
**AN INVESTIGATION INTO THE USE OF
MULTIPLE CRYPTOCURRENCIES IN A
DIVERSIFIED PORTFOLIO**

BY

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ABSTRACT

This study investigates the possible diversification benefits of multiple cryptocurrencies (Bitcoin, Ethereum and Litecoin) in a diversified portfolio from the perspective of a South African investor over the period 30 July 2015 to 20 December 2017. Cryptocurrencies are mostly still in their infancy, and reliable information regarding their usefulness as an asset class in a diversified portfolio is scarce to come by.

This study adopts a quantitative research methodology which incorporates the following statistical methods: i) mean-semivariance optimisation; ii) Kendall Tau-b correlations; and, iii) autocorrelation function for serial correlations. The JSE All Bond Index is used as bond investment proxy, a combination of the JSE Top 40, Resources Index and Financial-Industrials Index is used as an equity investment proxy, and the LBMA Gold PM is used as a gold investment proxy.

The study found that all three cryptocurrencies under investigation yielded risk-return benefits for a diversified portfolio. The alternative cryptocurrencies (Ethereum and Litecoin) exhibited higher levels of downside risk (semideviation) than Bitcoin, but proportionately greater returns. Hence, the addition of these two cryptocurrencies to a portfolio that includes Bitcoin and traditional assets resulted in an expansion of the efficient frontier. Ethereum exhibited slightly lower correlations to Bitcoin than Litecoin, which is most likely attributed to its greater technological differences, but performed worse as a diversifier. All three cryptocurrencies yielded similar low to very low correlations to all traditional assets, including gold - representative of the potential diversification benefits. The autocorrelation function resulted in high positive serial correlations for all three cryptocurrencies, indicative of strong trending behaviour and high volatility.

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CHAPTER 1: INTRODUCTION

This study investigates the possible diversification benefits of adding multiple cryptocurrencies to a traditional diversified portfolio from the perspective of a South African investor over the period 30 July 2015 to 20 December 2017. An issue for many South African investors is the inherent limitation associated with the diversification of portfolio returns. The aim of this study is to discover whether there are indeed additional assets useful for diversification and if they can actually provide a viable solution for the average South African investor. Hence, the objective of this study is to be able to improve a South African investor's portfolio on a risk-return basis via an expansion of the investable universe. Our method for potentially improving the risk-return efficiency is to utilise multiple cryptocurrencies. However, the addition of cryptocurrencies brings about a host of risk factors that need to be considered in formulating optimal investment strategies. The new age technology of cryptocurrencies has shown, in a relatively short span of time, that their value is driven mostly by forces independent to that of traditional assets. However, these forces have had drastic effects on their market value, resulting in extreme price fluctuations.

This study aims to provide insight into whether the inclusion of such volatile assets in a diversified portfolio can actually be viable and whether cryptocurrencies can be diversified amongst themselves. Where many studies have covered the use of Bitcoin, the largest and most renowned cryptocurrency, as a possible portfolio diversifier (see Carpenter (2016); and Eisl et al. (2015)), the inclusion of other cryptocurrencies such as Ethereum and Litecoin has been largely neglected. The differentiating properties of Ethereum and Litecoin could create utility for investors and users separate to that of Bitcoin, resulting in price fluctuations that could counteract volatility.

We begin our review of literature with previous studies on the broad benefits of diversification on a portfolio of assets. Subsequently, we investigate research that

relates to the diversification effect of Bitcoin specifically, taking note of methodologies and findings. Our focus then moves to how cryptocurrencies relate to each other and to traditional assets such as U.S. equities, bonds, real estate, gold, oil etc., using a variety of correlation tests for analysis. The remainder of literature reviewed in this study focuses on aspects which help shape our methodology such as the use of semivariance, the proxy for the risk-free rate, and the inclusion of the South African Resources Index and Financial-Industrials Index.

This study employs a quantitative research methodology and uses a non-experimental design. In particular, the study attempts to i) quantify the risk-return benefits of including Bitcoin, Ethereum and Litecoin in a diversified portfolio through the use of mean-semivariance optimisation; ii) investigate the relationship between assets in a multi-cryptocurrency portfolio through the use of correlations; and, iii) determine the long and short-term trending and mean-reverting behaviour of cryptocurrencies using serial correlations. The investigation into correlations makes use of the Pearson r correlation test. Should the data not meet the assumptions associated with this test, the Kendall Tau-b correlation test will be used as a replacement. The investigation into serial correlations utilises the autocorrelation function (ACF).

The remainder of chapter one provides a broad understanding of the function of cryptocurrencies, an overview of the specific cryptocurrencies investigated in this paper, how cryptocurrencies are traded through exchanges, and a discussion on how this new asset class should be classified.

1.1. UNDERSTANDING CRYPTOCURRENCIES AND BLOCKCHAIN TECHNOLOGY

Since the basis for our study to include multiple cryptocurrencies relies on the fact that each has their own distinct technology and use case, it is important to understand the fundamentals behind each one. Where some cryptocurrencies look

to simply be an efficient decentralised medium of exchange, others utilise blockchain technology for far more than that. Many seek to connect businesses through one global system or become powerful platforms where users can build their own decentralised applications. The use cases for blockchain technology are endless.

1.1.1. BITCOIN

The most renowned cryptocurrency is Bitcoin, invented by an unknown programmer, with the pseudonymity of Satoshi Nakamoto, in 2009. At the start of 2013 a single Bitcoin was worth \$13.50, by the start of 2016 its value had increased to \$443.56, and by 20 December 2017 the price reached a staggering \$17625 – having a market capitalisation of \$296.5 billion (Coindesk, 2017). Transaction growth has boomed over the previous four years (see Figure A1) and many countries have accepted it as legal tender, such as Japan. It has come to be the “gold standard” in the world of cryptocurrencies, since on many exchanges the prices of cryptocurrencies besides Bitcoin, called altcoins (alternative coins), are quoted in terms of units of Bitcoin (Blockgeeks, 2017). Many exchange users will make trades using Bitcoin instead of fiat currencies such as the U.S dollar, Euro, Yen etc.

1.1.2. ETHEREUM

Until recently, to build an application on a blockchain, whether it be a digital currency or database of intellectual property ownership, one would require extensive skills in coding, cryptography, mathematics and a significant amount of resources. The introduction of Ethereum in 2013 by Vitalik Buterin gave users the tools necessary to build decentralised applications using an open software platform, making things a lot simpler. Essentially, where Bitcoin is simply a blockchain that processes a peer to peer digital cash system and records ownership of digital currency, Ethereum focuses on running any sort of decentralised application built by its users on the network known as the Ethereum Virtual Machine (EVM). The

EVM hosts the application built by users so they do not have to code a completely new blockchain (Blockgeeks, 2017). This is beneficial for a lot of people that are looking to build blockchain applications of the future since it provides so much more than just a digital currency. The currency that runs the Ethereum network is called Ether, which is needed for users to pay for transactions processed by the network – it essentially fuels the entire system.

A functionality of the Ethereum network is its smart contracts, which enable the transfer of ownership of anything of value between parties. It is simply a piece of code that automatically executes when specific conditions are met (Blockgeeks, 2017). For instance, if party A wanted to sell his car to party B, both parties would enter into a smart contract using Ethereum. The terms of the contract would state that as soon as party A receives an amount of currency from party B, ownership of the vehicle would immediately be transferred to party B – all this without any possibility of non-payment, fraud or third-party interference. An example would be an increase in system efficiency for the sale and registration of motor vehicles with the traffic department. The department could be included as a third party in the smart contract and be notified of proof of payment immediately upon execution.

The price of Ethereum at the beginning of 2016 was \$0.95, by the start of 2017 it was \$9.66, and by 20 December 2017 the price was at \$799. The market capitalisation of Ethereum as of 20 December 2017 was \$77.8 billion (Coindesk, 2017).

1.1.3. LITECOIN

If Bitcoin is the digital gold, Litecoin is the digital silver. The coin was created by Charlie Lee, an ex-Google engineer, in 2011. The lesser-valued cryptocurrency makes improvements on the Bitcoin framework by making it faster to transact between users – utilising Scrypt, which is technically a more complicated hashing algorithm than Bitcoin's SHA-256. However, the Scrypt algorithm makes it easier

to mine the coin, which has the benefit of being able to use less powerful hardware and lower energy consumption for the network. This has been a big criticism against Bitcoin, since the network already consumes more energy than many small countries such as Denmark, making up 0.16% of the world's energy consumption (Digiconomist, 2018).

On 1 July 2013, a single Litecoin was worth \$2.98, by the beginning of 2016, its value was \$3.51, and by 20 December 2017 it was worth a staggering \$353 (Coingecko, 2017). The market capitalisation of Litecoin was \$17.63 billion on 20 December 2017. Many practitioners and academics see Litecoin as a better alternative to Bitcoin since it has a relatively newer and more efficient protocol that allows block times to average 2.5 minutes compared to Bitcoin's 10 minutes. In addition, Litecoin will always be more plentiful due to its maximum coin circulation which is four times that of Bitcoin – 84 million compared to 21 million. As a result, Litecoin's transaction fees are far lower than that of Bitcoin which makes it more likely to be used as a medium of exchange by consumers.

1.2. DIGITAL EXCHANGES

An attribute of cryptocurrencies is that they can trade on multiple online exchanges. Each exchange is completely separate from one another, having different trading volume and prices. Prices on exchanges can vary drastically, which grants a possibility for arbitrage. Most exchanges offer a digital wallet where the value of one's cryptocurrencies is held as well as any fiat money deposited. The most established exchanges that are used for trading by investors are:

- **Coinbase:** One of the most popular and trusted exchanges which is used by millions worldwide and backed by trusted investors. This particular exchange is limited to certain countries, including the US, UK, Europe, Canada, Australia, and Singapore. They also cover any stored currency through their Coinbase insurance.

- Kraken: The largest Bitcoin exchange in Euro volume and liquidity. Users can buy and sell other cryptocurrencies such as Ethereum, Litecoin, Monero, Ripple and many more. As the exchange offers margin trading capabilities, it is generally targeted towards more experienced trading professionals.
- Poloniex: A secure trading platform that allows for over 100 different Bitcoin cryptocurrency pairings, with the inclusions of data analysis and other advanced tools. Fees are dependent on the volume of trades made and can vary anywhere between 0-0.25%.
- Other notable exchanges include: Bitstamp, Bittrex, Bitfinex, CEX.IO, Shapeshift, Luno, CoinMama, and Bitsquare (Blockgeeks, 2017).

1.3. CRYPTOCURRENCIES: INVESTMENT OR CURRENCY?

Cryptocurrencies, such as Bitcoin, are defined as digital currencies or a peer to peer electronic payment system which allows its users to make payment transfers through a decentralised network (Baur, Hong & Lee, 2014). However, cryptocurrencies can also be thought of as an investment due to fluctuations in prices. Academics and practitioners repeatedly debate which of the two categories they should fall under.

The definition of cryptocurrencies could have huge implications on legislative requirements for investors. For instance, this would undoubtedly have a noteworthy effect on Regulation 28 in South Africa. Regulation 28 controls how pension/retirement funds can invest in certain assets by setting limits – currently only 25% of assets can be offshore, the remaining 75% is to be local (Old Mutual, 2013). So, if a South African pension fund were to purchase Bitcoin over a South African cryptocurrency exchange, such as Luno, using local currency, Rands, would this be considered a purchase of a local digital investment asset or a foreign currency holding?

First, we must look to what actually defines a currency. The first characteristic is that it is used as a medium of exchange for goods and services and is the basis for trade. Secondly, it is a store of value, and thirdly, it is a unit of account. The immediate problem with a cryptocurrency like Bitcoin being considered a currency is that its value is highly unstable and can often have price swings of well over 10% in a single trading day. If investments are made into projects using cryptocurrency as a medium of exchange and the investor cannot accurately ascertain the value of that investment in the future due to the large fluctuations in the currency, then fewer investments are likely to take place using the cryptocurrency. Such volatility also negates the possibility of it being used as a unit of account (a reference for comparing the value of goods and services), as well as a store of value. An additional problem is the fact that transactions over the Bitcoin network are too slow as they usually take over 10 minutes to complete (Dorfman, 2017). However, developers are constantly looking to improve this.

