Bitcoin analysis from an investor’s perspective

Insight into market relations and diversification possibilities

Master Thesis Financial Economics

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Abstract

This paper studies how the increased maturity of Bitcoin as an asset class influences its characteristics from an investor’s point of view. The first aim was to determine whether there is a relation between Bitcoin trade volume in 8 different currencies, change in equity trade volume and price, and three separate proxies for market uncertainty via a regression. Secondly, a regression is set up to quantify the relationship between Bitcoin prices and macroeconomic variables and lastly an efficient frontier with a wide variety of assets classes in constructed to determine what Bitcoin risk-return characteristics add to a diversified portfolio. The results show different findings to past research, with market uncertainty having a significant effect on Bitcoin trade volume for certain currencies. Furthermore, the results with regards to the macroeconomic variables show that the S&P500 price has a positive effect on Bitcoin prices. Lastly, the efficient frontier shows that there is no place for Bitcoin within the global minimum-variance portfolio, but there are benefits to adding Bitcoin to an investment portfolio. Taken together, these results suggest that the increase in maturity of Bitcoin as an asset class, leads to higher levels of predictability, making it an an asset class that could develop into a serious alternative for all investors.

Keywords: Bitcoin, Investing, Market Uncertainty, Macroeconomics, Efficient Frontier

TABLE OF CONTENT

1. INTRODUCTION

On the third of January, 2009, an anonymous group of programmers under the pseudonym of Satoshi Nakamoto launched the online communication protocol called Bitcoin, which included means for online payments by the means of a peer-to-peer electronic currency system. Internet usage is continuously expanding and virtual communities are thriving, with over 33% of the global population having internet access (ECB, 2012). With this high interdependence between daily life and the internet, the currency has received increasing attention worldwide (ECB, 2012). The currency is completely virtual and decentralized, meaning it is not issued by any government, bank or organization (Ron & Shamir, 2013). Valuation of Bitcoins depends strictly on supply and demand and is currently traded against a wide variety of hard currencies. Due to the lack of regulation and intrinsic value, Bitcoins show higher levels of volatility compared to those hard currencies, and is more susceptible to speculation and bubbles (Grinberg, 2011). However, the usage of Bitcoin as a currency has increased significantly since its introduction, with it becoming a standard means of payment for online providers of goods. Bitcoin being divisible to eight decimal places enables the use of Bitcoin in all kinds of transactions. In early 2017, a total of around 16 million bitcoins are in circulation, at a total value of 39 billion USD (Blockchain.info, 2017).

The benefits of Bitcoin over regular currencies are as follows; due to Bitcoin being decentralized, there is no risk of it being seized by government officials, and transactions are tax free. Furthermore, the anonymity allows for great levels of privacy, since no transactions can be traced back to the participants in the trade and thus there are no third parties with access to the personal financial data. Additionally, Bitcoin transaction require physical access to one's personal computer, making them highly theft proof. Lastly, the transactions have the benefit of no to negligible transaction costs and there is no risk of charge-backs meaning that once a transaction is completed, they can not be reversed (Onies, Daniele & Olayinka, 2011). Other online payment platforms such as PayPal do allow these charge-backs, which have proven to be highly sensitive to fraud (Chuq & Wareham, 2004). From an investment perspective, the ability to trade Bitcoins at all time increases the possibilities. There are still risks involved with Bitcoin, since the Bitcoin access keys are stored in a wallet file on a computer, there is the risk of hard drives crashing or a virus corrupting the data, either by a targeting hacker or by accident, which would essentially disable the stored Bitcoin without the possibility of recovery. Besides the technical risks, there could be future regulatory factors put in place which would limit the usability of Bitcoin, similar to the realization of a ban on Bitcoin exchanges in China in 2014 (Hill, 2014). The increase in interest in Bitcoin also caught the attention of the academic communities. Initially, the focus was mostly from a computer science perspective, understanding the mining process, the anonymity and privacy and the inner workings of a electronic peer-to-peer cash system. As time progressed, the emphasis within Bitcoin research shifted towards legal issues, such as the safety of the system, the use of Bitcoin during illegal transactions such as during weapon purchases, and fraud cases related to the laundering of money and the evasion of income tax payments (Brière, Oosterlinck & Szafarz, 2015). The academic focus from an economical perspective has been straggling, however nowadays it is receiving increasing attention. With e-currencies, and more specifically Bitcoin gaining viability as an investment or speculative vehicle, assessments needed to be made into how Bitcoin as an investment vehicle performs. Traditional studies into the volatility levels and risk-returns relationships have been performed (Baek & Elbeck, 2015). Later on, the prospect of incorporating Bitcoin into investment portfolios had been studied, determining the diversification opportunities which arose when including Bitcoin into the investment horizon (Brière, Oosterlinck & Szafarz, 2015). These studies however only provide a small sample of empirical research into the possibilities and inner workings of Bitcoins as an investment vehicle and its relation to other investment assets. This thesis aims at expanding the knowledge of Bitcoin from an investor's perspective, aiming to providing an insight into the relationship between Bitcoin and equity indices and market uncertainty, now that the market shows more maturity (Smith & Rosevear, 2017). More specifically, the increased maturity could have changed the relationship between both the Bitcoin price and the trade volume, and certain macroeconomic effects which are known to have an effect on traditional asset classes (Baek & Elbeck, 2015). Additionally, this thesis aims at updating and expanding on the work by Brière, Oosterlinck and Szafarz from 2015 to study the risk-return benefits within the framework of the modern portfolio theory. Since the aforementioned study into the inclusion of Bitcoin into the investment horizon, was based on data from 2010-2013. This thesis will focus on more current data, the 2010-2013 data showed higher levels of volatility compared to the present day levels which show a higher level of stability (Smith & Rosevear, 2017). The main research question to be answered within this research is:

How has the increased maturity of Bitcoin as an asset classed changed the characteristics of it as an investment vehicle?

To contribute to the answering of the main research question the following hypothesis have been formulated and will be researched:

1. H_0: Higher levels of market uncertainty lead to higher Bitcoin trade volumes.
2. H_0: External macroeconomic effects impact the changes in Bitcoin prices.
3. H_0: The lower, present-day levels of volatility allow for the inclusions of Bitcoin in the global minimal-variance portfolio.

This thesis is written to help increase the knowledge on the behavior and influence of Bitcoin within a changing financial environment. Within the following chapter a theoretical framework will be established, where a literature study will expand on the subject and reasoning behind this study and important concepts will be defined. After which the methodological approach for the empirical research will be discussed, with an explanation of the used data and how it was obtained. This will be followed by the empirical results, a discussion of the aforementioned results and a conclusion in which the research question and the accompanying hypothesis will be answered. The limitations of the research will also be mentioned. Lastly, recommendations for future research into the subject will be suggested.

2. THEORETICAL FRAMEWORK

This chapter provides a cohesive overview of the subject. In order to achieve this, an extensive literature study into the academics regarding Bitcoin has been conducted. Additionally, this chapter will elaborate on the theoretical basis on which the empirical research is based, looking at relationships between asset classes' trade volume, measurement levels of market uncertainty and an overview of modern portfolio theory and risk-return optimization.

2.1 GENERAL

On average, the main goal of investing is to achieve a maximum risk-adjusted return, which can be achieved by the optimization of a portfolio by diversification between the included asset classes (Markowitz, 1991). As previously stated, Bitcoin was not seen as a viable investment within academics up until very recently. Bitcoin was strictly seen as a speculative vehicle which was too prone to bubbles (Baek & Elbeck, 2015). However, before considering Bitcoin as an investment vehicle, questions about the fundamentals behind Bitcoin needed to be answered beforehand. In 2013, David Yermack performed an economic appraisal of Bitcoin, during which was stated that Bitcoin did not satisfy the traditional criteria for a currency. The three traditional attributes for currency are: That it functions as a medium of exchange, a unit of account and that it stores value (Yermack, 2013). The author argued that at the time Bitcoin met the first criterion, albeit whilst noting that on a global scale the use of bitcoin was still miniscule compared to traditional currencies. The second and third criteria were not met according to the author. When considering the role of a currency to function as a unit of account, Bitcoin does not meet the criterion, with the author stating that it's impractical for consumers to quote the prices of goods with Bitcoin to four or five decimal places with leading zeroes, whilst also showing extremely high levels of volatility. Lastly, as a store of value, once again Bitcoin does not meet the requirements according to the author. Stating that Bitcoin faces great obstacles due to the related security problems and levels of correlation to other currencies of close to zero (Yermack, 2013). Yet with Bitcoin maturing as an asset, these findings have changed. As a medium of exchange, the number of transactions since 2013 have grew almost sevenfold to almost 350 thousand daily trades (Blockchain.info, 2017). With this comes a much higher level of liquidity, measured with the tightening of the bid-ask spread. This ensures that trades are executed at the desired market prices increasing the usability of Bitcoin as a medium of exchange (Smith & Rosevear, 2017). The maturing process also contributed to Bitcoin satisfying the second criterion, with trade platforms and exchanges in place for the transactions and higher levels of automation, the impracticality of quoting prices of goods with Bitcoin decreased. Secondly, the level of volatility is more stable, allowing for less frequent and severe price recalculations, thus increasing the usability of Bitcoin as a unit of account (Smith

& Rosevear, 2017). Lastly, an argument can be made for Bitcoin adhering to the third criterion. With the increase in safe trade platforms and overall computer security, the risk has decreased significantly (Fröhlich *et al,* 2016), additionally the lower level of volatility also ensures that Bitcoin is able to store more value.

