Bitcoin: Safe Haven for Currencies in Times of Economic Uncertainty

Master Business Administration Thesis

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Abstract

The aim of this paper is to examine the role of Bitcoin as a safe haven for currencies in periods of economic distress. More specifically, three currencies within two periods are assessed; the pound sterling during the Brexit period, the US dollar and Chinese yuan during the trade war period. The hypotheses were that Bitcoin functions as a safe haven for the currencies during each of the periods. Data was sampled daily. For Brexit from June 2016 to January 2020, for the trade war from January 2018 until January 2020. The dynamic conditional correlation model (DCC-GARCH) was applied to estimate the dynamic correlations between Bitcoin and each of the currencies. The results indicated that Bitcoin can indeed function as a weak safe haven for any of the currencies. The results are robust, as the weak safe haven function is still present when halving the sample period and when the data is sampled weekly. The results have a high validity as it was shown that Bitcoin outperforms cryptocurrencies Ethereum, Litecoin and Ripple as well as traditional safe haven gold. The results imply it is possible for investors, traders and residents of a country to resort to Bitcoin as safe haven in future periods of economic distress.

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1. Introduction

In 2017, the rapidly rising value (from $1.000 to nearly $20.000) of blockchain-based cryptocurrency bitcoin spiked the interest of investors, developers and academics. Dabbagh, Sookhak and Safa (2019) visualize this within their bibliometric study. They show the number of blockchain and bitcoin related papers and citations grew remarkably throughout 2017. Within the field of finance, Holub and Johnson (2018) state price volatility, risk, (forecasting) returns and correlations with other financial assets are the main areas of interest. The latter focuses mostly on portfolio diversification, with the goal to hedge against stocks, bonds or against economic risks like price fluctuations in currencies or governmental influences. This research focuses on this last aspect, hedging. To be more precise, a specific form of hedging which occurs in a period of high economic uncertainty, called safe haven. Continuous economic uncertainty combined with the maturing cryptocurrency market spiked interest to research safe haven properties of cryptocurrencies. For example Shahzad, Bouri, Roubaud and Kristoufek (2020) with respect to the stock market. The COVID-19 pandemic added even more interest, as the pandemic is a potential event causing an increase in economic uncertainty. Examples are Conlon and McGee (2020) with respect to stocks and Dutta et al. (2020) with respect to commodities.

Bitcoin can potentially function as a safe haven for both locals and foreigners. On a national level (thus, locally) Bitcoin can provide constant access to one’s capital and it can be deemed a safe place for capital when national institutions are failing. In practice this can be seen in the Middle East, where these benefits are causing an increase of interest in Bitcoin[1]. Theoretical evidence supports the function of a safe haven. In hindsight, Bitcoin could have been an effective safe haven for the unstable Venezuelan currency Bolivar (Kliber, Marszałek, Musiałkowska, & Świerczyńska, 2019). Locals would have ended up with a stronger position against foreign currency. More interesting from a financial point of view however, is how investors and companies can reduce their exposure to a foreign currency. European investors for example, investing with foreign currencies in foreign stock markets of the United States, United Kingdom or China, are exposed to risk of devaluation, amongst others. Urquhart and Zhang (2018) find evidence of periods where Bitcoin can act as a hedge against the Swiss Franc, Euro and British Pound.

The relationship of Bitcoin with respect to the economic situation of a country is assessed within this research. While several researchers (e.g. Smales, 2019) conclude bitcoin is not (yet) suitable for hedging or to be a safe haven, there are also specific cases which claim the contrary. The aforementioned research of Kliber et al. (2019) and Urquhart and Zhang (2018) are examples that highlight this. The question is if Bitcoin can also be a safe haven in situations of distress besides the evidence that has already been found, to broaden the generalisability of cryptocurrencies functioning as a safe haven. The main research question is formulated as:

“*Can bitcoin act as a safe haven in periods of high economic uncertainty?”*

[1] www.coindesk.com/despite-bitcoin-price-dips-crypto-is-a-safe-haven-in-the-middle-east

Economic uncertainty can be increased by events like the COVID19 pandemic. Within this research it is chosen to focus on the impact of Brexit and the trade war, two other recent events with a global impact on economic uncertainty. Three currencies are assessed, the British pound sterling (GBP), the United States dollar (USD) and the Chinese yuan (CNY). The pound is chosen since Brexit has been the cause of a recent, long lasting increase in economic uncertainty. The economic direction and future of the United Kingdom is unsure due to its lengthy withdrawal from the European Union. The dollar and yuan are chosen since the United States and China are both involved in a trade war. Both countries are restricting each other on the import and export of goods, causing high economic uncertainty. Bitcoin is chosen as a cryptocurrency safe haven as it is expected to be the first cryptocurrency investors will resort to, due to its historic recognisability and most of all, having the largest trading volume. Other cryptocurrencies like Ethereum or Ripple do not aim to act as a (replacement) currency, but can potentially be used as an alternative investment. Therefore safe haven results of other cryptocurrencies might be compared to that of Bitcoin, to see if Bitcoin is indeed the best alternative cryptocurrency. Indices (e.g. BITA10[2]) are also not reviewed as a large percentage of the index consists of cryptocurrencies irrelevant to an investor, they suffer from insufficient liquidity or simply do not have the end goal to be a financial asset (e.g. Ethereum being a programmable blockchain). The following sub questions are made to create a division between the Brexit and trade war analysis :

"Can Bitcoin function as a safe haven for the GBP during the Brexit period?"
"Can Bitcoin function as a safe haven for the USD, CNY or both during the trade war period?"

The cryptocurrency market is changing and maturing fast. Developed academic theory based on research conducted with data from 2017 or before might already be outdated. Bitcoin data from 2018 and 2019 are distinctively different compared to before. 2018 started with a sharp decline in price of roughly 65%, followed by two years (2018 and 2019) of lesser trading activity and volatility compared to the previous years. New academic insights can be provided with respect to its function as a safe haven for currencies and as a safe haven in general. This research also aims to highlight the current development, adaptation and market positioning of Bitcoin. If one or multiple of the assessed situations created possibilities for Bitcoin to act as a safe haven, similar situations in the past, present or future might prove to be academically insightful as well. Next to the use of newer data, Bitcoin research has been geared towards an alternative investment to traditional safe haven gold, or even stocks. Research into currencies would extend the knowledge to a different asset class. Research that is already conducted about currencies often analyses specific scenarios, like in the aforementioned research of Kliber et al. (2019) about the Bolivar in Venezuela. Currencies that could have a global impact have not yet been analysed thoroughly. Brexit and the trade war are periods which could potentially show the possibilities of a more generalized application of Bitcoin as a safe haven for some of the world's most important currencies.

[2] www.avatrade.com/cfd-trading/indices/cryptocurrency-index

From a practical perspective, this research may provide clarity to investors and companies about the incorporation of Bitcoin in their portfolios. Underlying reasons might range from having an interest in blockchain developments to more advanced optimal portfolio composition with help of cryptocurrencies. Furthermore, Bitcoin might prove to be a valuable addition as a safe haven in times of economic instability, even going as far as a viable alternative to go-to safe haven gold. Next, this research might also indicate whether Bitcoin can serve as a viable alternative for currencies over all. Answering the research question will provide a future outlook on opportunities regarding investments, safe haven properties and developments of Bitcoin and cryptocurrencies in general.

2. Literature Review

2.1 Cryptocurrencies: Bitcoin and Altcoins

2.1.1 Historical Background and Fundamentals

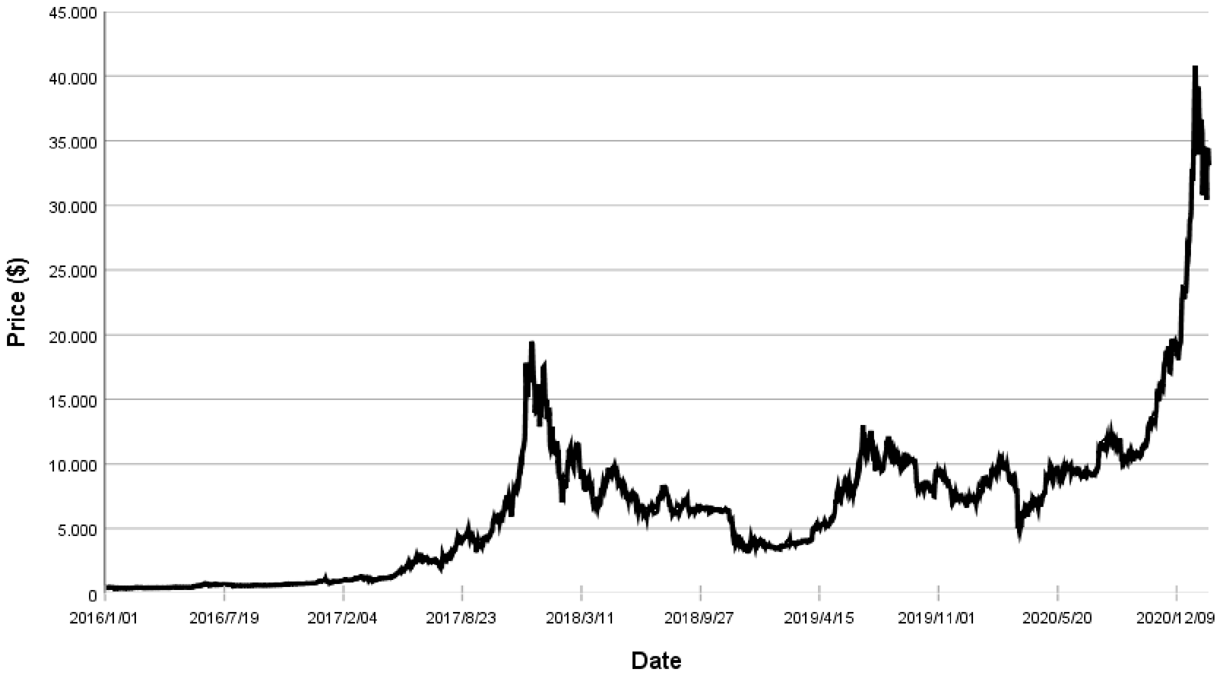
In the original whitepaper of Bitcoin (Nakamoto, 2008), it is stated to be a peer-to-peer electronic cash system, enabling online payments to be sent directly to the recipient, without going through a third party. The whitepaper argues for Bitcoin to be more secure, private, accessible, efficient and cost saving compared to traditional online payment methods like online banking. Bitcoin achieves this by using the blockchain, a ledger where transactions are made and stored. The network uses hashing and digital signatures for the verification of transactions. The blockchain is a concept that all cryptocurrencies make use of. Most claim to specialise in one of the benefits of blockchain technology. Examples are Ethereum, which focuses on efficiency and security by deploying smart contracts on the blockchain (Buterin, 2014) and Monero, aiming for absolute anonymity for the user (Noether, Noether, & Mackenzie, 2014). The umbrella term for cryptocurrencies that are not Bitcoin is “altcoins”, for alternative coins.

In 2011 WikiLeaks was one of the first to put the theory of blockchain and Bitcoin into practice by accepting donations of bitcoins.[3] By 2013 more companies started to experiment with accepting Bitcoin as a payment method as payment processors were actively processing bitcoin transactions. Discussions about regulations started as well. During 2013 and 2014 the cryptocurrency market started to grow as more projects and concepts were developed, like aforementioned Ethereum and Monero. For that reason prices of a lot of cryptocurrencies increased rapidly throughout 2013. The leading cryptocurrency exchange, Mount Gox, was hacked at the start of 2014, which drastically lowered trading volume and prices. The effect was so big that most of the trading activity of cryptocurrencies ceased. In 2017 more and more developers started working on blockchain projects, seeing the potential benefits the technology could offer. Many initial coin offerings (ICO, the cryptocurrency variant of IPO) were held and the attention of inventors and media returned. By the end of 2017 prices skyrocketed and most cryptocurrencies including Bitcoin reached new all-time high prices. However, throughout 2018 the hype cooled down, projects failed to deliver and investors panicked. The drop in prices for cryptocurrencies is similar to those of the Dotcom bubble. Throughout 2019 and 2020 cryptocurrency markets show signs of maturing by exhibiting less volatility and having a more constant volume. To illustrate the price behaviour throughout the years, the historical price movements of Bitcoin are visualized in Figure 1. Interestingly, the all-time high from 2017 was broken in November 2020.

[3] www.forbes.com/sites/andygreenberg/2011/06/14/wikileaks-asks-for-anonymous-bitcoin-donation

Figure 1

Historical price chart of Bitcoin and the US Dollar.



Note. The historical price chart from Bitcoin denominated in US Dollar from January 1st, 2016 until January 1st 2021.

From an economic point of view Ali, Barrdear, Clews and Southgate (2014) state whether cryptocurrencies, and specifically Bitcoin, are considered to be money, depends on the extent to which it acts as a store of value, a medium of exchange and a unit of account. Currently, cryptocurrencies check all the boxes. They can be stored digitally in on- and offline wallets and even on paper, acting as a store of value. All cryptocurrencies are tradable on exchanges for other cryptocurrencies, regular currencies and other products like futures. Buying can be done via online exchange offices like Bitonic, Litebit or Anycoindirect[4] or via exchange platforms, where buyers and sellers meet. Examples are Coinbase, Kraken and Huobi[5]. Lastly, cryptocurrencies can be bought peer to peer via online marketplaces like Localbitcoins[6]. Trading of cryptocurrencies happens via specialised exchange platforms like Binance, Bittrex and Bybit[7]. Cryptocurrencies and especially Bitcoin are also broadly accepted to be exchanged for goods or services (e.g. at Wikipedia or Microsoft). Hence, it can be seen as a medium of exchange in many aspects. Lastly, cryptocurrencies denominate the value of assets. Although the last point is debatable, the face value of a cryptocurrency can be denominated by a regular currency and a currency like Bitcoin can represent the value of an object like a house[8]. Ali et al. (2014) disagree about the unit of account, but it can be argued that the evidence from 2014 is

[4] www.bitonic.nl; www.litebit.eu; www.anycoindirect.eu
[5] www.coinbase.com; www.kraken.com; www.huobi.com
[6] www.localbitcoins.com
[7] www.binance.com; www.bittrex.com; www.bybit.com
[8] www.cryptoemporium.eu/category/property

outdated. Despite that most cryptocurrencies could suffice as money nowadays, Bitcoin is the most prominent example. It was developed with the pure goal of being a digital alternative to regular currencies. As shortly highlighted in the introduction, other cryptocurrencies like Ethereum, Ripple and Monero aim in a different direction. They make use of blockchain technology to base their concepts and applications on. Buying any of these cryptocurrencies is more like buying a stock in a company. Hence the focus on Bitcoin within this research. Potentially, other cryptocurrencies could be used to test if Bitcoin indeed is the best cryptocurrency for an investor to resort to.

2.1.2 Pricing of Cryptocurrencies and its Determinants

Athey, Parashkevov, Sarukkai and Xia (2016) conclude from their research that cryptocurrencies, and specifically Bitcoin, are priced based on economic fundamentals. In principle this implies the pricing relies on supply and demand, similar to any other regular currency. For Bitcoin, Athey et al. (2016) state it comes down to the fundamentals of “steady state transaction volume” and the “evolution of beliefs about the likelihood that the technology survives”. Both concepts refer back to a traditional determinant of regular currencies, supply and demand. Steady state transaction volume comes down to the ratio of transaction volume to the supply in a steady state, the evolution of beliefs concerns the user (not investor) rate of adoption and level of demand. Since cryptocurrencies are digital assets within a developing market a lot of cryptocurrency-specific determinants of pricing are found in literature. These factors include attractiveness for investors and users, market sentiment, the adoption rate by exchanges and stores, costs and rewards of the production of a cryptocurrency, regulations and governance. These factors are determinants for the price via the supply, demand or both.

Ciaian, Rajcaniova and Kancs (2016) findings support attractiveness as an important determinant for Bitcoin pricing. According to them, the attractiveness of a cryptocurrency for investors and users is determined by the transaction and information search cost. An investment opportunity with a lot of media attention may be preferred by investors as search costs are reduced. Essentially, a large part of the attractiveness determinant is the overall market sentiment measured by the news sentiment. Many theoretical models have been made to capture the market sentiment derived from news. Two known examples are those of Barberis, Shleifer and Vishny (1998) and Baker and Wurgler (2007). Whereas the first model focuses on the under- and overreaction of investors to news and the second on the actual measuring of investor sentiment, both models agree that market sentiment has an important and clear effect on the stock market. This theoretical foundation also holds for assets like options (Zghal et al., 2020) and futures (Gao & Süss, 2015; Smales 2014). The frameworks are derived from empirical data. Currently, empirical evidence supporting these foundations is found for the asset class of cryptocurrencies. Those researches mainly concern analysis of search machine data. Urquhart (2018) finds that the interest for Bitcoin is much higher when volatility, volume and returns were high for Bitcoin one or two days before, an example of short term market sentiment. Puri (2016) finds that a long term public interest in Bitcoin has a long term positive impact on the prices of Bitcoin. The interest is measured by the amount of Google searches on the term “Bitcoin”. Polasik et al. (2015) even goes as far as stating the popularity and sentiment in news to be one of the main drivers for Bitcoin prices in general. In short, market sentiment is and has been a big influence on pricing of assets, and it might even play a more important role for cryptocurrencies compared to other assets because of the digital nature of the asset.

The next determinant for cryptocurrencies is the adoption rate. Hilleman and Rauchs (2017) estimated the number of unique and active cryptocurrency users to be between 2.8 and 5.8 million in 2017. Estimates in 2020 range from 35 to 70 million users[9]. Theoretically seen, this or any growth in demand could resemble an increase in prices. This is in line with the effect of demand on price as described earlier. Theoretical research into this phenomenon for cryptocurrencies is still in its starting phase. However, current adoption scenarios for several countries and operating fields have already been looked into. Examples for country-specific research are Henry, Huynh and Nicholls (2018) researching actual awareness and usage of Bitcoin in Canada and Schuh and Shy (2016) looking into consumers' adoption and use of cryptocurrencies in the US. Both papers report similar figures, the majority of people know about the existence of cryptocurrencies but only a very small percentage own it. Thus, the adoption rate from consumers is low. One of the reasons given to explain this phenomenon is that consumers may view cryptocurrencies primarily as financial investments rather than a payment option, for example due to their volatility. It can be concluded that the impact on prices from the adoption rate of consumers is expected to be low, which leaves the commercial side. Jonker (2019) finds that the acceptance of cryptocurrency payments in her sample of online retailers is about 2%. Consumer demand is found to be one of the major influences on the adoption rate. The research confirms a current lack of consumer demand, as was found by the previous studies, and concludes it is unlikely that the adoption rate from the commercial side will increase considerably in the near future because of it. In short, reports with market penetration estimates like those of Cryptosearch[10] might be overvaluing the actual rate of adoption for the foreseeable future. Currently, the adoption rate is not of importance to the prices of cryptocurrencies, although this is able to change within a decade (Jonker, 2019).