The way in which holders utilise cryptocurrencies will give an indication of the market's consensus view as to whether they see it as a currency or investment. An analysis of the Bitcoin public ledger reveals that roughly one third of users will only ever receive Bitcoin and never send, whereas a small minority of holders will use Bitcoin as a medium of exchange, intermittently sending and receiving. This suggests that the market sees Bitcoin as an investment rather than a currency to be used as a medium of exchange, although this may be a matter of volatility (Baur, Hong & Lee, 2014).

Of course, the definition for legislative purposes is still to be decided in many countries given the recent gain in popularity of cryptocurrencies. In 2014, the South African Reserve Bank declared that virtual currencies were to have no legal status for the time being and will continue to monitor the situation, reserving the right to change its position (SARB, 2014).

1.4 FINAL REMARKS

This study continues in Chapter 2 by conducting a review of past literature on cryptocurrencies and methodology principles. The previous studies into cryptocurrencies use empirical analysis to quantify the diversification effects and relationships between asset components. Following this in Chapter 3, an overview of the sources that were used for data capture, an in-depth explanation of the research methodology implemented in this study, and an outline of the research questions. Chapter 4 continues by presenting the results obtained and then further delves into an analysis of results to answer the research questions. Lastly Chapter 5 concludes the study with an overview of the results, a description of the study's limitations, and an outline of recommendations for further research into diversification benefits of cryptocurrencies.

CHAPTER 2: REVIEW OF LITERATURE

In this section, we review previous literature on the nature of cryptocurrencies that made use of empirical data analysis. Our review first takes a broad approach by looking at the effect of diversification on a portfolio. Subsequently, we research of the diversification effects of Bitcoin, delving into its impact on a traditional U.S.-based diversified portfolio, and seeking to comprehend the individual relationships between Bitcoin and traditional assets through the use of correlations. Secondly, we seek to understand the fundamental relationships between cryptocurrencies themselves, again with the use of correlations. Note that little credible research has focused on the correlation and diversification benefits of Ethereum due to its relatively recent inception. The remainder of the literature review focuses on aspects which will guide the methodology for this study, such as the use of semivariance, the proxy for the risk-free rate, and the inclusion of the South African Resources Index and Financial-Industrials Index.

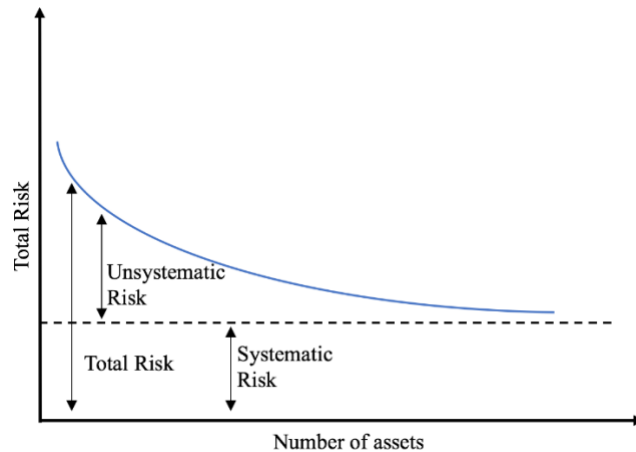
2.1 PORTFOLIO DIVERSIFICATION

For many years, investors have used the diversification of assets in their portfolio as a means of increasing risk-return efficiency. Spreading investments across various asset classes, such as equity, bonds, cash etc., helps investors minimise risk in achieving their financial goals. In theory, the negative performance of assets is completely or partially negated by the positive performance of other assets so that on average the portfolio yields a higher return per unit of risk compared to that of any individual asset.

One of the most common methods of depicting the expected risk-return payoff of a diversified portfolio is the Capital Asset Pricing Model (CAPM). Many practitioners and academics use the CAPM model to explain and estimate diversification benefits of a portfolio of assets. CAPM separates risk into two forms: systematic risk; and unsystematic. Systematic risk is the market risk which

cannot be diversified and is influenced by factors that impact the market as a whole, such as interest rates and changes in fiscal policies. Unsystematic risk composes of risks that are firm-specific and can be diversified away as the number of assets in a portfolio increases (see Figure 2.1.1) (Sharpe, 1970).

Figure 2.1.1: Elimination of unsystematic risk through diversification.



There has been much debate over what the ideal number of stocks to include in a portfolio should be in order to diversify unsystematic risk. Many researchers state that as few as 10-15 stocks are enough to exhaust diversification benefits in the U.S. market (Evans & Archer, 1968; Francis, 1986; Stevenson & Jennings, 1988). However, Statman (1987) suggests that at least 30 stocks are required for a borrowing investor, whereas a lending investor must have at least 40 stocks. Simply put, the number of stocks should be increased as long as the marginal benefit of diversification exceeds the marginal transaction cost.

Although systematic risk cannot be diversified within a specific market of assets, such as stocks, it can be mitigated by including assets which are part of a relatively disassociated market. Seeking alternative assets that are part of a market which is less sensitive to systematic risk factors, due to differentiated drivers of supply and demand, is beneficial for optimisation of portfolio returns. Examples of such markets which would provide an alternative to domestic equity could be: bonds;

commodities; international equity; cryptocurrencies; foreign exchange; and real estate. The quantitative reasoning for such an investment strategy relies on the basis of correlations (Sherman & Stein, 2016).

It is common knowledge amongst academics and practitioners that a low correlation between assets is an important attribute when seeking to maximise diversification benefits. This has been the basis for including both equity and bonds in a traditional diversified portfolio since they have historically exhibited a low correlation (Stewart, Piros & Heisler, 2011). A low correlation between two assets allows an investor to achieve a greater return for the same level of risk (or lower risk for the same level of return) than if the two assets were perfectly correlated (see Figure A2) (Blumenthal, 2014). This practice is greatly supported by modern portfolio theory (Markowitz, 1952) which states that diversification benefits exist as long as the correlation of returns is not equal to one. Thus, investors that wish to maximise diversification of their portfolio will seek to incorporate assets that exhibit such low correlations to the assets which they hold.

One such asset is gold. Historically, gold has played an important role in financial markets since it is often utilised as a safe haven during times of market crises or other unforeseen events, often referred to as “tail risks”. Whilst most industrial-based commodities tend to follow equities, gold’s correlation to equities tends to increase when U.S. equities rise and decrease when they fall (see Figure A3). Gold is also often used as an inflationary and currency hedge – essentially a tool of wealth preservation. However, the predominant value of gold, in investment terms, stems from its usefulness as a portfolio diversifier due to its low correlation to most traditional assets. The lack of correlation between gold and other assets is attributable to its differentiated drivers of supply and demand, which include such factors as new discoveries of gold, mining costs, Indian wedding season and fashion trends (Artigas, 2010). Post-2008 financial crisis investors have been placing more emphasis on alternative forms of risk management and have begun to realise the benefits of gold in a diversified portfolio for achieving both short and long-term

goals. Artigas (2010) concluded that allocations of gold from 2%-9% have a positive impact on risk whilst maintaining similar returns. The potential maximum weekly loss (weekly Value-at-Risk) was reduced between 0.1-18.5% at the 97.5% confidence interval (2.5% VaR).

The practice of investing internationally is a common form of diversification for many investors. A combination of less correlated foreign stocks results in greater risk-return benefits than that of less correlated domestic stocks (Solnik, 1974). Over the past decade, there has been increasing interest from developed market investors regarding the diversification benefits of emerging market investments (Oloko, 2017). Developed markets are highly globalised, attracting investors from all over the world, which makes them more prone to react faster to market crises than that of emerging markets. The less integrated emerging markets' lower exposure to international crises is able to provide adequate diversification benefits for foreign investors which is as a result of a low correlation due to differentiated fundamental economic factors (Oloko, 2017). In addition, the globalisation of financial markets, which provides enhanced liquidity, efficiency, and regulatory attributes, is promoted by increased diversification of developed market portfolios into emerging markets, and vice versa (Goldstein & Mussa, 1993).

A method for depicting the benefits of diversification is the "return gap" – the gap in returns between two assets or portfolios. Return gaps are helpful since they are able to account for the effects of both standard deviations and correlations whilst providing an intuitive measure of the benefits of diversification (Statman & Scheid, 2007). A high return gap implies a low correlation and high benefits of diversification, but could also be as a result of high standard deviation. Statman and Scheid (2007) analysed the returns of the S&P 500 and international stocks, represented by the EAFE Index, over a 60-month period. The S&P 500 returned 39.11% over the period, whilst the EAFE Index made a return of 117.92%. Compared to U.S. investors that invested in 60-40 proportions between domestic and international stocks respectively, U.S. stock concentrated investors lost out on

returns of 31.52%. Such a measure provides much more information regarding diversification benefits than the correlation measurement of 0.86 between the two indices (Statman & Scheid, 2007). Despite return gaps being an effective method of measuring the benefits of diversification, it provides little evidence to quantify the relative riskiness between two assets or portfolios.

It is important for investors to question the impact of the investment horizon on portfolio returns. This area of research is often referred to as time diversification. Time diversification relies on the belief that the longer investors hold a risky asset, the more the investor will benefit on a risk-return basis. The logic that supports this is relatively simple. If returns are independent of each other, year on year, then bad years in the market will be offset by good years, and so the risk of holding over many years would be lower than holding over just one (Thorley, 1995). This attribute is important in the context of cryptocurrencies given their high volatility. However, critics of time diversification argue that since annual returns are eventually compounded into a total period return, not just an average, this implies a greater risk as the asset is held for a longer period. This increase in risk is said to be equal to the increase in return, leaving the choice between risky and risk-free assets unaffected for a rational investor (Thorley, 1995). Time diversification continues to be the subject of spirited debate (Vanguard, 2008).

2.2 INCLUSION OF BITCOIN IN A TRADITIONAL DIVERSIFIED PORTFOLIO

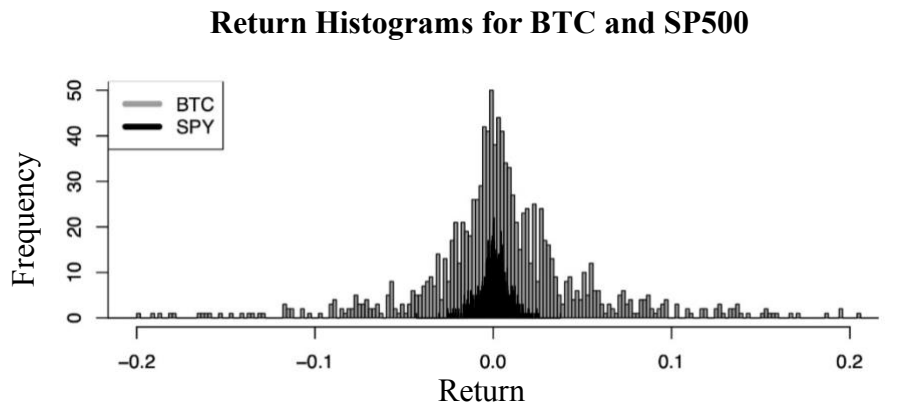
2.2.1 PORTFOLIO DIVERSIFICATION WITH BITCOIN

The inclusion of an asset in a diversified portfolio is dependent on whether it is able to make improvements on a risk-return basis. Under modern portfolio theory, this is usually characterised as outwards expansion of the efficient frontier. A notable study on the diversification effects of cryptocurrency by Carpenter (2016) first looked to measure the diversification effects using the Capital Asset Pricing Model

(CAPM), a standard in quantifying portfolio performance, from a U.S. perspective. However, his results found that the CAPM model failed to produce any significant beta values due to moments of excessive returns over the 2013-2014 period. The distribution of returns exhibited positive skewness and very high levels of excess kurtosis, which would not justify the application of the CAPM model since the model assumes a normal distribution of returns (see Figure 2.2.1) (Carpenter, 2016).

Figure 2.2.1: Histogram of returns – Bitcoin against SPDR S&P 500 EFT.

Source: Carpenter (2016).