Now as previously stated, Bitcoin has been receiving increased academic attention, however mostly from a legal and computer scientific standpoint. The first study empirically testing Bitcoin from an investment perspective is from 2015 by Baek and Elbeck. This research focuses on the aspect of volatility and return, determining Bitcoin's market volatility and the drivers of Bitcoin market returns. The findings show that Bitcoin is highly volatile in comparison to the stock market, furthermore Bitcoin return data shows a positive excess kurtosis, which indicates that there is a high possibility for extreme values (Baek & Elbeck, 2015). The study by Brière, Oosterlinck and Szafarz from 2015, aimed at understanding the potential benefits from incorporating Bitcoin into an investment portfolio, determining the diversification opportunities which arose when including Bitcoin. Similarly, this study finds Bitcoin volatility to be extremely high, close to 176% annually, in comparison to both traditional assets and alternative investments, however with an accompanying high average annual return of around 400% (Brière, Oosterlinck & Szafarz, 2015). In addition to these findings, they find empirical results indicating that the correlation between Bitcoin and the other studied asset classes is extremely low, suggesting it to be a good diversification option or a possible hedge during a crisis. Apart from these two articles, there is a gap in academic literature into the investment possibilities of Bitcoin and both of these studies focus on data obtained between 2010 and 2013.

2.2 MARKET UNCERTAINTY

Since 2008, relatively high levels of policy uncertainty are observed, with policy uncertainty being twice as high as the 23 years before (Economic Policy Uncertainty, 2017). During periods of market uncertainty, the general consensus is that higher levels of uncertainty have a negative impact on willingness to invest within an economy and as a result the performance of the stock market (Bloom, 2009). Research has shown that periods with high levels of policy uncertainty are negatively related to stock market returns (Antonakakis, Chatziantoniou & Filis, 2013). Periods with high levels of uncertainty are accompanied with high stock market volatility, which is often observed during financial crises. During the most recent financial crisis of late 2008, high levels of volatility were observed (Schwert, 2011). Additionally, a statistically significant positive relation between stock volatility and unemployment rates were found, indicating that a higher level of unemployment rate indicates an increased level of market uncertainty (Schwert, 2011).

These periods with high levels of uncertainty can lead to investors to show instances of flight-to-quality. Flight-to-quality suggests that investors seek to increase the risk premium they require per unit of volatility (Beber, Brandt & Kavajecz, 2009). The article by Smith and Rosevear from 2017, studied how Bitcoin prices reacted to two recent periods of market uncertainty, namely the Brexit Referendum and the United States Presidential Election from 2016. A pattern of flight-to-quality towards Bitcoin was observed during both periods. During the analysis of the Brexit Referendum, the Bitcoin price showed a near perfect correlation with the projected probability of the "leave" vote, which was considered the option with the greatest negative impacts on the global markets (Smith & Rosevear, 2017). A similar pattern was observed during the election results of the U.S Presidential Elections in 2016. Real-time probability models estimated the odds of Donald Trump winning the American elections, which were compared to the Bitcoin prices. A victory for Donald Trump was considered to bring high levels of market uncertainty, due to questions regarding his foreign and domestic policy (Smith, 2016). The results showed that Bitcoin prices moved in relation to the probability of Donald Trump winning the presidential election. These findings could indicate that Bitcoin could provide a hedging opportunity during higher levels of market uncertainty (Smith & Rosevear, 2017). This statement is supported by a finding by Brière, Oosterlinck and Szafarz, who suggest that Bitcoin could serve as a potential hedge against crises. This statement is based on the observation of extremely high positive skewness in the Bitcoin returns (Brière, Oosterlinck & Szafarz, 2015). These high levels of skewness found are regularly found during investment strategies which aim at hedging against financial crises (Brière et al., 2010).

2.3 EXTERNAL FACTORS

When considering traditional factor models for asset pricing, such as the Fama and French Five-Factor model, the factors incorporated into the model are internal (Fama & French, 2015). External factors are not regarded within the model, even though intuitively the reasoning behind external effects such as macroeconomic developments exerting a significant impact on stock returns is understandable. Earlier studies into the effect of these macroeconomic effects showed that stock returns are negatively related to inflation and money growth (Fama, 1981; Geske & Roll, 1983). An analysis by Flannery and Protopapadakis from 2002 showed that a certain level of exposure to a macroeconomic variable can cause a priced risk in an asset market equilibrium. This finding may benefit investors by indicating possible hedging opportunities and aids in the understanding of the pricing of assets (Flannery & Protopapadakis, 2002).

With regards to Bitcoin, the drivers behind the market returns were studied by Brière, Oosterlinck & Szafarz. During the empirical research, they regressed Bitcoin returns against external fundamental economic factors such as the consumer price index and the real personal consumption expenditures, as well as against the internal factor of the Bitcoin spread between the daily high and low prices. These regression results showed that only the internal factor of the spread was statistically significant, with all the external factor seemingly having no impact on the Bitcoin price changes. Thus finding no empirical evidence to support that macroeconomic variables influence the price of Bitcoin. They conclude that the reasoning behind this finding is that at the time Bitcoin was still in it's introductory life-cycle stage, stating that when the Bitcoin matured as an asset class, this could result in the external factors having significant impacts. With the daily trade volume increased with over 700% since their study, lower volatility and higher liquidity, the market shows more stabilization and characteristics of a more mature asset class (Blockchain, 2017). The empirical research within this thesis aims to provide insight into whether the increased maturity results in the external factors impacting the Bitcoin prices.

2.3 PORTFOLIO OPTIMIZATION

The optimal wealth allocation among a variety of investment assets has been a key focal point within economic and financial sciences since 1952, when Harry Markowitz developed the Modern Portfolio Theory (MPT). The aim of portfolio optimization within the MPT framework is to determine the optimal allocation weights among the assets, maximizing mean returns, whilst minimizing the variance which represents risk (Markowitz, 1952). Markowitz founded the idea of this mean-variance optimization as a measure of portfolio performance, and the interconnection and co-movements between assets affecting choices. After determining the covariance between assets, the mean return and variance of return over a single period, an efficient frontier could be constructed. The efficient frontier represents a choice set of asset allocation weights, which represents the optimal trade-offs between risk and return (Hull, 2015). From these options along the efficient frontier, an investor can select a preferred portfolio based on individual risk appetite. Over the years, and with the increase of computational efficiency, a wide variety of additional portfolio optimization methods have been developed, based on the basic theory by Markowitz (Elton & Gruber, 1997). These new theories initially focused on the addition of higher moments such as skewness and excess kurtosis (Kraus & Litzenberger, 1976) and the expansion to a multi-period analysis (Fama, 1970). Regardless, the traditional mean variance analysis remained the main focus in portfolio optimization theory, since the incorporation of higher moments proved to add very little additional benefits and complicated the process of portfolio construction (Elton & Gruber, 1997).

The previously mentioned article by Brière, Oosterlinck and Szafarz was the first to incorporate Bitcoin in a portfolio optimization model, assessing whether the addition of Bitcoin into their investment universe would benefit the risk/return trade-off. They found extremely high returns for

Bitcoin investments in comparison to other asset classes. However, due to the extreme volatility observed, they find that during portfolio optimization, Bitcoin can not be included into the minimum variance portfolio at that time. They do state that a small allocation of the portfolio funds to Bitcoin, increases the returns sharply for a slight increase in the risk tolerance. Comparing return performance for portfolios with the same volatility level with and without the addition of Bitcoin, the authors show that at the 6% volatility level, the portfolio with Bitcoin, produces an annual return 8.6% higher than the portfolio without Bitcoin. (Brière, Oosterlinck & Szafarz, 2015). However, to measure the risk-return performance, the authors take the Sharpe Ratio and the adjusted Sharpe ratio into account. The Sharpe Ratio answers the question how much excess return the portfolio gives for 1 unit of standard deviation, with the adjusted Sharpe ratio also taking extreme risks into account (Sharpe, 1994). They find that the Sharpe ratio, increases considerably with the addition of Bitcoin, but a significant decline in the adjusted Sharp ratio. This due to the high levels of excess kurtosis resulting in high probabilities for extreme losses. Smith and Rosevear observe a similar pattern, after plotting the risk return relationship for various traditional asset classes, they observe that Bitcoin produces significantly higher returns than the other classes, but once again with a high standard deviation of returns. Both papers conclude with the statement that adding Bitcoin to an investment portfolio may result in a significant increase in financial returns, albeit with high levels of tail risk (Brière, Oosterlinck & Szafarz, 2015).

3. DATA AND METHODOLOGY

This chapter will introduce the data used during the empirical research and successively the methodology will be discussed, which will allow for replication of this research. The data and methodology outlines will be provided per hypothesis, since the data and the approaches for the three models does not fully overlap.

