Bitcoin is not the New Gold
Evidence from the Covid-19 Pandemic

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Abstract

The recent market turmoil, caused by the Covid-19 pandemic, has negatively influenced the financial markets all over the world. Therefore, the search for safe haven assets by investors is of great importance. In this area of research, gold has for a long time been considered to be the traditional safe haven asset. However, recent literature states that Bitcoin is the new gold. Whether this is the case, and whether gold still has the ability to act as a safe haven, is of essence in this current time period. The aim of this paper is to investigate the similarities between Bitcoin and gold and foremost to see if Bitcoin can be considered as the new gold. Moreover, a comparison is conducted with other established asset classes. First, different ARCH models are used to study the volatility behaviour of the assets. Secondly, a dynamic correlation analysis is performed in order to study the correlation between the assets and stock indices. Finally, a portfolio analysis is done in order to examine the hedging properties of Bitcoin and gold. The results show that Bitcoin is neither a hedge, nor a safe haven, during the recent time period which is influenced by market distress. Bitcoin does, however, show diversification benefits. Moreover, the results confirm that gold has hedging properties and acts as a safe haven during the recent market turmoil. Furthermore, while Bitcoin and gold share some similarities, the conclusion is that Bitcoin does not fulfil the essential requirements to be named the new gold.

Contents

1 Introduction

The popularity of Bitcoin, along with other cryptocurrencies, has increased since the concept was introduced in an influential paper by Nakamoto (2008). Not only has it become popular in terms of introducing a new area of research, but it has also become more popular for individuals wishing to invest in it. The latter is perhaps mostly due to the tremendous price increase, which is evident in figure 1. As the paper by Nakamoto (2008) is published slightly after the Financial Crisis in 2008[1], the present time period which is influenced by another financial crisis, has become essential for further analysis of Bitcoin.

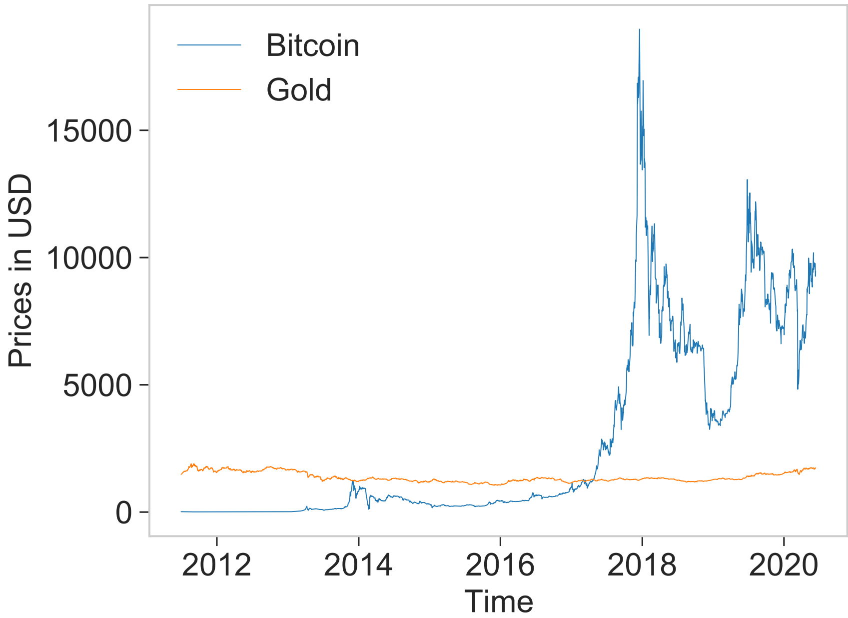


Figure 1: Level of Bitcoin and gold over time.

The concept of Bitcoin is based on the use of a peer-to-peer network and a distributed ledger technology which makes online payments possible without a financial institution acting as a third party (Nakamoto, 2008). The system is decentralised and in order to replace the intermediary, attributes such as cryptographic proof, digital signatures and proof-of-work are implemented to establish trust. The transactions are validated by miners, who produce blocks and add them to a ledger which eventually forms a block chain. This validation is made by solving an algorithm, which becomes harder to do with time as the ledger becomes longer. This method of validation makes it rather difficult to commit fraud[2]. Moreover, all the transactions and ledgers are made publicly available, but kept anonymous with the help of encrypted identities. This last property

[1]The Financial Crisis in 2008 managed to highlight the risks of storing money with financial institutions. It is commonly argued that Bitcoin was created as an answer to this and moreover, Nakamoto (2008) discusses weaknesses of the existing electronic payment system.

[2]For a fraud to be successful, it is required to simultaneously change and validate several ledgers at the same time and thus, beating the miners are their own work. By definition, it is the longest block chain that is considered to be the correct one and is trusted in the network.

helps with the privacy aspect, but is also a way to tackle the problem of double-spending.