The study states that such speculative bubbles, like the one over the 2013-2014 period, will undoubtedly continue for some time due to the host of new-age, untested technologies underlying its value. However, in spite of such non-normal returns, results revealed that the average daily volatility continued to decrease over the previous 5 years, whilst trading volumes increased by 400 times (Carpenter, 2016). Carpenter (2016) continues by using the CAPM model for all other asset classes, but for Bitcoin, an adjusted mean-variance framework was used. This framework was justified by the evidence of decreasing volatility and increasing trading volume. The adjustment that was included was a so-called “penalty” against Bitcoin returns, which essentially divided the average historical returns by a value (γ). The weightings of assets in the portfolio were calculated using a backtesting framework, which first uses equal weights and then rebalances to the optimal

weights using the mean-variance optimisation. Results were collected for both the periods including the excessive returns over 2013-2014, as well as post-2014 returns. In the case of no penalty adjustment, the optimal weighting of Bitcoin was 14%, which doubled returns from 13% to 26%, whilst risk only marginally increased from 13% to 17%. This of course resulted in a substantial increase in the Sharpe ratio, from 0.98 to 1.57. With the inclusion of the adjustment penalty, value added from Bitcoin was still prominent even up to a value of $\gamma = 10$, which equates to one tenth of historical returns (Carpenter, 2016). For the summary of results from this study using various gamma values, see Figure A4. The study does highlight the fact that if the excessive returns over the 2013-2014 period are removed, the favourable risk-return trade-offs offered by Bitcoin disappear (Carpenter, 2016) – this would largely be due to the downward market correction after the bubble period. In conclusion, the study states that in theory the value of Bitcoin should be based on its utility, however, the multiple uses of the cryptocurrency have now distorted its perceived utility and value. This has in the past nurtured an environment of speculative bubbles. Based on the inclusion of the return penalty, Bitcoin still holds a place in a diversified portfolio for a US investor (Carpenter, 2016).

Eisl, Gasser and Weinmayer (2015) investigated how Bitcoin can be used as a diversifier in a traditional, multi-asset class portfolio from a U.S. perspective. They too highlighted Bitcoin's low correlation with other traditional asset classes such as stocks, bonds, gold, oil, etc. The study focused on downside risk by adopting a conditional value-at-risk (VaR) approach. The conditional VaR method is superior to the traditional VaR method since it can quantify the expected loss that exceeds the quantile. In addition, the study utilised a backtesting technique which rebalanced the portfolio weights monthly over an investment period of 2.5 years (Eisl et al., 2015). Four different portfolio weighting frameworks were tested for: equally-weighted; long only; a range between -100% and 100%; and a completely constrained portfolio which allowed for any weight. The concluding results showed that the optimal Bitcoin weights for the various portfolio frameworks fall between 1.65% and 7.69% (see Table A1) - which are relatively low and stable (Eisl et al.,

2015). However, these weights are far lower than Carpenter (2016)’s more recent study which yielded an optimal weighting of 14% for the inclusion of Bitcoin.

2.2.2 CORRELATION OF BITCOIN TO VARIOUS ASSET CLASSES

By analysing the correlations between cryptocurrencies and other asset classes we can help determine whether the inclusion of an additional asset would provide further diversification benefits. In a research study conducted by Burniske and White (2016), Bitcoin was included in a correlation matrix with various other common asset classes using returns over the previous five years on a one year rolling average basis (see Table 2.2.1).

Table 2.2.1: Correlation of various asset classes, including Bitcoin. Source: ARK Investments Management LLC & Coinbase (2016).

	S&P 500	US Bonds	Bitcoin	Gold	US Real Estate	Oil	Emerging Market Currencies
S&P 500	0	-	-	-	-	-	-
US Bonds	-0.69	0	-	-	-	-	-
Bitcoin	0.36	-0.37	0	-	-	-	-
Gold	0.48	0.47	-0.33	0	-	-	-
US Real Estate	0.87	0.57	-0.36	0.45	0	-	-
Oil	0.73	-0.53	-0.36	0.52	0.63	0	-
Emerging Market Currencies	0.83	0.52	0.29	0.62	0.74	0.63	0

They concluded that Bitcoin’s price movements were “separate and distinct” and managed to maintain consistently low correlations with the other assets included in the analysis. Amazingly, the greatest absolute correlation of Bitcoin to any of the other assets was lower than the smallest absolute correlation between any of the other asset pairs. A separate analysis of Bitcoin’s correlation to US equities, US bonds, US real estate, emerging markets, gold and oil (see Figure A5) revealed an average correlation of -0.02 – further evidence to suggest the cryptocurrency’s stark price independence. The study also found that macroeconomic events that usually

have a substantial impact on traditional fiat currencies do not have any significant effect on Bitcoin, be it positive or negative (Burniske & White, 2016). Bitcoin also exhibited relatively high Sharpe ratios compared to many traditional assets over a variety of periods, except over the two-year period (see Figure A6).

During times of bear markets or in a state of financial crisis, investors often look to gold as a safe haven since its value is not strictly tied to macroeconomic conditions. Given that Bitcoin has shared this attribute over recent years, it is often stated as being the digital gold. Burniske and White (2016) look further into the relationship between Bitcoin and gold. The research they conducted found that prior to 2013, the correlation between the two assets was mostly low positive, until 2013 when Bitcoin made a huge bull run to over \$1000 (see Figure A7). Over the year the two largest gold ETFs roughly halved in market cap, whereas Bitcoin grew six-fold. The study found that ever since 2013 the correlation between the two assets has remained moderately negative (Burniske & White, 2016).

Dyhrberg (2016) takes an empirical approach using the asymmetric GARCH model in order to understand the effectiveness of using Bitcoin as a form of hedge. Given the similarities between gold and Bitcoin, the study utilised similar methodology and explanatory variables for both, drawing some inspiration from previous studies covering gold as a hedge. The paper first looked at the possibility of hedging against the FTSE 100 Index, assuming that Bitcoin does not affect the index in any way to avoid reverse causality and endogeneity – a reasonable assumption to make given that Bitcoin is unlikely to have much of an effect on the top 100 companies in the UK by market capitalisation. The findings from the analysis show that Bitcoin is uncorrelated with the FTSE index, which offers the possibility of hedging against systematic risk in the market – as so does gold. It goes further to suggest that UK investors may use a combination of Bitcoin and gold, which is negatively correlated, to counteract such risk (Dyhrberg, 2016). The study continues to analyse a possible hedge against exchange rate risk, using a crosscorrelogram between the dollar-sterling and the dollar-euro exchange rates. It found the presence of small

correlations between the exchange rates and Bitcoin, but states that the relationship is likely to be short term which would question its significance. Similar findings are present in studies for exchange rate hedging using gold (Dyhrberg, 2016).

2.3. CORRELATIONS BETWEEN CRYPTOCURRENCIES

A study conducted by Osterrieder, Lorenz, and Strika (2016) researched the relationship of returns of the largest cryptocurrencies. They provide statistical analysis and extreme value tests, with importance on tail risk characteristics. They study collected data from June 2014 until September 2016 for 6 out of the top 10 largest cryptocurrencies by market capitalisation. Note that Ethereum, the second largest, was excluded from the study since it only began trading on 30 July 2015. Overall, the study covered 88% of the entire cryptocurrency market capitalisation at the time. Basic statistical tests that were conducted included: distribution of returns, volatility and correlations. With our focus on the correlation results, three different tests were conducted, including the Kendall and Pearson correlation tests. (see Table 2.3.1). The Kendall Tau-b correlation is a non-parametric test that is able to measure the strength of dependence between two variables. The Pearson correlation test measures the strength of linear association between two variables (Hackborn, 2017).

Table 2.3.1: Kendall and Pearson correlations between cryptocurrency returns. Source: Osterrieder et al. (2016)

	Bitcoin	Dash	Litecoin	Maid	Monero	Ripple
Bitcoin	1	0.255	0.584	0.192	0.242	0.125
Dash	0.255	1	0.214	0.142	0.145	0.116
Litecoin	0.584	0.214	1	0.126	0.180	0.130
MAID	0.192	0.142	0.126	1	0.147	0.083
Monero	0.242	0.145	0.180	0.147	1	0.054
Ripple	0.125	0.116	0.130	0.083	0.054	1

Kendall correlation for cryptocurrencies

	Bitcoin	Dash	Litecoin	Maid	Monero	Ripple
Bitcoin	1	0.393	0.611	0.337	0.353	0.152
Dash	0.393	1	0.248	0.194	0.175	0.110
Litecoin	0.611	0.248	1	0.214	0.212	0.103
MAID	0.337	0.194	0.214	1	0.165	0.089
Monero	0.353	0.175	0.212	0.165	1	0.047
Ripple	0.152	0.110	0.103	0.089	0.047	1

Pearson correlation for cryptocurrencies

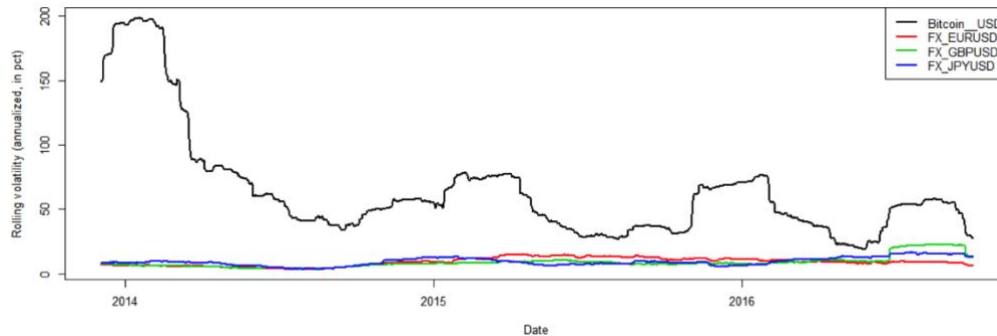
The study showed that returns for the period between the various cryptocurrencies were mildly correlated, except for Litecoin and Bitcoin which showed high levels of correlation. This high correlation was most likely due to the technical similarities between the two, given that they both simply aim to be a form of decentralised digital currency (Osterrider et al., 2016). Unlike Ethereum for instance, which aims to be much more than just a digital currency, but rather a platform to create decentralised blockchain applications. This is true for many other cryptocurrencies as they all attempt to invent unique differentiated properties designed to create value for users. However, it is important to note that the correlations between cryptocurrencies change over time (see Figure A8). This is as a result of two effects that oppose each other: substitution, where investors purchase other cryptocurrencies when one is getting too expensive (resulting in more positive correlation), and reinforcement, where one or more cryptocurrency is outperforming all the others (resulting in more negative correlation) (Osterrider et al., 2016).

2.4 DOWNSIDE RISK OF BITCOIN

A study conducted by Osterrieder and Lorenz (2017) provides an extreme analysis of the value of Bitcoin by focusing on tail risk characteristics, comparing them to traditional currencies versus the US dollar. This risk management perspective puts more emphasis on rare and extreme tail events, an important factor for both financial engineering (e.g. development of derivatives) and regulatory considerations (Osterrieder & Lorenz, 2017).

Volatility calculations over the period September 2013 till September 2016 revealed that Bitcoin was six to seven times more volatile than other traditional currencies. Figure 2.4 below summarises these results.

Figure 2.4: BTC and traditional currencies versus USD: 90-days rolling volatilities (annualised, percentages). Source: Osterrieder and Lorenz (2017).



As seen in Figure 2.4, Bitcoin exhibits very high levels of volatility which can last for extended periods of time over 50%. As a comparison, during the peak of the 2008 financial crisis, some currencies and equity stocks only reached 70% or more for very short periods of time (Osterrieder & Lorenz, 2017). This study highlights the cycle of speculation against volatile assets: when an asset is viewed as being unstable, people speculate for profits, resulting in more volatility. If this cycle can be reversed and Bitcoin is viewed as being more stable, the speculative cycle reinforces this stability (Osterrieder & Lorenz, 2017). Further traditional tail risk measures such as value-at-risk (VaR) and expected shortfall quantified losses for Bitcoin that were eight times more than traditional currencies. Such tail risk characteristics imply that on average every 20 days an investor should experience a 10% loss (Osterrieder & Lorenz, 2017).

