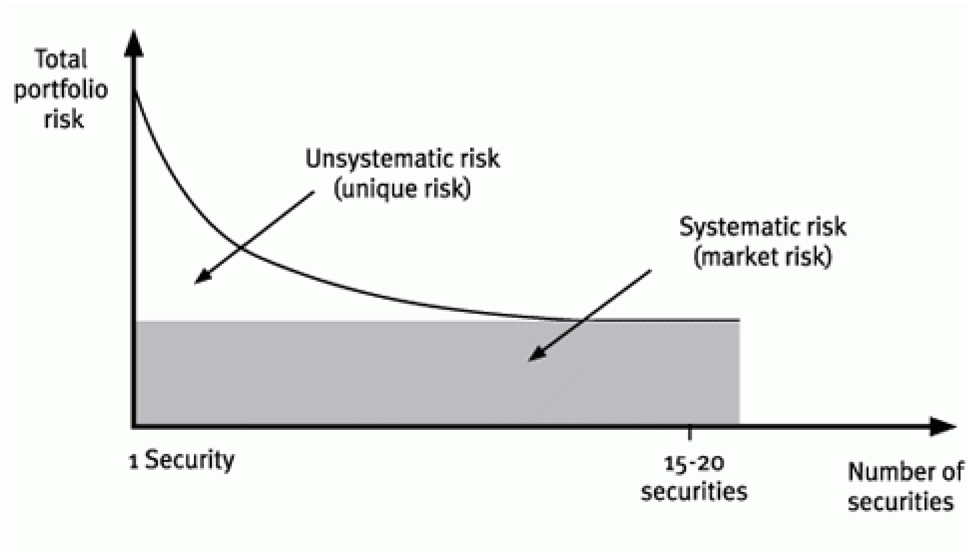
https://coinmarketcap.com/charts/

Appendix B, Efficient frontier example



Source: http://www.gettingyourich.com/blog/what-is-the-efficient-frontier-theory

Appendix C, Sorts of risk



Source: https://www.bbalectures.com/systematic-risk-and-unsystematic-risk/

Appendix D, Mean-variance Frontier

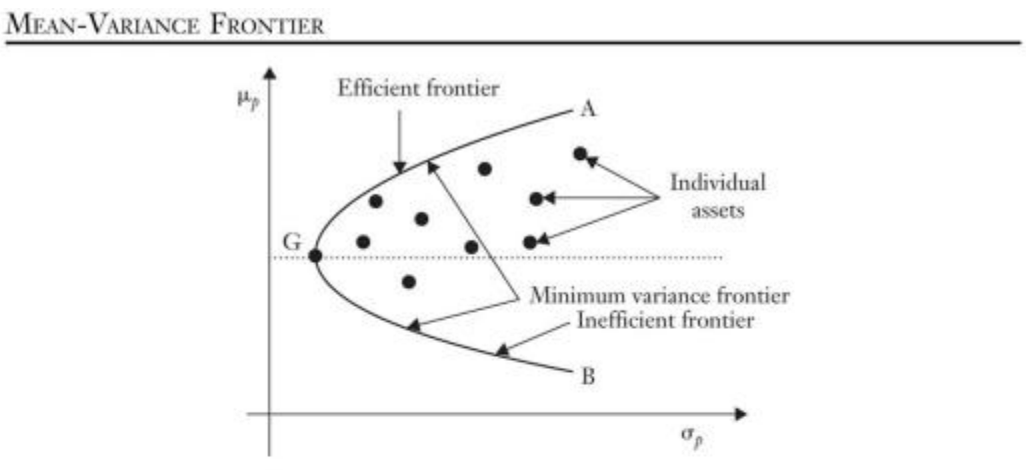


Figure: Efficient and Inefficient Portfolios

Source: Cuthbertson, K. and Nitzsche, D. (2004) 'Quantitative Financial Economics',second edition, WILEY Publisher