The supply of Bitcoin is fixed at a quantity of 21 million[3]. By design, the number of Bitcoin that miners can receive for their work is halved every four years, or more specifically for every 210 000 blocks[4]. Bitcoin is the cryptocurrency which has emerged as the most important one, and stands for 65 % of the entire cryptocurrency market. Altogether there exists 7683 cryptocurrencies and the three largest ones are Bitcoin, Ethereum and Tether. Together they represent 80 % of the entire cryptocurrency market. The market capitalisation of Bitcoin is currently equal to $301 billion. The market capitalisation when combining all of the cryptocurrencies gives us a value of $463 billion. These numbers can be compared to the market valuation of the largest companies such as Apple, Microsoft and Amazon in order to provide a sense of reference for the magnitude of the cryptocurrency market. It can further be observed in figure 1 that the price of Bitcoin spiked on the 17th December 2017 and reached a value of $20 089[5].

In recent years, there has been an ongoing discussion concerning whether Bitcoin should be considered to be a currency or a commodity[6]. By definition, properties including a medium of exchange, a store of value and a unit of account are required in order for an asset to be classified as a currency (Bariviera et al. 2017). In order to study this, Bariviera et al. (2017) compare the dynamics of Bitcoin to the dynamics of major currencies. The authors find that Bitcoin does not have the mentioned properties, and therefore should not be classified as a currency. However, it is suggested that Bitcoin shows evidence of being a speculative asset (Bariviera et al. 2017). Yermack (2015) draws the same conclusions. A common feature of a speculative asset is that it is difficult to determine its correct value (Bariviera et al. 2017). This is related to price bubbles being created, another property of Bitcoin which is frequently revisited in literature (Shiller 1990; Blau 2018).

The volatility of financial assets is a research topic which has received significant attention, and there is no difference when it comes to cryptocurrencies. Numerous studies of Bitcoin have focused on different aspects of the assets' volatility. In the previous literature, regarding asset markets in general, the presence of high volatility has been shown to be an indication of a bubble (Cheung, Roca, & Su 2015)[7]. In this regard, the volatility of Bitcoin is repeatedly shown to be higher than other assets, such as gold and stocks. In fact, the volatility of Bitcoin has been shown to be higher than the average volatility for 51 other currencies (Blau 2018), more volatile than both oil and gold (Chaim & Laurini 2019) and 26 times as volatile as the S&P 500 index (Baek & Elbeck 2015). Dwyer (2015) finds that the volatility of Bitcoin is higher than for gold and traditional currencies. They also confirm that the excess return and volatility provide evidence of

[3]As of 20th November 2020, the supply in circulation is 18,548,750 BTC.

[4]This implies that the process of an increased supply will last until the year 2140.

[5]The data which these calculations are based on is taken from coinmarketcap.com on November 16th, 2020.

[6]According to the Commodity Exchange Act (CEA), cryptocurrencies fall under the category of commodities along with gold and oil (Commodity Futures Trading Commission, CFTC).

[7]Some famous examples of bubbles are, for instance, the Tulip-mania, the internet bubble in 2000 and the real estate bubble in 2008 (Cheung, Roca, & Su 2015).

a speculative asset. Additionally, investments in cryptocurrencies are generally characterised by high expected returns[8] (Elendner et al. 2017), which further supports the idea of Bitcoin being a speculative asset (Baur, Dimpfl, & Kuck 2018). Moreover, Bitcoin has a higher idiosyncratic risk than gold (Dwyer 2015)[9]. Zhang and Li (2020) further investigate whether the idiosyncratic volatility is priced in the returns of cryptocurrencies and find a positive relationship between the idiosyncratic volatility and the returns of cryptocurrencies[10].

Blau (2018) uses a GARCH(1,1) model to investigate if the high volatility of Bitcoin can be explained by speculative trading in the market. However, Blau (2018) finds no correlation between speculative trading and volatility. Furthermore, the evidence also shows no correlation between speculative trading and the return of Bitcoin[11]. More specifically, researchers have found evidence suggesting that Bitcoin behaves more like a speculative asset than a traditional medium of exchange (Blau 2018). Baek and Elbeck (2015) investigate whether Bitcoin can be defined as an investment asset or a speculative asset, by comparing the volatility of Bitcoin with the volatility of the S&P 500, which serves as a proxy for the stock market. Their results indicate that Bitcoin is best defined as a speculative asset. Additionally, the results suggest that the volatility is internally driven. Cheah and Fry (2015) investigate if there are speculative bubbles present in the price of Bitcoin. The results from their paper imply that the market for cryptocurrencies is vulnerable to speculative bubbles, in the same way as other financial markets. Additionally, Härdle, Harvey, and Reule (2019) find that the price and volatility of Bitcoin is influenced by a bubble-like behaviour. Chaim and Laurini (2019) study the volatility of Bitcoin and compare it to the one of other financial assets. Interestingly, they find the existence of a bubble in the early years of Bitcoin but not at the time of their publication. Kristoufek (2019) confirms the existence of price bubbles in Bitcoin and states that the there is no bubble during the end of 2018. This is in line with the findings of Chaim and Laurini (2019).