Such a magnitude of volatility and downside risk is of course unfavourable for investors, hence the importance of understanding the effects of diversifying Bitcoin amongst other assets in a portfolio. At this time, this is the only study to analyse the intra-cryptocurrency market effects of how using multiple cryptocurrencies, such as Ethereum and Litecoin, might provide some level of diversification against extreme losses in a common diversified portfolio.

2.5 MEAN REVERSION AND TRENDING BEHAVIOUR

Mean reversion refers to the tendency of a series of values to return to the mean following a deviation. Strong movements in one direction are followed by a correction in the opposite direction. The majority of researchers look to behavioural finance to explain the anomaly of mean reversion. Individuals are subject to various heuristics when making financial decisions, often making decisions that oppose that of a rational investor. Humans rely on such heuristic principles since it reduces the complexity of making decisions under uncertainty. Having to form a response based on such principles is far faster than having to predict outcomes through an assessment of probabilities. This is useful for simple decision making, but can lead to severe errors at times (Tversky & Kahneman, 1974). Mean reversion can be explained by the presence of an anomaly which occurs as a result of such heuristics. This anomaly is investor overreaction, which is as a result of the heuristic called the availability bias. This can be described as individuals reacting disproportionately to new information, contradicting the efficient market hypothesis. This anomaly is best described by De Bondt and Thaler (1985). They placed the 35 top performing shares into a “winner” portfolio and the 35 worst performing shares into a “losers” portfolio. Over three years the loser portfolio consistently beat the index, whereas the winner portfolio consistently underperformed – this explains the reversion to the long-term mean subsequent to the overreaction of market participants.

A measurement used to quantify mean reversion in a series of data is serial correlation (also known as autocorrelation). The value of serial correlation can lie anywhere between -1 and +1. A negative serial correlation indicates that the variable has a mean reverting nature, movements in one direction are usually followed by a movement in the opposite direction. The frequency of mean reversion is relatively high, but gains are small for those investors looking to capitalise on such movements. A positive serial correlation indicates that the variable has a

trending behaviour. A strong trend move tends to be an outlier, occurring less often, but yields far greater returns than that of a mean reversion movement (Shen, 2015).

Both trending and mean reverting behaviour have implications for a portfolio of assets. Mean reverting behaviour will tend to stabilise an asset's volatility over long horizons, which is an attractive attribute for a risk averse investor. Trending behaviour is depicted by high returns followed by further high returns, or low returns followed by further low returns. This escalates an asset's volatility over time, which makes it less attractive to a risk averse investor (Stewart, Piros & Heisler, 2011).

The increase in volatility of a portfolio with the addition of an asset that exhibits trending behaviour would need to be compensated with relatively greater returns in order to be beneficial. Of course, during a downtrend, the inclusion of such an asset would be detrimental to a portfolio's risk-return efficiency due to high volatility and the continuation of negative returns.

2.6 USE OF SEMIVARIANCE AS A RISK MEASUREMENT

As we have seen in previous literature, the distribution of returns greatly affects the model that will be used to test such returns. The distribution of Bitcoin's returns exhibits excessive kurtosis and skewness to an extent that renders the use a model such as mean-variance optimisation unjust. For us to provide a more accurate representation of risk, we look to semivariance risk measures which focus on the possibility of negative returns. Even when Markowitz pioneered portfolio optimisation in 1959, he claimed that semivariance produces better portfolios than standard variance and states that "semivariance is the more plausible measure of risk" (Feldman, 1991). In addition, due to human nature, investors are more sensitive to the underperformance (associated downside risk) of their portfolios rather than over performance (Estrada, 2008). One would then expect that all practitioners and academics would use solely the semivariance over variance, but

due to the cost and convenience issues variance as a measure of risk was the main focus of Markowitz. However, due to ever-increasing computing power and the powerful bull markets that have been exhibited over the last few decades, there has been increased attention surrounding the use of semivariance (Estrada, 2008).

Given the South African context to this study, we look to a study by Vasant et al. (2014), which analyses the effectiveness of a mean-semivariance model compared to a mean-variance model on Johannesburg Stock Exchange (JSE) equities. Results showed that the use of mean-semivariance optimisation produced lower absolute returns, but better returns on a risk-adjusted basis (Vasant et al., 2014) – furthering our will for the semivariance model in this study.

2.7 PROXY FOR THE RISK-FREE RATE

An important factor to consider is the proxy for the risk-free rate in our study. Previous studies have revealed that having to choose a proxy from a South African perspective has proven to be more difficult than in markets such as the U.S. due to market characteristics.

A study by Strydom and Charteris (2009) delves into such an issue and seeks to assess the appropriateness of the use of Treasury Bills (maturity is less than one year) and Treasury Bonds (maturity greater than one year) as a proxy for the risk-free rate in South Africa. The study compares the U.S. and South Africa through use of theoretical requirements, which revealed that U.S. Treasury securities were not a perfect proxy for the risk-free rate and that the South African comparatives deviated substantially (Strydom & Charteris, 2009). Further analysis revealed that short-term South African bonds were not as useful as a proxy compared to longer-term maturity bonds. This was mainly due to the inclusion of greater short-term market volatility and default risk priced into the short-term bonds. In contrast, longer-term bonds inherently exhibit inflation and liquidity risk. However, the study argues that the use of longer-term bonds is still appropriate if the maturity of

the risk-free proxy is matched to the investment horizon (Strydom & Charteris, 2009:22).

2.8 FINANCIAL-INDUSTRIALS INDEX AND RESOURCES INDEX

To represent the equity portion of our diversified portfolio we look to the use of the JSE Top 40 index which comprises of the 40 largest shares by market capitalisation. However, there has been a great deal of research regarding the cross-section of returns on the Johannesburg Stock Exchange (JSE), most notably by van Rensburg & Robertson (2003). Through component analysis, it was found that JSE returns were better explained through the use of the Financial-Industrials Index combined with the Resources Index, than simply using the Top 40 or All Share Index (ALSI) (Laird-Smith, Meyer, Rajaratnam, 2016).

CHAPTER 3: DATA AND RESEARCH METHODOLOGY

3.1 DATA

Daily closing price data was obtained for the period from 30 July 2015 to 20 December 2017 – amounting to a total of 875 days. This study is limited to obtaining data further back than 30 July 2015 due to Ethereum’s relatively late inception. The price data for Bitcoin and Ethereum were both pulled from Coindesk with reference to the Coindesk exchange, whilst Litecoin data was accessed via the Quandl platform with reference to the Bittrex exchange.

Non-cryptocurrency asset data, for the Top 40 Index, Resources Index, Financial-Industrial index and LBMA Gold PM, were obtained from a Bloomberg terminal for the same period. All Bond Index (ALBI) data was obtained from the McGregor i-Net terminal. The proxy chosen for the risk-free rate is the R208 South African government bond which matures on 21 March 2021, yields were obtained from the Bloomberg terminal. Average annual inflation rates for the period 2015-2017 were obtained from Statistics South Africa.

This study makes use of cryptocurrency price data, index data for equity and bonds, government bond data for the risk-free rate, and inflation statistics, summarised below in Table 3.1.1 and Table 3.1.2.

Table 3.1.1: Summary of data for portfolio assets.

Name	Ticker	Type	Source
Bitcoin	BTC	Cryptocurrency	Coindesk
Ethereum	ETH	Cryptocurrency	Coindesk
Litecoin	LTC	Cryptocurrency	Quandl
Composite All Bond Index	ALBI	Bonds	i-Net
FTSE/JSE Top 40	JTOPI	Equity	Bloomberg
Resources Index	JRESI	Equity	Bloomberg
Financial-Industrial Index	JFNDI	Equity	Bloomberg
LBMA Gold PM	LBMA	Commodity	Bloomberg

Table 3.1.2: Summary of data as inputs for statistical method.

Name	Ticker	Type	Source
R208 SA Government Bond	R208	Bond (R_f)	Bloomberg
SA Inflation Rate	-	Inflation	Statistics SA

FTSE/JSE Top 40

The FTSE/JSE Top 40 is included to represent the equity portion in the South African market. This index is comprised of the 40 largest shares out of the over 400 which are listed on the Johannesburg Stock Exchange (JSE). This is still a fair reflection of the South African market since concentration on the JSE is quite high, the Top 40 represents over 80% of the market capitalisation of the JSE (SA Shares, 2018).

Resources and Financial-Industrials Index (RESI and FINDI)

As discussed previously in Section 2.3 of this dissertation, previous research has suggested that the inclusion of both of these sub-indices will provide a more accurate representation of the Johannesburg Stock Exchange's (JSE) returns. For this study, we use a combination of both the Top 40 Index and the Financial-Industrial (JFNDI) and Resources Index (JRESI). The JFNDI includes 30 of the top

market capitalisation shares in the financial and industrial sectors and the JRESI includes 20 of the top market capitalisation shares in the resources sector. Based on the statistical method that we have chosen for analysing portfolio returns, any factors that do not contribute significantly to portfolio returns should be entirely negated or apportioned a comparatively lower weight.

Composite All Bond Index

The Composite All Bond Index (ALBI) is comprised of the top 20 fixed maturity, fixed-rate bonds, ranked both by liquidity and market capitalisation (JSE, 2018). Given that the ALBI consists of both sovereign and non-sovereign bonds and covers a range of maturities, we believe this index to be a suitable proxy for the South African bond market (JSE, 2018).

LBMA Gold PM

The London Bullion Market Association (LBMA), based in London, is an over-the-counter market which allows members of its association to trade gold. The market also provides a global benchmark for spot gold prices twice a day, an AM price at 10:30 am and a PM price at 3:00 pm. Prices are quoted in US Dollars since auction settlement is in US Dollars (LBMA, 2018).

3.2 RESEARCH METHODOLOGY

This study makes use of a quantitative research method. A quantitative research method starts by finding an area of study, whereby questions are asked or hypotheses are proposed. Subsequently, data is collected and variables are quantified by employing statistical methods, providing information which can be interpreted and used to form an answer to such questions or hypotheses. We can form conclusions by combining the information we have produced with generalised principles (Creswell, 2015). This study begins with an investigation into possible diversification benefits of cryptocurrencies and furthers such research with additional investigations into correlation properties between assets, as well as an analysis of cryptocurrencies in terms of their serial correlations.

3.2.1. INVESTIGATION OF THE DIVERSIFICATION EFFECTS OF MULTIPLE CRYPTOCURRENCIES

We propose questions and describe the methodology in answering them below.

Q1: Does the inclusion of Bitcoin, Ethereum and Litecoin improve the risk-return efficiency of a diversified portfolio?

Q2: Does the addition of alternative cryptocurrencies (Ethereum and Litecoin) lessen the risk-return efficiency of a diversified portfolio which already includes Bitcoin?

This study investigates Q1 and Q2 above by implementing a traditional Markowitz mean-variance framework, but with an adjustment that replaces variance with semivariance. The reasoning for making such an adjustment was based on the fact that cryptocurrency returns are extremely volatile, but such that this volatility has been mostly positive for investors. The research outlined in Section 2.3 of this study

also guides us to use semivariance, focusing our attention on the downside risk associated with holding such volatile assets in a diversified portfolio. Daily returns were translated into percentages for all eight of the assets to be included in the diversified portfolio, as defined in Equation 3.2.1.

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}, \quad (\text{Equation 3.2.1})$$

where

R_t is the percentage return for the asset,

P_t is the price on day t for the asset,

P_{t-1} is the price on day $t - 1$ for the asset.

Daily portfolio returns are calculated by making use of eight random weightings for each of the eight assets in the portfolio, defined in Equation 3.2.2. In order to simulate the investing possibilities of an average South African investor, assets may only be taken on in long positions – no shorting (negative weighting) is possible.

$$R_p = R_1 \times w_1 + R_2 \times w_2 \dots R_8 \times w_8, \quad (\text{Equation 3.2.2})$$

where

R_p is the daily portfolio return,

$R_1, R_2 \dots R_8$ are the daily returns for individual assets,

$w_1, w_2 \dots w_8$ are random percentage weighting for individual assets,

subject to constraints,

$$\sum_{i=1}^n (w_i) = 1,$$

where $0 \leq w \leq 1$.