3.1 DATA

To study the three individual hypotheses, separate data sets needed to be constructed. The first hypothesis aims to answer whether there is a relation between market uncertainty, change in equity trade volume, change in equity prices and Bitcoin trade volume. The monthly Bitcoin trade volume in eight different currencies, are obtained via CryptoCompare, an online information platform and forum about a wide variety of crypto currencies. This platform shows live prices and trade activity from the 25 largest crypto exchanges (CryptoCompare, 2017). For equity trade volume the monthly trade volume of the underlying stocks within the national indices is collected in the national currency via DataStream. Additionally, the price index for the aforementioned national indices are obtained to determine the changes in price, also with the use of Datastream/

To determine the market uncertainty, three variables are chosen: The CBOE Volatility Index (VIX), the Economic Policy Uncertainty index (EPUI) and the Conference Consumer Confidence Index (CCI). The VIX data is obtained via a Bloomberg terminal, which is available at the Erasmus University Rotterdam, whilst the EPUI and the CCI are obtained from their respective institutes' websites directly. The VIX index is a measure of near-term volatility, based on S&P 500 30-day stock index options. The index is a clear indicator of investor sentiment, risk aversion and the market's expectations regarding the volatility of the S&P 500 (Moran & Dash, 2007). The second proxy for market uncertainty is the Economic Policy Uncertainty Index per country/zone and on a global scale. The monthly data for the countries is obtained from the Economic Policy Uncertainty Index (EPUI). This index is based on three underlying components, in order to quantify policy-related economic uncertainty. The three underlying components are based on: news paper coverage of policy-related events, federal tax code provisions and disagreement among economic forecasters (Economic Policy Uncertainty, 2017). Higher values for the EPUI reflect periods with more economic policy uncertainty. As a last proxy for market uncertainty, the data from the Consumer Confidence Index provided by the Organisation for Economic Cooperation and Development (OECD) is used. The Consumer Confidence Index (CCI) reflects the attitude of households with their intention to complete big purchases and a reflection of their overall economic situation, both now and in the near future. Low levels of confidence are associated with high levels of uncertainty (OECD, 2017).

Table 1 provides an overview of the currencies, the countries or zones they represents and the equity index for that specific country. The countries were chosen based on sufficient data being available and their market share within the total Bitcoin trade, with the selected currencies making up for over 94% of all Bitcoin trading.

Table 1 Overview currencies, countries and indices

Currency	Country/zone	Index
USD	United States of America	S&P500
EUR	Europe	Euro Stoxx 50
JPN	Japan	Nikkei 225
CNY	China	Shanghai SE Composite
GBP	United Kingdom	FTSE 100
AUD	Australia	ASX200
RUB	Russia	RTSI
BRL	Brazil	IBOV

The second hypothesis aims to test the correlation and relations between Bitcoin prices and external macroeconomic effects. Focussing on the United States, due to it being the most mature Bitcoin market. Firstly, Bitcoin prices in U.S dollars were collected from the Bloomberg financial data base. Additionally, a wide variety of common macro-economic factors has been collected to asses whether they have an effect on the prices of Bitcoin. The first two variables studied are the closing price and the trading volume of the S&P 500 index. The index is based on the market capitalizations of 500 large companies in the United States and is considered a representative measure of the performance of the American equity market (Bollerslev, *et all,* 2009). The third variable, as a variable related to fixed income, is the U.S Generic Government 10 Year Yield from Bloomberg, this is based on the on-the-run government bonds. Fourth is the Consumer Price Index (CPI), which measures the inflation rate in the United States and was also obtained from Bloomberg. The effect of inflation on the stock market has been studied extensively, however due to Bitcoin not being affiliated with a National Central bank or government, the relationship between the variables is questioned. The fifth variable is the price of West Texas Intermediate (WTI) oil spot prices, collected from the US Energy Information Administration (EIA, 2017). The empirical relationship between oil prices and stock markets has been repeatedly observed, with a high correlation between the performance within the financial market and the oil price (Nandha & Faff, 2008). The sixth variable is the United States Unemployment Rate, obtained from the database from the Federal Reverse Bank of St. Louis. The seventh variable concerns the exchange rate between the U.S. dollar and the Euro. The values are in dollars and obtained via the DataStream Database. The last macroeconomic variable is the change in gold price in U.S. dollars per ounce, obtained from Bloomberg. Gold is often seen as a good hedge during a variety of investment strategies, raising the question how it relates to Bitcoin prices. Lastly, monthly data for the Consumer Confidence index, VIX index and The Economic Policy Uncertainty index (EPUI), all used during the answering of the first hypothesis, are also added as variables for the second hypothesis. For EPUI, both the world wide index and the index strictly relating to the United states are used. The data used for the second hypothesis is based on monthly data between January 2013 and July 2017. Monthly data was chosen due to the frequency of the data available for certain variables. The descriptive statistic for the data of the second hypothesis can be found in table 3 on page 15.

For the answering of the third hypothesis, an efficient frontier needs to be constructed. In order to construct an extensive investment universe, a wide variety of U.S. asset classes will be considered between January 2014 and July 2017. The choice for strictly focussing on the American market with regards to the construction of the efficient frontier, is due to the fact that the American bitcoin market is the most mature. Firstly, the weekly price data for Bitcoin in U.S. dollar is again obtained from Bloomberg. For the equity asset class, three indices are obtained from DataStream: S&P 500, S&P Midcap 400 and the S&P Smallcap 600. As previously stated, the S&P 500 consists of the 500 largest companies within the United States, where the S&P Midcap 400 and S&P Smallcap 600 are benchmark indices for mid-sized and small-sized companies respectively. This reflects the distinctive risk and return characteristics specific to these market segments in comparison to the large companies (Floros, 2009; Ivanov, Jones & Zaima, 2013). For fixed income we consider both government and corporate bonds. For government bonds the U.S Benchmark 10-year Government index is obtained and for corporate bonds the iShares J.P. Morgan EM Corporate Bond ETF is used as a proxy. Furthermore, a collection of frequently invested-in alternative asset classes is also obtained from DataStream. The S&P400 Real Estate Price index serves as a proxy for public real estate and the Dow Jones Commodity Index is used as a broad measure of the commodity market. Additionally, the Thomson Reuters Private Equity Buyout index is a measure of the performance of U.S. private equity buyout industry, with the Thomson Reuters Post Venture Capital index providing a similar performance measure for the venture capital market. The last asset class added is gold, measured in dollars per pound.

Table 3 on page 15 shows the descriptive statistics per each asset class. Similar to previous findings, Bitcoin shows the highest weekly returns, with the expected high levels of volatility compared to the other asset classes. The correlation between the asset classes are shown in table 2 on the following page. From the table a pattern can be observed where Bitcoin shows a very low correlation to the other asset classes, indicating that when one asset within the portfolio changes in value, Bitcoin does not move in relation to it. This low correlation contributes to the diversification opportunities that could arise when incorporating Bitcoin to the investment portfolio. The highest level of correlation to Bitcoin is found be the Venture Capital index with a correlation of 0,105, however a correlation of 10,5% is still considered to be very weak (Fields, 2013).

Table 2 Correlation Matrix Hypothesis 3

Assets	Bitcoin	S&P500	S&P 400	S&P 600	R. Estate	Commodity	P. Equity	V. Capital	C. Bonds	G. Bonds	Gold
Bitcoin	1	0,075	0,088	0,084	0,000	0,001	0,066	0,105	0,017	-0,084	0,005
S&P500	0,075	1	0,920	0,845	0,521	0,304	0,964	0,673	0,327	-0,360	0,002
S&P 400	0,088	0,920	1	0,937	0,597	0,239	0,892	0,677	0,284	-0,290	0,014
S&P 600	0,084	0,845	0,937	1	0,507	0,246	0,796	0,631	0,174	-0,345	-0,009
R. Estate	-0,001	0,521	0,597	0,507	1	0,122	0,489	0,326	0,344	0,283	0,126
Commodity	0,001	0,304	0,239	0,246	0,122	1	0,250	0,235	0,250	-0,190	0,090
P. Equity	0,066	0,964	0,892	0,796	0,489	0,250	1	0,656	0,300	-0,333	-0,064
V. Capital	0,105	0,673	0,677	0,631	0,326	0,235	0,656	1	0,277	-0,264	-0,047
Corp. Bonds	0,017	0,327	0,284	0,174	0,344	0,250	0,300	0,277	1	0,152	0,024
Gov. Bonds	-0,084	-0,360	-0,290	-0,345	0,283	-0,190	-0,333	-0,264	0,152	1	0,027
Gold	0,005	0,002	0,014	-0,009	0,126	0,090	-0,064	-0,047	0,024	0,027	1

Table 3 Descriptive statistics for hypothesis 2

Descriptive	Bitcoin	$P_{S\&P500}$	$V_{S\&P500}$	Gov. Bonds	CPI	OIL	U	EURUSD	GOLD	$EPUI_{WORLD}$	CCI	$EPUI_{US}$	VIX
Mean	9,084%	0,916%	1,180%	0,200%	2,468%	-0,879%	-1,091%	-0,339%	-0,506%	3,208%	1,513%	0,558%	-0,608%
Median	4,054%	1,072%	-0,995%	0,519%	0,000%	0,132%	-0,658%	-0,070%	-0,960%	4,348%	1,420%	4,060%	-0,613%
Max	170,662%	7,972%	33,017%	26,562%	150,000%	23,846%	4,255%	3,188%	9,057%	90,509%	16,447%	135,758%	85,259%
Min	-42,023%	-6,462%	-33,464%	-28,016%	-112,500%	-21,771%	-7,463%	-5,791%	-7,105%	-41,433%	-9,751%	-142,592%	-48,597%
St Dev	33,486%	2,810%	15,108%	9,922%	46,871%	8,879%	2,367%	1,849%	3,422%	25,150%	5,699%	61,737%	23,545%
Volatility	57,867%	16,762%	38,869%	31,499%	68,462%	29,797%	15,384%	13,599%	18,499%	50,150%	23,873%	78,573%	48,523%
Skewness	2,4942	-0,1688	0,1755	0,0236	0,2437	0,0196	-0,2922	-0,6724	0,2973	1,1230	0,2415	-0,0731	0,6416
Kurtosis	10,0005	0,3684	-0,5924	1,5199	2,3886	0,5212	-0,1276	0,7908	-0,2045	2,7655	-0,1408	-0,5459	2,3008
N	52	52	52	52	52	52	52	52	52	52	52	52	52