Kristoufek (2015) shows that Bitcoin behaves both as a traditional financial asset and a speculative asset. In particular, the results show that the price of Bitcoin is dominated by explosive bubbles. Kristoufek (2015) argues that the price dynamic of Bitcoin is not similar to that of gold. Corbet, Lucey, and Yarovaya (2018) examine the fundamental drivers of the price of Bitcoin and find evidence of periods with bubble behaviour but do not manage to find a persistent bubble, which is in line with the study by Kristoufek (2015). Moreover, an econometric investigation to study the potential bubbles in the Bitcoin market is performed according to the same methodology (Phillips, Shi, & Yu 2013) which was used to investigate the United States housing bubble (Cheung, Roca, & Su 2015). A few short-lived bubbles are detected, but what is more crucial,

[8] Interestingly, it is shown that investments in cryptocurrencies lead more often to losses than gains, but that the gains are larger suggesting that the positive tails are bigger in absolute value (Elendner et al. 2017).

[9] Investors are said to be more exposed to idiosyncratic risk when they invest in Bitcoin than, for instance, when they invest in gold.

[10] Hence, the standard deviation of the returns is higher in portfolios if cryptocurrencies have higher idiosyncratic volatility.

[11] This information is vital in the sense that speculation is suggested to result in the destabilisation of asset prices and as a consequence, a decrease in the possibility of being considered as a currency (Blau 2018).

evidence of three larger bubbles, with intervals of 66 to 106 days, are found (Cheung, Roca, & Su 2015)[12]. Furthermore, Bouri, Shahzad, and Roubaud (2019) find evidence of co-explosivity in the cryptocurrency market[13]. Camerer (1989) states that the presence of bubbles may result in negative skewness and excess kurtosis, thus a leptokurtic distribution. These results are confirmed by Chaim and Laurini (2019) and imply that Bitcoin returns do not follow a normal distribution, which motivates a possible presence of bubbles in the market.

Urquhart (2016) studies the market efficiency of Bitcoin and finds that the returns are significantly inefficient when considering the whole time period. However, when the sample is split into subsamples, there is evidence of efficiency. It is therefore argued that the Bitcoin market is moving towards being efficient. Nadarajah and Chu (2017) replicate the study by Urquhart (2016) and show that a transformation of the returns result in an efficient market[14]. The cryptocurrencies are found not to follow a random walk, but are instead found to be weakly persistent (Caporale, Gil-Alana, & Plastun 2018). However, the degree of persistence is found to be time variant. These characteristics are inconsistent with the market being efficient[15] (Bouri et al. 2019; Caporale, Gil-Alana, & Plastun 2018). In addition, Bouri et al. (2019) state that there exists a predictable component in the price dynamics of Bitcoin. This means that there is a possibility of forecasting the volatility and presents a hedging advantage by making it possible for investors to benefit from this market inefficiency. In contrast to these findings, Alvarez-Ramirez, Rodriguez, and Ibarra-Valdez (2018) argue that there is an indication of efficiency in the Bitcoin market, but stress the fact that the efficiency is only evident for a short time period.

The market of cryptocurrencies is still relatively young. This novelty has inspired researchers to study its statistical properties with the aim of finding common properties for the asset class, and thereby to derive stylised facts. These are, by definition, based on a statistical analysis of the empirical findings (Cont 2001). For this purpose, the fact that Bitcoin is traded continuously serves as an advantage. The reason is that it results in more available data points to analyse and hence, contributes to an improved analysis. In general, high volatility and large values of the higher other moments are found to be common properties for cryptocurrencies. This is in combination with the previously mentioned attributes, such as speculative behaviour and a presence of bubbles. However, more importantly, this paper will focus on the two stylised facts long memory, which is a common feature of financial returns, and asymmetry, which results from the leverage effect and feedback effect in the stock market (Klein, Thu, & Walther 2018). Long memory is often observed in various asset classes, such as stocks, commodities and exchange rates (Baillie 1996; Bollerslev & Mikkelsen 1996). Research shows that precious metals have

[12]Cheung, Roca, and Su (2015) state that the lack of a clear definition of a bubble, and the difficulty of valuing Bitcoin, results in a difficulty to observe bubbles in the market. However, Phillips, Shi, and Yu (2013) suggest that a bubble is described as explosive behaviour, hence a characteristic which is observed in Bitcoin (cf. figure 1).

[13]They study the extent of which price explosivity in one cryptocurrency is transferred to other cryptocurrencies and find that Bitcoin is affected the least by price explosivity in other cryptocurrencies. Although, evidence suggests that Bitcoin is subject to long lasting price explosivity.

[14]The transformed returns are shown to behave more like a random walk than the original returns.