The mean semivariance for the portfolio is calculated using the return deviation from a benchmark return, as defined by Equation 3.2.3. The benchmark return for semivariance is usually the mean return of the portfolio. However, in this study, we used a more realistic scenario which was to adjust such a benchmark using the

average inflation rate over the period (Vasant et al., 2014). Only deviations from the benchmark return that are negative are included in the calculation of semivariance.

$$V_S = \frac{\sum_{i=1}^n (q_i^2)}{n}, \quad (\text{Equation 3.2.3})$$

where

V_S is the mean semivariance for the portfolio over the period,
 q_i is the i^{th} daily return deviation from the adjusted benchmark return,
subject to constraints:

$$-1 \leq q_i < 0.$$

We then are able to measure the risk-return efficiency of the portfolio as defined in Equation 3.2.4. This measure is akin to the Sortino ratio, a risk-return measure that only considers downside risk. We use the R208 South African government bond as a proxy for the risk-free rate as it matches our investment horizon, as discussed in Section 2.4.

$$E = \frac{\mu_p - R_f}{\sqrt{V_S}}, \quad (\text{Equation 3.2.4})$$

where

E is the portfolio's risk-return efficiency (or Sortino ratio),
 μ_p is the mean return for the portfolio over the period,
 R_f is the risk-free rate.

With an efficiency measure now in place, we can adjust the weightings of the assets in the portfolio to a point where efficiency is maximised (optimal portfolio). Scenarios for random weightings are run 20,000 times, generating an efficient frontier (see Figure A9). The scenario with the greatest risk-return efficiency (maximum Sortino ratio) is the optimal portfolio.

In addition, the test is run multiple times with a weighting of zero forced for one or more assets for each test. This helps us to identify assets that may have been included in the initial test, but are in fact limiting portfolio efficiency.

3.2.2. INVESTIGATION OF THE CORRELATION BETWEEN CRYPTOCURRENCIES AND TO OTHER ASSET CLASSES

We propose questions and describe the methodology in answering them below.

Q3: Are gold and South African bonds and equities correlated to cryptocurrencies?

Q4: Do alternative cryptocurrencies (Ethereum and Litecoin) offer diversification benefits by being uncorrelated with Bitcoin?

In our investigation for Q3 and Q4 above, we compare daily percentage returns over the period 30 July 2015 to 20 December 2017 by employing the Pearson correlation test. The Pearson correlation test, denoted by r (see Equation 3.2.5), measures the strength of linear association between two variables (Hackborn, 2017). Assumptions for the test include: i) a linear relationship between variables; ii) homoscedasticity; and, iii) no outliers. Tests for these assumptions will follow in the explanatory analysis below (Section 4.1).

$$r = \frac{Cov(X,Y)}{\sigma_X\sigma_Y}, \quad (\text{Equation 3.2.5})$$

where

r is the Pearson correlation coefficient,

$Cov(X,Y)$ is the covariance between variables X and Y ,

σ_X is the standard deviation of variable X ,

σ_Y is the standard deviation of variable Y .

Should the data not meet the assumptions of the Pearson r correlation test, the Kendall Tau-b test will be used. The Kendall Tau-b test is a non-parametric measure of the strength and direction of the association between two variables. Assumptions for the Kendall Tau-b test are: i) variables are measured on an ordinal (continuous) scale; and, ii) there is a monotonic relationship between the two variables. The Tau-b test can generate values in a range from -1 (perfect inversion) to +1 (perfect agreement), where zero indicates no association between variables. The Kendall Tau-b coefficient is denoted by r_B (see Equation 3.2.6).

$$r_B = \frac{n_c - n_d}{\sqrt{(n_0 - n_1)(n_0 - n_2)}}, \quad (\text{Equation 3.2.6})$$

where

$$n_0 = \frac{n(n-1)}{2},$$

$$n_1 = \sum_i \frac{t_i(t_i-1)}{2},$$

$$n_2 = \sum_j \frac{u_j(u_j-1)}{2},$$

where,

n_c is the number of concordant pairs,

n_d is the number of discordant pairs,

t_i is the number of tied values in the i^{th} group of ties for the first quantity,

u_j is the number of tied values in the j^{th} group of ties for the first quantity.

3.2.3. INVESTIGATION OF MEAN REVERSION AND TRENDING BEHAVIOUR IN CRYPTOCURRENCIES

We propose questions and describe the methodology in answering them below.

Q5: Do cryptocurrencies exhibit positive serial correlation, indicating trending behaviour?

In our analysis of trending and mean reverting behaviour in cryptocurrencies, we utilise the sample (or empirical) autocorrelation function (ACF). The ACF makes use of the linearity of time series data to measure the correlation between two points, separated by a defined time lag (Davis & Mikosch, 2012). The equation for the ACF is defined in Equation 3.2.7.

$$\rho_k = \frac{\text{cov}(y_t, y_{t-k})}{\sigma_t \sigma_{t-k}}, \quad (\text{Equation 3.2.7})$$

where,

ρ_k is the autocorrelation coefficient with lag k ,

y_t is the time series under investigation,

$\text{cov}(y_t, y_{t-k})$ is the covariance between observation y_t and y_{t-k} (which occurs k lags earlier),

σ is the standard deviation.

The ACF requires a lag input (k) which determines the delay in number of days between the points that are to be correlated. Three lags will be used in this study, a one day lag, a one week lag and a two week lag. By using various lags, we are able to visualise the change in strength of serial correlation between points that are further and further apart. Thus, despite the lag being an input, a variety of different lags is actually an output of this statistical analysis since it provides additional information. The ACF will be run over a short and long-term period. With the short-term covering the last 365 days of data and the long-term covering the entire range of data (30 July 2015 to 20 December 2017).

CHAPTER 4: RESULTS AND ANALYSIS

4.1 EXPLORATORY DATA ANALYSIS

An initial explanatory analysis is conducted to assess the characteristics of the data and to ascertain that the data meets the assumptions of the statistical tests.

KEY STATISTICS

Table 4.1.1: Summary of key statistics for daily returns of portfolio inputs for period 30 July 2015 to 20 December 2017.

	BTC	ETH	LTC	ALBI	Top 40	RESI	FINDI	Gold
# of Observations	875	875	875	875	875	875	875	875
Min Return	-0.17	-0.60	-0.49	-0.04	-0.040	-0.06	-0.04	-0.03
Max Return	0.254	0.467	0.875	0.039	0.036	0.077	0.041	0.043
Range (Max-Min)	0.424	1.067	1.365	0.079	0.076	0.137	0.081	0.073
Average	0.54%	0.90%	0.83%	0.01%	0.015%	0.01%	0.018%	0.02%
Standard Deviation	0.037	0.090	0.087	0.006	0.009	0.016	0.008	0.008
Skewness	0.464	-1.32	3.175	-0.12	-0.135	0.026	-0.17	0.548
Kurtosis	6.728	22.51	33.30	2.49	2.824	3.031	3.314	5.013

SCATTER PLOTS FOR TESTING PEARSON CORRELATION ASSUMPTIONS

The Pearson r correlation test must abide by its assumptions; hence we test such assumptions to ensure its correctness. By graphing one asset against another using a scatter plot, we can determine if the relationship between variables breaks any one of the aforementioned assumptions. Based on the scatter plots generated (see Figure A10-A14), there seems to be no sufficient linear relationship between the variables. In addition, there are many outliers that would skew the results when conducting a Pearson r correlation test. Two assumptions regarding the data have been broken, both linearity and outliers. Based on these explanatory tests, a non-parametric test such as the Kendall Tau-b test would be better suited for the correlation analysis.

4.2 RESULTS AND ANALYSIS

4.2.1. INVESTIGATION OF THE DIVERSIFICATION EFFECTS OF MULTIPLE CRYPTOCURRENCIES

Q1: Does the inclusion of Bitcoin, Ethereum and Litecoin improve the risk-return efficiency of a diversified portfolio?

Table 4.2.1: Optimal weightings for portfolios: A, B, C and D.

Portfolio	Assets							
	BTC	ETH	LTC	ALBI	Top 40	RESI	FINDI	Gold
A	x	x	x	0.3224	0.0755	0.0399	0.3046	0.2576
B	0.4024	0.0696	0.1724	0.1259	0.1721	0.0133	0.0034	0.0409
C	0.4858	0.0794	0.2006	0.0365	x	x	0.1093	0.0884
D	0.6438	0.0851	0.2711	x	x	x	x	x

Table 4.2.2: Summary of daily return, semideviation and efficiency statistics for portfolios: A, B, C and D.

Portfolio	Statistics		
	Return	Semideviation	Efficiency
A	0.057%	0.313%	0.1197
B	0.426%	1.524%	0.2668
C	0.503%	1.796%	0.2692
D	0.648%	2.322%	0.2706

In Table 4.2.1 above, four portfolios with various zeros forced into weightings were generated in order to test Q1 of this study. First, a portfolio without the inclusion of cryptocurrencies (Portfolio A) was optimised using the methodology described in Section 3.2.1. The All Bond Index was weighted highest, with the Financial-Industrial Index and Gold weighted 2nd and 3rd. The Top 40 Index, which includes large market capitalisation equities, was only weighted at 7.55% - this is most likely because the poorly performing Resources Index (with a 3.99% weighting) is closely

associated with large market capitalisation equities. The Resources Index fell 38% from 36107 points at the start of the period, to a low of 22276 points on 20 January 2016, finishing on 20 December 2017 at 35195 points. We compare Portfolio A to the inclusion of all three cryptocurrencies (Portfolio B) using the daily return, semideviation, and efficiency (Sortino ratio) statistics presented in Table 4.2.2 above. The semideviation statistic measures the dispersion of all values that fall below the benchmark value. It is also the square root of semivariance, defined in Section 3.2.1. The inclusion of cryptocurrencies vastly improved the diversified portfolio's risk-return efficiency, an increase of 112.97% from Portfolio A to Portfolio B. The highest weighted asset in the portfolio was Bitcoin at 40.24%, this weighting is far higher than those exhibited in the earlier studies of Carpenter and Eisl et al. It seems the strength of cryptocurrencies over the period more than outweighed the downside risk associated with their excessive volatility. Given the poor performance of the resources sector, Portfolio C demonstrates how the exclusion of the resource sector (by zeroing the weights of the Top 40 Index and the Resources Index) further improved the risk-return efficiency over Portfolio B.

Portfolio D demonstrates a cryptocurrency only portfolio, where all traditional assets are allocated a weighting of zero. Despite the 52.4% increase in semideviation from Portfolio A to Portfolio D, this was the most efficient optimal portfolio that our statistical model was able to generate. The outperformance of the cryptocurrency only portfolio is most likely attributed to the fact that the period of data collection in this study ended at point close to all time high prices. Incorporating more recent data may very well have altered these results, but due to the time constraints of completing this study this could not be realised. Regardless, the focus of this study is aimed at using cryptocurrencies as a diversifier for a portfolio that comprises of traditional assets rather than only cryptocurrencies. An attribute that is noticeable in all portfolios that include cryptocurrencies is the dominance of Bitcoin over Ethereum and Litecoin, this is investigated further in Q2 and Q4 using portfolio optimisation and correlations respectively.

Q2: Does the addition of alternative cryptocurrencies (Ethereum and Litecoin) lessen the risk-return efficiency of a diversified portfolio which already includes Bitcoin.

As mentioned previously, the majority of research surrounding the diversification effects of cryptocurrency has only been investigated with consideration to Bitcoin. In this section, we seek to identify whether the inclusion of Ethereum and/or Litecoin is beneficial on a risk-return basis. The all-inclusive cryptocurrency portfolio discussed above in Q1, Portfolio B, is compared to a variety of portfolios with and without Ethereum and Litecoin.

Table 4.2.3: Optimal weightings for portfolios: B, E, F, G and H.