Making use of the blockchain involves another aspect which might influence the pricing of a cryptocurrency, namely the cost and reward structure. Costs are made to mine a cryptocurrency and rewards are given to verify transactions on the blockchain (Nakamoto, 2008). Hayes (2017) finds empirical evidence that supports the important role of the cost and reward structure of bitcoin. Again, theory about this new concept is just starting to be developed. The drivers of value related to the cost and reward structure are found to be the amount of competition between producers, the rate of production and the difficulty of the mining algorithm (Hayes, 2017). As adoption rate would impact the demand side, the cost and rewards structure impacts the supply. More competition between miners and increased difficulty for mining both imply higher costs, less supply and therefore will increase prices. A low rate of production causes less supply, which in turn will drive prices up. Ma, Gans and Tourky (2018) highlight this by showing a highly positive correlation between the difficulty of mining and the Bitcoin exchange rate. Recently developed equilibrium pricing models like those of Biais et al. (2018) also support these findings by including the cost structure for miners in their pricing models.

[9] https://cryptoresearch.report/crypto-research/the-status-of-cryptocurrency-adoption/
[10] https://cryptoresearch.report/crypto-research/the-status-of-cryptocurrency-adoption/

Lastly, there is the impact of regulations and governance on cryptocurrency prices. Regulations for cryptocurrencies come from not only governments, but also from service providers like exchanges. The type of regulation, its timing and its reach all seem to cause big changes in its impact. Pieters and Vivanco (2017) for example, find systematic price differences in 11 bitcoin markets. Since the principle of Bitcoin is the same around the globe, the differences can only be derived from market attributes. They conclude that some forms of regulations can have a significant impact on pricing. In their case the focus is on the "know-your-customer" (KYC) procedures. These KYC procedures have been introduced by exchanges in order to prevent scamming and phishing, this is accomplished by having to identify yourself with a photo and an ID card or passport. A regulation with big impact, since most big exchanges enforce it and then the consumer has to perform a considerable amount of extra actions before being able to access the exchange. Pieters and Vivanco (2017) conclude that regulations enforced by parties like exchanges have an impact on the prices of cryptocurrencies that can not be ignored, while governmental regulations do not have a significant impact. Park, Tian and Zhao (2020) confirm this conclusion and find that governmental regulations have a really short term, negligible effect on prices over all. However, they add governmental regulations that have an impact on prices for local markets. The market of cryptocurrencies like Bitcoin is global, thus a government of a country enforcing regulations is perceived as local. Investors might sell off their bitcoins and other cryptocurrencies as a response to newly imposed local regulations, but Park, Tian and Zhao (2020) measure this has no impact on the actual price. The event of a selloff would also be too short to make any impact. To conclude, Bitcoin prices are globally determined and not influenced by local regulations. Other parties than governments, like exchanges, can however impact prices with their regulations.

2.1.3 Volatility of Cryptocurrencies and its Determinants

Interestingly, pricing models for Bitcoin use the assumption that the volatility of Bitcoin is unrelated to its fundamentals. For example, the earlier mentioned equilibrium model of Biais et al. (2018) assumes: "The model emphasizes that the fundamental value of the cryptocurrency is the stream of net transactional benefits it will provide, which depend on its future prices. The link between future and present prices implies that returns can exhibit large volatility unrelated to fundamentals." This is one of the reasons why volatility, next to pricing, is one of the unique characteristics of Bitcoin and essentially all other cryptocurrencies. Cryptocurrencies are found to be significantly more volatile than stocks (Baek & Elbeck, 2015), currencies (Baur & Dimpfl, 2017) and commodities (Klein, Thu, & Walther, 2018). Volatility is often used as an indicator for financial market-risk, therefore influencing the decision making process in investment, risk and portfolio management (Mittnik, Robinzonov, & Spindler, 2015). Lastly, high volatility relates to the concept of a high economic uncertainty (Dzielinski, 2012).

The first factors commonly researched to impact volatility are information demand and supply. They resemble the sentiment within a market, and are mostly measured by search volume (Dzielinski, 2012). Vlastakis and Markellos (2012) create a division, and measure information demand by internet search volume while supply is measured by information availability coming from financial news. Both studies draw similar conclusions. The demand for information positively correlates to the trading volume and more importantly, the volatility of stocks. Thus, in a scenario like the 2008 economic crisis, the demand for information is high at the beginning, highest at the peak of the crisis and decreases towards the end. The volatility of stocks follows this movement. Vlastakis and Markellos (2012) find evidence specifically for NYSE and NASDAQ stocks, which is supported by findings of Dimpfl and Jank (2016) in a more recent study. The relationship is also valid for stock exchanges of Norway (Kim et al., 2019), France (Aouadi, Arouri, & Teulon, 2013) and possibly many others. To conclude, for stocks search volume functions as a legitimate proxy for investor sentiment which, in turn, is useful for forecasting volatility (Joseph, Wintoki & Zhang, 2011). This relationship is also valid for other asset classes, like all commodities categories (Basistha, Kurov, & Wolfe, 2015) and foreign currency markets (Smith, 2012). Bitcoin relies on digital devices and internet connectivity, so naturally one could assume the demand and supply of (online) information and news influences market sentiment and possibly the price and volatility. This assumption is indeed supported by literature (Eom et al. 2019; López-Cabarcos et al. 2019; Lyócsa et al. 2020), the sentiment for Bitcoin contains significant information value to explain differences in Bitcoin volatility.

Next to market sentiment, trading volume impacts volatility. This finding is well documented and provides insights in the supply and demand. Granger and Morgenstern (1963) were one of the first to present evidence of the relationship between price changes and trading volume. Epps and Epps (1976) elaborate and find a positive relationship of volume and volatility for a set of stocks. Sinha and Agnihotri (2014) research small, medium and large indices of stocks and find relationships for all index sizes, although not all in a similar direction. Next to stocks, Batten and Lucey (2010) find evidence of the impact of trading volume on volatility for futures. In the futures market, sudden increases in trading volume have a large positive effect on volatility. The relationship is bidirectional and interestingly, asymmetric (Bessembinder & Seguin, 1993). Research into the futures markets includes commodity futures like oil and gold, since they are of most practical use to investors instead of analysing commodity prices directly. Research into the options market also confirms the relationship (Sarwar, 2003). Interestingly, in the bond market evidence is found that volatility is a determinant of trading volume, and not the other way around (Alexander, Edwards, & Ferri, 2000). It is argued that bond return volatility reflects differences in views of investors, which causes an increase in speculative trading. This seems very plausible, as the market dynamics and internals of the bond market function differently than other asset classes like stocks. Finally, studies researching Bitcoin reach contrasting conclusions. With respect to each other, but also with respect to the research into the other asset classes. Referring back to the research of Granger and Morgenstern (1963), a Granger causality study shows no evidence that changes in volume of cryptocurrencies impact volatility in any way (Bouri, Lau, Lucey, & Roubaud, 2019). A quantiles based approach, which also tests for causality, confirms this finding (Balcilar, Bouri, Gupta, & Roubaud, 2017). On the other hand, research aimed to forecast volatility does identify a link between volume and volatility (e.g. Dyhrberg, 2016; Stråle, Johansson, & Tjernström, 2014). The (GARCH) models employed in these studies require a frequency match between response and explanatory variable, thus eliminating other potential explanatory variables from the research. This may be a reason why a relationship is found. Also, in contrast to the bond market, it is found that speculative trading does not directly influence the volatility of Bitcoin (Blau, 2017). To conclude, in contrast to other asset classes there is no definitive verdict on the impact of volume on the volatility of Bitcoin.

Naturally, there are many smaller, less researched or indirect effects that can impact volatility. An interesting example for Bitcoin are spillover effects. Generally, it is proven the volatility of an asset class like stocks (S&P500) can impact the volatility of another asset class like oil or gold commodities (Mensi et al. 2013). These are so-called cross-market volatility spillovers. For Bitcoin however, no convincing spillover effects have been found. Not in stocks markets, futures or currencies (Qarni et al., 2019; Trabelsi, 2018). Even a non-asset class like economic policy uncertainty does not have an effect on the volatility of Bitcoin (Wang et al., 2019). Spillover effects that do exist are not cross-market, but within the cryptocurrency market. For example, Gillaizeau et al. (2019) finds spillover effects from the BTCUSD to the BTCEUR pair and Katsiampa, Corbet and Lucey (2019) find bi-directional effects between Bitcoin, Ether and Litecoin. These findings are in line with a finding of Baek & Elbeck (2015), namely that Bitcoin's volatility is mostly created internally. It implies volatility is largely influenced by fluctuations in volume (supply and demand), as described previously. In short, the lack of spillover effects imply Bitcoin and cryptocurrencies in general are very detached from any other asset class. It should be noted that with further development and integration of Bitcoin it may impact other asset classes in the future (Qarni et al., 2019).

Next to the literature, empirical evidence confirms that the volatility of Bitcoin is extremely high, and incomparable to any other asset. Many cases can be found where the market becomes more volatile due to new information, changes in volume or spillover effects. Information can be either positive news like partnerships and developments, or negative like security breaches, failures to deliver on time or an uncertain outlook. Some major examples are the Mount Gox hack[11], tweets from influential people or reactions to uncertainty within other asset classes. Mount Gox was one of the only exchanges for Bitcoin, handling 70% to 80% of all volume in its prime in 2013[12]. Naturally, when the hack took place in 2014 the overall market volume dropped drastically. As trading largely halted, the volatility fluctuations cooled down as well. The volatility index of Bitcoin[13] shows peaks of 15% of standard deviation from daily returns of the previous 30 days. After the hack happened at the end of March 2014, next month the volatility peaked out at a maximum of only 4.28%. Next, Bitcoin news influencing the sentiment revolves largely around developers, regulations and governments. When Donald Trump gives attention to Bitcoin, in the form of tweets for example[14]. The market reacts strongly in many cases and volatility increases. Other examples are news from developers like Ethereum creator Vitalik Buterin[15], or influential figures within the crypto-scene like John McAfee[16]. Lastly, uncertainty in stock the market can also cause an increase in volatility for Bitcoin[17]. Although the literature does not confirm the linkage, it often happens that the volatility increases of a stock market is

[11] https://www.ledger.com/hack-flasback-the-mt-gox-hack-the-most-iconic-exchange-hack
[12] https://www.investopedia.com/terms/m/mt-gox.asp
[13] https://www.buybitcoinworldwide.com/nl/volatiliteits-index/
[14] https://www.cnbc.com/2019/07/15/bitcoin-price-falls-below-10000-as-president-trump-slams-crypto.html
[15] https://www.trustnodes.com/2019/12/16/vitalik-buterin-crashed-ethereums-price-blockchain-analysis-shows
[16] https://news.bitcoin.com/survey-finds-john-mcafee-is-most-influential-crypto-trading-figure/
[17] https://www.forbes.com/sites/youngjoseph/2020/06/11/3-crucial-factors-why-bitcoin-price-plunged-from-10160-to-9000-in-28-hours

linked to a volatility increase of Bitcoin. Naturally, all the evidence can never be linked with full certainty to a price or volatility movement, but examples like the Mount Gox hack are evident.

Interestingly, in 2015 Baek & Elbeck (2015) stated that if Bitcoin gets widely adopted the volatility is expected to drop, creating better investment opportunities. The speculative nature would decrease. This statement was made in 2015, and while volatility dropped massively before 2015, it never did after. Klein et al. (2018) state volatility will remain high as long as future developments and the direction of Bitcoin is unclear. As Bitcoin has not taken a definitive position in the market yet, this might very well hold through for the foreseeable future.

2.1.4 Correlation of Cryptocurrencies with Other Assets

The Oxford dictionary defines correlation as a mutual relationship between two or more things[18]. In this case, the return or volatility of one financial asset can correlate with another financial asset's return or volatility. Correlation is a measure of strength, thus a correlation can be weak, moderate or strong. Correlation can show the options of incorporation in an investment portfolio. Performance in different circumstances and compositions can be studied. Correlation can exist across asset classes, across different markets of the same asset or within the same market. These three categories will each be discussed.

Firstly, asset classes like commodities, stocks, bonds or currencies can have a correlation with each other. The return correlation of stocks and bonds has been the most relevant and researched correlation. As equity is bought with stocks and debt is bought with bonds, they pose hedging possibilities for an investment portfolio. Yang, Zhou and Wang (2009) analyse the negative stock-bond correlation from the past 150 years. This correlation reflects the degree to which bonds are able to function as a hedge against the risk of an economic crisis. This is the case when considerable amounts of equity are sold off in a crisis. Yang, Zhou and Wang (2009) identify different patterns in this relationship throughout their sample period. One of their findings is that bonds are a better hedge against stocks in the United States than in the United Kingdom. Two other historically important correlations are those of oil and gold with the USD. The correlation between WTI crude oil prices and the USD has been both positive and negative in the past, but since the economic crisis from 2008 it has been a statistically significant inverse relationship (negative) (Grisse, 2010; Reboredo, Rivera-Castro, & Zebende, 2014). The same negative relationship holds for gold and the US dollar (Capie, Mills, & Wood, 2005). Clements and Fry (2008) go further and conclude that in the sample period of 1975 to 2005 a relationship for commodities and currencies in general exists. They state that currencies are driven by commodities, but also the other way around. For Bitcoin however, evidence suggests the opposite: Bitcoin does not correlate with any other asset class. It mostly depends on the chosen sample period and scope of the research. Baur, Dimpfl and Kuck (2018) show that Bitcoin returns and volatility are unique and uncorrelated to the commodity gold, the currency pairs USD/EUR and USD/GBP, and stock market indices MSCI World and FTSE100. The inclusion of all of the asset classes extends further evidence for correlation between the classes, as all exchange rates are found to be correlated with all other asset classes except with Bitcoin.

[18] https://www.lexico.com/definition/correlation

Aslanidis, Bariviera and Martínez-Ibañez (2019) confirm this finding in even more recent research, and state correlations between Bitcoin and other assets are negligible.

Assets of the same class can also correlate when they are in two different markets. An example is a stock market's correlation with a stock market from another country. Solnik, Boucrelle and Le Fur (1996) provide the example of leading countries in the European Union like Germany and France. They have stock (bond) markets that correlate, as their economies are to some extent dependent on each other. Also, most of the world's stock (bond) markets tend to mimic behaviour of the stock (bond) market in the United States. Solnik, Boucrelle and Le Fur (1996) state that international correlation tends to increase in periods of high market volatility. Chui and Yang (2012) add evidence of a positive, strong stock–bond correlation when the futures markets of two countries are extremely bullish or bearish (in this case the United Kingdom and the United States). For commodities the correlation between assets is also an important factor. Two of the main categories of commodities are agriculture and energy. Saghaian (2010) researched the oil–ethanol–corn linkage, the chain used for the creation of biofuels, and found there is a strong price correlation between oil and other commodity prices. Naturally, more of these kinds of relationships exist. Pindyck and Rotemberg (1990) even go as far to state correlation between commodities in different markets goes beyond the effects of values or macroeconomic variables. For Bitcoin, the situation is totally different. As a digital currency Bitcoin is available globally. Therefore, Bitcoin, Bitcoin-based derivatives and other cryptocurrencies are viewed as having no correlation between different markets.

Since the cryptocurrency market is a single, global market, currencies could correlate with each other. Especially since the volume of the Bitcoin accounts for a large portion of the trading volume within the cryptocurrency market as a whole[19]. Other cryptocurrencies could follow the price and volatility movements of Bitcoin. This occurs in some stock markets, indices like the CSI300 (Wang et al., 2013) and the NASDAQ (Manimaran, Panigrahi, & Parikh, 2008) are found to have correlating assets. For the cryptocurrency market, research shows positive correlations between cryptocurrencies (Aslanidis et al., 2019; Burnie, 2018). Mixed pairs consisting of some of the largest cryptocurrencies based on volume are researched, for example Bitcoin, Ripple, Dash and Monero. Burnie (2018) also finds positive correlations for forks (independent branches) of original cryptocurrencies, like Ethereum and Ethereum Classic. There are two practical purposes to make use of correlations between cryptocurrencies. Firstly, some cryptocurrencies could potentially be hedged against, like Katsiampa (2019) suggests can be done with Ethereum against Bitcoin. Secondly, an investment portfolio might benefit from incorporating multiple cryptocurrencies for the purpose of diversification and thus, risk mitigation. The possibilities of Bitcoin in an investment portfolio are further explored in chapter 2.4.

2.2 Economic Uncertainty

Economic uncertainty can be quantitatively measured by numerous indicators and models. For example by the number of internet searches (Dzielinski, 2012), stock market volatility (Bloom,

[19] https://coin360.com/charts

2009) or corporate bond spread (Bachmann, Elstner & Sims, 2013). Examples of more elaborate measures are factor-based estimates of macroeconomic uncertainty composed by Jurado, Ludvigson and Ng (2015) and lastly, with help of an economic policy uncertainty index as created by Baker, Bloom, Davis (2016). As can be derived from these indicators, economic uncertainty mostly involves unpredictability, volatility and a possible negative regional, national, continental or even global economic effects. However, uncertainty is difficult to quantify, it can not be directly observed and is partly based on subjective assumptions. This is shown by all the different measures that researchers have used. In this chapter, the focus is on the countries important for this research and it is explained why an increase in uncertainty took place.

In case of Brexit, the United Kingdom (UK) is impacted by economic uncertainty as they are leaving the European Union (EU). Their economic direction, stability and future became less secure and obvious leading up to the voting moment and of course, afterwards. Begg and Mushövel (2016) address some of the factors causing economic uncertainty. For example, the loss of GDP, decreasing amounts of investments, the height of the transition cost to leave, the fear of high currency volatility and strong reactions from the financial markets. Busch and Matthes (2016) add another important issue, namely the import and export. The UK could potentially benefit by having less regulatory constraints, but as most trading is done with EU countries it could imply higher costs and longer duration for import and export. Tetlow and Stojanovic (2018) agree on the trading issues and add less foreign direct investments and decreased productivity will have long term effects as well. On the other hand, Brexit might also impact the EU. The same factors play a role but are carried by the EU member countries together, naturally it will have a much weaker impact. Lastly, the increased volatility of the GBP and high media attention make it a viable candidate to analyse with respect to safe haven property testing. Since the Euro is supported by many countries the impact is expected to be insignificant to create any need for a safe haven. Therefore, only the GBP will be included in the research.