[15]The results indicate that Bitcoin is the most efficient cryptocurrency.

properties of asymmetry and long memory in their variance. For instance, Klein (2017) observes these properties for gold and silver, but argues that the asymmetric effect dominates. Additionally, the properties of asymmetry and persistence are observed in the returns of gold by Capie, Mills, and Wood (2005). Similarly, long memory is found to be present in Bitcoin (Bouri et al. 2019)[16]. However, Dyhrberg (2016b) finds an insignificant leverage effect in Bitcoin. In contrast to this, Catania and Grassi (2017) present results which indicate an inverse leverage effect when studying the volatility of Bitcoin. Moreover, their results imply that the property of long memory is visible in cryptocurrencies in general.

Klein, Thu, and Walther (2018) state that Bitcoin has been named the new gold. A simple approach of suggesting similarities between the two assets is to highlight common attributes in terms of, for instance, the limited supply and the creation by miners. Gold has over the years repeatedly been considered as a typical hedge and safe haven asset. Baur and Lucey (2010) suggest that one of the reasons that gold is often referred to as a safe haven is that it fulfils the essential feature of being uncorrelated with other types of assets. Consequently, a lot of research involves the investigation of gold, and its characteristics as an investment asset, for this particular purpose. For instance, it is found that gold acts as a hedge against stocks, bonds and the US dollar (Baur & Lucey 2010; Capie, Mills, & Wood 2005). Capie, Mills, and Wood (2005) make use of the threshold GARCH (TGARCH) model, together with the exponential GARCH (EGARCH) model, to investigate the hedging capabilities of gold and conclude that gold acts as a hedge against the US dollar. However, the hedging capabilities of gold are time variant, which suggests the need of repeated research (Capie, Mills, & Wood 2005). Klein (2017) uses a dynamic conditional correlation model (DCC) to study the flight-to-quality phenomenon and concludes that gold is a safe haven[17]. It is noteworthy that neither one of these two investment assets show these properties after 2013 (Klein 2017). However, the results show that gold behaves as a safe haven against the S&P 500 during the 2008 financial crisis, following with a positive correlation one year later, which is in line with the definition of a safe haven (Baur & Lucey 2010).

Baur and Lucey (2010) analyse whether gold is a safe haven asset. Their findings suggest that gold functions as a hedge against stocks. Moreover, it is shown that gold performs as a safe haven asset during extreme market conditions. However, when carrying out a portfolio analysis they find that the safe haven property is not long lasting. Baur and McDermott (2016) analyse whether gold is a safe haven by focusing on studying time periods characterised as black swan events and find that the reaction of gold is more pronounced than other potential safe haven assets. Thus, gold serves as a safe haven asset during black swan events[18]. Although, they state that the preference for gold during market turmoil fails to solely be explained by gold's risk-return characteristics, a similar issue is raised by Baur and McDermott (2010). Furthermore, Baur and McDermott (2016) discuss why gold is considered to be a safe haven in the first place, particularly

[16]Long memory creates the predictable component in the price dynamics which was mentioned earlier.

[17]Silver is also observed to have a safe haven property to some extent.

[18]Note that holding gold as an asset on its own is observed to be more risky than holding a diversified portfolio only consisting of stocks.

when there are assets with lower risk available. A comparison is made with a government bond, which is more in line with the definition of a safe asset. Baur and McDermott (2016) explain this by behavioural biases, which are shown to be a possible explanation to why investors choose gold during market stress. In this respect, it is moreover suggested that this behaviour can be explained by Prospect theory (Kahneman & Tversky 1979). Nevertheless, their results show that gold acts as a safe haven during previous periods of market turmoil (Baur & McDermott 2016).

Due to the similarities raised between Bitcoin and gold, it is suggested that the two assets share the same properties. In this respect, Dyhrberg (2016a) explores if Bitcoin has hedging capabilities and additionally, investigates if the asset is similar to gold. More specifically, Dyhrberg (2016a) investigates if Bitcoin can be seen as virtual gold. The results by Dyhrberg (2016a) suggest that Bitcoin can be classified as something between a commodity and a currency, or more specifically, something between gold and the US dollar. In order to do this, Dyhrberg (2016a) uses the TGARCH model[19], with the motivation that it is beneficial to use the same methodology which is used when studying gold (Capie, Mills, & Wood 2005). Dyhrberg (2016a) finds that Bitcoin can be used as a hedge against stocks and the US dollar, but the latter lasts for a short time period only. Interestingly, Dyhrberg (2016a) argues that this might be enough, keeping in mind that Bitcoin is an asset which is traded continuously. Baur, Dimpfl, and Kuck (2018) replicate the paper by Dyhrberg (2016a) and find, on the contrary, that Bitcoin shows different characteristics in terms of returns, volatility and correlation when compared to gold and the US dollar. They use univariate GARCH models which account for asymmetry and persistence. In addition, the volatility of Bitcoin is shown to be higher compared to these assets which implies that Bitcoin is not similar to gold or the US dollar. Baur, Dimpfl, and Kuck (2018) perform a correlation analysis which shows that the returns of Bitcoin are uncorrelated with the returns of gold, exchange rates and stock markets. This indicates that Bitcoin has diversification benefits. Moreover, the correlation analysis demonstrates that Bitcoin, as an investment asset, differs from a traditional currency (Baur, Dimpfl, & Kuck 2018).