Table 4 Descriptive statistics for hypothesis 3

Descriptive	Bitcoin	S&P500	S&P 400	S&P 600	Real Estate	Commodity	P. Equity	Vent. Capital	Cor. Bonds	Gov. Bonds	Gold
Mean	0,623%	0,201%	0,183%	0,156%	0,176%	-0,123%	0,260%	0,031%	0,110%	0,084%	0,011%
Median	0,504%	0,289%	0,255%	0,250%	0,422%	-0,190%	0,378%	0,382%	0,147%	0,160%	0,003%
Max	26,461%	4,058%	4,423%	9,653%	5,914%	4,260%	9,567%	9,948%	2,849%	1,845%	6,786%
Min	-33,007%	-6,087%	-6,379%	-7,407%	-5,513%	-4,840%	-11,059%	-13,995%	-2,911%	-3,052%	-6,318%
St Dev	7,991%	1,645%	1,830%	2,188%	1,995%	1,734%	2,776%	2,967%	0,805%	0,890%	2,042%
Volatility	28,267%	12,824%	13,528%	14,793%	14,123%	13,168%	16,661%	17,225%	8,974%	9,435%	14,291%
Skewness	-0,1983	-0,6703	-0,5081	0,1727	-0,3245	-0,0789	-0,7480	-0,9721	-0,4124	-0,7423	-0,0109
Kurtosis	1,8082	1,6066	0,9016	1,9090	0,4171	-0,2066	2,6912	4,0192	1,5899	0,6921	0,5616
Sharpe	0,1463	0,0253	0,0491	0,0506	0,1418	0,2062	0,0355	0,0248	0,0179	0,0267	0,1208
N	178	178	178	178	178	178	178	178	178	178	178

3.2 METHODOLOGY

The first hypothesis aims to quantify the relationship between Bitcoin trade volume, equity market trade volume, equity market prices and variables for market uncertainty. This to observe whether there is a flight-to-quality phenomenon into the Bitcoin market when there is much uncertainty within the overall market. To determine the relationship between the Bitcoin trade volume and the aforementioned variables, an ordinary least squares (OLS) regression will be conducted within the statistical software package Stata. The OLS regression allows for the quantification of the linear relationships between variables, enabling the determination of the explanatory power of the market uncertainty variables with regards to the Bitcoin trade volume. The model is formulated as equation 1:

$$V_{BIT} = \beta_0 + \beta_1 \Delta V_{equity} + \beta_2 \Delta P_{equity} + \beta_3 \Delta GOLD + \beta_4 \Delta EPUI_w + \beta_5 \Delta Uncertainty_t + \varepsilon_t \qquad (1)$$

The dependent variable, V_{BIT} represents the monthly Bitcoin trade volume denominated in U.S. dollars. The first independent variable, ΔV_{equity}, represents the monthly change in trade volume of the country specific equity indices. The second independent variable, ΔP_{equity}, represents the change in the price of the national equity indices. With the third variable being the change in gold price to determine the relationship between Bitcoin trade volume and the gold price. The fourth variable represents the monthly change in the global Economic Policy Uncertainty Index. The last independent variable represents monthly change in one of the three proxies for the market uncertainty. The three proxies tested are the The CBOE Volatility Index (VIX), the Economic Policy Uncertainty Index (EPUI) and the Consumer Confidence index (CCI). The CBOE Volatility Index which is based on the American S&P500 and is not country specific. With the American stock exchange being the largest and most influential market in the world, the assumption is that the VIX also portrays the investor sentiment of investors globally. The remaining two proxies for market uncertainty are country or zone specific The respective exposure to each independent variable is quantified by the accompanying betas (β). The last term, ε_t, represents the error term. However, before the regression can be performed, there are certain conditions which are required to be met, according to the Gauss-Markov theorem. The Gauss-Markov theorem states that if these conditions are met, then OLS estimators are best linear conditionally unbiased estimators (Stock & Watson, 2015). The Gauss-Markov conditions assumptions that need to be met to ensure the validity of the model are that the data shows no heteroskedacity, no multicollinearity between the independent variables and the error term needs to have a mean of zero (Brooks, 2014). The Gauss-Markov assumptions will be elaborated on, tested and the data possibly rectified in section 3.3.

In order to quantify the relationship between Bitcoin prices and macroeconomic factors, similarly to during hypothesis 1, an (OLS) regression will be conducted within the statistical software package Stata. Within this hypothesis the OLS regression quantify the linear relationships between variables, enabling the determination of the explanatory power of the macroeconomic variables with regards to the Bitcoin price. The model approach is similar to the study conducted by Baek and Elbeck from 2015. The model is formulated as equation 2:

$$R_{BIT} = \beta_0 + \beta_1 \Delta SP500_t + \beta_2 \Delta\ VSP500_t + \beta_3 \Delta\ GOV_t + \beta_4 \Delta CPI_t + \beta_5 \Delta OIL_t + \beta_6 \Delta U_t + \beta_7 \Delta EURUSD_t + \beta_8 \Delta GOLD + \beta_9 \Delta EPUI_{world} + \beta_{10} \Delta Uncertainty + \varepsilon_t \qquad (2)$$

The dependent variable, R_{Bit}, represents the monthly change in the Bitcoin price in U.S. dollars, with the nine independent variables representing the external macroeconomic variables as discussed in section 3.1. With the last variable representing one of the three proxies for the country specific market uncertainty as in hypothesis 1. Following the approach by Baek and Elbeck (2015), the monthly changes (Δ) for each variable are used. The respective exposure to each variable are quantified by the accompanying betas (β). The last term, ε_t, represents the error term. Similar to with hypothesis 1, before the regression can be performed, the conditions according to the Gauss-Markov theorem are required to be met to ensure the validity of the model (Stock & Watson, 2015). For the second hypothesis, the Gauss-Markov assumptions will also be elaborated on, tested and the data possibly rectified in section 3.3.

The construction of the efficient frontier is done in Microsoft Excel, following the original approach by Markowitz (1952). The initial step is the calculation of the weekly returns for each asset class across the time frame, allowing for the calculation of the average weekly return and standard deviation. The results of these calculations are found in section 3.1. The aim of the model is to optimize the level of risk in relation to the level of returns, thus minimizing the amount of risk in order to achieve the highest level of risk adjusted return. Here an example of the mathematical formulation of the problem if provided. Equation 3 represents the optimization in a situation which consists of 2 assets, asset i and asset j. The goal is to minimize the variance of the portfolio which is represented by the following equation 3:

$$\sigma^2 = \sum_{i,j=1}^{n} \omega_i \omega_j \sigma_{ij} \qquad (3)$$

The weights to the respective assets are represented by ω_i and ω_j with the covariance between the two represented by σ_{ij}. This minimization is subjected to two requirements when an investor is aiming to minimize the variance with respect to a fixed level of the expected return, $E(r_p)$. The first requirement is mathematically formulated as in equation 4:

$$E(r_p) = \sum_{i=1}^{n} \omega_i r_i \quad (4)$$

The returns are calculated by taking the sum of each individual asset weight, ω_i, multiplied by the average return for each asset, r_i. The second requirement, displayed in equation 5, is that the sum of the asset weights is 1. This represents that 100% of the investors' assets are invested.

$$\sum_{i=1}^{n} \omega_i = 1 \quad (5)$$

Following equation 3, allows for the construction of the efficient frontier. Minimizing the portfolio variance for a wide variety of fixed levels of expected returns gives the line of the efficient frontier, also known as the capital allocation line (Amu & Millegård, 2009. After the construction of the efficient frontier two portfolios are calculated. The first portfolio is the optimal portfolio, which consists of the asset allocations at which the risk return trade-off is optimized. The second portfolio is the global-minimum variance portfolio which consist of the assets allocation weights at which the lowest risk exposure is obtained. There will be no limitations put onto the allocation weights, thus there are leveraging and short-selling possibilities. This in line with the possibilities institutional investors have.

3.3 OLS ASSUMPTION TESTS

This section aims at identifying potential sources of biases due to the violations of the three Gauss-Markov conditions for the OLS regressions. Starting with the variables for the first hypothesis, which aims to study the relationship between Bitcoin trade volume, equity market trade volume and proxies for market uncertainty. The first assumption to be tested is whether the mean of the error terms is zero. Calculating the mean of the errors showed that the mean is closely approximating zero. The second assumption to be tested is that the data requires to be homoscedastic, meaning that the variance levels are similar throughout the dataset (Field, 2013). In order to test the data set for heteroskedacity, the Breach-Pagan test is applied on the models with each of the three proxies. The results of the tests can be found in appendix 1, table 1 and 2. For all three of the proxies for market uncertainty the models show heteroskedacity. The p-values indicate that the variance is not constant throughout, since it is lower than the threshold of the 5%

significance level. Thus the conclusion can be drawn that there is heteroskedacity in the dataset. Thus, to ensure the validity of the model, the Newey-West's heteroskedacity and autocorrelation consistent covariance estimator is applied during the conduction of the regressions, this manner ensures that robust standard errors are used. The last assumption relates to the multicollinearity between the independent variables. Multicollinearity indicates that there is a close linear relation between two or more variables. A high level of correlation between the variables can destabilize the coefficients and inflate the standard errors (Fields, 2013). To test for multicollinearity, the variance inflation factors (VIF) are calculated for all the independent variables. The levels of the VIFs are shown in appendix 1 table 3 The VIFs indicate that there is multicollinearity present in the data, this can be concluded from the values for each variable being greater than 1. However, empirical research has shown that when the VIFs are no greater than 4, the multicollinearity can be disregarded (Cohen *et all,* 2003). Thus for the first hypothesis, there are no further adjustments that need to be made to the data to ensure the validity of the model for all the currencies. Since the assumptions are met using the Newey-West's heteroskedacity and autocorrelation consistent covariance estimator this ensures that the model are best linear conditionally unbiased estimators.