The trade war between the United States and China has similar characteristics of increased economic uncertainty. The so-called Trump tariffs were introduced, and China was a target in specific. A list of 1300 goods getting extra taxes was published as a first measure[20]. Whereafter retaliation measures from the Chinese government were announced and the trade war began. The severity to the economy and duration of this conflict is difficult to predict beforehand as well as during, this is what introduces economic uncertainty. Chong and Li (2019) state that the worst case scenario for China could be a 1% loss in GDP and a 1,1% loss in employment. Both Chong and Li (2019) and Li, He and Lin (2018) conclude that China will be significantly hurt, but are able to cope with the negative effects well. The authors also agree that negative effects for China will be more than those of the US. The US will be most hit in its trading (im- and export), but is technically able to compensate for this loss with the import tariffs and raising employment rates. Finally, just like with the GBP characteristics like high media attention and increased volatility of both the USD and CNY make these currencies viable candidates to analyse with respect to safe haven property testing for Bitcoin.

[20] ustr.gov/sites/default/files/files/Press/Releases/301FRN.pdf

2.3 Hedge and Safe Haven

Baur and Lucey (2010) and Baur and McDermott (2010) describe and define the concepts of a hedge and safe haven thoroughly. These definitions are commonly used for research into hedging and safe havens. A safe haven is defined as an asset that investors purchase when uncertainty increases. The price of a safe haven asset is not supposed to move similarly to the asset in question, especially in times of uncertainty.

- A strong safe haven is negatively correlated with another asset or portfolio within a specific time period.
- A weak safe haven is uncorrelated with another asset or portfolio within a specific time period.

The specific time period in this case being the period of increased economic uncertainty which is pre-selected in this research. Essentially, a safe haven can be called the best hedge in a certain time period. Thus, a hedge is almost the same, but is uncorrelated or negatively correlated with another asset on average, instead of within a specific time period. On average, the correlation of a hedge to another asset could potentially change in times of high uncertainty, for example from a negative to a positive correlation.

- A strong hedge is an asset that is negatively correlated with another asset or portfolio on average.
- A weak hedge is an asset that is uncorrelated with another asset or portfolio on average.

There is a wide array of examples where hedging and safe haven capabilities of stocks, bonds, currencies and commodities have been identified. The most prominent and relevant examples will be given in this chapter. They are the traditional safe haven gold, currencies and finally evidence that has already been found regarding Bitcoin and cryptocurrencies.

One of the most important commodities for research regarding hedging and safe haven possibilities is gold. It is the traditional safe haven in times of economic uncertainty. Bitcoin is quite often proposed to be the “new gold”, as it could have the same potential with its distinct characteristics. Many applications for gold have been found throughout the years. For example Joy (2011) found evidence that gold has functioned as a direct hedge against the US dollar from 1986 to 2008, while gold currently acts as a hedge against the currency risk inherent to the US dollar. Moreover, gold can also act as a hedge against stocks and functions as a safe haven in extreme stock market conditions (Baur & Lucey, 2010). Gold can also be a safe haven against other commodities, like extreme oil price movements (Reboredo, 2013a).

Next, the hedge and safe haven possibilities for currencies are important for the scope of this research. Investing in foreign securities with a foreign currency brings extra risk. The exchange rate of both the local as well as the foreign currency can fluctuate, thereby influencing the investment result. A currency swap can be used to hedge against a foreign investment (Takezawa, 1995), where two parties swap their foreign currency risk to local currency while paying an interest rate. One could also buy a currency future in order to lock down a minimum price for the foreign currency. Next to these non-scientific standard hedging procedures, some studies show evidence that hedging with a currency is possible. Tachibana (2018), shows that hedging with a foreign currency against a local stock market is possible. Examples are hedging against the stocks of the European market with the Swiss Franc and for stocks from the United States market the Japanese yen is used as a safe haven ánd a hedge.

Most importantly, evidence has been found about the possibilities of using Bitcoin as a hedge or safe haven. Kliber et al. (2019) find evidence that Bitcoin can act as a safe haven asset. This was the case for Venezuela and investment in Bolivars from 2014 to 2017. They diversified their research by picking the countries Estonia, Venezuela, Japan, China, Sweden to analyse, due to their diversity in stock markets, currencies and economic well-being. Only the extreme economic situation in Venezuela showed possibilities for Bitcoin as a safe haven. Urquhart and Zhang (2018) use a similar stochastic volatility approach but focus on intraday analysis. They find evidence that Bitcoin can function as a safe haven during periods of high market uncertainty for the currencies CAD, CHF and GBP.

Lastly, it is important to note that besides a hedge and safe haven, the function of diversifier exists. Baur and Lucey (2010) define a diversifier as an asset that is positively (but not perfectly correlated) with another asset or portfolio on average. Essentially its properties are the same as a hedge, but the correlation sign is different. Since a diversifier is defined on an average as well, it is possible that a correlation with another asset can change in times of turmoil, similarly to a hedge. The diversification aspect is less important for the purpose of this research and therefore not extensively discussed.

2.4 Cryptocurrency Performance in a Portfolio

Investors most likely have a portfolio of investments instead of a single asset that needs to be hedged. Literature is divided about the performance of Bitcoin within a portfolio, mostly due to what its particular function within a portfolio can or should be. Although the previously mentioned studies of Kliber et al. (2019) and Urquhart and Zhang (2018) show safe haven possibilities, these are in one-to-one relation with a currency. For a whole portfolio of assets the incorporation of Bitcoin might have different effects. Although it is not the goal of this research, it is an important practical aspect that should not be disregarded. Characteristics like extreme volatility and the lack of correlation to any other assets make Bitcoin difficult to assess for portfolio incorporation. This is exactly what Klein et al. (2018) confirm: Bitcoin has no hedge possibilities against any equity investments so there is no function within a portfolio other than the diversification of (risky) assets. However,this statement might be extreme, as several arguments can be made as to why Bitcoin could be integrated.

Evidence is found that Bitcoin can positively influence the risk and return ratio of a portfolio. Eisl, Gasser and Weinmayer (2015) find Bitcoin can positively affect the risk-return ratios of an optimal portfolio. This implies that Bitcoin’s high risk and high return profile can actually be used to the benefit of investors. The approach used is the conditional value-at-risk framework. Compared to the most applied mean-variance approach it does not depend upon assets being normally distributed, as is the case with Bitcoin. Investing with Bitcoin does increase the value at risk of the optimal portfolio, but is compensated by the significantly higher returns of Bitcoin. The risk-return ratio is therefore higher. A drawback of this method is presented by Aslanidis et al. (2019). The return and standard deviation are large compared to the other assets in a portfolio, a small portion of cryptocurrency has the possibility to dominate the stochastic dynamic of the whole portfolio. In an optimal portfolio however, this should and can be accounted for simply by making accurate divisions. Since the risk and return profiles of other cryptocurrencies are similar, it is likely this finding is valid for several of the cryptocurrencies with a large market capitalization.

The second argument which can be made for the inclusion of Bitcoin or another cryptocurrency in a portfolio, is the solution of using multiple cryptocurrencies. To mitigate the exposure to the stock market, a portfolio generally contains a variety of stocks, the same can be done with respect to the cryptocurrency market. Brauneis and Mestel(2019) study the usage of a portfolio incorporating several cryptocurrencies, instead of relying solely on Bitcoin. They find it has the potential of significant risk minimization. This offers options for investors who do not want to take the high risk of the incorporation of a single cryptocurrency like Bitcoin. Liu (2019) confirms this finding by showing that portfolio diversification across different cryptocurrencies can significantly improve the investment results.

To conclude, there are multiple plausible ways to include Bitcoin or other cryptocurrencies in a portfolio which lead to better performance on average. The distinct characteristics of distribution, the risk and return profile, volatility, returns and correlation will lead to substantial implications for portfolio and risk management as well as financial engineering (Osterrieder & Lorenz, 2017).

2.5 Hypotheses

Due to a similar research design from aforementioned papers like Kliber et al. (2019), it is likely that Bitcoin has the potential to act as a weak or a strong safe haven for the USD, GBP and CNY in times of economic uncertainty. The impact of economic uncertainty for these currencies is expected to be lower compared to the Bolivar, as the USD, GBP and CNY have more volume and historic data showing more stability over longer periods of time. Bitcoin reached its first peak in price in 2017, and has broken that peak in 2020 again. Thus, using newer data may differentiate the results heavily. Especially concerning the trade war period with dates ranging from 2018 to 2020, the sample has little overlap compared to similar research which has been conducted with samples from before 2018. Another important aspect as to why Bitcoin or other cryptocurrencies can function as a safe haven is that people are looking for alternative safe havens. J.P. Morgan reported in 2019[21] that bonds still play a significant role as safe haven within a portfolio and gold is still a store of value to hedge against stock volatility, but alternatives are often looked at. As described in the previous chapters, cryptocurrencies are also often deemed to be a store of value, have a limited correlation to other assets and are independent from monetary policies, thus seeming like a natural alternative to consider. J.P. Morgan supports this and finds evidence that institutional investors are getting involved, as money flows out from gold exchange traded funds (ETF's) and into Bitcoin Trust funds[22]. One of the main reasons is that Bitcoin has long-term upside potential when more parties start considering it compared to gold. The performance of cryptocurrencies are closely monitored in

[21] https://am.jpmorgan.com/content/dam/jpm-am-aem/global/en/insights/portfolio-insights/ltcma/ltcma-rethinking-safe-haven-assets.pdf
[22] https://www.coindesk.com/family-offices-may-now-see-bitcoin-as-alternative-to-gold-jpmorgan-report

events like the covid-19 bear market, as uncertainty is high and a next economic crisis can start at any moment.

The first hypothesis concerns the effect of Brexit on the price and volatility of the GBP, consequently impacting the possibility of Bitcoin functioning as a safe haven for the GBP. Evidence of Brexit's effect on currency price is found in many forms. Alvarez-Diez, Baixauli-Soler and Belda-Ruiz (2019) find a loss in correlation between the sterling pound and euro due to Brexit. When looking at the pound compared to the euro, a sharp depreciation is seen directly following the events of voting on 23rd of June in 2016 and the announcement to proceed with Brexit on the second of october 2016 (Gourinchas & Hale, 2017). Plakandaras, Gupta and Wohar (2017) conclude most of the depreciation is caused due to economic uncertainty. Due to the uncertainty, British people are stuck with a weakened currency compared to other currencies with global impact like the Euro. Meanwhile foreign investors run extra risk with investments and trades denominated in GBP. Therefore, Brexit creates the liable scenario that Bitcoin can significantly function as a safe haven for the GBP leading up to the date of voting and in the years of uncertainty after. The first hypothesis is:

H1: Bitcoin is a safe haven for the GBP during the Brexit period.

The second hypothesis concerns the effect of the trade war on the price and volatility of the USD, which also impacts the safe haven properties of Bitcoin as a safe haven for the USD. The USD exchange rate largely influences prices and volumes worldwide (Boz, Gopinath, & Plagborg-Møller, 2017). Therefore, many investors would benefit by having some form of a safe haven for this currency. Furthermore, the trade war (partly) influences the performance of the U.S. economy and trade is decreasing. This boosts concern about the dollar as the global primary reserve currency. If the dollar loses ground as an international currency, there is no question the dollar will depreciate significantly (Siddiqui, 2020). Therefore, it is expected that the possibility of Bitcoin functioning as a safe haven for the USD is significant during the trade war period.

H2: Bitcoin is a safe haven for the USD during the trade war period.

The last hypothesis concerns the effect of the trade war on the price and volatility of the CNY, which also impacts the safe haven properties of Bitcoin as a safe haven for the CNY. As China is on the other side of the trade war, a similar scenario for this hypothesis is valid. A difference is that China does not have a world-leading currency, yet. The CNY has depreciated more than 7% compared to the US dollar over the course of 2019 and the trade war undermines confidence in China's economic outlook. The importance of CNY has been steadily increasing for global trading, which will in time challenge the current position of the US dollar (Chong & Li, 2019). The introduction of economic uncertainty and the CNY challenging the position of the US Dollar may raise practical interest for a safe haven possibility. It is expected that Bitcoin can significantly function as a safe haven during the trade war period.

H3: Bitcoin is a safe haven for the CNY during the trade war period.

3. Methodology and Data

All aforementioned research papers regarding safe haven properties of any asset use a form of regression analysis. They range from implementing a simple regression model to using more extensive models. In this chapter the data sources and sample periods are defined. Then, the best fitting research design is picked following the methodologies of comparable research, keeping in mind this dataset and specific application. It is determined which preliminary tests need to be conducted to identify which approach is applicable to the dataset. Simple linear regression, the standard GARCH approach and its more extensive variants like DCC-GARCH are reviewed. Lastly, posterior tests are added to validate and robustize the main analysis.

3.1 Data collection

Daily price data of the US dollar, Chinese yuan and British pound is gathered from a single source for consistency. The selected source is the official pricing data published by the European Central Bank[23]. The price is sampled at the same hour every day. Commonly, similar research denominates currencies in US dollars (Urquhart & Zhang, 2018). Since the dollar is included for this research the Euro (EUR) is chosen. The euro is the second biggest currency based on volume, after the dollar[24], which makes it most applicable as a common denominator. The price of bitcoin is correctly reflected if data is gathered from exchanges that are the biggest in terms of volume and liquidity. These might differ per country, as not all exchanges are available or similarly preferred around the world. Trading data from the global exchanges like Coinbase, Bitfinex, CEX.io and Bitmex are widely available. The daily price of Bitcoin is obtained via Yahoo Finance[25], which averages a large portion of these big exchanges with data from Coinmarketcap[26]. To avoid any (bias) issues in the analysis, Bitcoin is chosen to be denominated in euros. Since Bitcoin is traded continuously, the data has to be synchronized to that of the currencies. For the reason that interpolation causes bias in the model estimation (Klein et al., 2018). Therefore, weekends are left out and the data is sampled daily at the same hour as the currencies. The data for Ethereum, Litecoin and Ripple is also gathered following this approach. The daily historical price data for gold is retrieved from investing.com[27]denominated in euros.

The start of the period of economic uncertainty for the GBP is largely determined by the date the Brexit referendum was held, namely the 23th of June in 2016. On the 31st of January in 2020, the United Kingdom officially left the European Union, but is still in its transitional period[28]. The years in between mark a period of high uncertainty. Economic uncertainty was already introduced a couple of weeks before the referendum, since voting polls made clear beforehand the results were going to be close to a tie. Therefore the first of June in 2016 is picked as a starting point of the sample period. Also, the withdrawal agreement was fully set before January

23 http://sdw.ecb.europa.eu/
24 https://www.bis.org/statistics/rpfx19_fx.pdf
25 https://finance.yahoo.com/quote/BTC-EUR/history/
26 www.coinmarketcap.com
27 https://nl.investing.com/currencies/xau-eur-historical-data
28 https://www.government.nl/topics/brexit/brexit-where-do-we-stand

2020, therefore the end of the sample period is the 31st of December 2019. The sample period has a length of three years and seven months. Next, the start of the period of economic uncertainty for the dollar and yuan is just before the date the trade war was initiated with sanctions introduced by Donald Trump, on the 22nd of January in 2018 the first tariffs were accepted[29]. Therefore, the first of January is taken as a starting point for the sample period. Throughout the start of 2020, exemptions on tariffs were made from both sides, also with eye on the COVID-19 pandemic[30]. Although the trade war is far from over, the period with the highest economic uncertainty introduced by the trade war ended when COVID-19 became the main priority. Therefore, the end of the sample period is chosen to be the first of January of 2020, providing a sample period of two full years.

The sample size for Bitcoin and the pound of three years and seven months leads to 936 data entries. The sample size for Bitcoin, the dollar and yuan leads to 523 data entries. Hwang and Valls Pereira (2006) recommend using a sample of at least 500 observations for GARCH models. Ng and Lam (2006) find using around 1000 samples leads to the most accurate results in general. This is one of the reasons why daily sampling is chosen, the amount of observations is close to ideal and higher than the recommended minimum. Choosing to conduct an intraday analysis would change the scope of the research to extremely short term safe haven property testing. The effects of choosing a sample size which is too large are still unknown, but it could be expected there are drawbacks for safe haven testing as data will be smoothened. On the other hand, weekly or monthly intervals would imply the specific focus on a period of high economic uncertainty is not possible. Data for cryptocurrencies is also less reliable, volume is too low before 2014 and the current market dynamics have changed significantly. By using the daily interval combined with the length of the sample, the model is expected to produce the most accurate parameter estimates.

3.2 Dataset Analysis

The volatility of Bitcoin is significantly higher than the volatility of currencies, the standard deviation and variance are compared to the ones from the currencies to highlight this. Minimum, maximum and mean returns are used to further show the differences in characteristics of Bitcoin and currencies. Next, kurtosis and skewness provide insight in the distribution of the returns. A symmetrical return distribution has a skewness of zero. Following the research of Klein et al. (2018) and Urquhart and Zhang (2018) a skewness between -0.5 and 0.5 is judged as fairly symmetrical. Between -1 and -0.5 and between 0.5 and 1 the data are moderately skewed. Anything below -1 and above 1 is highly skewed. Kurtosis provides details about the tail characteristics, as it measures the extreme values in the outliers of the data. A high kurtosis implies heavy tails and thus many outliers, a low kurtosis implies a lack of outliers. A kurtosis of 0 is mesokurtic, the tails approximate the normal distribution. A value lower than 0 implies the tails are leptokurtic, compared to a normal distribution the tails are longer. A value higher than 0 implies a platykurtic distribution, where the tails are shorter than a normal distribution and the peak of the distribution is lower and shorter. To draw a statistical conclusion from the

[29] https://ustr.gov/about-us/policy-offices/press-office/press-releases/2018/january/president-trump-approves-relief-us
[30] https://www.china-briefing.com/news/the-us-china-trade-war-a-timeline/

descriptives, the Jarque-Bera (JB) test statistic is applied. The test combines the measures of skewness and kurtosis to analyse if the returns are close to being normally distributed. In general, a large JB value indicates non-normal distribution. The test statistic of the JB test is presented in Equation 1*,* where *n* is the sample size. The null hypothesis of the test is that the skewness and kurtosis are both zero. Thus, when taking a sample from a normal distribution, the test provides an outcome of 0.

$$JB = n\left[\frac{skewness^2}{6} + \frac{(kurtosis - 3)^2}{24}\right] \quad (1)$$

The data is expected to be non-normal, fat-tailed and asymmetrical. It should be noted that Baur et al. (2018) assume normal distribution for the error term and report implementation of the Student T distribution did not improve their results. Chu et al. (2017) confirm this finding by testing a wide range of distributions, and end up concluding the normal distribution to provide the best fit overall. Therefore, following Baur et al. (2018) normal distribution of the error term is assumed. Similar research into financial assets like that of Klein et al. (2018), Kliber et al. (2019) and Urquhart and Zhang (2018) all use skewness, kurtosis, the Jarque-Bera test and other general descriptives like standard deviation to analyse their sample and confirm the application of their models. They also assume a normal distribution of the error term.