Considering that Bitcoin is mainly used for investment purposes, examining the asset's volatility is of importance. Therefore it is not surprising that there exists an extended amount of research with the focus on studying the volatility of Bitcoin. GARCH models are frequently used when studying the volatility of assets and Bariviera et al. (2017) mention that this can be motivated by the existence of long memory in Bitcoin. Conrad, Custovic, and Ghysels (2018) find that the short-term volatility of Bitcoin can be described by a simple GARCH(1,1) model, which is often used as a benchmark in contemporary literature (Conrad, Custovic, & Ghysels 2018; Chkili, Hammoudeh, & Nguyen 2014). Moreover, the TGARCH and EGARCH model are used to study the volatility of Bitcoin (Dyhrberg 2016b; Bouri et al. 2017b).

Katsiampa (2017) investigates which econometric model is best able to describe the volatility

[19]An advantage of using this model is that it accounts for an asymmetric component, which is shown to be present in both gold and Bitcoin.

of Bitcoin, and compares the following models: GARCH, EGARCH, TGARCH, asymmetric power ARCH (APARCH), component GARCH (CGARCH) and asymmetric component GARCH (ACGARCH). After estimating these models, information criterion is used to determine which model performs the best, and the results show that the AR-CGARCH is preferred. Conrad, Custovic, and Ghysels (2018) use the GARCH-MIDAS model to study the different components which influence the volatility of cryptocurrencies. Bitcoin is found to be negatively related to the volatility index (VIX), which is argued to be in line with that Bitcoin can be considered as a potential safe haven asset by investors. Interestingly, Bitcoin's volatility acts pro-cyclically, which is the opposite of the stock market. In particular, this behaviour is the complete opposite compared to the volatility of gold and therefore provides a contradiction of these two assets being very similar. Chu et al. (2017) examine the volatility of cryptocurrencies by using twelve different GARCH models. However, in contrast to Katsiampa (2017), the IGARCH(1,1) model is shown to give the best fit for Bitcoin. Long memory and asymmetry in the volatility are common properties in crude oil, gas, gold and silver (Chkili, Hammoudeh, & Nguyen 2014). Catania and Grassi (2017) investigate the time series of a large sample of cryptocurrencies by developing a new dynamic model which accounts for long memory and asymmetry. Chkili, Hammoudeh, and Nguyen (2014) use linear and nonlinear GARCH models in order to study the relevance of including these components in the models when forecasting volatility. The results show that there is not one model which outperforms the rest. However, the nonlinear GARCH models, such as FIAPARCH and FIGARCH, are superior.

The correlation of Bitcoin with other assets has been studied frequently over the last years, and is essential in terms of diversification benefits, hedging capabilities and the property of an asset being a safe haven. In general, cryptocurrencies show a positive correlation with other cryptocurrencies (Härdle, Harvey, & Reule 2019). However, evidence shows that the correlation between cryptocurrencies and other assets, such as gold and stocks, is low (Härdle, Harvey, & Reule 2019). In particular, Gajardo, Kristjanpoller, and Minutolo (2018) examine the cross-correlation between major currencies, such as Bitcoin, GBP and YEN, and financial assets, e.g. gold and crude oil, and find that Bitcoin behaves differently than the other currencies in terms of correlation. The features of high volatility and low correlation between cryptocurrencies and other assets provide an opportunity to make use of diversification benefits when constructing a portfolio. Dyhrberg (2016a) studies the hedging capabilities of Bitcoin using GARCH(1,1) and the EGARCH model, which accounts for asymmetry, and argues that it is essential to define what kind of asset Bitcoin is classified as. The results by Dyhrberg (2016a) suggest that Bitcoin can be classified as something between a commodity and a currency, or more specifically, something between gold and the US dollar. Results show that Bitcoin offers both diversification and hedging benefits when included into a portfolio, consisting of gold, oil and stock, by effectively reducing the portfolio risk (Guesmi et al. 2019). Research has also provided evidence that Bitcoin is able to hedge against global uncertainty, which is measured by the VIX, but the effect is stronger in the short term (Bouri et al. 2017a). The results by Bouri et al. (2017a) provide implications of not only hedging capabilities but also diversification benefits of holding Bitcoin. Bitcoin is also observed to act as a hedge and safe haven for stock indices, bonds, oil, gold, the commodity index and the US dollar (Bouri et al. 2017b). It is noteworthy that Bouri et al. (2017b) find that these properties show variations over time and for different markets. Moreover, it is found that diversification benefits are not constant over time either. These findings represent an essential need for revisiting this question repeatedly, especially since the Bitcoin market is still relatively young and has the potential to change. Dyhrberg (2016b) states that Bitcoin has a diversification advantage because the asset differs from other financial assets. Corbet et al. (2018) investigate the relationship between cryptocurrencies and other financial assets and find that they are isolated from each other. This result indicates diversification benefits for investors (Corbet et al. 2018). This conclusion is moreover confirmed by Bouri et al. (2017b) and Dyhrberg (2016a).