	Assets							
Portfolio	BTC	ETH	LTC	ALBI	Top 40	RESI	FINDI	Gold
B	0.4024	0.0696	0.1724	0.1259	0.1721	0.0133	0.0034	0.0409
E	0.5683	x	x	0.0371	0.0115	0.0032	0.2429	0.1370
F	0.4451	0.1252	x	0.1411	0.0086	0.0803	0.0937	0.1060
G	0.4310	x	0.1848	0.0643	0.0314	0.0112	0.1802	0.0971
H	x	0.2165	0.4868	0.0497	0.0387	0.0840	0.0215	0.1028

Table 4.2.4: Summary of daily return, semideviation and efficiency statistics for portfolios: B, E, F, G and H.

	Statistics		
Portfolio	Return	Semideviation	Efficiency
B	0.426%	1.524%	0.2668
E	0.314%	1.461%	0.2016
F	0.358%	1.539%	0.2200
G	0.391%	1.442%	0.2576
H	0.561%	2.906%	0.1861

Portfolio E excludes both Ethereum and Litecoin (see Table 4.2.3). Comparing this to Portfolio B, we can see that the exclusion of these two alternative cryptocurrencies has resulted in a decrease in the risk-return efficiency (see Table 4.2.4). Note that the decrease in efficiency was due to a decrease in the daily return

of the portfolio with a proportionately smaller decrease in risk (semideviation). This evidence allows us to answer Q2, by suggesting that combining alternative cryptocurrencies with Bitcoin in a diversified portfolio is beneficial to an investor on a risk-return basis. The remainder of the portfolios (F, G and H) in Table 4.2.4 illustrate the relative performance of Ethereum and Litecoin alone, as well as the two together. The exclusion of Litecoin in Portfolio F demonstrates that Ethereum does improve portfolio efficiency over a Bitcoin-only portfolio (Portfolio E). Comparing this to Portfolio G, which includes Litecoin instead of Ethereum, we can assume that the diversification effects of Litecoin are superior to that of Ethereum based on the higher risk-return efficiency. The weaker diversification effects of Ethereum can be attributed to the cryptocurrency's highly negatively skewed returns (see Table 4.1.1). The focus on downside risk through the use of semivariance in this study would have heavily penalised Ethereum since negatively skewed returns indicate a greater chance of experiencing extreme negative outcomes (Greenwichai, 2017). For interest's sake, Portfolio H excludes Bitcoin. This portfolio generated a relatively low efficiency ratio and the highest semideviation in this study, illustrating the risk associated with holding only the Ethereum and Litecoin as cryptocurrencies. This supports the evidence in explanatory analysis (see Table 4.2.1) which shows that alternative cryptocurrencies (Ethereum and Litecoin) are far riskier than Bitcoin based on their standard deviation and kurtosis values.

4.2.2. INVESTIGATION OF THE CORRELATION BETWEEN CRYPTOCURRENCIES AND TO OTHER ASSET CLASSES

Based on the explanatory analysis in Section 4.1, it was determined that the Pearson r correlation test was not deemed suitable for the data over the period. Thus, we resort to the Kendall Tau-b correlation to test the relationship between assets in the diversified portfolio.

Table 4.2.5: Summary of Kendall Tau-b correlations between assets.

	BTC	ETH	LTC	ALBI	Top 40	RESI	FINDI	Gold
BTC	1	.718	.753	-.121	.316	.313	.287	.353
ETH	.718	1	.693	-.095	.395	.221	.383	.361
LTC	.753	.693	1	-.096	.412	.290	.383	.365
ALBI	-.121	-.095	-.096	1	-0.011	.188	-.094	0.036
Top 40	.316	.395	.412	-0.011	1	.363	.800	.269
RESI	.213	.221	.290	.188	.363	1	.179	.121
FINDI	.287	.383	.383	-.094	.800	.179	1	.216
Gold	.353	.478	.365	0.036	.269	.121	.216	1

Q3: Are gold and South African bonds and equities correlated to cryptocurrencies?

Based on Table 4.2.5 above, all three cryptocurrencies have a low to very low negative correlation to either gold, or South African equities or bonds. Such low correlations are indicative of the differentiated factors of supply and demand that drive the cryptocurrency market, similar to that of gold as discussed in Section 2.1. Interesting to note that the three cryptocurrencies fell very close to each other in their correlations to traditional assets. The lowest correlation was to the all bond index, with values being very low negative – this would suggest that cryptocurrencies would be an outstanding diversifier for a heavily bond weighted portfolio. The correlation of cryptocurrencies to equities is low positive over the period, which suggests that some form of relationship exists between these variables. However, based on fundamental factors this positive relationship is likely not compelling. The South African market plays an insignificant part in the broader cryptocurrency market. Fiat currencies like the USD, Euro, Japanese Yen, Chinese Yuan, and South Korean Won make up close to all of the market (see Figure A15 and Figure A16). Regardless of its significance, the lack of a relationship between cryptocurrencies and South African equities provides more than adequate diversification benefits.

The low positive correlation of the three cryptocurrencies to gold is very favourable since it provides an alternative diversifier for investors. This does not agree with moderately negative correlation found by Burniske and White (2016). Gold is often used as a diversifier since it provides a safe haven from equities and bonds during economic crises given its low correlation (Tandon, 2013). Such a characteristic in cryptocurrencies would further legitimise their use case for a place in a diversified portfolio, albeit that they are far more volatile.

Q4: Do alternative cryptocurrencies (Ethereum and Litecoin) offer diversification benefits by being uncorrelated with Bitcoin?

Table 4.2.5 shows that the correlation between all three cryptocurrencies is positive and high. This is to be expected as they all participate in a market that is relatively new and are all affected by fundamental factors, news and rumours that relate to the cryptocurrency space as a whole. Ethereum yielded a slightly lower correlation to Bitcoin than Litecoin did, this is likely indicative of the technical differences of Ethereum to Bitcoin and Litecoin. It is important to note that although correlations are critical in constructing a diversified portfolio, they should not be used by themselves. Correlations are subject to statistical error and can vary depending on different circumstances (Vanguard, 2012). Although correlations were high, the two alternative cryptocurrencies (Ethereum and Litecoin) in combination with Bitcoin, offered significant risk-return benefits to the diversified portfolio. The correlations depicted in Table 4.2.5 support our findings in Section 4.2.1 with regards to portfolio risk-return efficiency, confirming that the addition of alternative cryptocurrencies to Bitcoin provides efficiency benefits through increased returns and a relatively lower increase in risk. The correlation between Ethereum and Litecoin is moderately positive, which would imply that the two together would result in reasonable diversification benefits. However, as seen by Portfolio H in Table 4.2.4, this combination resulted in a relatively low risk-return efficiency as a result of the very high semideviation. To conclude, despite the

relatively high correlations between the cryptocurrencies, a combination of all three provides the best performance.

Q5: Do cryptocurrencies exhibit positive serial correlation, indicating trending behaviour?

Table 4.2.6: Serial correlation coefficients of cryptocurrencies with various lags over period 30 July 2015 - 20 December 2017.

	BTC	ETH	LTC
1 Day Lag	0.979	0.983	0.945
1 Week Lag	0.857	0.903	0.693
2 Week Lag	0.707	0.826	0.499

Table 4.2.7: Serial correlation coefficients of cryptocurrencies with various lags over last 365 days of data (21 December 2016 – 20 December 2017).

	BTC	ETH	LTC
1 Day Lag	0.974	0.975	0.934
1 Week Lag	0.827	0.857	0.628
2 Week Lag	0.643	0.742	0.391

Based on the serial correlation coefficient outputs in Table 4.2.6 and Table 4.2.7, there is no evidence of mean reversion for any of the three cryptocurrencies. All depict strong trending behaviour over the short and long term and over a variety of lag periods, indicating dependence and evidence of predictable patterns in observable historical returns. This is corroborated by the fact that the cryptocurrency market is traded by a large portion of retail investors, who are more likely to overreact in accordance to behavioural heuristics compared to experienced institutional investors (Tversky & Kahneman, 1974). Of course, this is beneficial to a diversified portfolio when returns are positive and the market is bullish, but can be devastating when the market is in a downturn. Due to the lack of mean reversion, strong movements as a result of investor overreaction are likely to continue for some time, with any correction of an overreaction being negligible in relation to the overall trending behaviour.

If cryptocurrencies continue to exhibit such high levels of positive serial correlation, they are likely to maintain their highly volatile nature going forward (Stewart, Piros & Heisler, 2011). As mentioned previously, the period under analysis has ended on a strong uptrend. If such an uptrend had to reverse into a downtrend, it is likely to result in a lengthy period of negative returns given the positive strength of serial correlations for all three cryptocurrencies. The inclusion of such an event would greatly impact the results of this study with regards to the diversification benefits of cryptocurrencies.

CHAPTER 5: CONCLUSION

5.1 REVIEW OF THE STUDY

The focus of this study was to investigate the possible benefits of multiple cryptocurrencies in a diversified portfolio over the period 30 July 2015 to 20 December 2017. The motivation of this study being the need for further information regarding the relationship of cryptocurrencies to each other and to traditional assets in the South African market. We applied a variety of statistical methods to our data, including: i) mean-semivariance optimisation; ii) Kendall Tau-b correlations; and, iii) autocorrelation function.

Previous research reviewed in this study had discovered evidence of the benefits of Bitcoin as a portfolio diversifier. Thus, our focus was on alternative cryptocurrencies, namely Ethereum and Litecoin, and whether they might provide further benefits. Based on the results of the mean-semivariance optimisation, the addition of both, or either, of these alternative cryptocurrencies to a diversified portfolio, that already included Bitcoin, improved the risk-return efficiency. Ethereum and Litecoin exhibited higher levels of semideviation than Bitcoin, but were able to compensate with proportionately higher returns.

Based on portfolio weights and its relatively low risk-return efficiency, Ethereum was a weaker diversifier than Litecoin, which is likely as a result of its higher standard deviation and negatively skewed returns. Ethereum was slightly less correlated to Bitcoin than Litecoin, which can be attributed to its technological differences. By providing a platform for technological development in addition to acting as a medium of exchange, Ethereum attracts news, be it good or bad, that has little to no effect on either Bitcoin or Litecoin. Hence, with the diversification benefits of technological differentiation comes a host exogenous influences.

Our analysis of serial correlations brought about no evidence of mean reversion in either Bitcoin, Ethereum or Litecoin. All three cryptocurrencies exhibited strong trending behaviour over the long and short term. We warn that while the presence of such strong positive serial correlation may be beneficial during an uptrend, the associated danger of such high volatility could be extremely detrimental if a downtrend ensues.

5.2 LIMITATIONS OF THE STUDY

A limitation of this study is that in order to maximise our data collection period, we began at the inception of Ethereum trading. Including returns so early on brings with it the volatility as the market attempts to determine an intrinsic value.

A further limitation is that the strength of trending behaviour makes it difficult to find a neutral viewpoint to collect data which is an accurate representative of the statistical characteristics of cryptocurrencies. To summarise, the technology still has a lot of hurdles, including regulatory and technological, before it finally finds mainstream adoption and a permanent place in the world economy where its value can be more accurately aligned with its underlying utility.

5.3 FURTHER INVESTIGATIONS

Future research into the diversification benefits of cryptocurrencies may want to investigate other cryptocurrencies, given that there are hundreds in circulation, each with their own unique properties. It may be possible that there are better alternatives than Bitcoin, Ethereum or Litecoin. Another valuable investigation would be into the use of a portfolio that may hold long and short positions that may benefit from the strong trending behaviour observed in cryptocurrencies. Furthermore, the inclusion of more data will also be beneficial to this area of research, although this is simply a matter of time.