3.3 Simple Linear Regression

Regression is a method used when the strength of a relationship between a dependent variable and one (simple linear regression) or more (multiple linear regression) independent variables (Draper & Smith, 1998). In this instance the regression method would be applied to currencies, as Baur et al. (2018) do for the United States Dollar and Urquhart and Zhang (2018) for the Australian dollar, Canadian dollar, Swiss franc, Euro, British pound and the Japanese yen.

$$r_{btc,t} = a + b \; r_{currency,t} + e_t \quad (2)$$

Equation 2 is a simple regression equation, and predicts the dependent variable r_{btc} (Bitcoin return) as a function of independent variable $r_{currency}$ (currency return) by fitting a straight line to the data. The slope of the line is represented as b*,* the y-intercept is a (the value of r_{btc} when $r_{currency}$ is zero), and e_t is the error term. Since the line is fitted to the data and not a direct representation, there are differences between the expected return at time *t* and the actual return as included in the dataset, the errors. To test if the hypotheses, the definition of a safe haven needs to be translated into a measure or threshold. Shahzad et al. (2020) copy the solution of Baur and McDermott (2010) and apply it to Bitcoin. They identify periods of economic uncertainty by their extreme return distribution with thresholds. The slope of line$b$at time *t* in Equation 2 is modelled as in Equation 3.

$$b_t = c_0 + c_1 D(r_{currency} q_{10}) + c_2 D(r_{currency} q_5) + c_3 D(r_{currency} q_1) \quad (3)$$

If one of the *r* values in Equation 3 exceeds a threshold given by the 10% ($r_{currency} q_{10}$) , 5% ($r_{currency} q_5$) and 1% ($r_{currency} q_1$) quantile of the return distribution, dummy variable *D* returns a value of one, otherwise zero. The parameters to estimate are c_o, c_1, c_2 and c_3. Shahzad, Bouri, Roubaud and Kristoufek (2020) follow the same definition for a safe haven as this research; if the parameters are negative, the dependent variable functions as a weak safe haven. If the parameters are negative and statistically different from zero, the dependent variable is a strong safe haven.

There are three drawbacks to using a simple linear regression approach. Firstly, Baur and McDermott (2010) explicitly state they assume the gold price is dependent on changes in the stock market. Evidence presented in this literature review suggests this is not valid for Bitcoin and cryptocurrencies in general, as they are independent and uncorrelated to changes in any asset market. Next, since the sample periods for this research are hypothesized to be the exact period of economic uncertainty, there is no need for identification of these periods within the model like in Equation 3. Lastly, and most importantly, simple linear regression assumes constant volatility over time. Periods of high volatility followed by periods of low volatility are likely to cause large estimation errors for the parameters and thus high, non-constant residual levels from the errors. The volatility of cryptocurrencies varies heavily for long periods and is unrelated to previous periods of volatility, errors arising from this phenomenon (heteroskedasticity) largely influence the accuracy and correctness of an analysis. Essentially, all research regarding hedge and safe haven properties for assets underscribe and integrate a solution to counter heteroskedasticity by using a regression approach which accounts for fluctuations in volatility. The model is called GARCH, and stands for generalized autoregressive conditional heteroskedasticity.

3.4 GARCH Model

Many GARCH model variants have been made, each countering a specific set of problems or assumptions. For financial analysis regarding cryptocurrencies Klein, Thu, and Walther (2018) use BEKK-GARCH, Baur et al. (2018) use asymmetric GARCH and Dutta et al. (2020) use DCC-GARCH, amongst many others. Each approach uses the conditional variance equation of a standard GARCH(1,1) model as in Equation 4 as foundation.

$$h_t = \omega + \alpha r_{t-1}^2 + \beta h_{t-1} \qquad (4)$$

h_t is conditional variance in Equation 4, calculated by the sum of the long term variance ω, the lagged (*t - 1)* squared return r_{t-1}^2 and the lagged conditional variance h_{t-1}. By using a GARCH model the general assumption of constant variance of the error term is avoided. Instead, conditional variance for the error term is measured by previous returns and previous variance. Thus, the aforementioned problems arising from the assumptions caused by using the simple linear regression approach are compensated, and volatility can be estimated more precisely. However, a standard GARCH(1,1) model assumes a constant conditional correlation over time; this assumption has been rejected for many financial assets (Bera & Kim, 2002). They claim the globalization of markets and increasing volatility makes it logical that correlations change over time. With respect to cryptocurrencies, these correlations could vary heavily in a much shorter time period. Parhizgari and Cho (2008) state that the dynamic conditional correlation (DCC) model proposed by Engle (2002) is able to better estimate the dynamics of the relationship over the span of a more volatile return series over longer periods. As it is expected the preliminary analysis will indeed show high volatility for Bitcoin, this approach is more suited compared to simple linear regression.

The scope and focus of this research is closest to studies using the DCC-GARCH approach. For example by Ratner and Chiu (2013) who investigate hedging of stock sector risk with credit default swaps. Another example is aforementioned Dutta et al. (2020), who use the approach to analyse the safe haven properties of gold and Bitcoin for the oil market. Urquhart and Zhang (2018) also conduct a similar analysis, they analyse intraday hedging and safe haven properties of Bitcoin. Kliber et al. (2019) analyse the effect of uncertainty in a country on the hedge and safe haven aspects of Bitcoin. Other approaches like BEKK (Klein, Thu, & Walther, 2018) overcomplicate the model with additional requirements and restrictions not fitting this research design, and have different practical purposes. DCC-GARCH results are expected to be more precise than standard GARCH results, but it does not imply general GARCH estimates would be incorrect by default. It is irrelevant for this research to review the performance of various GARCH models, a lot of research has already been conducted about this aspect (e.g. Katsiampa, 2017).

3.5 Model Specification: DCC-GARCH

The DCC-GARCH model first fits univariate GARCH(1,1) models as in Equation 4 by putting in the rate of the return for each of the assets into separate univariate models, one for Bitcoin and one for a currency. The roots of estimates h_t are put on the diagonal of conditional standard deviation matrix D_t, making the analysis bivariate. The dynamic conditional correlations are then modelled by composing conditional covariance matrix H_t with conditional standard deviation matrices D_t and time-varying conditional correlation matrix R_t, as in Equation 7. Finally, unconditional heteroskedasticity e_t is modelled as in Equation 6, where z_t are randomly distributed errors. e_t is the error term in Equation 5. A detailed description of the background of the DCC-GARCH model following the method of Engle (2002), with help from the practical elaboration of Orskaug (2009), can be found in Appendix I.

$$r_t = \mu_t + e_t \quad (5)$$
$$e_t = H^{1/2} z_t \quad (6)$$
$$H_t = D_t R_t D_t \quad (7)$$

In Equation 5, μ_t represents the conditional mean. This parameter can be modelled as constant (*c*), AR(1), MA(1) or ARMA(1,1) (Orskaug, 2009). The AR(1) term concerns the weighted average of the previous value of the series, thus μ_{t-1}. The MA(1) term concerns the weighted average of the previous errors, thus e_{t-1}. As this research focuses on the conditional variance equation which is needed to extract the conditional correlations, the conditional mean equation is only integrated to enable accurate parameter estimation within a complete model (Orskaug, 2009). After fitting all the data, the main analysis contains three separate bivariate DCC models: one for Bitcoin and the pound, one for Bitcoin and the dollar and finally, one for Bitcoin and the yuan. The conditional correlation parameter estimates are extracted from each of the models. The hypotheses for Bitcoin and a specific currency are confirmed when the average correlation value of Bitcoin and one of the currencies lies between -1 and 0, following the definition for a safe haven from Baur and Lucey (2010). To be more precise, a correlation between -0.3 and 0 is a weak negative correlation, and thus a weak safe haven. A correlation in the range of -0.7 to -0.3 is a moderately negative correlation and therefore Bitcoin is a moderate safe haven. All correlation values under -0.7 are strongly negative, and thus indicate Bitcoin functioning as a strong safe haven. An average correlation value between 0 and 1 means rejecting the hypothesis for that specific currency.

To add strength to the results and conclusion, the dynamic conditional correlation throughout the whole sample period is analysed, with help of data descriptives and graphs. For example, the conditional correlation can be largely positive throughout the sample period, but the average value can be negative due to several large outliers. This confirms the hypothesis of Bitcoin being a safe haven based on the average value, but might misrepresent the actual situation of its safe haven properties. Plotting the correlation throughout the sample period will provide a complete picture.

3.6 Goodness of Fit Testing

After the GARCH model has been employed various tests are done to check if the model captures all dynamics of the data. It is checked if the model captures serial autocorrelation arising from heteroskedasticity. Stationarity is also checked. The joint significance of the univariate models is tested and lastly, it is tested which terms in the mean equation provide the most accurate estimates for the conditional correlations, based on information criteria.

When the squared residuals of a DCC model exhibit serial autocorrelation, ARCH effects are present. It implies the model is not fitted correctly and is unable to capture the heteroskedasticity in the data. Autocorrelation can be checked visually by creating a scatter plot or histogram of the residuals, but a more precise method is using a portmanteau test, in this case the Li-Mak test (Li & Mak, 1994). Fisher and Gallagher (2012) made a weighted, improved version of the Li-Mak test. They state the goodness of fit outperforms other portmanteau tests, especially considering long-memory models. The test uses standardized residuals, obtained by dividing residuals e_t from Equation 5 by the square root of conditional variances h_t from Equation 4. The null hypothesis of the Li-Mak test states no autocorrelation should be present in the squared standardized residuals. If the *p*-value of the test is high, the null hypothesis can not be rejected and therefore no autocorrelation is present after applying the model. The assumption of the DCC model that standardized innovations are independent and identically distributed random variables is confirmed if the hypothesis is rejected.

Next to checking the residuals, the joint significance of each of the univariate GARCH models is tested. In order for the model assumption of non-constant conditional correlation to hold, the joint significance parameters should be significant. When one or more parameters in each of the univariate models is insignificant, the joint significance can determine whether the parameters from Equation 4 are significant as a group. The joint significance test parameters will be named d*cca1* and *dccb1. Dcca1* should be significantly different from zero, and *dccb1* significantly different from one. It could be the case that one of the parameters is not significant, which implies the conditional correlation is decaying over time. In this case, the model fit is not ideal but still is able to capture a large part of non-constant correlation present in the data. When both of the joint significant parameters are insignificant, the model fails to capture the dynamic correlation present in the data.

Another model assumption that should be checked for is stationarity. Engle (2002) states stationarity for a GARCH(1,1) process implies having serially uncorrelated processes with nonconstant variances conditional on the past, but constant unconditional variances. Even though volatility clustering can be a possible indication of non-stationarity, by modelling the conditional variance as a dynamic process, the assumption of constant unconditional variance can still be met. Bollerslev (1986) defines the properties of the univariate GARCH(1,1) model as in Equation 4, and finds that $\alpha + \beta < 1$should hold to confirm second order stationarity.

Lastly, each of the models are tested with different regression terms in the mean equation to see which complete model best describes the data. As stated in the model description, according to Engle(2002) and the practical approach of Orskaug (2009) this implies incorporating a constant, an AR term, a MA term, or both. The best fit is found by looking at the significance of the terms. The term that is significant is chosen for further analysis. If multiple terms are significant or none of them are, the Akaike (Akaike et al., 1998) and Bayesian (Neath & Cavanaugh, 2012) information criteria are reviewed. The test statistic provides a value of how much information a model loses. The lower the value, the closer the model is to actual representation of the process and data. The model providing the lowest values for both of the tests is chosen for further analysis. The mean equation is not the focus of this research, as the variance equation is of interest for the hypotheses. However, the best fitting mean equation has to be chosen to provide the most accurate and reliable parameter estimates. The approach of selection by AIC and BIC is common within GARCH analysis. Mariana, Ekaputra and Husodo (2021) find that including a MA(1) term is most appropriate within their analysis, while others like Urquhart and Zhang (2018) find the inclusion of an AR(1) term is most fitting to their data.

3.7 Validity and Robustness

A division in the sample is made to check if estimation results change when smaller sample periods are used. When results are the same, the subsample analysis adds robustness to the main research results. Smaller periods might capture better opportunities of Bitcoin functioning as a safe haven in a shorter term. On the other hand, Hwang and Valls Pereira (2006) recommend using a sample of at least 500, otherwise the estimates might be inaccurate. Two equally sized subsamples are made for Brexit as well as the trade war sample, a first half and a second half. This is done so if needed, the results of both subsamples can be compared directly. Splitting the sample also shows if safe haven properties of Bitcoin are stronger in the beginning of a period of economic distress, or that these properties maintain their strength throughout the whole duration of the sample period. It might be the case that in the first part of the sample the function of a safe haven is much stronger since economic uncertainty was introduced more recently. Specifically for this research, it will add support to reject or confirm the hypotheses, as they include an assumed correct period of economic uncertainty. Subsample analysis is common for these kinds of analysis, for example Baur and Lucey (2010) use it for their analysis on gold. Since this is merely a check for the robustness, each second half of the sample will be analysed in the results.

Other checks to validate choosing Bitcoin as a go-to safe haven is comparing the safe haven performance of other cryptocurrencies and gold to that of Bitcoin. Results indicate if investors are right for choosing Bitcoin as the first cryptocurrency to resort to, as some researchers find evidence of Ethereum functioning as a better safe haven in certain periods (Mariana, Ekaputra, & Husodo, 2021). The comparison with gold will show if Bitcoin should be considered as an alternative to traditional safe haven gold. For the cryptocurrencies, Ethereum (ETH), Ripple (XRP) and Litecoin (LTC) are selected on having the highest market capitalizations next to Bitcoin[31]. The comparisons provide a more complete foundation to reject or confirm the main hypotheses of the research. For example, Baur et al. (2018) also use multiple assets to provide a better overview about the current state of the overall market, as do many others.

[31] https://coinmarketcap.com/

4. Results

In this chapter the analysis will be conducted and the results will be discussed. Firstly, the samples and general descriptives are described and the Jarque-Bera test is performed. Secondly, the models are fitted to the data and the goodness of fit test results are presented. Then, the dynamic correlations are extracted from the models and conclusions on the hypotheses are made. Lastly, results of additional models for subsample analysis, weekly timeframes, alternative cryptocurrencies and gold are presented and discussed.

4.1 Statistical Analysis

Table 1 reports the general descriptives of the compounded returns in percentages. The descriptives for both Bitcoin and the currencies confirm expectations of volatility and correspond to those of comparable research. For example, the mean return of Bitcoin in the Brexit sample is 0.28% while the mean return of the pound is -0.01%. Only in the second half of the Brexit subsample Bitcoin showed a mean return of -0.01%. It was the period where the hype cooled down and price movement was minimal. Interestingly, a mean value of 0% can be observed for the yuan. In practice the mean return is $-1.65*10^{-17}$%, no rounding errors that would display a distorted image have been made. This can be a coincidence, but it can also be an indication of governmental control on the forex rates of the yuan (Staiger & Sykes, 2010). The standard deviation also contributes to explaining the high return volatility of Bitcoin. Looking at daily time frames the lowest standard deviation of a cryptocurrency is 4.22%, while the highest standard deviation is 0.61% for the pound and 0.64% for gold. The differences are substantial. The findings for the means and standard deviations of cryptocurrencies correspond to those of Baur et al. (2018) and Shahzad et al. (2020). For the currencies the values are comparable to those of Urquhart and Zhang (2018). It indicates data from this sample period is similar to those of other research, and includes no extraordinary observations that could potentially disrupt the reliability of the results.

The minimum and maximum values confirm cryptocurrencies as volatile assets, with extreme values incomparable to those of currencies. It should be noted that the minimum and maximum return values of Bitcoin could present a distorted view, as the data are synchronized. Applying the technique of weekend smoothening as suggested by Klein, Thu, and Walther (2018) leaves out a period of 72 hours where Bitcoin markets are open and the price is changing. For example, if Bitcoin prices dropped during the span of a whole weekend, the minimum return value captures the difference between the Friday and Monday, instead of separate days. Therefore, inaccurately representing actual events. For the purpose of the analysis however, Klein, Thu, and Walther (2018) state smoothening provides the most accurate results opposed to extrapolating the data. For currencies, the minimum return value of the pound (-5.99%) is high compared to those of the dollar (-1.27%) and yuan (-2.42%). This is in correspondence with the finding that the pound experienced steeper price drops then the other currencies.

Table 1

Descriptive statistics for the compounded returns in percentages of Bitcoin, the Pound, Dollar and Yuan for each of the analyses.

Currency	Mean	St. Dev.	Min.	Max.	Skew.	Kurt.	Jarque Bera
			Brexit n = 936				
Bitcoin	0.2775	4.7721	-25.9217	24.3414	-0.0102	3.8987	584.5583***
Pound	-0.0102	0.5253	-5.9931	2.0215	-1.5741	19.0460	1437.3***
			Trade war n = 523				
Bitcoin	-0.1238	4.6757	-25.9217	20.3452	-0.3729	3.7639	313.0616***
Dollar	0.0129	0.3830	-1.2714	1.8921	0.1937	1.0263	25.2638***
Yuan	0.0000	0.4022	-2.4192	1.7938	-0.2362	3.0650	204.1485***
			Brexit subsample n = 468				
Bitcoin1	0.5659	5.2231	-25.9217	24.3414	-0.1226	3.9801	301.5563***
Pound1	-0.0292	0.6065	-5.9931	2.0215	-2.0568	20.3732	8240.1***
Bitcoin2	-0.0110	4.2600	-16.1245	20.3452	0.0945	3.1022	182.8526***
Pound2	0.0088	0.4290	-1.8001	1.6696	0.1441	2.4039	110.7225***
			Trade war subsample n = 261				
Bitcoin1	-0.5075	5.0735	-25.9217	13.3745	-0.7981	2.9610	117.6935***
Bitcoin2	0.2584	4.2176	-14.9794	20.3452	0.4864	4.3677	208.5095***
Dollar1	0.0172	0.4454	-1.2714	1.8921	0.2082	0.5446	4.7068*
Dollar2	0.0087	0.3093	-0.8973	1.0607	0.0743	0.8251	6.9937**
Yuan1	-0.0039	0.4250	-1.1165	1.7938	0.1629	0.8598	8.4622**
Yuan2	0.0039	0.3789	-2.4192	1.3318	-0.7884	6.4898	466.1562***
			Brexit weekly sample n = 187				
Bitcoin	1.3584	11.4965	-36.6845	34.0241	0.0006	0.7776	4.0958*
Pound	-0.0430	1.0834	-3.9044	3.7055	-0.1817	1.5450	17.8977***
			Trade war weekly sample n = 105				
Bitcoin	-0.7570	10.5608	-36.6845	24.7397	-0.3080	0.7860	3.7123*
Dollar	0.0665	0.7720	-1.6140	1.8397	0.0528	-0.6221	4.8544*
Yuan	0.0090	0.8090	-2.4982	1.9448	-0.4755	0.5764	4.8544*
			Brexit alternative cryptocurrencies n = 936				
Gold	0.0230	0.6457	-3.3311	7.1061	1.2191	16.3425	10528***
Ethereum	0.2375	6.7180	-51.9555	41.3826	-0.1897	7.2944	2055***
Ripple	0.3752	8.0123	-35.2383	75.7225	2.5435	17.5301	12855***
Litecoin	0.2343	6.8732	-30.9612	56.4628	1.6726	11.6340	5651,7***
			Trade war alternative cryptocurrencies n = 523				
Gold	0.0421	0.5799	-2.1529	2.4521	0.1719	1.5774	54,9737***
Ethereum	-0.3264	5.9045	-30.0510	25.3088	-0.2980	2.9393	190,5638***
Ripple	-0.4541	6.2310	-35.2383	31.3121	0.0645	4.9093	513,1827***
Litecoin	-0.3288	5.8621	-20.6227	28.1617	0.4595	3.0540	216,1865***

Note. The table presents all descriptive statistics for each of the analyses separately. All of the data is sampled daily with exception of the weekly sample. For the subsamples a '1' indicates first half of the subsample and a '2' is the second half. St. Dev. is the standard deviation, Min. and Max. are the minimum and maximum of the time series. Skew. is the skewness and Kurt. is the kurtosis. ***, ** and * indicate 1%, 5% and 10% levels of significance respectively.