Assets holding a safe haven property are important to investors during a time of market crisis (Smales 2019). Moreover, Smales (2019) mentions that gold is seen as the traditional safe haven and has repeatedly been shown to have a negative relationship with stocks. Although the previous research is trying to answer if Bitcoin can be considered as a safe haven, the results are ambiguous. For instance, it is suggested by Urquhart and Zhang (2018) that Bitcoin works as a safe haven for currencies. However, the results from Bouri et al. (2017b) and Klein, Thu, and Walther (2018) suggest that Bitcoin does not have the property of a safe haven asset. Indeed, as this question is of great importance to investors during times of crisis, this issue is yet again studied by Smales (2019). The results show that Bitcoin is not correlated with other assets, which in turn implies that there are possible diversification benefits of including the asset in an investment portfolio. Although this is a positive property, the results by Smales (2019) do not show a presence of a safe haven property in Bitcoin. In contrast, Smales (2019) finds that gold has a negative relationship with the stock returns. Moreover, the results by Kristoufek (2015) also indicate that Bitcoin does not have the property of a safe haven.

As previously mentioned, a major motivation for writing this paper is based on that Bitcoin is part of a relatively young market and therefore deserves further research. As time goes by and more data points become available, replications of previous papers do not seem unreasonable. Instead, including more data can hopefully contribute to an improvement of the analysis. Due to this, the methodology in this paper is in accordance with the one performed by Klein, Thu, and Walther (2018). As described, this paper will in part focus on exploring the hedge and safe haven properties of Bitcoin. The definitions of a hedge and safe haven are explained by Baur and Lucey (2010), and are as follows. An asset which is uncorrelated or negatively correlated with another asset is considered to be a hedge. In order for an asset to be a safe haven, it must have the same properties just mentioned, and most importantly they should hold in times of market turmoil. Moreover, Baur and Lucey (2010) define assets that have the property of a diversifier as positively but not perfectly correlated with other assets. These definitions are used throughout the paper. It becomes apparent that a time period when the financial market is in distress has a vital role when investigating the property of a safe haven in an asset. Following this, it is important to note that the Covid-19 pandemic presents the first time period when this happens in the lifetime of Bitcoin.

Thus, it is only now that it is possible to test whether or not Bitcoin has the property of a safe haven. Hence, this time period is not covered by Klein, Thu, and Walther (2018).

The current pandemic provides the first widespread bear market condition since the beginning of Bitcoin. In order to investigate this important happening in our financial markets, Conlon and McGee (2020) study the diversification benefits of holding Bitcoin during this high market volatility. Their findings show that Bitcoin does not manage to serve as a safe haven during this time period, which is characterised as a bear market. This is tested by adding Bitcoin to a portfolio which consists of the S&P 500 index. The results of their portfolio analysis show that Bitcoin does not act as a safe haven asset and moreover, that Bitcoin contributes to the downside risk of the portfolio. In addition, it appears that Bitcoin and the S&P 500 index move in tandem during this financial crisis, showing a feature which is not in line with an asset acting as a safe haven (Baur & Lucey 2010). Similarly, Ji, Zhang, and Zhao (2020) try to find safe haven assets by individually including one asset after another into a mean-variance portfolio and then observing what effect this has on the return distribution, specifically focusing on the left tail. Interestingly, it is only gold and soybean commodity that have the property of a safe haven asset during this time period. The evidence shows that global financial markets have been affected negatively by the current pandemic. This has unfortunately resulted in an even higher level of volatility and thus, risk (Zhang, Hu, & Ji 2020). Due to this, investors all around the world have been facing huge losses. The relationship between these unprecedented risks in the financial markets and the pandemic has been examined by Zhang, Hu, and Ji (2020).

It is commonly known in financial literature that loss aversion implies that investors are more sensitive to losses than gains of equal amounts (Tversky & Kahneman 1991). This induces further motivation for why investors would wish to find safe haven assets, especially when the market is turbulent. As it is clear that the pandemic had a short-term negative influence on the financial markets, it is possible to assume that investors have an even greater need to find such an asset. This paper will go beyond these simple comparisons and study this question of similarity by focusing on an econometric perspective of Bitcoin. The contribution of this paper is therefore to compare gold and Bitcoin from an econometric perspective, where the focus is placed on the economic aspects of cryptocurrencies as an investment asset. More importantly, this paper covers a time period which is influenced by market turmoil. The aim is to answer how cryptocurrencies can be classified based on their volatility behaviour and their correlation with other asset classes. In particular, special focus is placed on the most recent time period with market distress caused by the Covid-19 pandemic.