Appendix E, Correlation table

	BTC	ETH	XRP	LTC	XLM	XMR	DASH	XEM	ETC	LSK	ZEC	SC	REP	FCT	NXT	^SPX	^VIX	^GLD	^TNX
BTC	1	0.6	0.34	0.56	0.4	0.59	0.54	0.51	0.54	0.53	0.5	0.49	0.51	0.56	0.48	0.08	-0.13	0.02	-0.03
ETH	0.6	1	0.42	0.58	0.45	0.66	0.69	0.59	0.71	0.63	0.71	0.55	0.66	0.69	0.49	0.12	-0.15	0.11	-0.01
XRP	0.34	0.42	1	0.42	0.64	0.4	0.3	0.47	0.31	0.31	0.37	0.43	0.36	0.41	0.34	0.07	-0.05	0.08	-0.06
LTC	0.56	0.58	0.42	1	0.42	0.57	0.55	0.5	0.59	0.49	0.44	0.49	0.49	0.56	0.44	0.13	-0.13	0	0.05
XLM	0.4	0.45	0.64	0.42	1	0.49	0.38	0.52	0.39	0.41	0.42	0.53	0.41	0.55	0.46	0.1	-0.08	0.04	-0.01
XMR	0.59	0.66	0.4	0.57	0.49	1	0.69	0.5	0.57	0.6	0.65	0.54	0.64	0.71	0.48	0.05	-0.13	0.07	-0.01
DASH	0.54	0.69	0.3	0.55	0.38	0.69	1	0.51	0.56	0.58	0.66	0.49	0.61	0.65	0.44	0.08	-0.12	0.04	0.08
XEM	0.51	0.59	0.47	0.5	0.52	0.5	0.51	1	0.48	0.51	0.52	0.5	0.5	0.56	0.51	0.13	-0.15	0	0.01
ETC	0.54	0.71	0.31	0.59	0.39	0.57	0.56	0.48	1	0.56	0.58	0.43	0.57	0.6	0.42	0.16	-0.21	0.03	0.01
LSK	0.53	0.63	0.31	0.49	0.41	0.6	0.58	0.51	0.56	1	0.59	0.55	0.6	0.67	0.49	0.08	-0.14	0.04	0.02
ZEC	0.5	0.71	0.37	0.44	0.42	0.65	0.66	0.52	0.58	0.59	1	0.47	0.62	0.65	0.42	0.07	-0.13	0.06	-0.01
SC	0.49	0.55	0.43	0.49	0.53	0.54	0.49	0.5	0.43	0.55	0.47	1	0.52	0.61	0.55	0.07	-0.03	0.11	-0.06
REP	0.51	0.66	0.36	0.49	0.41	0.64	0.61	0.5	0.57	0.6	0.62	0.52	1	0.66	0.44	0.04	-0.07	0.04	0.08
FCT	0.56	0.69	0.41	0.56	0.55	0.71	0.65	0.56	0.6	0.67	0.65	0.61	0.66	1	0.5	0.06	-0.1	0.08	-0.07
NXT	0.48	0.49	0.34	0.44	0.46	0.48	0.44	0.51	0.42	0.49	0.42	0.55	0.44	0.5	1	0.12	-0.13	-0.01	0.01
^SPX	0.08	0.12	0.07	0.13	0.1	0.05	0.08	0.13	0.16	0.08	0.07	0.07	0.04	0.06	0.12	1	-0.8	-0.08	0.24
^VIX	-0.13	-0.15	-0.05	-0.13	-0.08	-0.13	-0.12	-0.15	-0.21	-0.14	-0.13	-0.03	-0.07	-0.1	-0.13	-0.8	1	0.1	-0.26
^GLD	0.02	0.11	0.08	0	0.04	0.07	0.04	0	0.03	0.04	0.06	0.11	0.04	0.08	-0.01	-0.08	0.1	1	-0.47
^TNX	-0.03	-0.01	-0.06	0.05	-0.01	-0.01	0.08	0.01	0.01	0.02	-0.01	-0.06	0.08	-0.07	0.01	0.24	-0.26	-0.47	1

Source: https://www.sifrdata.com/cryptocurrency-correlation-matrix/

Appendix E', P values of correlation table

	BTC	ETH	XRP	LTC	XLM	XMR	DASH	XEM	ETC	LSK	ZEC	SC	REP	FCT	NXT	^SPX	^VIX	^GLD	^TNX
BTC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.13	0.01	0.77	0.58
ETH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.03	0	0.04	0.78
XRP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.17	0.34	0.14	0.29
LTC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.01	0.02	0.97	0.33
XLM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.06	0.13	0.49	0.84
XMR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.32	0.01	0.16	0.87
DASH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.14	0.02	0.46	0.15
XEM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.01	0	0.96	0.84
ETC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.52	0.83
LSK	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.11	0.01	0.43	0.76
ZEC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.19	0.01	0.24	0.86
SC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.21	0.56	0.03	0.26
REP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.41	0.19	0.45	0.11
FCT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.27	0.06	0.11	0.2
NXT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.02	0.01	0.82	0.79
^SPX	0.13	0.03	0.17	0.01	0.06	0.32	0.14	0.01	0	0.11	0.19	0.21	0.41	0.27	0.02	0	0	0.11	0
^VIX	0.01	0	0.34	0.02	0.13	0.01	0.02	0	0	0.01	0.01	0.56	0.19	0.06	0.01	0	0	0.07	0
^GLD	0.77	0.04	0.14	0.97	0.49	0.16	0.46	0.96	0.52	0.43	0.24	0.03	0.45	0.11	0.82	0.11	0.07	0	0
^TNX	0.58	0.78	0.29	0.33	0.84	0.87	0.15	0.84	0.83	0.76	0.86	0.26	0.11	0.2	0.79	0	0	0	0