The skewness is close to zero for Bitcoin returns, especially in the Brexit sample with a value of -0.01. It implies the returns are distributed fairly symmetrical. The return skewness of the dollar (0.19) and yuan (-0.24) also falls within the range for them to be judged as symmetrical. On the other hand, the pound has a skewness of -1.57. The highly negatively skew implies the tail on the left side of the distribution is longer than the tail on the right side, and thus a non-symmetrical return distribution. The kurtosis of Bitcoin shows a value of 3.90 in the Brexit sample and 3.76 in the trade war sample, indicating a leptokurtic distribution. Bitcoin returns have fat-tail characteristics compared to a normal distribution. The kurtosis of the pound is extremely high compared to the other currencies. The tails of the distribution are fat, implying the returns for the pound are diverse and may include many outliers. Currency data from Urquhart and Zhang (2018) confirms these values for currencies are normal and support the idea of a current, highly economically uncertain period for the United Kingdom and the effect on its currency.

The standard deviations, minima and maxima of the weekly samples indicate higher volatility compared to the daily sampled data. For instance, the standard deviations of Bitcoin and the pound are more than twice as high compared to their daily sampled counterparts. A longer timeframe implies more price fluctuations can happen within the time period. The values are proportional to the daily sample data. The data of gold is similar to the currencies, with exception of the kurtosis, which shows extremely fat tails in the return distribution. This finding is in line with Klein, Thu and Walther (2018). The data of alternative cryptocurrencies are comparable to those of Bitcoin. A notable difference are the maximum and minimum return values. Within the Brexit sample, Bitcoin's extremes lie at -25,92% and 24,34%. Ethereum shows a minimum return value of -51,96% and Ripple shows a maximum of 75,72% within the same period. Jeribi and Manzli (2021) as well as Mariana, Ekaputra and Husodo (2021) present similar differences between Bitcoin and Ethereum in their data.

Lastly, the last column of Table 1 contains the results of the Jarque-Bera test. All results reject the null hypothesis of the Jarque-Bera test, as the highly significant test statistic (1%) indicates the test statistic is statistically different from zero and therefore does not approximate normal distribution. It also confirms volatility clustering in the data. The low significance for the weekly sample period originates from the low level of cases, as the accuracy and reliability of the test increases for bigger sample sizes. To conclude, both the descriptives and the Jarque-Bera test confirm the return series are not normally distributed and cryptocurrencies are highly volatile. It indicates the use of GARCH models is adequate to capture the non-normality derived from high volatility in the return series.

4.2 Results Goodness of Fit Testing

In Table 2 the parameters for the univariate GARCH models show all AR and MA terms are highly significant on a 1% level. The yuan is the only exception, the parameter estimates of -0.27 (AR) and 0.19 (MA) show no statistical significance. For the highly significant terms, the inclusion ARMA(1,1) is adequate to account for the non-zero autocorrelation existing in the conditional mean of the dependent variable. Including none or one of the terms leads to insignificant parameter estimates and has been tested for. Since only ARMA(1,1) is significant for these parameters, they do not need to be reviewed with AIC and BIC criteria. The AR terms of Bitcoin are highly negative, -0.90 for the Brexit sample and -.93 for the trade war sample. It means a given sign tends to be followed by an opposite sign, inducing sawtooth behaviour. This confirms the high volatility of the error term and the presence of autocorrelation. For the yuan however, the models are compared to find the one with the lowest amount of information criteria. The values of the AIC and BIC criteria are lowest when both terms are included. The inclusion of the mean term differs per research. Mariana, Ekaputra and Husodo (2021) only use MA(1) and Baur, Dimpfl and Kuck (2018) only use AR(1) for their applications, as those criteria show the best explanatory value for them. For this research the data is best described when including ARMA(1,1) in the mean equation

Next, the assumption of stationarity is met. Table 2 shows that the alpha and beta parameters are statistically significant for each of the models and stationarity holds with $\alpha + \beta < 1$. For the univariate GARCH model of the dollar for example, alpha is 0.02 and beta is 0.098. Both of the values are statistically significant at the 1% level. Their combined value is 0.999. The mu parameter of Bitcoin in the Brexit sample is 0.2557, the only significant mu parameter in the analysis. However, removing the intercept will cause other estimates to be biased and thus all insignificant mu parameters are kept in the models. Dropping the mu parameter causes the model to hold less explanatory value represented by a higher value for the AIC and BIC, and a smaller log-likelihood. This also applies to the omega parameter, which has equivalent parameter results. Removing the parameter implies forcing it to take a value of zero. According to Francq and Zakoïan (2009) this could lead to unwanted changes to the conditional variance estimates over time. In short, the individual, important parameters indicating the goodness of fit for the univariate GARCH models indicate appropriate fitting.

Table 2

Univariate GARCH model parameters, joint estimations and Li-Mak test for the main analyses.

	Mu	AR	MA	Omega	Alpha	Beta	DCCA1	DCCB1	LM
					Brexit				
Bitcoin	0.2557 *	-0.9033 ***	0.8826 ***	1.5218 **	0.1998 ***	0.7584 ***			
Pound	-0.0122	-0.6078 ***	0.6010 ***	0.0242	0.1532 **	0.7630 ***	0.0103 **	0.9536***	5.8393
					Trade war				
Bitcoin	-0.1384	-0.932 ***	0.8952 ***	2.0085	0.1286 ***	0.787 ***			
Dollar	0.0127	0.8543 ***	-0.9093 ***	0.0004	0.0229 ***	0.9761 ***	0.0167 **	0.9558***	5.1244
Yuan	0.0000	-0.2697	0.1866	0.0001	0.0576 *	0.9394 ***	0.0155 *	0.9591***	5.4650

Note. Mu, AR and MA are the parameter estimations for the conditional mean as in Equation (5). Omega, Alpha and Beta are the parameter estimations from the univariate GARCH model as in Equation (4). DCCA1 and DCCA1 are the joint estimates of Bitcoin and a single currency. LM is the weighted Li-Mak test. ***, ** and * indicate 1%, 5% and 10% levels of significance respectively.

Lastly, Table 2 shows the joint estimates *dcca1* and *dccb1* as well as the weighted Li-Mak test. The joint estimates are statistically significant for all of the models. For instance, within Brexit *dcca1* is 0.0103 and significant at the 5% level. The value of *dcca1* is therefore significantly different from zero. *Dccb1* is 0.9536 and significant at the 1% level, thereby different from one. For all samples this confirms the presence of a non-constant conditional correlation as aimed for, and the ability of the models to fully capture it. The weighted Li-Mak test is shown in the last column of Table 2. The tests are not statistically significant, since the values are too high to confirm the null hypothesis of the test. Therefore, the null hypothesis of no autocorrelation in the residuals can not be rejected. All models correctly capture the ARCH effects present in the data. For the main analysis all general assumptions are met and the relevant parameters indicate appropriate fitting of the GARCH method.

4.3 Results Safe Haven Testing

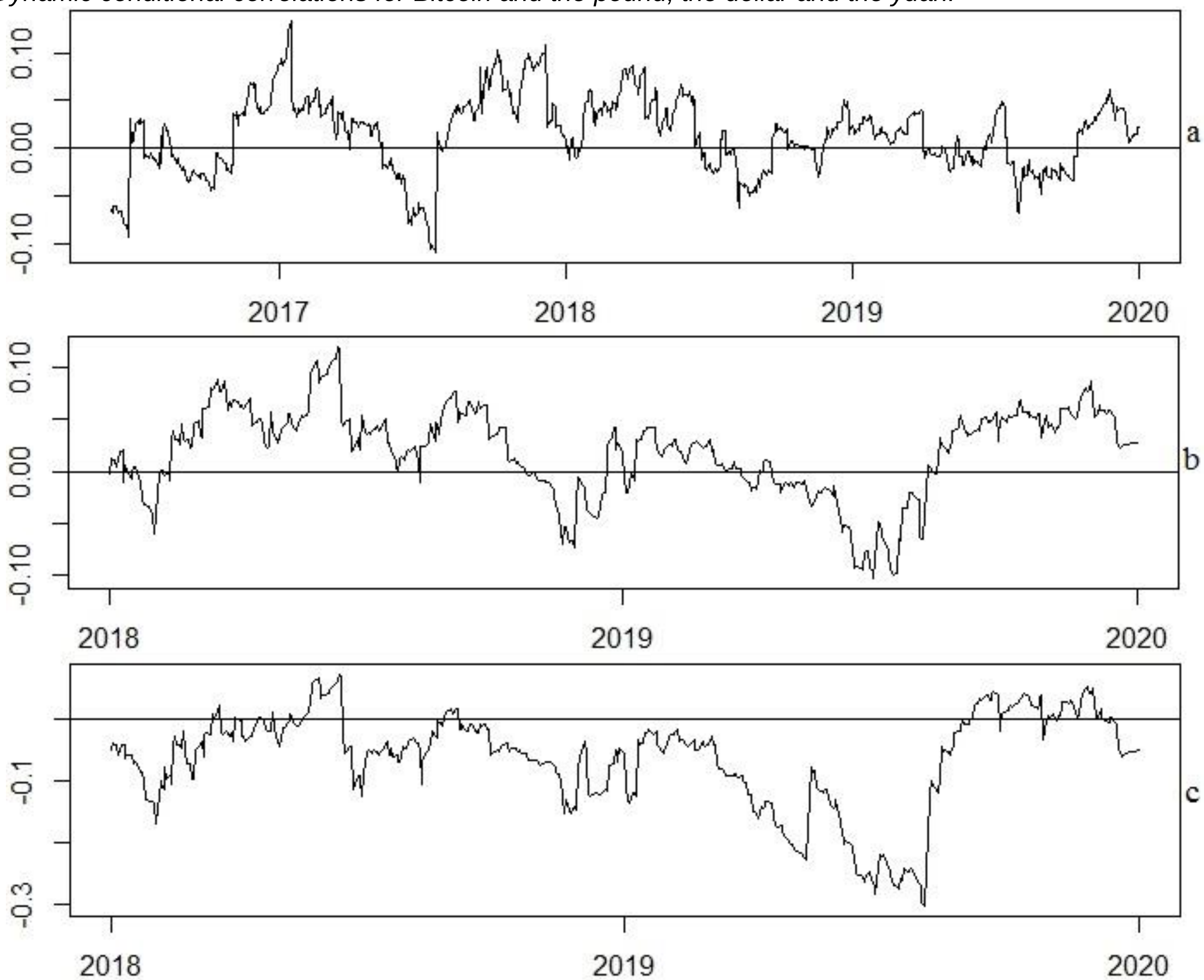
Figure 2 plots the pairwise DCC-GARCH correlation estimates for Bitcoin and each of the currencies. For Bitcoin and the pound the correlations vary between -0.1091 and 0.1336, with a mean of 0.0142. The minimum and maximum values show a weak correlation, the mean confirms the Bitcoin and pound to be uncorrelated on average. As can be seen in Figure 2a, the first half of the sample period includes the most volatility as well as the minimum and maximum values. The weak correlation throughout the sample period together with a mean correlation of approximately 0 indicates Bitcoin functions as a weak safe haven for the pound during the Brexit period and therefore confirms hypothesis *H1*. Urquhart and Zhang (2018) show an average dynamic correlation of 0.0346 between Bitcoin and the pound in their intradaily analysis. During their sample period the values mostly range between -0.1 and 0.1. Their approach to identify highly economic uncertain periods within their sample provides the same conclusions as the hypothesized highly economic uncertain Brexit period within this research; Bitcoin is a (weak) safe haven for the pound within periods of high economic uncertainty.

The dynamic correlation of Bitcoin and the dollar varies between -0.1043 and 0.1210, with a mean of 0.0187 (Figure 2b). Similarly to the pound, Bitcoin and the dollar are viewed as uncorrelated. The first half of the sample is mostly positively correlated. During the second half of the sample the pairwise correlation turns negative. Towards the end of the sample the correlation turns positive again. Hypothesis *H2* is supported and Bitcoin is found to act as a weak safe haven for the dollar during the trade war period. Kang et al. (2019) show a dynamic correlation of Bitcoin and the US dollar ranging between -0.15 and 0.1 in their sample from 2011 to 2016, comparable to the results of this analysis. The results are therefore believed to be representative; within the trade war period Bitcoin functions as a weak safe haven for the dollar.

The time varying correlation of Bitcoin and the yuan fluctuates between -0.3030 and 0.0714. The average correlation is -0.0655, which implies Bitcoin is a weak safe haven for the yuan, similarly to the pound and dollar. Hypothesis *H3* is supported. However, the periods showing a positive correlation are short. During most of the sample period the correlation is negative, as can be seen in Figure 2c. The negative minimum value of -0.3030 is significantly lower than the minimum correlation values of the pound and dollar. Thus, Bitcoin ca be seen as a weak safe haven for the yuan, but a more convincing one compared to the other currencies. Dynamic correlations of Bitcoin and the yuan have not been researched before. Results are identical to

Figure 2

Dynamic conditional correlations for Bitcoin and the pound, the dollar and the yuan.



Note. The Dynamic correlation of Bitcoin and the Pound within the Brexit sample is presented in figure *a.* The dynamic correlations of Bitcoin and the Dollar and Yuan within the trade war sample are presented in figure b and c respectively. Daily return correlations are plotted on the y-axis, the time in days is plotted on the x-axis.

those of the pound and dollar in terms of magnitude and correlation behaviour throughout the sample. Therefore, it is expected the results correctly represent the implementation of the model and Bitcoin indeed functions as a weak safe haven for the yuan during the trade war period. However, the Chinese yuan has been a topic of legal discussion. It is claimed the price is manipulated (Jung, 2012), which seems to be one of the reasons interest in hedging against the yuan has been minimal. Therefore, it could be questioned if results of the yuan add to general knowledge of cryptocurrency safe haven properties. For the specific scenario of high economic uncertainty it is believed the results are meaningful. It is also believed there is a need for research, as globalization and interconnectedness of financial markets proceeds to develop (Wang & Sun, 2021).

4.4 Subsample and Weekly Interval Analysis

For the subsamples, Table 1 shows the differences in mean returns for Bitcoin and the pound between each of the subsample halves are substantial. For example, for the Brexit period the mean return for Bitcoin is 0.57% in the first half while being -0.01% in the second half. This is due to the aforementioned dropping and stagnating of prices. All standard deviations correspond to the standard deviations of the full sample period. The maximum and minimum returns vary widely between both sample halves, but on average correspond to those of the full sample. The skewness and kurtosis differ substantially in some cases, for example for the yuan. The first half has minimal positive skewness of 0.16, and thus a distribution with a slightly fatter tail on the right side. The second half however, has a negative skewness of -0.79. This also applies to the kurtosis of the yuan. The first half is moderately close to following a normal distribution as it is close to zero, whereas the second half does not approximate a normal distribution. As expected, the weekly sampled data shows even more extreme numbers. Looking at Bitcoin for the Brexit sample we see a mean return of 1.36% instead of the 0.28% in the regular sample. The standard deviation is 11.5% compared to 4.8% and the minimum and maximum values are more extreme as well. Measuring over the span of a week instead of a day increases the expected volatility and enlarges the representation of price movement. The measurements of skewness and kurtosis might be more inaccurate due to the small sample size. Again, all Jarque-Bera tests are significant, implying the null hypothesis of the test is rejected and the return distribution does not follow a normal distribution by approximation. It is believed the results for the weekly intervals are invalid, as the sample size is too small for the test to provide reliable results.

The goodness of fit indicators of each of the subsamples show the same results as those of the full sample. The same parameters are significant, have the same sign and are of similar magnitude. The model assumptions are met, the joint estimates are valid and the weighted Li-Mak test confirms the model captures autocorrelation present in the data. The goodness of fit of the weekly sample analysis however, shows almost exclusively insignificant parameters. Only for the Brexit sample the joint estimates are significant and below 1. It is therefore believed only the Brexit sample will provide results and the DCC approach for the dollar and yuan will fail to provide meaningful insights.

The dynamic conditional correlations of the second half of subsamples are presented in Appendix II. The results from the first half and second half are comparable, therefore only one half is chosen for reflection. The correlation of Bitcoin and the pound has a similar maximum and minimum value compared to the full sample, although the minimum value is a single outlier. The average correlation is higher than that of the full-size sample, namely 0.0212 compared to 0.0142. However, the values are not substantially different from each other, or from zero. Therefore, the subsample results for the pound support the conclusion of Bitcoin functioning as a weak safe haven. The value of the correlation of Bitcoin and the US dollar is negative in more than half of the sample. The average correlation is -0.0302 compared to 0.0187 of the full sample. The correlation average along with the correlation value throughout the subsamples confirms hypothesis *H2*, Bitcoin functions as a weak safe haven for the dollar. Finally, the correlation of the Bitcoin and yuan is negative throughout the sample period, reaching a maximum value of -0.0147 close to the end. The average correlation is -0.1578 compared to -0.0655 in the full sample. Although the correlation is still weak, and therefore the safe haven properties for Bitcoin are also weak, the correlation value is more negative and confirms the finding that Bitcoin is a slightly better safe haven for the yuan compared to the dollar or pound. Thus, the subsample of the yuan supports the previous findings and hypothesis *H3* as well. Although slight differences in results occurred, results from the subsamples lead to the same conclusions as those of the main analysis. Bitcoin acts as a weak safe haven for each of the currencies during a shorter period where high economic uncertainty is present. It should be noted that one of the factors that determined the usage of the DCC-GARCH method was the sample length and interval. Hwang and Valls Pereira (2006) state a sample of at least 500 observations should be used for accurate parameter estimates. This requirement is not met, and therefore it should be expected that the estimates and results of the model are less accurate than those of the main analysis.