The analysis of this paper is threefold and the focus is specifically placed on the following objectives, where the intention of each objective is to obtain additional insight of the econometric properties of Bitcoin. First, the volatility behaviour of Bitcoin is investigated using several different ARCH models. This is done in accordance to the methodology by Klein, Thu, and Walther (2018). I extend their research by including new data and by covering a time period which is influenced by market turmoil. Following, I compare the volatility of Bitcoin to other asset classes in order to see if it is possible to classify cryptocurrencies within an already established asset class. Secondly, I explore the hedge and safe haven capabilities of Bitcoin and compare these to the ones of gold, which is commonly recognized as the traditional safe haven asset. This is done by conducting a dynamic correlation analysis. The final part of this paper is based on a portfolio analysis, where the focus is placed on how Bitcoin and gold behave during times of market distress, which by definition, is an essential time period in order to draw a conclusion regarding if Bitcoin has the ability to act as a safe haven.

This paper is organised into five different sections. Following this introductory section, the methodology is explained in section 2, followed by a preliminary data analysis in section 3. Section 4 presents the results and provides an analysis of them. Finally, section 5 includes a summary and the derived conclusions based on the results and analysis of this paper.

2 Methodology

The first part of the analysis performed in this paper is based on the volatility behaviour of Bitcoin. In addition, a comparison is made with the other assets. Modelling the variance is common, and of importance as the returns of assets are found to be unpredictable and therefore not appropriate to use in estimation and forecasting. Financial time series, e.g. the ones used in this paper, are often shown to exhibit heteroscedasticity, meaning that the variance is time varying, in the form of volatility clustering[20]. This property indicates that there is structure in the variance and this information is made use of by studying the conditional variance of a time series, which is conditioned on the past. More specifically, I use the autoregressive conditional heteroscedasticity (ARCH) models, introduced by Engle (1982), in order to study the properties of conditional variance[21]. Since the introduction by Engle (1982), these models are frequently employed to model time-varying volatility of financial time series, which has contributed to modifications and extensions of the ARCH model. For instance, Bollerslev (1986) extends the ARCH model by Engle (1982) into a Generalised ARCH (GARCH) model by introducing a more flexible lag structure which takes the property of long memory in the conditional variance of the time series into account. Furthermore, in order to account for asymmetry in the conditional variance, Ding, Granger, and Engle (1993) introduce the asymmetric power ARCH (APARCH) model. The fractionally integrated generalized ARCH (FIGARCH) model by Baillie, Bollerslev, and Mikkelsen (1996) attempts to model the long memory feature, which is based on an expansion of the model by Bollerslev (1986). Finally, the fractionally integrated APARCH (FIAPARCH) by Tse (1998), which allows for both long memory and asymmetry features, is used for the purpose of examining the properties of conditional variance. The methodology of studying the properties of conditional variance is in accordance with the methodology in Klein, Thu, and Walther (2018). Following the methodology by Klein, Thu, and Walther (2018), I model the asset returns with ARCH models. All the models comprise a first order autoregressive part as depicted in equation (1) where r_t is the asset return at time t. The residuals, ε_t, from equation (1) are modeled according to equation (2) where h_t is the conditional variance and η_t is modeled with a Student's t-distribution according to equation (3).

$$r_t = \theta_0 + \theta_1 r_{t-1} + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \sqrt{h_t}\eta_t \tag{2}$$

$$\eta_t \sim \text{St-t}_\nu(0,1) \text{ i.i.d. for all } t = 1, \ldots, n \tag{3}$$

The conditional variance is then modelled using the following four models previously mentioned, GARCH, APARCH, FIGARCH, and FIAPARCH. While Klein, Thu, and Walther (2018) only

[20]Volatility clustering implies that the variance of a time series is a function of past shocks.

[21]The ARCH models were proposed by Engle (1982) with the purpose of forecasting time varying variances conditional on the past, which is suggested to be of usefulness and create better forecasts. By derivation, it is shown that these models have constant unconditional variances.

use APARCH and FIAPARCH, I include GARCH as a benchmark comparison and FIGARCH[22], being a generalisation of the latter model, is used for further comparison. These models are chosen because they, to different degrees, account for the stylised facts long memory and asymmetry, which are of focus in this paper. The model definitions are presented in table 1.

Table 1: ARCH models used in this work to model the conditional variance.