References

- Andersen, T., Bollerslev, T., Diebold, F. & Vega, C. 2007. Real-Time Price Discovery in Global Stock, Bond and Foreign Exchange Markets. *SSRN Electronic Journal*. DOI: 10.2139/ssrn.1150085.
- Artigas, J. 2010. Rediscovering Gold As An Asset Class. *Journal of Indexes*. 13(6):26-32. [2018, February 18].
- Baur, D., Hong, K. & Lee, A. 2014. Bitcoin: Currency or Investment?. *SSRN*. Available: <http://ssrn.com/abstract=2561183> [2017, November 06].
- Blockgeeks. 2017. *What is Cryptocurrency: Everything You Need To Know*. New York: Blockgeeks. Available: <https://blockgeeks.com/guides/what-is-cryptocurrency/> [2017, July 19].
- Bloomberg (2017) Bloomberg Terminal. Available: Subscription Service. [2017, 21 December]
- Blumenthal, S. 2014. *Understanding Correlation & Diversification*. Philadelphia: CMG. [2018, February 18].
- Burniske, C. & White, A. 2016. *Bitcoin: Ringing the bell for a new asset class*. [2017, July 19].
- Carpenter, A. 2016. Portfolio diversification with Bitcoin. James Madison University. [2017, July 20]
- Coindesk (2017) Coindesk website. Available: <https://www.coindesk.com/price/>. [2017, 21 December]
- CoinGecko. 2018. *Litecoin Price Chart (LTC/USD) | CoinGecko*. Available: https://www.coingecko.com/en/price_charts/litecoin/usd [2017, December 21].
- Creswell, J. 2015. *A concise introduction to mixed methods research*. 1st ed. California: SAGE. [2017, 20 December]
- Davis, R. & Mikosch, T. 2018. The sample autocorrelations of financial time series models. Colorado State University. [2017, 4 November]
- De Bondt, W. & Thaler, R. 1985. Does the Stock Market Overreact?. *The Journal of Finance*. 40(3):793. DOI: 10.2307/2327804.
- Digiconomist. 2018. *Bitcoin Energy Consumption Index - Digiconomist*. Available: <https://digiconomist.net/bitcoin-energy-consumption> [2017, November 29].
- Dyhrberg, A. 2016. Hedging capabilities of bitcoin. Is it the virtual gold?. *Finance Research Letters*. 16:139-144. DOI: 10.1016/j.frl.2015.10.025.

- Eisl, A., Gasser, S. & Weinmayer, K. 2015. Caveat Emptor: Does Bitcoin Improve Portfolio Diversification?. *SSRN Electronic Journal*. DOI: 10.2139/ssrn.2408997.
- Estrada, J. 2008. Mean-Semivariance Optimization: A Heuristic Approach. *SSRN Electronic Journal*. DOI: 10.2139/ssrn.1028206.
- Evans, J. & Archer, S. 1968. Diversification and the Reduction of Dispersion: An Empirical Analysis. *The Journal of Finance*. 23(5):761. DOI: 10.2307/2325905.
- Feldman, K. (1992). Portfolio Selection, Efficient Diversification of Investments. By Harry M. Markowitz (Basil Blackwell, 1991). *Journal of the Institute of Actuaries*. 119(01):165-166. DOI: 10.1017/s0020268100019831.
- Francis, J. 1986. *investments: Analysis & Management*. 4th ed. New York: McGraw-Hill Book Company.
- Goldstein, M. & Mussa, M. 1993. The Integration of World Capital Markets. *IMF Working Papers*. 93(95). DOI: 10.5089/9781451950397.001.
- Greenwichai. 2017. *Measure of Risk*. Available: <http://www.greenwichai.com/index.php/hf-essentials/measure-of-risk> [2017, December 14].
- Hackborn, R. 2017. *Does Pearson correlation require normality? - Geek went Freak!*. Available: http://geekwentfreak.com/posts/stats/pearson_correlation_normality/ [2017, December 27].
- JSE. 2018. *Debt Market*. Available: <https://www.jse.co.za/trade/debt-market> [2018, January 11].
- Laird-Smith, J., Meyer, K. & Rajaratnam, K. (2016). A study of total beta specification through symmetric regression: the case of the Johannesburg Stock Exchange. *Environment Systems and Decisions*. 36(2):114-125. DOI: 10.1007/s10669-016-9596-3.
- LBMA. 2018. *About Us*. Available: <http://www.lbma.org.uk/about-us> [2017, December 26].
- Markowitz, H. 1952. Portfolio Selection. *The Journal of Finance*. 7(1):77. DOI: 10.2307/2975974.
- McGregor iNet (2017) iNet BFA. Available: Subscription Service. [2017, 21 December]
- Morris, D. 2017. *Why Bitcoin Just Dropped 30%*. Available: <http://fortune.com/2017/05/27/bitcoin-price-drop/> [2017, September 21].
- Old Mutual. 2013. *Old Mutual Unit Trusts - Retirement Annuity Fund*. Cape Town: Old Mutual. Available: <https://www.oldmutual.co.za/docs/default->

- source/unit-trust/products/group-solution/retirementannuityfundsalesaid.pdf?sfvrsn=2 [2017, August 10].
- Oloko, T. 2017. Portfolio diversification between developed and developing stock markets: The case of US and UK investors in Nigeria. *Research in International Business and Finance*. DOI: 10.1016/j.ribaf.2017.07.153.
- Osterrieder, J. & Lorenz, J. 2017. A Statistical Risk Assessment of Bitcoin and its Extreme Tail Behaviour. *Annals of Financial Economics*. 12(01). DOI: 10.1142/s2010495217500038.
- Osterrieder, J., Strika, M. & Lorenz, J. 2016. Bitcoin and Cryptocurrencies—Not for the Faint-Hearted. *International Finance and Banking*. 4(1):56. DOI:10.5296/ifb.v4i1.10451.
- Quandl (2017) Quandl database. Available: https://www.quandl.com/data/BNC2/GWA_LTC-BraveNewCoin-Daily-Global-Price-Index-for-Litecoin/. [2017, 21 December]
- SA Shares. 2018. *JSE Top 40 Companies Index, Price Chart - View all listed TOP40 firms*. Available: <https://www.sashares.co.za/jse-top-40/> [2018, 11 January].
- SARB. 2014. *Position Paper on Virtual Currencies*. Cape Town: South African Reserve Bank. Available: [https://www.resbank.co.za/RegulationAndSupervision/NationalPaymentSystem\(NPS\)/Legal/Documents/Position%20Paper/Virtual%20Currencies%20Position%20Paper%20%20Final_02of2014.pdf](https://www.resbank.co.za/RegulationAndSupervision/NationalPaymentSystem(NPS)/Legal/Documents/Position%20Paper/Virtual%20Currencies%20Position%20Paper%20%20Final_02of2014.pdf) [2017, November 20].
- Sharpe, W. 1970. *Portfolio theory and capital markets*. 1st ed. New York: McGraw-Hill.
- Shen, D. 2015. Order Imbalance Based Strategy in High Frequency Trading. Masters. University of Oxford. [2017, 20 December]
- Sherman, M. & Stein, R. 2016. Systemic Risk and Alternative Investments: A Summary of Selections from the State of the Art. *The Journal of Alternative Investments*. 18(4):6-12. DOI: 10.3905/jai.2016.18.4.006.
- Solnik, B. 1974. Why Not Diversify Internationally Rather Than Domestically?. *Financial Analysts Journal*. 30(4):48-54. DOI: 10.2469/faj.v30.n4.48.
- Statistics South Africa (2017) Stats SA publication. Available: http://www.statssa.gov.za/?page_id=1854&PPN=P0141&SCH=7103 [2017, 4 November]
- Statman, M. 1987. How Many Stocks Make a Diversified Portfolio?. *The Journal of Financial and Quantitative Analysis*. 22(3):353. DOI: 10.2307/2330969.

- Statman, M. & Scheid, J. 2007. Correlation, Return Gaps and the Benefits of Diversification. *SSRN Electronic Journal*. DOI: 10.2139/ssrn.995844.
- Stevenson, R. & Jennings, E. 1988. *Fundamentals of investments*. St. Paul: West Publishing. [2017, 8 November]
- Stewart, S., Piros, C. & Heisler, J. 2011. *Running Money: Professional Portfolio Management*. 1st ed. London: McGraw-Hill Education - Europe.
- Strydom, B. & Charteris, A. 2009. A Theoretical And Empirical Analysis Of The Suitability Of South African Risk-Free Rate Proxies. *University of KZN: Working Papers in Finance*. 21-22. [2017, December 23].
- Tandon, A. 2013. Gold: Safe Haven. *National Council of Applied Economic Research*. [2018, February 04].
- Thorley, S. 1995. The Time-Diversification Controversy. *Financial Analysts Journal*. 51(3):68-76. DOI: 10.2469/faj.v51.n3.1907.
- Tversky, A. & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*. 185(4157):1124-1131. DOI: 10.1126/science.185.4157.1124.
- Vanguard. 2008. *Time Diversification and Horizon-Based Asset Allocations*. Vanguard. [2018 , February 03].
- Vanguard. 2012. *Dynamic correlations: The implications for portfolio construction*. Vanguard. [2018, February 04].
- van Rensburg, P. & Robertson, M. (2003). Explaining the cross-section of returns in South Africa: Attributes or factor loadings?. *Journal of Asset Management*. 4(5):334-347. DOI: 10.1057/palgrave.jam.2240114.
- Vasant, J., Irgolic, L., Kruger, R. & Rajaratnam, K. 2014. A Comparison Of Mean-Variance And Mean-Semivariance Optimisation On The JSE. *Journal of Applied Business Research (JABR)*. 30(6):1587.

APPENDIX

Figure A1: Bitcoin transactions per day. Source: blockchain.info



Figure A2: Risk-return of stocks and bonds. Source: Morningstar Direct

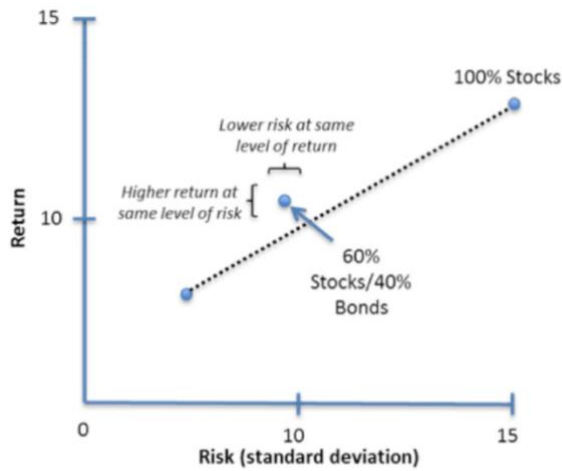


Figure A3: Correlation of gold to US equities. Source: London Bullion Market Association, Standard & Poor's, WGC.

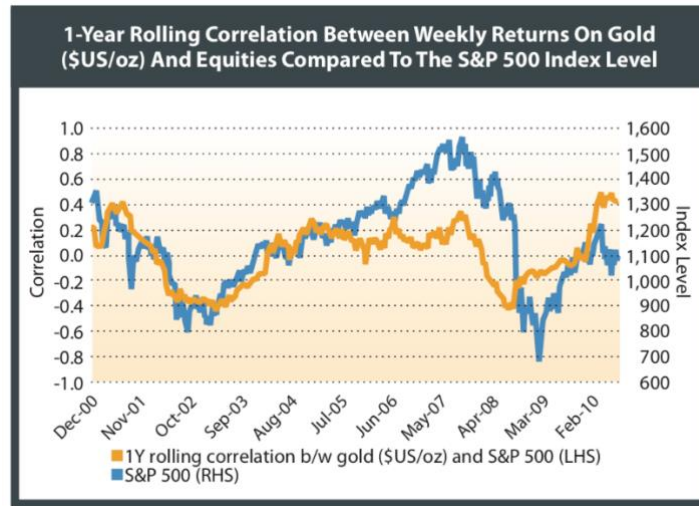


Figure A4: The percentage of an efficient max Sharpe portfolio allocated to BTC as a function of gamma. Source: Carpenter

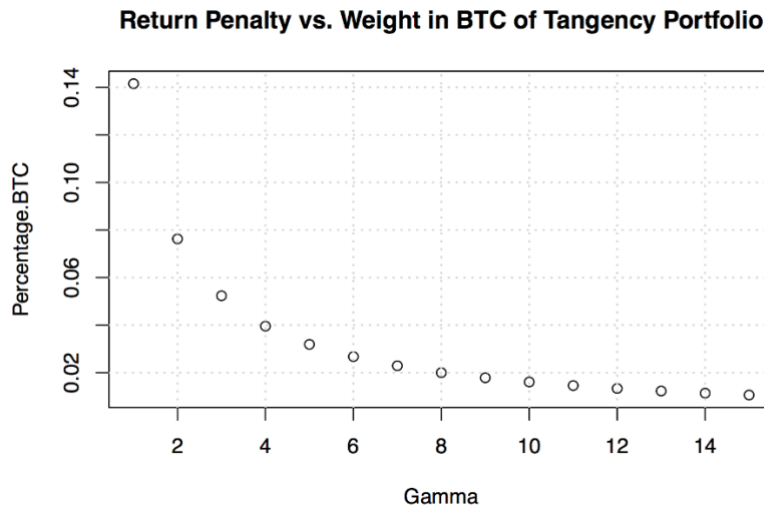


Figure A5: Correlation of Bitcoin to US equities, US bonds, US real estate and oil. Source: Burniske & White