The graph of the weekly dynamic correlation of the pound is included in Appendix IIb. It shows a maximum correlation value of -.008 and a minimum value of -0.26. This further confirms Bitcoin and the pound have a weak negative correlation within the Brexit period. The average correlation value of -0.12 confirms hypothesis *H1,* Bitcoin is viewed as a weak safe haven for the pound. The pairwise correlations for the dollar and yuan are not included. As expected, the insignificant parameters cause the DCC model to fail. The model shows a constant correlation, therefore misrepresenting the data. The weekly sample of the dollar and yuan does not contribute to validating the evidence found to support hypotheses *H2* and *H3*. Although the findings for Bitcoin and the pound contribute to the research, the sample size is too small to guarantee accuracy of the results. However, the results do add validity and robustness to the confirmation of the main hypotheses.

4.5 Analysis of Alternative Cryptocurrencies and Gold

Comparing alternative cryptocurrencies will provide evidence if Bitcoin should indeed be the “go-to” cryptocurrency or if alternatives are better. Comparing gold to Bitcoin will indicate the differences, similarities and recent performance with respect to their safe haven function for currencies. In short, it will further validate and robustize the main findings.

The general descriptives for cryptocurrencies Ethereum (ETH), Litecoin (LTC), Ripple (XRP) as well as gold are in the last panel of Table 1. Cryptocurrency values are of the same magnitude as those of Bitcoin, although some differ. The maximum daily return for example, ranges up to 75.72% for Ripple in the Brexit sample, while Bitcoin only shows a maximum return of 24.34%. The skewness and kurtosis indicate that the return distribution of the cryptocurrencies are even further away from being normally distributed than Bitcoin is. The descriptives of gold are similar to those of the currencies in the main analysis. Interestingly, the maximum return and kurtosis are high in the Brexit sample, indicating a high volatility and a non-normal return distribution. The Jarque-Bera results for each of the cryptocurrencies and gold confirm the returns do not approximate a normal distribution.

Out of the twelve alternative cryptocurrency models, eight show a model fit comparable to those in the main analysis. The parameter estimates are significant, the assumptions are met and the weighted Li-Mak test confirms the capturing of autocorrelation; their correlations are included in Appendix III. Both Ethereum samples have a mean close to zero. For both the pound and yuan a rounded -0.002 and -0.001. The evidence indicates that Ethereum functions as a weak safe haven for both the pound and yuan during the sample period. The correlation of Litecoin and the dollar is only positive. The minimum value is 0.02 and the mean is 0.05. Since the values are close to zero, technically Litecoin is viewed as a weak safe haven for the dollar. The samples of Ripple for the trade war period present similar results. Ripple and the dollar have a positive correlation on average, with a mean of 0.02. Ripple and the yuan show a slightly negative mean correlation of -0.001. Both samples follow a very comparable dynamic correlation throughout the sample. Ripple is also viewed as a weak safe haven for the trade war period currencies.

The analysis for the alternative cryptocurrencies provides the same conclusions with respect to safe haven aspects as those of Bitcoin; all of the alternative cryptocurrencies have potential to function as safe haven. This is in line with findings in literature that alternative cryptocurrencies can indeed function as a hedge, safe haven or diversifier (Meshcheryakov & Ivanov, 2020; Mariana, Ekaputra, & Husodo, 2021). However, the higher return volatilities are a big practical risk (Mariana, Ekaputra, & Husodo, 2021) as are the lower market capitalizations (Bouri, Shahzad, & Roubaud, 2020). Next to a lower volatility and higher market capitalization Bitcoin is the most known and established cryptocurrency. Therefore, it is perceived to be the most logical cryptocurrency to choose as a safe haven. The results of the alternative cryptocurrency analysis add support to the concept of cryptocurrencies in general being able to function as a safe haven in times of high economic uncertainty. The findings also add support to research like that of Brauneis and Mestel (2019), investigating the inclusion of multiple cryptocurrencies in a portfolio. It is possible that including a combination of cryptocurrencies in a portfolio outperforms a single cryptocurrency with respect to reducing the likelihood of extreme losses. Brauneis and Mestel (2019) confirm diversification across cryptocurrencies lowers the risk, Liu (2019) even shows portfolio diversification can significantly improve investment results. Andrianto and Diputra (2017) find that including multiple cryptocurrencies in a portfolio helps to minimize the large standard deviation of cryptocurrencies. However, the impact to minimize the likelihood of extreme losses (safe haven properties) for a whole portfolio of assets like currencies or assets denoted in different currencies are unclear.

Interestingly, the DCC-GARCH model specification fails to capture the dynamic correlations of some of the alternative cryptocurrencies, as the joint estimates and Li-Mak test show the autocorrelation present can not be captured. As a result, the model produces a constant correlation. The model is misspecified as the parameters are not correctly estimated. The most likely causes are that the model fails to capture high asymmetric volatility and requires an asymmetric GJR-GARCH approach (Baur, Dimpfl, & Kuck, 2018) or fails to capture long term memory and IGARCH is appropriate (Chu, Chan, Nadarajah, & Osterrieder, 2017).

Lastly, all results for the correlations of gold show a positive mean correlation. The graphs are shown in Appendix IV. For gold and the pound the mean correlation is 0.05, for the dollar it is

0.11 and for the yuan it is 0.20. The minimum and maximum values of all correlations are more extreme compared to cryptocurrencies. For example the minimum value for the gold and pound correlation is -0.79 and the maximum value of the correlation between the gold and yuan is 0.70, while those of the alternative cryptocurrencies are more than ten times smaller. It shows how cryptocurrencies are uncorrelated to other assets like currencies, while assets like gold generally have stronger correlations. Gold can be seen as a safe haven in the Brexit period for the pound, since the average correlation is close to zero. But, the correlation is often moderately positive within the sample, with values as high as 0.45. Therefore, gold is perceived to be an unreliable safe haven. The non-zero values for the dollar and yuan indicate gold is not a safe haven within the trade war period for these currencies.

Next, the results of gold show a significantly stronger correlation to the currencies than any of the cryptocurrencies. Confirming the literary findings of cryptocurrencies being uncorrelated to any asset (Baur, Dimpfl, & Kuck, 2018; Aslanidis, Bariviera, & Martínez-Ibañez, 2019). The minimum and maximum values are more extreme for gold compared to any of the cryptocurrencies. For example, the minimum value for the gold and pound correlation is -0.7949 and the maximum value of the correlation between the gold and yuan is 0.7019, while those of the alternative cryptocurrencies are more than ten times smaller. Thus, gold reacts stronger to movements in the currency markets. Gold is often found to be a hedge, mostly for stocks (Baur & McDermott, 2010), but also for the US dollar (Reboredo, 2013b). Reboredo (2013b) also indicates the potential of gold to act as a safe haven for the US dollar. The results from the Brexit period are in line with this finding, as Bitcoin is found to act as a weak safe haven for the pound. But the results from the trade war period show that gold does not act as a safe haven for the dollar or yuan. And thus contrast the literature, showing gold is not a safe haven per definition. This finding adds to the general concept that Bitcoin can be a viable alternative to gold with respect to safe haven properties. Gold does not necessarily outperform Bitcoin in situations with high economic uncertainty.

However, in its current stage, Bitcoin’s returns and volatility still make it a speculative asset (Baur, Dimpfl, & Kuck, 2018) and research into general hedging capabilities and portfolio performance is still in its infancy (Klein, Thu, & Walther, 2018). With respect to portfolio performance: It might be possible that a combination of gold and cryptocurrencies outperforms the inclusion of a single cryptocurrency with respect to hedge or safe haven properties. As Bouoiyour, Selmi and Wohar (2019) confirm, gold and Bitcoin are likely to be complementary since they both have their distinctive properties.

5. Conclusion

This study examines the dynamic conditional correlation relations between Bitcoin and three major currencies. It was investigated whether Bitcoin can function as a safe haven for the Great British pound, United States dollar and Chinese yuan. More specifically, in times of high economic uncertainty. For the pound this implies Bitcoin being a safe haven during the Brexit period. For the dollar and yuan it implies Bitcoin being a safe haven during the trade war period.

Following the DCC-GARCH framework by Engle (2002), the produced time varying correlations suggest that there is evidence Bitcoin can indeed function as a safe haven for each of the currencies, although a weak one. More specifically, the dynamic conditional correlations of the returns of Bitcoin and the pound showed Bitcoin could have functioned as weak safe haven during the Brexit period. The same applies to Bitcoin and the dollar and yuan during the trade war period. Therefore, all hypotheses are confirmed. Following the presented evidence along with evidence presented in previous research, it is believed Bitcoin possesses characteristics to function as possible safe haven for financial assets and specifically currencies in future periods of economic distress. A current example is the COVID19 pandemic, where evidence is found of Bitcoin functioning as a safe haven as well (Corbet et al., 2020).

The subsample and weekly analyses are conducted to add robustness to the results of research. The subsample analysis split up the dataset in two parts, while the weekly analysis' input data were the weekly sampled returns. Both analyses led to the same conclusions as the main results, and confirm the hypotheses of Bitcoin acting as a (currently weak) safe haven for each of the currencies. Furthermore, another posterior analysis to add validity was conducted. Bitcoin's performance as safe haven was compared to that of Ethereum, Ripple, Litecoin and gold. It was shown that Bitcoin outperforms the other cryptocurrencies with high market capitalizations. Although all cryptocurrencies have the potential to function as weak safe haven, Bitcoin is the most convincing based on empirical evidence as well as historical performance. The posterior analysis also confirms Bitcoin should be considered as an alternative to traditional safe haven gold, as it outperforms gold within the sample periods as safe haven. Thus, the results of the performance comparison of Bitcoin to cryptocurrencies and gold both support the hypotheses of this research, as Bitcoin is the most logical safe haven to resort to within the sample periods.

The research does not allow for extensive statistical model comparisons and therefore theoretical reasoning has been used. As shown in the alternative cryptocurrency analysis, the DCC-GARCH method does not capture all dynamics in the data consistently. As improvement, several GARCH model adaptations could be tested for each analysis (Katsiampa, 2017) . Each case will be paired with a model providing the highest information criteria and log-likelihood. The continually maturing cryptocurrency market is another limitation. Figure 1 showed Bitcoin is rallying in price during the last quarter of 2020. Therefore, an analysis conducted about the hedge and safe haven properties including new price developments could lead to different results while also helping to generalise the conclusions about this asset class, Shahzad et al. (2020) also recognise this problem in their conclusive remarks. A recent example is the COVID19 pandemic, where contrasting evidence is found by Conlon and McGee (2020). They state Bitcoin is not a safe haven at all for this specific event. Most logically, all results would need to be verified after the periods of economic distress have ended. Other limitations like the legitimacy of the Chinese yuan and lack of portfolio implementation have been mentioned in the analysis.

The findings are important for local citizens of a country in economic distress as well as investors and traders. Residents of a country experiencing high economic uncertainty can resort to cryptocurrencies to grant continued access to their capital, while also maintaining their position in the international market. Investors and traders are enabled to better mitigate exposure to economic uncertainty with foreign currency investments and capital. Consequently, the safe haven properties of Bitcoin during periods of economic distress might affect investment decisions, minimize the likelihood of extreme losses or portfolio compositions. Therefore highlighting the practical integration of cryptocurrencies within a portfolio as well as their usability in periods of economic distress from various points of view.

The results have important implications for research regarding cryptocurrencies as financial assets, their development and position in the market, as well as their role as potential safe haven, hedge or diversifier. Generally, the results expand the foundations into the understanding and modelling of the interaction between Bitcoin and financial assets. It also invites to conduct more research into Bitcoin as a digital asset and its potential added value for investors. Currently, most research focuses on specific periods of economic distress and provides an analysis about past, potential possibilities. To further establish the practical use, periods of economic uncertainty should be able to be recognized. Models like GARCH can be deployed to focus on their predictive power instead. Lastly, the results of this research could be used to investigate the possibility of portfolio inclusion and optimization of cryptocurrencies. Since the safe haven properties have been tested within a specific timeframe, an optimal portfolio could be constructed for the Brexit or trade war periods to see how much the safe haven aspect of cryptocurrencies can impact portfolio performance in a period of high economic uncertainty.

7. References

Andrianto, Y., & Diputra, Y. (2017). The effect of cryptocurrency on investment portfolio effectiveness. *Journal of Finance and Accounting, 5*(6), 229-238. https://doi.org/10.11648/j.jfa.20170506.14

Akaike, H., Parzen, E., Tanabe, K., & Kitagawa, G. (1998). Selected papers of Hirotugu Akaike. Springer Science & Business Media, New York, USA. https://doi.org/10.1007/978-1-4612-1694-0

Alexander, G. J., Edwards, A. K., & Ferri, M. G. (2000). The determinants of trading volume of high-yield corporate bonds. *Journal of Financial Markets, 3*(2), 177-204. https://doi.org/10.1016/S1386-4181(00)00005-7

Ali R., Barrdear J., Clews R., and Southgate J. (2014). The economics of digital currencies. *Bank of England Quarterly Bulletin, 54*(3), 276-286. Retrieved from: http://www.bankofengland.co.uk/publications/Documents/quarterlybulletin/2014/qb14q3digitalcurrenciesbitcoin2.pdf

Alvarez-Diez, S., Baixauli-Soler, J. S., & Belda-Ruiz, M. (2019). Co-movements between the British pound, the euro and the Japanese yen: the Brexit impact. *Journal of Economic Studies, 46*(2), 467-481. https://doi.org/10.1108/JES-01-2018-0007

Aouadi, A., Arouri, M., & Teulon, F. (2013). Investor attention and stock market activity: Evidence from France. *Economic Modelling*, *35*, 674-681. https://doi.org/10.1016/j.econmod.2013.08.034

Aslanidis, N., Bariviera, A. F., & Martínez-Ibañez, O. (2019). An analysis of cryptocurrencies conditional cross correlations. *Finance Research Letters, 31*, 130-137. https://doi.org/10.1016/j.frl.2019.04.019

Athey, S., Parashkevov, I., Sarukkai, V., & Xia, J. (2016). Bitcoin pricing, adoption, and usage: Theory and evidence (Master Thesis). *Stanford University Graduate School of Business Research Paper, 16*(42). Retrieved from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2826674

Bachmann, R., Elstner, S., & Sims, E. R. (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics, 5*(2), 217-49. https://doi.org/10.1257/mac.5.2.217

Baek, C., & Elbeck, M. (2015). Bitcoins as an investment or speculative vehicle? A first look. *Applied Economics Letters, 22*(1), 30-34. https://doi.org/10.1080/13504851.2014.916379

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives, 21*(2), 129-152. https://doi.org/10.1257/jep.21.2.129

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics, 131*(4), 1593-1636. https://doi.org/10.1093/qje/qjw024

Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, *64*, 74-81. https://doi.org/10.1016/j.econmod.2017.03.019

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics, 49*(3), 307-343. https://doi.org/10.1016/S0304-405X(98)00027-0

Basistha, A., Kurov, A., & Wolfe, M. H. (2015). Forecasting commodity price volatility with internet search activity. *NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management*. St. Louis, Missouri. https://doi.org/10.22004/ag.econ.285827

Batten, J. A., & Lucey, B. M. (2010). Volatility in the gold futures market. *Applied Economics Letters, 17*(2), 187-190. https://doi.org/10.2139/ssrn.996235

Baur, D. G., & Dimpfl, T. (2017). Realized bitcoin volatility. *SSRN Electronic Journal*, *2949754*, 1-26. https://doi.org/10.2139/ssrn.2949754

Baur, D. G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, gold and the US dollar–A replication and extension. *Finance Research Letters, 25*, 103-110. https://doi.org/10.1016/j.frl.2017.10.012

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review, 45*(2), 217-229. https://doi.org/10.1111/j.1540-6288.2010.00244.x

Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance, 34*(8), 1886-1898. https://doi.org/10.1016/j.jbankfin.2009.12.008

Begg, I., & Mushövel, F. (2016). The economic impact of Brexit: jobs, growth and the public finances. *The London School of Economics and Political Science*, London, UK. Retrieved from: http://eprints.lse.ac.uk/id/eprint/67008

Bera, A. K., & Kim, S. (2002). Testing constancy of correlation and other specifications of the BGARCH model with an application to international equity returns. *Journal of Empirical Finance, 9*(2), 171-195. https://doi.org/10.1016/S0927-5398(01)00050-0

Bessembinder, H., & Seguin, P. J. (1993). Price volatility, trading volume, and market depth: Evidence from futures markets. *Journal of Financial and Quantitative Analysis, 28*(1), 21-39. https://doi.org/10.2307/2331149

Biais, B., Bisiere, C., Bouvard, M., Casamatta, C., & Menkveld, A. J. (2018). Equilibrium bitcoin pricing. *Society for Economic Dynamics 2019 Meeting Papers, 360.* https://doi.org/10.2139/ssrn.3261063

Blau, B. M. (2017). Price dynamics and speculative trading in bitcoin. *Research in International Business and Finance, 41*, 493-499. https://doi.org/10.1016/j.ribaf.2017.05.010

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica, 77*(3), 623-685. https://doi.org/10.3982/ECTA6248

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1

Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances. *Journal of Political Economy, 96*(1), 116-131. https://doi.org/10.1086/261527

Bouoiyour, J., Selmi, R., & Wohar, M. (2019). Bitcoin: competitor or complement to gold?. *Economics Bulletin, 39*(1), 186-191. Retrieved from: https://hal.archives-ouvertes.fr/hal-01994187

Bouri, E., Lau, C. K. M., Lucey, B., & Roubaud, D. (2019). Trading volume and the predictability of return and volatility in the cryptocurrency market. *Finance Research Letters, 29*, 340-346.

https://doi.org/10.1016/j.frl.2018.08.015

Bouri, E., Shahzad, S. J. H., & Roubaud, D. (2020). Cryptocurrencies as hedges and safe-havens for US equity sectors. *The Quarterly Review of Economics and Finance, 75*, 294-307. https://doi.org/10.1016/j.qref.2019.05.001