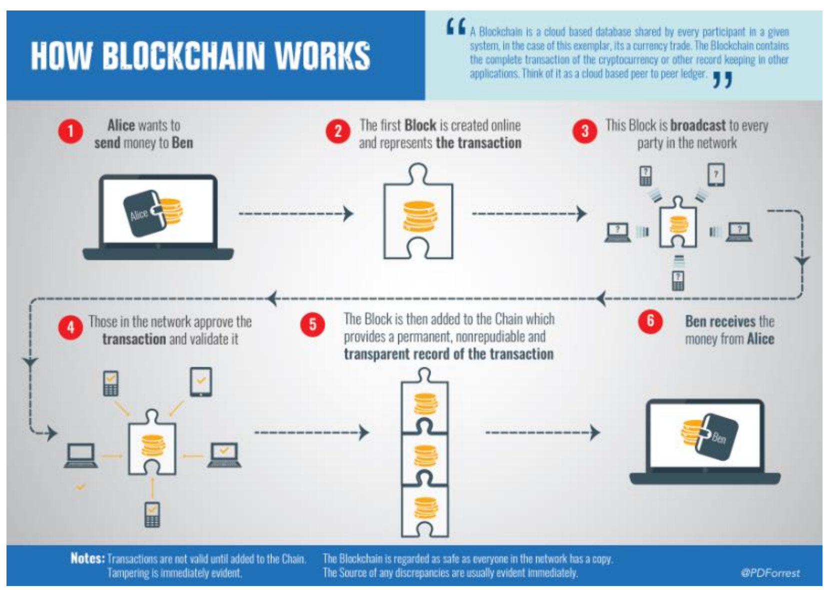
Source :

Appendix F, What is a cryptocurrency ? (Simplistic explanation)[28]

A cryptocurrency is literally a digital currency. Its goal is to serve as a substitute for the traditional currencies like the Dollar or the Euro. The first cryptocurrency ever is the Bitcoin. Which explains its popularity in practice and existing literature. Another name you will often encounter for cryptocurrencies is “Altcoins”. The most interesting characteristic of cryptocurrencies is its underlying block chain technology. But first, let me explain how cryptocurrencies work in practice.

Just like normal monetary transactions, all the confirmed transactions are stored in a public ledger. In this system the owners of the currencies are encrypted. And another cryptographic technology will be used to ensure the privacy of the cryptocurrency holders. Just like a normal wallet, the transactions online are sending money, but now cryptocurrencies, from the one wallet to the other. Since this contains a cryptographic signature, the transaction is done in a closed circuit. So how are the cryptocurrencies achieved in the first place?

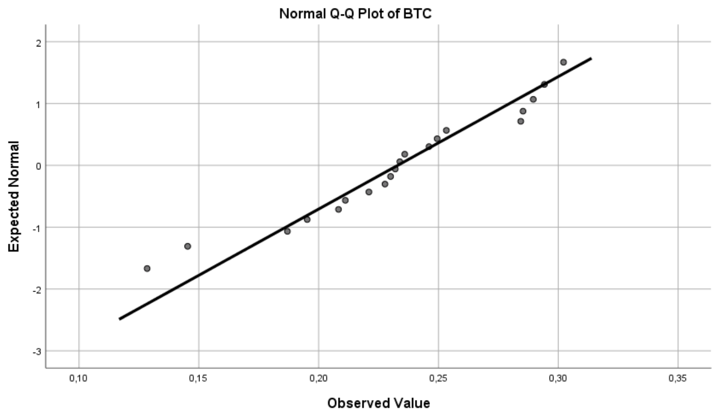
By the process of “Mining”, the transactions are added to the public ledger. When a “Miner” mines cryptocurrencies it actually solves an increasingly complex computational problem. When a block is mined, it is added to the ledger. Afterwards it is not possible to change these blocks, therefore all correlating transactions which will be done in the future are permanent. The mining system provides rewards for the miners and is the reason that cryptocurrencies have value.