The same requirements need to be met for the model of the second hypothesis to produce the best linear conditionally unbiased estimators. The first assumption, whether the mean of the error terms is zero, is tested and showed that the mean of the error terms closely approximates zero again. For the second assumption the homoscedasticity is tested with the the Breach-Pagan test for all three proxies. The results of the tests can be found in appendix 1 table 4 and 5. The p-values again indicate that the variance is not constant throughout and thus there is heteroskedacity in the dataset. So similarly as during hypothesis 1, the Newey-West's heteroskedacity and autocorrelation consistent covariance estimator is applied during the conduction of the regressions to ensure the validity of the model. To test for multicollinearity, the levels of the VIFs for the variables of hypothesis 2 are shown in appendix 1 table 6. For the second hypothesis, the VIFs also indicate that there is multicollinearity present in the data. However, the VIFs are no greater than 4 and thus the multicollinearity can be disregarded (Cohen *et all,* 2003). The assumptions are again met using the Newey-West's heteroskedacity and autocorrelation consistent covariance estimator, ensuring that the model produces best linear conditionally unbiased estimators.

4. RESULTS

Within this chapter the empirical results from the research will be discussed for each of the three separate hypothesis. For the first two hypotheses, the results of the quantification of the relationships between the Bitcoin trade volume and price respectively. The results for the third hypothesis show the constructed efficient frontiers with and without the addition of Bitcoins to the investment universe.

The results from the model for hypothesis 1 can be found in table 5 and 6. The results within the tables are shown per currency, per model with the separate proxies for market uncertainty. The table shows the beta coefficients for each independent variable, with below it the accompanying p-value. For the U.S. dollar, the first model which uses the VIX as the proxy shows no statistically significant relationship between the five independent variables and Bitcoin trade volume. Suggesting that the trade volume of the equity market, in this model represented by ΔV_{equity} (p=0,572) does not significantly affect Bitcoin trade volume and neither does the change in the the price of the equity index, $\Delta P_{equity,}$ (p=*0,988),* gold price (p=*0,818*), EPUI World (p=*0,212*), or the VIX (p=0,296), since non exceed the threshold of the 5% significance level. Furthermore, the model with VIX shows a very low explanatory power with an R-squared of 0,029. The second model, using EPUI, shows similar results with none of the independent variables showing a significant relationship and with an even lower R-squared of 0,011. The third model with the Consumer Confidence index (CCI) variable as a proxy for market uncertainty shows a contradicting finding. Where the ΔV_{equity} (p=*0.394*), ΔP_{equity} (p=*0711)* and the remaining independent variables again show non-significant relationships. The variable CCI shows a statistically significant relationship at the 5% level (p=0,013). The beta of -7,050 indicates a negative relationship between the CCI and the Bitcoin trade volume. The R-squared of 0,136 is in comparison to the other two models also higher, suggesting that the explanatory power of the model is higher. The empirical results when using the Bitcoin trade volume in Euros or Japanese Yen provide no significant relationships for any of the variables and market uncertainty proxies. Analyzing the Bitcoin traded against the Chinese Yuan shows a relationship between trade volume and the change gold price. In model 1, the beta is -1,588 (p=0,014) suggests a negative relationship between the gold price and bitcoin trade volume. The proxy for market uncertainty, the VIX, also shows a significant negative relationship at the 5% level with a beta of -1,197 (p=0,047). The remaining 2 models both also show a significant negative relationship with the change in Gold price at the 5% significance level, but no relationship to the other proxies for market uncertainty. Similar results are found when testing the trade volume in Great British Pounds and Australian dollars, with the change in gold price showing a significant relationship in all models, and only the VIX showing a negative statistically significant relationship of the proxies for market uncertainty. Lastly, analysis when using the Bitcoin trade volume in Russian Ruble and Brazilian Real yield no significant results.

Table 5 This table represents the results from hypothesis 1, based on equation 1, with the models differentiating from one another based on the currencies and variables incorporated as a proxy for market uncertainty. The p-values are noted in parenthesis below the coefficients. *, ** and * indicates that the coefficient is significant at the 1%, 5% and 10% level respectively**

Currency	USD			EUR			JPN			CNY		
Model	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Variables												
Constant	0,365**	0,374**	0,424**	0,922	0,909	0,693	2,618	2,710	2,541	0,788**	0,739**	0,767**
	(0,019)	*(0,034)*	*(0,011)*	*(0,202)*	*(0,202)*	*(0,160)*	*(0,332)*	*(0,318)*	*(0,309)*	*(0,014)*	*(0,018)*	*(0,015)*
ΔV_{equity}	0,580	0,211	0,919	5,184	5,246	4,862	-5,968	-5,503	-6,563	-0,291	-0,284	-0,319
	(0,572)	*(0,817)*	*(0.394)*	*(0,367)*	*(0,387)*	*(0,377)*	*(0,396)*	*(0,357)*	*(0,333)*	*(0,491)*	*(0,248)*	*(0,466)*
ΔP_{equity}	0,074	-1,244	1,800	4,479	2,348	1,189	-3,281	-4,228	-5,347	-2,521	-2,539	-2,665
	(0,988)	*(0,762)*	*(0,711)*	*(0,383)*	*(0,662)*	*(0,860)*	*(0,357)*	*(0,360)*	*(0,336)*	*(0,263)*	*(0,248)*	*(0,466)*
ΔGOLD	-0,763	-1,141	-0,834	-1,589	-1,462	-1,520	-5,001	-6,285	-5,941	-1,588**	-1,507**	-1,525**
	(0,818)	*(0,736)*	*(0,850)*	*(0.135)*	*(0,143)*	*(0,146)*	*(0,357)*	*(0,345)*	*(0,330)*	*(0,014)*	*(0,017)*	*(0,032)*
$\Delta EPUI_W$	-0,488	-0,4359	-0,161	-1,673	1,712	-1,534,	4,062	14,800	6,902	-1,115	-1,479	-1.106
	(0,212)	*(0.303)*	*(0,805)*	*(0,480)*	*(0,472)*	*(0,495)*	*(0,399)*	*(0,320)*	*(0,354)*	*(0,427)*	*(0,438)*	*(0,448)*
ΔVIX	-0.587			-1,744			-2,621			-1,197**		
	(0,296)			*(0,256)*			*(0,396)*			*(0,047)*		
$\Delta EPUI_C$		-0.042			*-4,436*			*-23,549*			*0,279*	
		(0,841)			*(0,397)*			*(0,316)*			*(0,665)*	
ΔCCI			-7.050**			*27,856*			*28,246*			*-13,043*
			(-0,013)			*(0,391)*			*(0,304)*			*(0,988)*
N	52	52	52	52	52	52	52	52	52	52	52	52
R-squared	0,029	0,011	0,136	0,041	0,057	0,060	0,030	0,082	0,104	0,134	0,110	0,108

Table 6 This table represents the results from hypothesis 1, based on equation 1, with the models differentiating from one another based on the currencies and variables incorporated as a proxy for market uncertainty. The p-values are noted in parenthesis below the coefficients. *, ** and * indicates that the coefficient is significant at the 1%, 5% and 10% level respectively**

Currency	GBP			AUD			RUB			BRL		
Model Variables	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Constant	0,253**	0,242**	0,269**	0,246*	0,220*	0,214*	7,023	3,664	6,622	0,594*	0,609**	0,511**
	(0,027)	*(0,026)*	*(0,024)*	*(0,060)*	*(0,054)*	*(0,054)*	*(0,303)*	*(0,364)*	*(0,307)*	*(0,063)*	*(0,071)*	*(0,048)*
ΔV_{equity}	0,161	-0,021	0,035	1,139	0,756	1,078	-5,246	-3,354	-4,842	-0,173	-0,150	-0,310
	(0,742)	*(0,966)*	*(0,947)*	*(0,110)*	*(0,173)*	*(0,116)*	*(0,319)*	*(0,326)*	*(0,323)*	*(0,897)*	*(0,915)*	*(0,814)*
ΔP_{equity}	0,124	-1,006	-0,462	0,976	0,709	2,245	-1,872	-5,080	-13,690	-5,069	-4,966	-4,787
	(0,948)	*(0,652)*	*(0,819)*	*(0,757)*	*(0,818)*	*(0,505)*	*(0,667)*	*(0,902)*	*(0,751)*	*(0,156)*	*(0,159)*	*(0,136)*
ΔGOLD	-6,846**	-6,962**	-7,035**	-7,479*	-6,979*	-5,764*	-3,353	-3,591	-3,267	-1,871	-1,876	-1,742
	(0,019)	*(0,025)*	*(0,020)*	*(0,060)*	*(0,073)*	*(0,010)*	*(0,294)*	*(0.283)*	*(0,296)*	*(0,143)*	*(0,151)*	*(0,121)*
$\Delta EPUI_W$	0,195	0,015	0,142	0,076	-0,425	0,014	5,549	3,774	5,565	-0,533	-0,243	-0,364
	(0,617)	*(0.974)*	*(0,736)*	*(0,865)*	*(0,582)*	*(0,974)*	*(0,351)*	*(0,399)*	*(0,350)*	*(0,444)*	*(0,792)*	*(0,645)*
ΔVIX	-0.541**			-0,638*			-1,595			-0,504		
	(0,019)			*(0,083)*			*(0,382)*			*(0,218)*		
$\Delta EPUI_C$		0,242			*0,397*			*1,577*			*-0,326*	
		(0,476)			*(0,483)*			*(0,311)*			*(0,536)*	
ΔCCI			*-6,353*			*-19,926*			*-24,347*			*-10,108*
			(0,101)			*(0,178)*			*(0,943)*			*(0,566)*
N	52	52	52	52	52	52	52	52	52	52	52	52
R-squared	0,012	0,091	0,115	0,123	0,103	0,147	0,105	0,131	0,100	0,092	0,090	0,095