Figure A6: Sharpe ratio of various asset classes. Source: Burniske & White

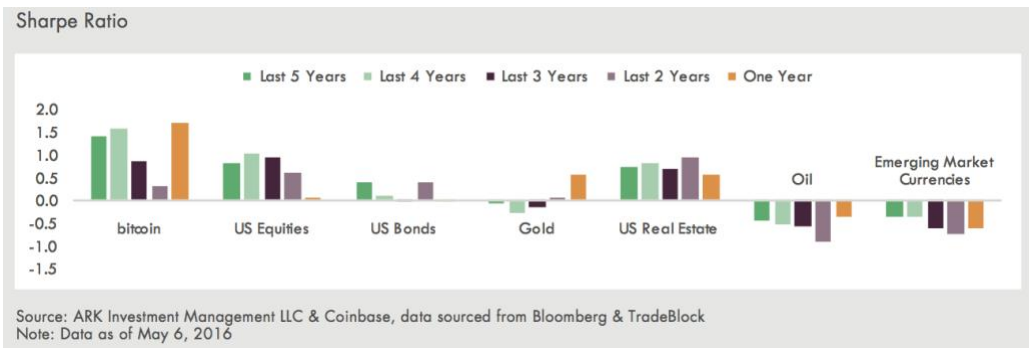


Figure A7: Correlation of Bitcoin to gold. Source: Burniske & White

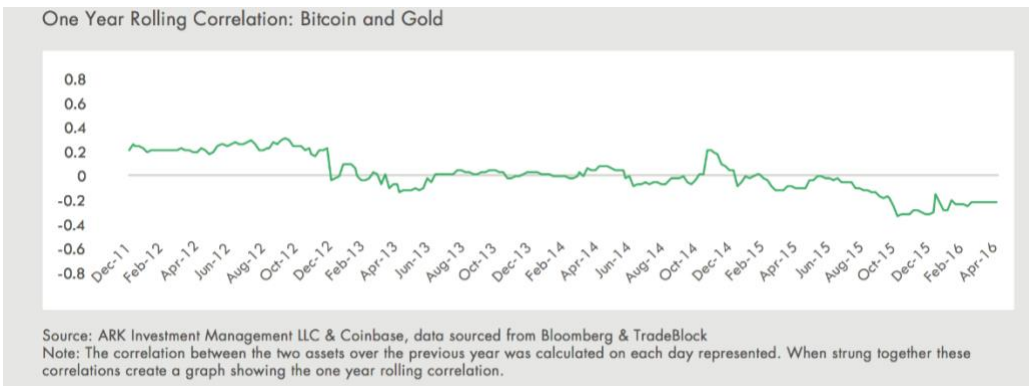


Table A1: Portfolio statistics for various weights of Bitcoin. Source: Eisl et al.

Portfolio Optimization Framework	Mean Monthly BTC Weight	Mean Monthly Return	Mean Monthly CVaR	Mean Monthly Risk-Return Ratio
Equally-Weighted BTC	7.69%	1.93%	1.01%	3.75%
Equally-Weighted No BTC	-	0.38%	0.64%	2.32%
Long-Only BTC	2.09%	0.43%	0.60%	1.04%
Long-Only No BTC	-	0.28%	0.51%	0.60%
Unconstrained BTC	6.65%	5.21%	1.94%	5.88%
Unconstrained No BTC	-	0.43%	0.34%	1.81%
-100%/+100% BTC	1.65%	1.03%	0.53%	2.77%
-100%/+100% No BTC	-	0.43%	0.34%	1.81%

Figure A8: Correlations between cryptocurrency return using a 90-day rolling average. Source: Osterrider et al.

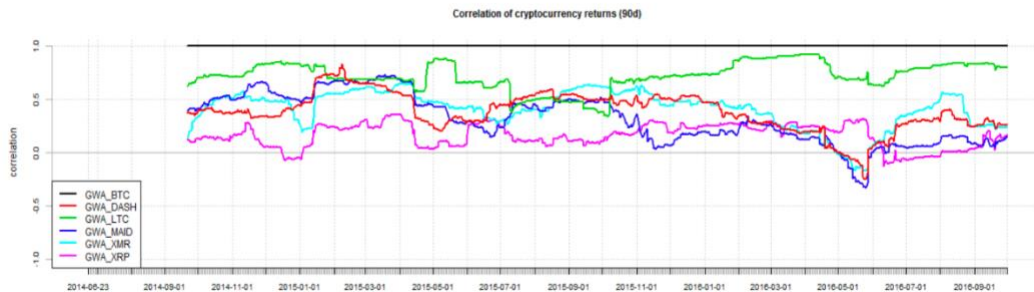


Figure A9: Efficient frontier output.

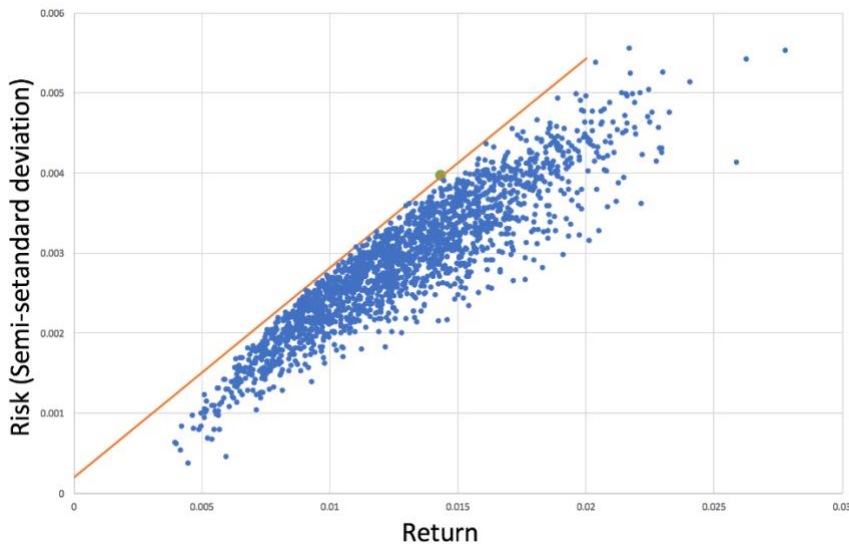


Figure A10: Scatter plot of BTC vs Top 40 (2015-2017)

Scatter plot of BTC vs Top 40 - 2015-2017

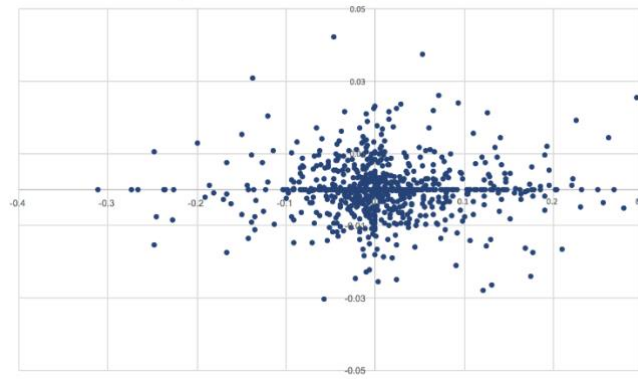


Figure A11: Scatter plot of BTC vs Gold (2015-2017)

Scatter plot of BTC vs Gold - 2015-2017

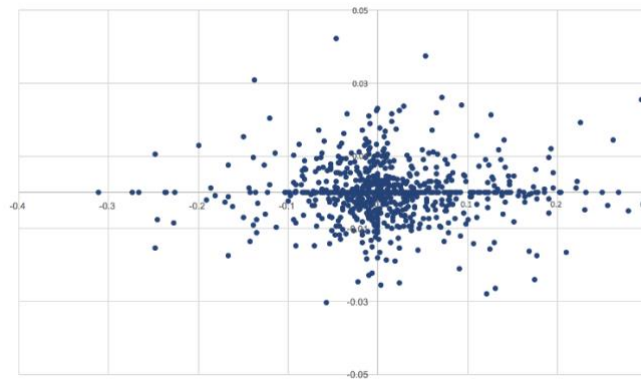


Figure A12: Scatter plot of ETH vs LTC (2015-2017)

Scatter plot of ETH vs LTC - 2015-2017

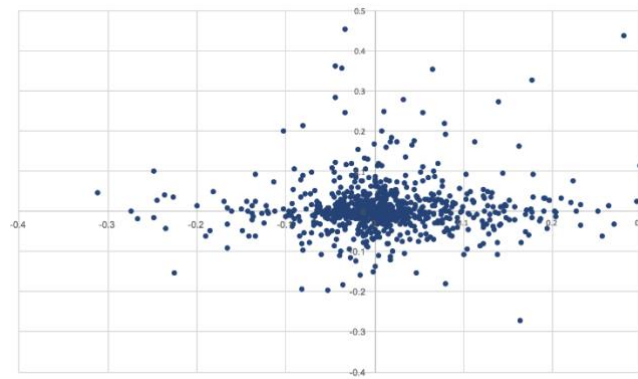


Figure A13: Scatter plot of BTC vs LTC (2015-2017)

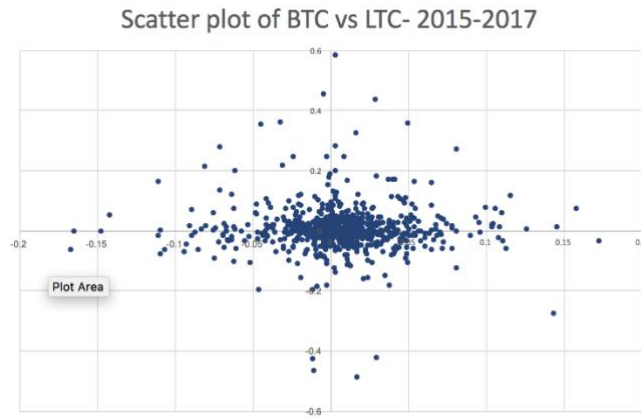


Figure A14: Scatter plot of BTC vs ETH (2015-2017)

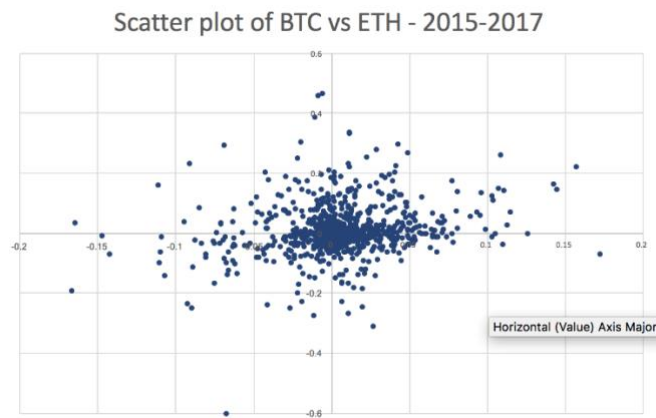


Figure A15: Bitcoin exchange trading volume by fiat currency for Q2 2017.
Source: Cryptocompare.com

**Bitcoin Exchange Trading Volume
Allocation Across Currencies Traded**

Q2 2017 to Date
(April 1, 2017 - June 10, 2017)

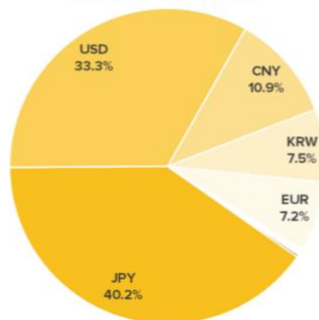


Figure A16: Bitcoin exchange trading volume by fiat currency over period 2012-2017. Source: Bitcoin.com