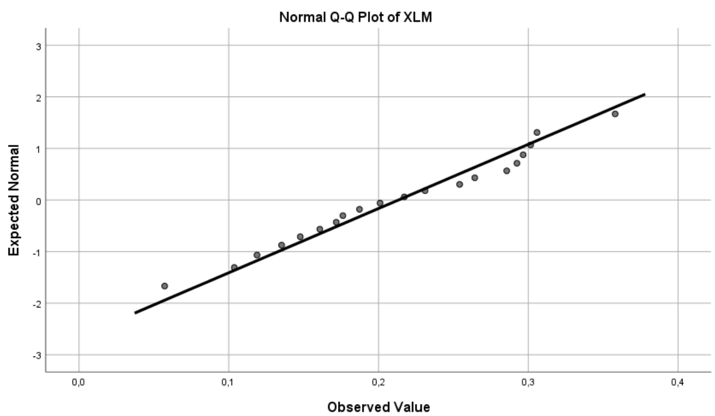


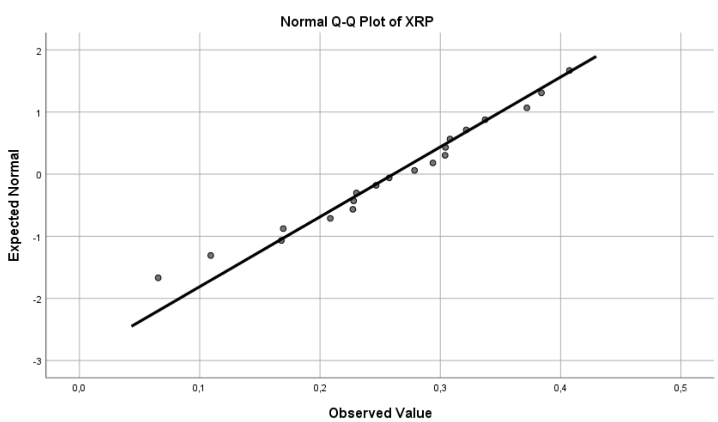
So in the end it is possible to trace every transaction back to the wallet holder which sent or received the cryptocurrency. This means that a person could trade with somebody at the other end of the world and receive the payment much faster than it would by using a regular bank. Also the transaction fees are competitive for the current banking system.

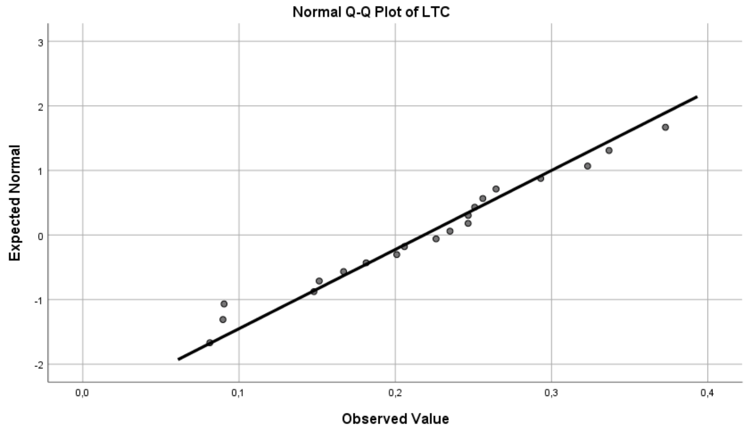
[28] https://cryptocurrencyfacts.com/how-does-cryptocurrency-work-2/

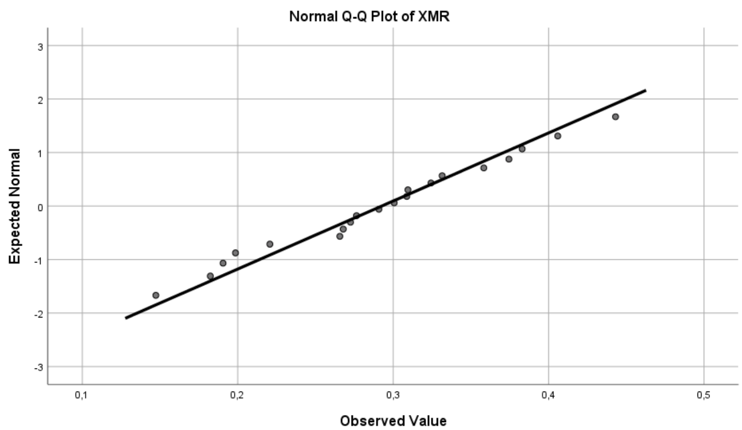
Appendix G, Spread of estimation values of estimated portfolio's.











Source: SPSS output.