For hypothesis 2, the regression results per model are shown in table 7 on the next page. Similarly, to the results from hypothesis 1, the table shows the beta coefficients for each independent variable, with the associated p-value below. The first model again uses the VIX as the proxy for market uncertainty. The results show that expect for one variable, none of the macro economic variables or the proxy for market uncertainty show a statistically significant relationship to the changes in Bitcoin prices. The only variable showing a positive significant relationship at the 10% level, to Bitcoin prices is the price change of the S&P500 with a beta of 3,821 (*p*=0,096). The positive relationship suggests that when the price of the S&P500 goes up by 1%, the Bitcoin goes up with 3,821%. The second model, using $EPUI_{US}$ as the proxy for market uncertainty shows similar results to the first model where only the change in price of the S&P500 having a statistically significant effect on the Bitcoin prices with a beta of 2,972 (*p*=0,099). Within the third model, the empirical results again show the positive significant relationship at the 10% level with the price change in the S&P500, with a beta of 2,160 (*p*=0,092). However, within model 3, the variable GOLD also shows a significant relationship at the 10% level with the Bitcoin prices, with a beta of -2,272 (*p*=0,087). The final observation that can be made is the different levels of the R-squared for each model. Similar as to the findings of the empirical analysis of hypothesis 1, the R-squared is the highest when incorporating CCI as the proxy for market uncertainty (R^2=0,217). Followed by the model which used VIX (R^2=0,195) and the lowest explanatory power is given by the model which used EPUI (R^2=0,192).

Table 7 This table represents the results from hypothesis 2, based on equation 2, with the models differentiating from one another based on the variable incorporated as a proxy for market uncertainty. The p-values are noted in parenthesis below the coefficients. *, ** and * indicates that the coefficient is significant at the 1%, 5% and 10% level respectively.**

Model	(1)	(2)	(3)
VARIABLES			
Constant	0,042	0,051	0,0741*
	(0,307)	*(0,201)*	*(0,073)*
ΔPSP500	3,821*	2,972*	2,160*
	(0,096)	*(0,099)*	*(0,010)*
ΔVSP500	-0,440	-0,412	-0,325
	(0,294)	*(0,311)*	*(0,432)*
ΔGovBonds	-0,346	-0,319	-0,2931
	(0,494)	*(0,528)*	*(0,594))*
ΔCPI	-0,018	-0,018	-0,042
	(0,757)	*(0,768)*	*(0.523)*
ΔOIL	-0,594	-0,605	-0,602
	(0,414)	*(0,412)*	*(0.414)*
ΔU	-2,100	-2,055	-1,839
	(0,234)	*(0,243)*	*(0,270)*
ΔEURUSD	2,751	2,863	3,138
	(0,268)	*(0,253)*	*(0,144)*
ΔGold	-1,939	-2,019	-2,272*
	(0,135)	*(0,238)*	*(0,087)*
$\Delta EPUI_{world}$	-0,236	-0,266	-0,245
	(0,306)	*(0,238)*	*(0,274)*
ΔVIX	0,167		
	(0,531)		
$\Delta EPUI_{US}$		0,013	
		(0,862)	
ΔCCI			-1,053
			(0,274)
Observations	52	52	52
R-squared	0,195	0,192	0,217

The constructed efficient frontiers are shown below in figure 1. The upper, light blue line shows the capital allocation line when incorporating Bitcoin into the investment universe, where the lower, dark blue line shows the capital allocation line without Bitcoin. The dots within the graph are the assets which make up the investment horizon. With the asset on the far right representing Bitcoin. The graph shows that the frontier with the Bitcoin included is slightly steeper compared to the frontier without Bitcoin, as can be concluded by the small diverging pattern of the Bitcoin included frontier in relation to the non-Bitcoin frontier. When increasing the scale of the efficient frontier, thus calculating the mean return for higher levels of risk, this pattern remains and the two frontiers diverge farther.

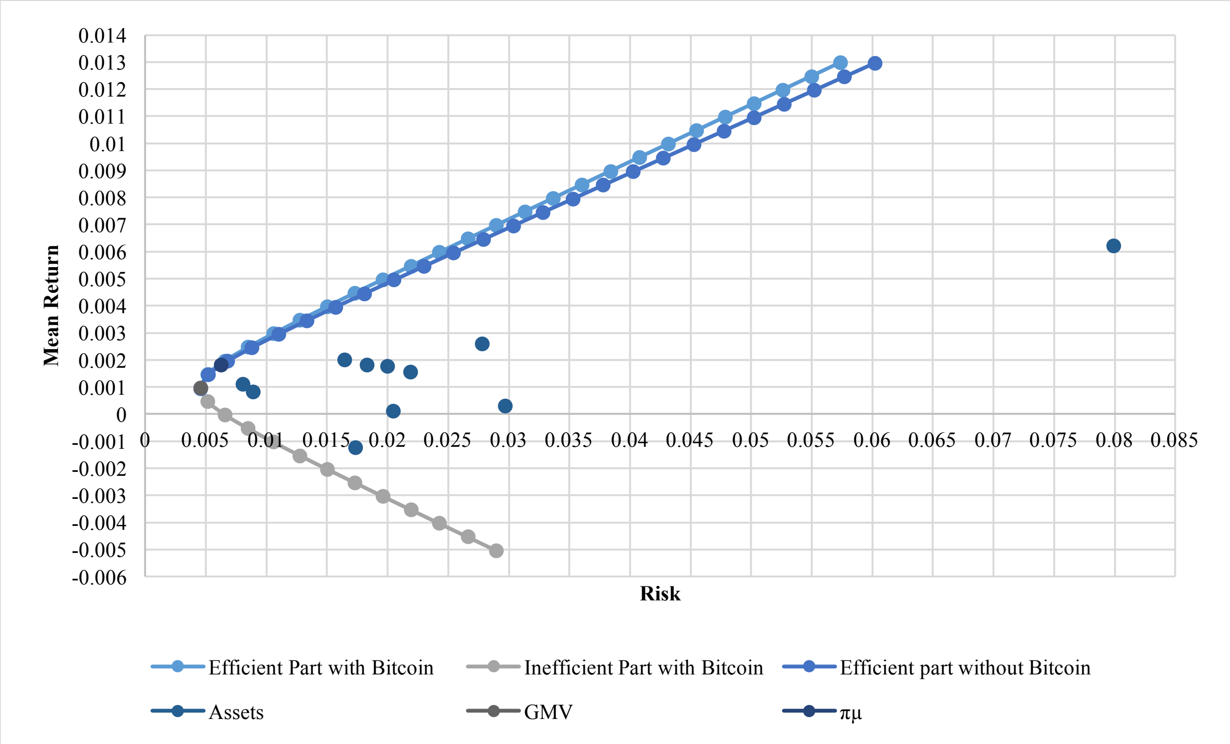

Figure 1 The efficient frontiers with and without Bitcoin

After the construction of the capital allocation lines, the optimal portfolio, which consists of the asset allocations at which the risk return trade-off is optimized, and the global-minimum variance portfolio, the allocation with lowest risk exposure are calculated. The asset weights for both of the portfolio can be found in appendix 2 table 1. The weights show that within the optimal portfolio, there are large short positions and leveraging takes places. However, only 2,04% of the total assets are invested in Bitcoin, with a large part of the assets being invested in the traditional asset classes of equity and both government and corporate bonds. Within the global-minimum variance portfolio the assets invested into Bitcoin only make up for 0,34%, with again the traditional asset classes receiving higher weights. With the largest allocation of 51,4% being towards the government bonds which are considered relatively safe.

5. DISCUSSION

In this chapter an in-depth discussion of the empirical results found in the previous chapter will be conducted. The discussion will be supported by previous literature to gain a perspective into the interpretation of the empirical results, and to determine where the results diver from the aforementioned literature.