Boz, E., Gopinath, G., & Plagborg-Møller, M. (2017). Global trade and the dollar (w23988). N*ational Bureau of Economic Research.* https://doi.org/10.3386/w23988

Brauneis, A., & Mestel, R. (2019). Cryptocurrency-portfolios in a mean-variance framework. *Finance Research Letters, 28*, 259-264. https://doi.org/10.1016/j.frl.2018.05.008

Burnie, A. (2018). Exploring the interconnectedness of cryptocurrencies using correlation networks. *The Cryptocurrency Research Conference 2018.* Cambridge, UK. Retrieved from: https://arxiv.org/ftp/arxiv/papers/1806/1806.06632.pdf

Busch, B., & Matthes, J. (2016). Brexit-the economic impact: A meta-analysis (working paper). *IW-Reports 10/2016, Institut der deutschen Wirtschaft (IW) / German Economic Institute, Köln, Germany.* Retrieved from: https://EconPapers.repec.org/RePEc:zbw:iwkrep:102016

Buterin, V. (2014). A next-generation smart contract and decentralized application platform (white paper). Retrieved from: https://ethereum.org/en/whitepaper/

Capie, F., Mills, T. C., & Wood, G. (2005). Gold as a hedge against the dollar. *Journal of International Financial Markets, Institutions and Money, 15*(4), 343-352. https://doi.org/10.1016/j.intfin.2004.07.002

Ciaian, P., Rajcaniova, M., & Kancs, D. A. (2016). The economics of BitCoin price formation. *Applied Economics, 48*(19), 1799-1815. https://doi.org/10.1080/00036846.2015.1109038

Chong, T. T. L., & Li, X. (2019). Understanding the China–US trade war: causes, economic impact, and the worst-case scenario. *Economic and Political Studies, 7*(2), 185-202. https://doi.org/10.1080/20954816.2019.1595328

Chu, J., Chan, S., Nadarajah, S., & Osterrieder, J. (2017). GARCH modelling of cryptocurrencies. *Journal of Risk and Financial Management, 10*(4), 17-32. https://doi.org/10.3390/jrfm10040017

Chui, C. M., & Yang, J. (2012). Extreme correlation of stock and bond futures markets: international evidence. *Financial Review, 47*(3), 565-587. https://doi.org/10.1111/j.1540-6288.2012.00340.x

Clements, K. W., & Fry, R. (2008). Commodity currencies and currency commodities. *Resources Policy, 33*(2), 55-73. https://doi.org/10.1016/j.resourpol.2007.10.004

Conlon, T., & McGee, R. (2020). Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. *Finance Research Letters, 35*, 101607. https://doi.org/10.1016/j.frl.2020.101607

Corbet, S., Hou, Y. G., Hu, Y., Larkin, C., & Oxley, L. (2020). Any port in a storm: Cryptocurrency safe-havens during the COVID-19 pandemic. *Economics Letters, 194*, 109377. https://doi.org/10.1016/j.econlet.2020.109377

Dimpfl, T., & Jank, S. (2016). Can internet search queries help to predict stock market volatility?. *European Financial Management, 22*(2), 171-192. https://doi.org/10.1111/eufm.12058

Draper, N. R., & Smith, H. (1998). Applied regression analysis (Vol. 326). John Wiley & Sons Inc., Hoboken, NJ, USA. https://doi.org/10.1002/9781118625590

Dutta, A., Das, D., Jana, R. K., & Vo, X. V. (2020). COVID-19 and oil market crash: Revisiting the safe haven property of gold and Bitcoin. *Resources Policy, 69*, 101816. https://doi.org/10.1016/j.resourpol.2020.101816

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar – A GARCH volatility analysis. *Finance Research Letters, 16*, 85–92. https://doi.org/10.1016/j.frl.2015.10.008

Dzielinski, M. (2012). Measuring economic uncertainty and its impact on the stock market. *Finance Research Letters, 9*(3), 167-175. https://doi.org/10.1016/j.frl.2011.10.003

Eisl, A., Gasser, S., & Weinmayer, K. (2015). Caveat emptor: Does Bitcoin improve portfolio diversification?. *SSRN Electronic Journal, 2408997,* 1-21. https://doi.org/10.2139/ssrn.2408997

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. J*ournal of Business & Economic*

Statistics, 20(3), 339-350. https://doi.org/10.1198/073500102288618487

Enocksson, D., & Skoog, J. (2012). Evaluating VaR with the ARCH/GARCH Family. *LAP LAMBERT Academic Publishing, Saarbrücken, Germany.* Retrieved from: https://api.semanticscholar.org/CorpusID:118136938

Eom, C., Kaizoji, T., Kang, S. H., & Pichl, L. (2019). Bitcoin and investor sentiment: statistical characteristics and predictability. *Physica A: Statistical Mechanics and its Applications, 514*, 511-521. https://doi.org/10.1016/j.physa.2018.09.063

Epps, T., & Epps, M. (1976). The Stochastic Dependence of Security Price Changes and Transaction Volumes: Implications for the Mixture-of-Distributions Hypothesis. *Econometrica, 44*(2), 305-321. https://doi.org/10.2307/1912726

Fisher, T. J., & Gallagher, C. M. (2012), New Weighted Portmanteau Statistics for Time Series Goodness-of-Fit Testing. *Journal of the American Statistical Association*, *107*(498), 777-787. https://doi.org/10.1080/01621459.2012.688465

Francq, C., & Zakoïan, J. M. (2009). Testing the nullity of GARCH coefficients: correction of the standard tests and relative efficiency comparisons. *Journal of the American Statistical Association, 104*(485), 313-324. https://doi.org/10.1198/jasa.2009.0117

Gao, L., & Süss, S. (2015). Market sentiment in commodity futures returns. *Journal of Empirical Finance, 33*, 84-103. https://doi.org/10.1016/j.jempfin.2015.07.001

Gillaizeau, M., Jayasekera, R., Maaitah, A., Mishra, T., Parhi, M., & Volokitina, E. (2019). Giver and the receiver: Understanding spillover effects and predictive power in cross-market Bitcoin prices. *International Review of Financial Analysis, 63*, 86-104. https://doi.org/10.1016/j.irfa.2019.03.005

Gourinchas, P. O., & Hale, G. (2017). Brexit: Whither the Pound?. *FRBSF Economic Letter, Federal Reserve Bank of San Francisco, 11*. Retrieved from: https://www.frbsf.org/economic-research/publications/economic-letter/2017/april/brexit-whither-the-pound/

Granger, C.W.J. & Morgenstern, O. (1963). Spectral Analysis of New York Stock Market Prices. *Kyklos(16),* 1-27. https://doi.org/10.1111/j.1467-6435.1963.tb00270.x

Grisse, C. (2010). What drives the oil-dollar correlation. Unpublished manuscript. Retrieved from: https://api.semanticscholar.org/CorpusID:17071917

Hayes, A. S. (2017). Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telematics and Informatics, 34*(7), 1308-1321. https://doi.org/10.1016/j.tele.2016.05.005

Henry, C. S., Huynh, K. P., & Nicholls, G. (2018). Bitcoin awareness and usage in Canada. *Journal of Digital Banking, 2*(4), 311-337. https://doi.org/10.3905/joi.2019.28.3.021

Hwang, S., & Valls Pereira, P. L. (2006). Small sample properties of GARCH estimates and persistence. *The European Journal of Finance, 12*(6-7), 473-494. https://doi.org/10.1080/13518470500039436

Jeribi, A., & Manzli, Y. S. (2021). Can cryptocurrencies be a safe haven during the novel COVID-19 pandemic? Evidence from the Tunisian Stock Market. *Journal of Research in Emerging Markets, 3*(1), 14-31. https://doi.org/10.30585/jrems.v3i1.555

Jonker, N. (2019). What drives the adoption of crypto-payments by online retailers?. *Electronic Commerce Research and Applications, 35*, 100848. https://doi.org/10.1016/j.elerap.2019.100848

Joseph, K., Wintoki, M. B., & Zhang, Z. (2011). Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal of Forecasting, 27*(4), 1116-1127. https://doi.org/10.1016/j.ijforecast.2010.11.001

Joy, M. (2011). Gold and the US dollar: Hedge or haven?. *Finance Research Letters, 8*(3), 120-131. https://doi.org/10.1016/j.frl.2011.01.001

Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring uncertainty. *American Economic Review, 105*(3), 1177-1216. https://doi.org/10.1257/aer.20131193

Jung, H. (2012). Tackling Currency Manipulation with International Law: Why and How Currency Manipulation Should be Adjudicated. *Manchester Journal of International Economic Law, 9*(2), 184-200. Retrieved from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2155859

Kang, S. H., Yoon, S. M., Bekiros, S., & Uddin, G. S. (2019). Bitcoin as hedge or safe haven: Evidence from stock, currency, bond and derivatives markets. *Computational Economics*, *56*, 529–545. https://doi.org/10.1007/s10614-019-09935-6

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters, 158*, 3-6. https://doi.org/10.1016/j.econlet.2017.06.023

Katsiampa, P. (2019). Volatility co-movement between Bitcoin and Ether. *Finance Research Letters, 30*, 221-227. https://doi.org/10.1016/j.frl.2018.10.005

Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters, 29*, 68-74. https://doi.org/10.1016/j.frl.2019.03.009

Kim, N., Lučivjanská, K., Molnár, P., & Villa, R. (2019). Google searches and stock market activity: Evidence from Norway. *Finance Research Letters, 28*, 208-220. https://doi.org/10.1016/j.frl.2018.05.003

Klein, T., Thu, H. P., & Walther, T. (2018). Bitcoin is not the New Gold – A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis, 59*, 105-116. https://doi.org/10.1016/j.irfa.2018.07.010

Kliber, A., Marszałek, P., Musiałkowska, I., & Świerczyńska, K. (2019). Bitcoin: Safe haven, hedge or diversifier? Perception of bitcoin in the context of a country's economic situation - A stochastic volatility approach. *Physica A: Statistical Mechanics and its Applications, 524,* 246-257. https://doi.org/10.1016/j.physa.2019.04.145

Li, C., He, C., & Lin, C. (2018). Economic impacts of the possible China–US trade war. *Emerging Markets Finance and Trade, 54*(7), 1557-1577. https://doi.org/10.1080/1540496X.2018.1446131

Li, W. K., & Mak, T. K. (1994). On the squared residual autocorrelations in non- linear time series with conditional heteroskedasticity. *Journal of Time Series Analysis, 15*(6), 627-636. https://doi.org/10.1111/j.1467-9892.1994.tb00217.x

Liu, W. (2019). Portfolio diversification across cryptocurrencies. *Finance Research Letters, 29*, 200-205. https://doi.org/10.1016/j.frl.2018.07.010

López-Cabarcos, M. Á., Pérez-Pico, A. M., Piñeiro-Chousa, J., & Šević, A. (2019). Bitcoin volatility, stock market and investor sentiment. Are they connected?. *Finance Research Letters, 38,* 101399. https://doi.org/10.1016/j.frl.2019.101399

Lyócsa, Š., Molnár, P., Plíhal, T., & Širv́aňová, M. (2020). Impact of Macroeconomic News, Regulation and Hacking Exchange Markets on the Volatility of Bitcoin. *Journal of Economic Dynamics and Control*, *199,* 103980. https://doi.org/10.1016/j.jedc.2020.103980

Ma, J., Gans, J. S., & Tourky, R. (2018). Market structure in bitcoin mining (working paper). *National Bureau of Economic Research.* Retrieved from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3112029

Manimaran, P., Panigrahi, P. K., & Parikh, J. C. (2008). Difference in nature of correlation between NASDAQ and BSE indices. *Physica A: Statistical Mechanics and its Applications, 387*(23), 5810-5817. https://doi.org/10.1016/j.physa.2008.06.033

Mariana, C. D., Ekaputra, I. A., & Husodo, Z. A. (2021). Are Bitcoin and Ethereum safe-havens for stocks during the COVID-19 pandemic?. *Finance research letters, 38*, 101798. https://doi.org/10.1016/j.frl.2020.101798

Mensi, W., Beljid, M., Boubaker, A., & Managi, S. (2013). Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic Modelling, 32*, 15-22. https://doi.org/10.1016/j.econmod.2013.01.023

Meshcheryakov, A., & Ivanov, S. (2020). Ethereum as a hedge: the intraday analysis. *Economics Bulletin, 40*(1), 101-108. Retrieved from: https://api.semanticscholar.org/CorpusID:214341404

Mittnik, S., Robinzonov, N., & Spindler, M. (2015). Stock market volatility: Identifying major drivers and the nature of their impact. *Journal of Banking & Finance, 58,* 1-14. https://doi.org/10.1016/j.jbankfin.2015.04.003

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system (whitepaper). Retrieved from: http://bitcoin.org/bitcoin.pdf

Neath, A. A., & Cavanaugh, J. E. (2012). The Bayesian information criterion: background, derivation, and applications. *Wiley Interdisciplinary Reviews: Computational Statistics, 4*(2), 199-203. https://doi.org/10.1002/wics.199

NG, H. R., & Lam, K. P. (2006). How does sample size affect GARCH Models?. *Proceedings of the 2006 Joint Conference on Information Sciences (JCIS-06)*. Kaohsiung, Taiwan. https://doi.org/10.2991/jcis.2006.139

Noether, S., Noether, S., & Mackenzie, A. (2014). A note on chain reactions in traceability in cryptonote 2.0. *Research Bulletin MRL-0001 Monero Research Lab, 1,* 1-8. Retrieved from: https://assets.ctfassets.net/sdlntm3tthp6/resource-asset-r382/307d29abc5c9cd6df200530a2fdc691d/9c049030-8d49-4802-8e11-17f156c82755.pdf

Orskaug, E. (2009). Multivariate dcc-garch model:-with various error distributions (Master Thesis). *Institutt for matematiske fag (NTNU).* Trondheim, Norway. Retrieved from: https://api.semanticscholar.org/CorpusID:8129270

Osterrieder, J., & Lorenz, J. (2017). A statistical risk assessment of Bitcoin and its extreme tail behavior. *Annals of Financial Economics, 12*(1), 1750003. https://doi.org/10.1142/S2010495217500038

Parhizgari, A. M. and Cho, J. H. (2008). East Asian financial contagion under DCC-GARCH. *International Journal of Banking and Finance, 6*(1), 17–30. https://doi.org/10.32890/ijbf2009.6.1.8380

Park, C. Y., Tian, G., & Zhao, B. (2020). Global Bitcoin Markets and Local Regulations (WPS200006-2). *Asian Development Bank Economics Working Paper Series*. https://doi.org/10.22617/WPS200006-2

Pieters, G., & Vivanco, S. (2017). Financial regulations and price inconsistencies across Bitcoin markets. *Information Economics and Policy, 39*, 1-14. https://doi.org/10.1016/j.infoecopol.2017.02.002

Pindyck, R. S., & Rotemberg, J. J. (1990). The excess co-movement of commodity prices. *The Economic Journal, 100*(403), 1173-1189. https://doi.org/10.2307/2233966

Plakandaras, V., Gupta, R., & Wohar, M. E. (2017). The depreciation of the pound post-Brexit: Could it have been predicted?. *Finance research letters, 21*, 206-213. https://doi.org/10.1016/j.frl.2016.12.003

Polasik, M., Piotrowska, A. I., Wisniewski, T. P., Kotkowski, R., & Lightfoot, G. (2015). Price fluctuations and the use of bitcoin: An empirical inquiry. *International Journal of Electronic Commerce, 20*(1), 9-49. https://doi.org/10.1080/10864415.2016.1061413

Puri, V. (2016). Decrypting Bitcoin prices and adoption rates using Google search (CMC Senior Theses, 1418.). Retrieved from: https://scholarship.claremont.edu/cmc_theses/1418

Qarni, M. O., Gulzar, S., Fatima, S. T., Khan, M. J., & Shafi, K. (2019). Inter-markets volatility spillover in US bitcoin and financial markets. *Journal of Business Economics and Management, 20*(4), 694-714. https://doi.org/10.3846/jbem.2019.8316

Ratner, M., & Chiu, C. C. J. (2013). Hedging stock sector risk with credit default swaps. *International Review of Financial Analysis, 30*, 18-25. https://doi.org/10.1016/j.irfa.2013.05.001

Reboredo, J. C. (2013a). Is gold a hedge or safe haven against oil price movements?. *Resources Policy, 38*(2), 130-137. https://doi.org/10.1016/j.resourpol.2013.02.003

Reboredo, J. C. (2013b). Is gold a safe haven or a hedge for the US dollar? Implications for risk management. *Journal of Banking & Finance, 37*(8), 2665-2676. https://doi.org/10.1016/j.jbankfin.2013.03.020

Reboredo, J. C., Rivera-Castro, M. A., & Zebende, G. F. (2014). Oil and US dollar exchange rate dependence: A detrended cross-correlation approach. *Energy Economics, 42,* 132-139. https://doi.org/10.1016/j.eneco.2013.12.008

Saghaian, S. H. (2010). The impact of the oil sector on commodity prices: correlation or causation?. *Journal of Agricultural and Applied Economics, 42*(3), 477-485. https://doi.org/10.1017/S1074070800003667

Sarwar, G. (2003). The interrelation of price volatility and trading volume of currency options. *Journal of Futures Markets: Futures, Options, and Other Derivative Products, 23*(7), 681-700. https://doi.org/10.1002/fut.10078

Schuh, S., & Shy, O. (2016, April). US consumers' adoption and use of Bitcoin and other virtual currencies. *Conference on Retail payments: mapping out the road ahead.* Amsterdam, Netherlands. Retrieved from: https://www.bankofcanada.ca/wp-content/uploads/2015/12/us-consumers-adoption.pdf

Shahzad, S. J. H., Bouri, E., Roubaud, D., & Kristoufek, L. (2020). Safe haven, hedge and diversification for G7 stock markets: Gold versus bitcoin. *Economic Modelling, 87*, 212-224. https://doi.org/10.1016/j.econmod.2019.07.023

Siddiqui, K. (2020). The US dollar and the world economy. *Athens Journal of Business & Economics, 6*(1), 21-44. https://doi.org/10.30958/ajbe.6-1-2

Sinha, P., & Agnihotri, S. (2014). Investigating impact of volatility persistence, market asymmetry and information inflow on volatility of stock indices using bivariate GJR-GARCH (working paper). *MPRA Paper 58303*. University Library of Munich, Munich, Germany. Retrieved from: https://mpra.ub.uni-muenchen.de/58303/

Smales, L. A. (2014). News sentiment in the gold futures market. J*ournal of Banking & Finance, 49*, 275-286. https://doi.org/10.1016/j.jbankfin.2014.09.006

Smales, L. A. (2019). Bitcoin as a safe haven: Is it even worth considering?. *Finance Research Letters, 30*, 385-393. https://doi.org/10.2139/ssrn.3204237

Smith, G. P. (2012). Google Internet search activity and volatility prediction in the market for foreign currency. *Finance Research Letters, 9*(2), 103-110. https://doi.org/10.1016/j.frl.2012.03.003

Solnik, B., Boucrelle, C., & Le Fur, Y. (1996). International market correlation and volatility. *Financial analysts journal, 52*(5), 17-34. https://doi.org/10.2469/faj.v52.n5.2021

Staiger, R. W., & Sykes, A. O. (2010). 'Currency manipulation' and world trade. *World Trade Review, 9*(4), 583-627.