The empirical results from hypothesis 1 shows that for all models and currencies there are no significant relationships between the Bitcoin trade volume and equity trade volume. This suggests that Bitcoin, possibly due to its characteristics as a decentralized asset, is not seen as a viable flight-to-quality alternative for investors. Similarly, there is no observed relationship between the trade volume of Bitcoin and the change in price for the equity indices. To determine whether there is a relationship between Bitcoin trade volume and market uncertainty, the first model used the CBOE Volatility Index (VIX) and the second model the Economic Policy Uncertainty index (EPUI) as proxies for market uncertainty. Both of these proxies have shown to influence equity trading, with investors using volatility trading and short selling strategies to benefit from the increased market volatility which occurs when the market uncertainty goes up (Zhang, Shu & Brenner, 2010; Brogaard & Detzel, 2015). However, when considering Bitcoin traded against U.S. dollars, the two aforementioned proxies show no statistically significant relationship with Bitcoin trade volume. Since volatility trading and short selling require sophisticated methods, they are often only applied by institutional investors. A reasoning behind why the two proxies have no effect, is that Bitcoin investors are mostly non-institutional investors, who apply basic buy-and-hold strategies as was observed by Baur, Hong and Lee (2014). The third proxy for market uncertainty, the Consumer Confidence index, did show a negative relationship significant at the 1% level. This suggest that when consumer confidence goes up, Bitcoin trade volume goes down and vice versa. The Consumer Confidence index most closely reflects the confidence perception and buying intentions from consumers out of the three proxies. This is part could explain why this proxy has a significant effect on the Bitcoin trade volume. As mentioned, Bitcoin investors mostly consist of non-institutional investors. This statement is further supported by the study by Yelowitz and Wilson from 2015, that showed that when studying the characteristics of American Bitcoin users based on Google Trends data, there was no correlation between Bitcoin interest and investment terms (Yelowitz & Wilson, 2015). These results suggest that a majority of the Bitcoin users are common consumers, whose attitude is closely portrayed by the Consumer Confidence index. This could also explain why the explanatory power of model 3 is the highest. The negative relationship suggests that when the consumer confidence decreases, the Bitcoin trade volume goes up. The lower consumer confidence and accompanying buying intentions in traditional markets, appears to contribute to them trading in Bitcoin, which due to its mentioned characteristics is viewed upon differently as traditional products. The European and Japanese currency markets showing no significant relationships to any of the independent variables could suggest that these market are not basing Bitcoin purchases on the overall market conditions, possibly due to the market being less mature compared to the U.S. Dollar market. Another explanation as to why the proxies for the zone and country specific market uncertainty proxies show no relation to Bitcoin trade volume could be due to the fact that the consumers who purchase the coins in these currencies are not residents of the zone or country. With Bitcoin and other currencies being easily accessible world wide by use of the internet, users are not bound to a location. The next three studied currencies, the Chinese Yuan, the Great British Pound Sterling and the Australian Dollar all showed similar results. All Bitcoin trade volumes showed negative significant relationships with the change in gold prices. The negative relationship indicates that when the gold prices go up, the Bitcoin trade volume in these currencies go down. For the United Kingdom, the relationship could be explained by the uncertainty within the market due to Brexit. The market is highly uncertain, which could result in investors investing their money in safe havens (Beber, Brandt & Kavajecz, 2009). Based on the empirical results, when the gold prices go down, the Bitcoin investments seem to go up. Considering Australia, it is the largest miner of gold globally, which could explain why within the country gold has a significant influence on purchasing behavior of Bitcoin (Shafiee & Topal, 2010). More specifically for China, there has been shown that the Chinese stock market and the gold price show significant cross effects as it is a popular investment within the country (Arouri, Lahiani & Nguyen, 2015). The negative relationship between the Gold prices and Bitcoin, could suggest that when the gold prices go down, Chinese investors tend to seek refuge in investing in Bitcoin. When considering the proxies for market uncertainty for the aforementioned three currencies, a statistically significant relationship is found only for the VIX variable. This finding suggests that albeit it being a proxy for the American stock market uncertainty, it still influences the foreign currencies. An explanation could be that American investors try to diversify and hedge certain currency risks by seeking refuge in investing in the Chinese currency, which represents their biggest trade counterparty (United States Census Bureau, 2017). Similarly, the United Kingdom and Australia are historically related to the United States as they are all part of the Anglosphere.

For hypothesis 2, the results are compared to the findings by Baek and Elbeck from 2015. Their results showed that there were no significant relationships between the Bitcoin price and studied macroeconomic effects. The study concluded with the suggestion that increased Bitcoin market maturity could result in different findings. However, when using a later timeframe where Bitcoin shows more signs of maturity, the empirical results do not differ greatly. For the first two models tested, eight of the nine macroeconomic variables do not show a statistically significant relationship with the Bitcoin price. The exception being the S&P500, who now does appear to be statistically significant in both models, albeit it only being at a 10% significance level. The positive relationships suggest that when the the S&P500 price moves up, the Bitcoin prices moves in a similar direction. More specifically when the S&P500 prices goes up with 1%, the Bitcoin price changes by +3,8%, +3,9% or +2,2% depending on the proxy for market uncertainty used. With the beta coefficient for the S&P500, representing the market exposure, being higher than 1, this indicates that the risk exposure from Bitcoin is greater than the market risk exposure. Which confirms that Bitcoin is a risky asset with high volatility levels. The finding also suggests that Bitcoin as an asset class matured, suggesting that Bitcoin is passed the introductory life-cycle stage (Baek & Elbeck, 2015). The reasoning behind why the S&P500 influences the Bitcoin price could stem from the fact that the S&P500 reflects the overall economic performance within the United States. Suggesting that now with the increased maturity of the Bitcoin market, due to higher levels of popular acceptance as suggested by Baek & Elbeck, there is a positive relationship between the performance of the economy and the Bitcoin prices (Van Wijk, 2013). The lack of other macroeconomic variables influencing the prices suggests that even with the increase in maturity, the movement of Bitcoin prices is still mostly internally driven. When it comes to the two proxies for market uncertainty, both do not show any significant relationship when it comes to Bitcoin prices. The third model, using the Consumer Confidence index as a proxy for market uncertainty shows similar results to the first two models with regards to the S&P500, suggesting that when the S&P500 prices goes up with 1%, the Bitcoin price changes by 2,4%. However, within the third model there is a second variable with a significant relationship to the Bitcoin price, namely the change in the price of an ounce of gold. The relationship between stock prices and gold is often studied, with gold being considered a safe haven for stocks (Baur & Lucey, 2010). The negative relationship found within this study could suggest a similar relationship, since the empirical results suggest when the price of the gold goes up by 1%, the Bitcoin price goes down with 2,2% and vice versa.

With the observed increased maturity, and lower volatility, expectations were that when including the Bitcoin into the investment portfolio it would contribute to a higher risk-return trade-off. With the construction of the efficient frontiers for hypothesis 3 this assumption was tested. Nevertheless, even with those changed characteristics, Bitcoin only makes up 0,34% of the total assets invested within the global minimum-variance portfolio. Thus even with the low correlation with the other assets, and thus the relatively high diversification opportunities that occur when incorporating Bitcoin, the asset still shows a level of volatility too high to be included in the lowest-risk portfolio. Whilst constructing the optimal portfolio, approximately 2% of the weights was attributed to Bitcoin, thus there is a positive risk-return relationship for Bitcoin, however again the high volatility only allows for a small allocation to the asset class. To further get an understanding as to how the addition of Bitcoin to the investment universe affect the risk return relationship a comparison is made of performance indicators for portfolio with similar levels of risk-exposure. Four portfolios are constructed based on volatility levels. The first two portfolio have a volatility level of 5%, and one includes Bitcoin and the other does not. The other portfolios have a volatility level of 10% and again the difference between the two being the inclusion of Bitcoin in the first one. The performance measures used are the Sharpe ratio and the modified Sharpe ratio. The Sharpe ratio determines how much return the portfolio gives for 1 unit of standard deviation. The Modified Sharpe Ratio (MSR) is based on the premises that the returns are not normally distributed and takes the skewness and kurtosis of the data into account (Mistry & Shah, 2013). The results of the comparison can be found below in table 8. The results show that when adding the returns are marginally higher on an annual basis. For the 5% volatility portfolio, the returns are 0,35% higher annually. Additionally, the Sharpe ratio also increases from 1,580 to 1,650, suggesting a higher level of return per level of risk. Similar results are found for the 10% volatility portfolio. However, when considering the MSR, the results show that for both volatility levels, the portfolios without Bitcoin have a higher MSR. This demonstrates that adding Bitcoin to your investment portfolio may lead gaining additional returns, however the levels of extreme risk do increase. This due to the extreme risk associated with Bitcoin, which was observed by high levels of excess kurtosis and skewness.

Table 8 results from the comparison of portfolios with similar volatility levels with and without Bitcoin

	Efficient Portfolios			
	5% volatility		**10% volatility**	
	With BTC	**Without BTC**	**With BTC**	**Without BTC**
Weekly Return	1,14%	1,10%	2,20%	2,10%
Annualized Mean Return	8,25%	7,90%	15,84%	15,11%
Sharpe ratio	1,650	1,580	1,584	1,511
Modified Sharpe Ratio	0,116	0,186	0,112	0,179
% Bitcoin	19,40%	0%	40,50%	0%

6. CONCLUSION

With the Bitcoin market being relatively young, rapid changes are taking place within it. Due to it being virtual and decentralized currency, it is gaining in popularity both as a medium of exchange and as an investment opportunity. Albeit investing in Bitcoin has traditionally been associated with high levels of risk, with lack of oversight and intrinsic value Bitcoin and was deemed more susceptible to speculation and bubbles. However, with the increase in popularity there has been an accompanying growth in the maturity of Bitcoin as an asset. The trade volume has grown exponentially since its introduction in 2009 and the price volatility has steadily declined over time. These changes resulted in academic communities taking notice and lead to the studying of the Bitcoin, initially from a computer science perspective and later on from an economic perspective. This study was aimed at contributing with insight to the latter perspective, aiming at determining how the changes in the Bitcoin market changed the characteristics of Bitcoin as an investment tool. To gain inside into the characteristics, three elaborate data sets were constructed. The first data set consisted of Bitcoin trade volume in eight currencies and trade volume of national equity indices, together with three proxies for market uncertainty: The CBOE Volatility Index, the Economic Policy Uncertainty index, and the Consumer Confidence index. This data set allowed for the quantification of the relationships between Bitcoin trade volume, equity market trade volume and market uncertainty. The second data set consisted of American Bitcoin prices and a wide variety of American macroeconomic variables and market uncertainty variables to determine whether these factors contributed to the changes in Bitcoin prices. Lastly, the returns of an assortment of asset classes were collected, to gain an insight into how the risk-return relationship of Bitcoin as an asset class compares to the other assets. These three data sets allowed for the answering of the three hypothesis which were established to answer the main research question which was the following:

How has the increased maturity of Bitcoin as an asset classed changed the characteristics of it as an investment vehicle?

The first hypothesis applied to the relationship between Bitcoin and equity trade volume and market uncertainty. To answer this question, the Bitcoin trade volume was regressed against the national equity index trade volume and the three separate proxies for market uncertainty for 8 separate currencies. The results showed that there was no relationship between the Bitcoin trade volume and the equity trade volume or price change in the equity indices for any country. For the U.S. Dollar nor was there a relationship with two of the market uncertainty proxies, namely The CBOE Volatility Index and the Economic Policy Uncertainty index. The only significant relationship found was a negative relationship between the Bitcoin trade volume in U.S. Dollars and Consumer

Confidence index. Three other currencies, namely the Chinese Yuan, the Great British Pound Sterling and the Australian Dollar, did show a relationship with the CBOE Volatility Index, as well as with the change in gold prices. Thus when answering the first hypothesis, we can state that higher levels of market uncertainty do lead to higher Bitcoin trade volumes, however it does depend on which currency and which proxy for market uncertainty is used. The second hypothesis was aimed at determining whether the macroeconomic variables contributed to the changes in Bitcoin prices. Regressing the Bitcoin prices against the variables and the market uncertainty proxies showed that the only variable with a significant relationship in all models was the price change in the S&P500 index. From this we can conclude that with the increased maturity of the Bitcoin market the effects of the variable changed in comparison to the study by Baek & Elbeck from 2015. The possible explanation being that the maturity lead to the Bitcoin prices starting to reflect the overall economic performance of the United States, which is related to the S&P500 performance. Within the third model, the price chance in gold was also found to show a significant relationship, suggesting hedging possibilities. Thus answering the second hypothesis we can state that there are macroeconomic effects that impact the changes in Bitcoin prices, however only one was found within this study. The last hypothesis was aimed at determining how the changed risk-return relationship of Bitcoin, with the lower level of present-day volatility, changed the weights attributed to the Bitcoin as an asset within a constructed efficient frontier. The results showed that even with the increased Bitcoin maturity the Bitcoin shows relatively high levels of volatility, thus proved to show levels of risk too high to be included into the global minimal-variance portfolio, thus rejecting the third hypothesis.

Now finally as an answer to the main research question we can conclude that the increased maturity of Bitcoin as an asset class changed the characteristics of it as an investment vehicle. The first hypothesis shows that as a result of the increased maturity, there are observable patterns when looking at market uncertainty and the Bitcoin trade volume. Furthermore, the maturity lead to the S&P500 showing a significant relationship with the Bitcoin prices. This is turn could benefit investors, in helping with the construction of investment strategies and the possible predictability of Bitcoin prices. Lastly, the construction of the efficient frontier indicated that Bitcoin remains highly risky but is accompanied by relatively high returns compared to the other asset classes. Even though there is no place for Bitcoin within the global minimum-variance portfolio, there are benefits to adding Bitcoin to an investment portfolio, if the investor’s risk appetite allows it. Conclusively, Bitcoin has continued to develop, both as a form of currency and as an investable asset. The increased maturity is leading to higher levels of predictability and, making it an an asset class that could develop into a serious alternative for all investors. This conclusion does leave room for the possibilities for future research into the subject. With regards to the market uncertainty and trade volume relationship, it showed that the Consumer Confidence index shows a significant relationship. This study tried to give an explanation for why this proxy for market uncertainty did show a relationship where the other two did not. In order to test whether this explanation holds, a more in-depth analysis into Bitcoin users could be conducted. Whilst this could prove difficult due to the anonymity involved with Bitcoin, there are large communities of Bitcoin investors who could possibly be interviewed. This would provide more insight into the demographics of the Bitcoin users and could help explain the trade volume-market uncertainty relationship. Additionally, for all the regression models with regards to the Bitcoin price, the explanatory power was considered moderate to weak. This allows for the possibility to study other macroeconomic variables which could possibly influence the Bitcoin prices, where special attention should be paid towards the relationship between Bitcoin and gold. Lastly, the investment horizon used during hypothesis 3 could be further expanded with additional asset classes, to determine how the diversification benefits of Bitcoin could possible be enhanced. Conclusively, some limitations were encountered whilst writing this thesis. Firstly, for the first 2 hypotheses, for certain variables only monthly data was available. With the goal of this study to strictly focus on a recent period, this limited the data availability. The last limitation which needs to be considered is the previously mentioned explanatory power of the models being quite low, which reflects noise within the model.

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APPENDIX 1

Table 1 Results Breach-Pagan test for hypothesis 1

	USD			EUR			JPN			CNY		
Model	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	(1)	(2)	(3)
$Chi^2(5)$	11,90	11,02	13,31	39,54	71,12	44,07	37,50	95,55	108,10	31,20	26,58	27,37
P-value	0,036	0,049	0,021	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000

Table 2 Results Breach-Pagan test for hypothesis 1 continued

	GPB			AUD			RUB			BRL		
Model	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	(1)	(2)	(3)
$Chi^2(5)$	11,72	11,78	9,49	16,96	37,57	41,37	118,35	144,21	114,86	42,54	45,99	54,07
P-value	0,039	0,038	0,091	0,005	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000

Table 3 Results multicollinearity for hypothesis 1

	USD			EUR			JPN			CHN		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Variable	**VIF**	**VIF**	**VIF**	**VIF**	**VIF**	**VIF**	**VIF**	**VIF**	**VIF**	**VIF**	**VIF**	**VIF**
Vequity	1,43	1,32	1,32	1,55	1,51	1,50	1,22	1,20	1,20	1,03	1,05	1,03
Pequity	1,32	1,22	1,29	1,28	1,21	1,25	1,49	1,40	1,43	1,04	10,5	1,10
Gold	1,14	1,14	1,14	1,09	1,09	1,09	1,46	1,45	1,44	1,03	1,03	1,15
$EPUI_W$	1,33	1.32	1,35	1,64	2,83	1,64	1,08	1,64	1,10	1,01	1,66	1,03
VIX	1,28			1,11			1,12			1,01		
$EPUI_C$		1,10			2,35			1,58			1,66	
CCI			1,22			1,06			1,06			1,19

Table 4 Results multicollinearity for hypothesis 1 1 continued

	GBP			AUD			RUB			BRL		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Variable	VIF	VIF	VIF	VIF	VIF	VIF	VIF	VIF	VIF	VIF	VIF	VIF
Vequity	1,29	1,27	1,26	1,03	1,08	1,01	1,10	1,15	1,05	1,08	1,08	1,07
Pequity	1,11	1,13	1,07	1,17	1,15	1,22	1,19	1,19	1,48	1,04	1,04	1,05
Gold	1,02	1,06	1,03	1,03	1,02	1,05	1,03	1,04	1,04	1,02	1,02	1,05
$EPUI_W$	1,34	1,88	1,35	1,14	1,71	1,14	1,17	1,33	1,20	1,12	1,34	1,16
VIX	1,08			1,05			1,06			1,01		
$EPUI_C$		1,68			1,75			1,27			1,26	
CCI			1,04			1,12			1,26			1,09

Table 5 Results Breach-Pagan test for hypothesis 2

Model	(1)	(2)	(3)
$Chi^2(4)$	30,57	31,14	30,61
P-value	0,000	0,000	0,000

Table 6 Results multicollinearity for hypothesis 1, all models

	Model 1	Model 2	Model 3
Variable	VIF	VIF	VIF
P_{SP500}	3,56	1,48	1,38
V_{SP500}	1,62	1,59	1,60
Gov. Bonds	1,60	1.63	1,56
CPI	1,13	1,15	1,17
OIL	1,53	1,53	1,53
U	1,36	1,37	1,37
EURUSD	1,29	1,38	1,29
GOLD	1,51	1,50	1,52
$EPUI_{world}$	1,52	1,38	1,37
VIX	3,42		
$EPUI_{US}$		1,25	
CCI			1,26

APPENDIX 2

Table 1 The allocation weights within the optimal and global minimum variance portfolios

	Portfolios	
Assets	**πμ**	**GMV**
Bitcoin	2,04%	0,34%
S&P500	105,94%	54,98%
S&P 400	9,94%	5,31%
S&P 600	-8,17%	3,25%
Real Estate	-13,86%	-16,24%
Commodity	-16,38%	3,51%
Private Equity	-37,72%	-23,67%
Venture Capital	-9,53%	-1,65%
Corporate Bonds	24,06%	19,25%
Government Bonds	45,32%	51,40%
Gold	-1,65%	3,53%
Mean	0,00190	0,00097
Volatility	0,01201	0,00453