Stråle Johansson, N., & Tjernström, M. (2014). The Price Volatility of Bitcoin: A search for the drivers affecting the price volatility of this digital currency (Master Thesis). *Umeå School of Business and Economics*. Umeå, Sweden.. Retrieved from: https://www.diva-portal.org/smash/get/diva2:782588/FULLTEXT01.pdf

Tachibana, M. (2018). Safe-haven and hedge currencies for the US, UK, and Euro area stock markets: A copula-based approach. *Global Finance Journal, 35*, 82-96. https://doi.org/10.1016/j.gfj.2017.07.001

Takezawa, N. (1995). Currency swaps and long-term covered interest parity. *Economics Letters, 49*(2), 181-185. https://doi.org/10.1016/0165-1765(95)00664-2

Tetlow, G., & Stojanovic, A. (2018). Understanding the economic impact of Brexit. *Institute for government*. London, England. Retrieved from:

https://www.instituteforgovernment.org.uk/sites/default/files/publications/2018%20IfG%20%20Brexit%20impact%20[final%20for%20web].pdf

Trabelsi, N. (2018). Are there any volatility spill-over effects among cryptocurrencies and widely traded asset classes?. *Journal of Risk and Financial Management, 11*(4), 66. https://doi.org/10.3390/jrfm11040066

Urquhart, A. (2018). What causes the attention of Bitcoin?. *Economics Letters, 166*, 40-44. https://doi.org/10.1016/j.econlet.2018.02.017

Urquhart, A., & Zhang, H. (2018). Is Bitcoin a hedge or safe-haven for currencies? An intraday analysis. An Intraday Analysis. *International Review of Financial Analysis, 63,* 49-57. https://doi.org/10.1016/j.irfa.2019.02.009

Vlastakis, N., & Markellos, R. N. (2012). Information demand and stock market volatility. *Journal of Banking & Finance, 36*(6), 1808-1821. https://doi.org/10.1016/j.jbankfin.2012.02.007

Wang, D. H., Suo, Y. Y., Yu, X. W., & Lei, M. (2013). Price–volume cross-correlation analysis of CSI300 index futures. *Physica A: Statistical Mechanics and its Applications, 392*(5), 1172-1179. https://doi.org/10.1016/j.physa.2012.11.031

Wang, G. J., Xie, C., Wen, D., & Zhao, L. (2019). When Bitcoin meets economic policy uncertainty (EPU): Measuring risk spillover effect from EPU to Bitcoin. *Finance Research Letters, 31.* https://doi.org/10.1016/j.frl.2018.12.028

Wang, Z., & Sun, Z. (2021). From globalization to regionalization: The United States, China, and the post-Covid-19 world economic order. *Journal of Chinese Political Science, 26*(1), 69-87. https://doi.org/10.1007/s11366-020-09706-3

Yang, J., Zhou, Y., & Wang, Z. (2009). The stock–bond correlation and macroeconomic conditions: One and a half centuries of evidence. *Journal of Banking & Finance, 33*(4), 670-680. https://doi.org/10.1016/j.jbankfin.2008.11.010

Zghal, I., Hamad, S. B., Eleuch, H., & Nobanee, H. (2020). The effect of market sentiment and information asymmetry on option pricing. *The North American Journal of Economics and Finance, 54*, 101235. https://doi.org/10.1016/j.najef.2020.101235

8. Appendix

8.1 Appendix I - DCC(1,1)-GARCH model by Engle (2002)

r_t is the vector ($n \times 1$) of the log returns of *n* assets at time *t*, and can be calculated as follows:

$$r_t = \mu_t + e_t$$

Where μ_t is the vector ($n \times 1$) of the expected value of conditional r_t at time *t*, and e_t is the vector ($n \times 1$) of mean-corrected returns of *n* assets at time *t.* Thus, e_t is used to model unconditional heteroskedasticity. e_t is formulated as:

$$e_t = H_t^{1/2} z_t$$

Where z_t is the vector ($n \times 1$) of independent and identically distributed errors (thus, random variables with a mean of 0 when standard normality is assumed) and $H_t^{1/2}$ is any matrix ($n \times n$) at time *t* such that H_t is the conditional variance matrix of e_t *.* The matrix process H_t can be determined in multiple ways. Originally, the Vector Error Correction model by Bollerslev, Engle, and Wooldridge (1988) was suggested. For the DCC-GARCH approach however, the covariance matrix H_t is decomposed in conditional standard deviation matrices D_t, which consists of the components of univariate GARCH(1,1) models, and a symmetrical, conditional correlation matrix of standardized residuals R_t *,* thus*:*

$$H_t = D_t R_t D_t$$

H_t is positive and definite, since it is a covariance matrix, therefore R_t and D_t have to be positive and definite. D_t is positive and definite by nature, since all diagonal elements of the matrix are positive. This implies all elements in the correlation matrix R_t have to be equal to or less than one by definition. R_t is further decomposed into unconditional covariance matrices containing scalars which can not be lower or equal to zero to ensure the properties for R_t , and therefore H_t, are met.

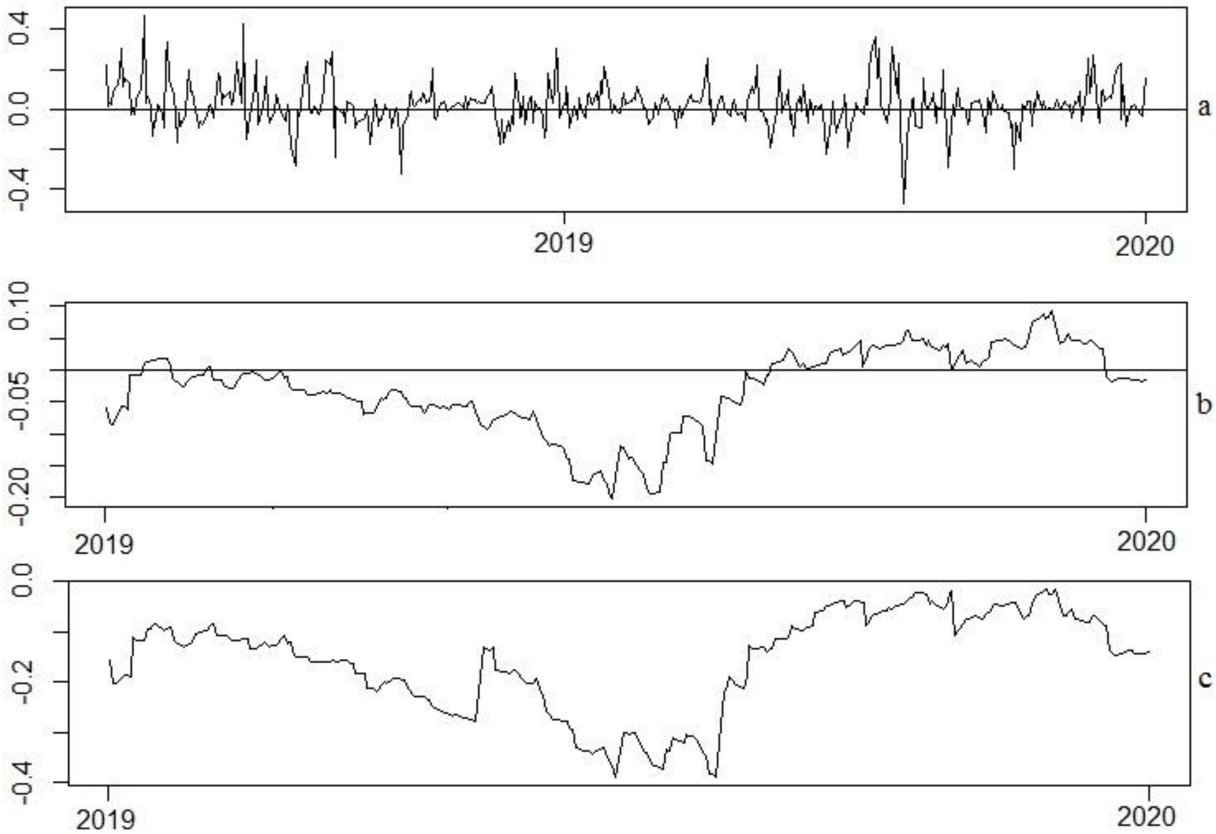
As the DCC-GARCH method is applied to Bitcoin's correlation to one another asset, in this case one of the currencies, it means the vector size *n* is set to two. For D_t it implies two univariate GARCH(1,1) models are integrated on its diagonal.

$$D_t = \begin{bmatrix} \sqrt{h_{1t}} & 0 \\ 0 & \sqrt{h_{2t}} \end{bmatrix}$$

h_t are the standard, univariate GARCH(1,1) variance equations, described in the methodology chapter in Equation 4.

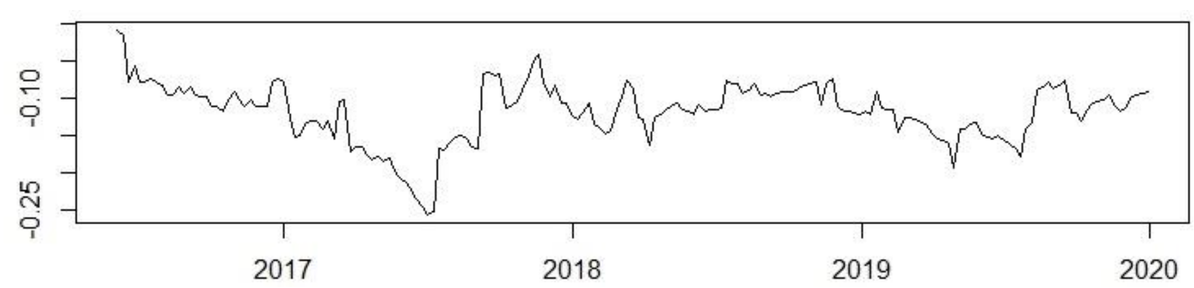
8.2 Appendix II - Dynamical Conditional Correlations of the Robustness Analyses

IIa: Dynamic Conditional Correlations of the subsamples' second halves of Bitcoin and the pound, dollar and yuan.



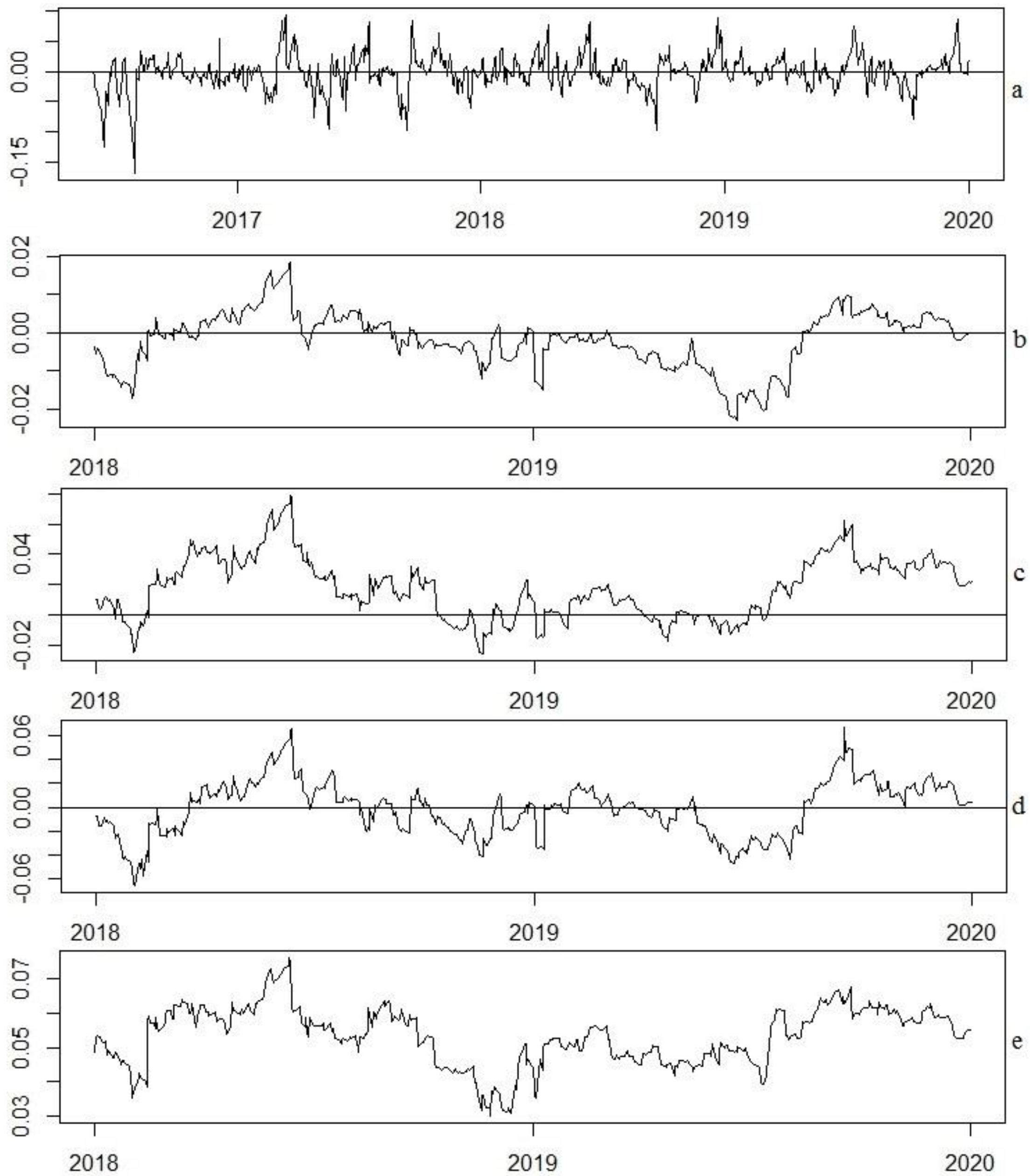
Note. Figure *a* includes the dynamic correlation of Bitcoin and the pound in the second half of the Brexit sample. Figure *b* and *c* include the dynamic correlation of Bitcoin and the dollar and yuan in the second half of the trade war sample, respectively. The return correlations are plotted on the y-axis, time in days is plotted on the x-axis.

IIb: Dynamic Conditional Correlations of the Weekly sampled analysis of Bitcoin and the pound.



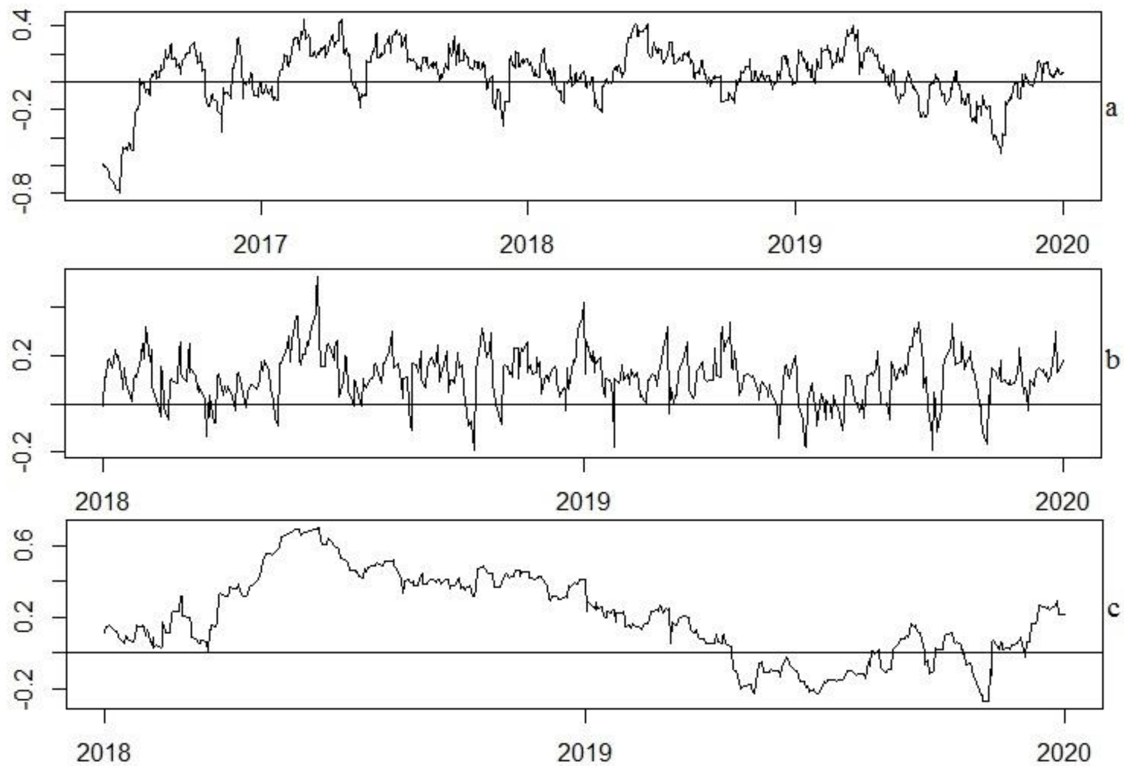
Note. The dynamic conditional correlation of Bitcoin and the pound in the weekly sampled Brexit sample. The return correlations are plotted on the y-axis, the time in weeks on the x-axis.

8.3 Appendix III - Dynamical Conditional Correlations of Alternative Cryptocurrencies with the Pound, Dollar and Yuan.



Note. The dynamic conditional correlation of Ethereum and the pound and yuan is presented in figure *a* and *b* respectively. Figure *c* and *d* include the dynamic conditional correlations of Ripple and the dollar and yuan, respectively. Figure *e* presents the dynamic conditional correlation of Litecoin and the dollar. All return correlations are plotted on the y-axis, time in days on the x-axis.

8.4 Appendix IV - Dynamical Conditional Correlations of Gold and the Pound, Dollar and Yuan.



Note. Figure *a* presents the dynamic conditional correlation of gold and the pound in the Brexit sample. Figure *b* and *c* present the dynamic conditional correlation of gold and the dollar and yuan respectively. The return correlations are plotted on the y-axis, time in days on the x-axis.