Model	Definition	Asymmetry	Long memory
GARCH(1,1)	$h_t^2 = \omega + \alpha \lvert \varepsilon_{t-1} \rvert^2 + \beta h_{t-1}^2$	No	No
APARCH(1,1)	$h_t^{\delta/2} = \omega + \alpha \left(\lvert \varepsilon_{t-1} \rvert - \gamma \varepsilon_{t-1} \right)^{\delta} + \beta h_{t-1}^{\delta/2}$	Yes	Indirectly
FIGARCH(1,d,1)	$h_t^{\delta/2} = \omega + \left(1 - \beta L - (1 - \phi L)(1 - L)^d \right) \left(\lvert \varepsilon_t \rvert \right)^{\delta} + \beta h_{t-1}^{\delta/2}$	No	Yes
FIAPARCH(1,d,1)	$h_t^{\delta/2} = \omega + \left(1 - \beta L - (1 - \phi L)(1 - L)^d \right) \left(\lvert \varepsilon_t \rvert - \gamma \varepsilon_t \right)^{\delta} + \beta h_{t-1}^{\delta/2}$	Yes	Yes

As table 1 presents several new parameters, they are briefly mentioned. To name the ones of interest, $\gamma \in (-1, 1)$ denotes the leverage parameter, $\delta \in (0.25, 5.0)$ denotes the power parameter, and $d \in (0, 1)$ denotes the fractional integration parameter, which implies long memory. L is a lag operator. To ensure stationarity and non-negativity of the variance process we require $\omega, \beta, \alpha \geq 0$. FIGARCH and FIAPARCH require $0 \leq \beta \leq \phi + d$ and $0 \leq d \leq 1 - 2\phi$.

Next, besides comparing Bitcoin and gold in terms of their volatility behaviour, their properties are additionally investigated from a multivariate perspective, where the relationship between them and other assets is examined. Subsequently, the dynamic pairwise correlation of the assets is investigated. This is done using the diagonal Baba-Engle-Kraft-Kroner (BEKK-GARCH) model defined in equation (4) and follows the methodology explained in Klein, Thu, and Walther (2018).

$$\boldsymbol{H}_t = \boldsymbol{C}^T \boldsymbol{C} + \boldsymbol{A}^T \varepsilon_{t-1} \varepsilon_{t-1}^T \boldsymbol{A} + \boldsymbol{G}^T \boldsymbol{H}_{t-1} \boldsymbol{G} \tag{4}$$

The final part of the methodology is done with the aim of investigating and comparing the hedging capabilities of gold and Bitcoin. This is done by examining the performance of minimum-variance portfolios which are constructed with one market index, either S&P 500 or MSCI World, and one of the investment assets, Bitcoin or gold. This construction is based on weights which are time variant, and which are derived based on an optimization made for every time period. Following, the Value-at-Risk (VaR) of the S&P 500 and MSCI World is calculated over the whole time period studied. Then, the portfolios are evaluated, and because the reason of this investigation is to observe if the assets show a presence of hedging capabilities, a special focus is placed on the time period when the market is in distress. Hence, the mean of portfolio returns is calculated and presented over the time period consisting of market turmoil.

[22]It should be noted that in the original FIGARCH representation by Baillie, Bollerslev, and Mikkelsen (1996), the power term δ is equal to 2 whereas here it is estimated.

3 Preliminary Data Analysis

3.1 Data sample

The data used for the analysis in this paper consists of eight different time series. These include the following: Bitcoin (USD per BTC), gold and silver (USD per oz), crude oil WTI, the S&P 500 index, the MSCI World index, the MSCI Emerging Markets 50 index, all in USD, and finally the FTSE 100 index (£). The data for Bitcoin is obtained from coindesk.com, while the data for the other assets is obtained from Datastream, all of which have a GMT timestamp. Finally, a robustness check is performed with the cryptocurrency index (CRIX)[23]. The time period covered is between 2011-07-01 and 2020-06-12. In total, there are 2336 observations for every time series[24]. The closing prices are considered, which is important to note, especially since Bitcoin is traded continuously. Furthermore, only the prices on weekdays are included in the analysis. Returns r for every time period t are taken as the logarithmic difference of closing prices P according to equation (5).

$$r_t = 100 \cdot \log \frac{P_t}{P_{t-1}} \tag{5}$$

3.2 Descriptive statistics

The descriptive statistics of the returns are presented in table 2. Bitcoin is observed to have the highest mean return. This value is substantially larger than the mean returns for the other assets. Moreover, the mean returns for silver and WTI are negative. The rest of the assets show slight positive mean returns. When it comes to the standard deviation, the WTI that has the highest value of 7.40 %, followed by Bitcoin with a value of 6.81 %. This is in contrast to the results presented by Klein, Thu, and Walther (2018), where the standard deviation of Bitcoin is found to be more than twice as large as for WTI. The deviation in this paper is likely due to the fact that the price of WTI dropped to a historically low level during the Covid-19 pandemic. The standard deviation of the rest of the assets are substantially lower ranging from 0.95 % to 1.67 %. Following, the minimum and maximum values of all the assets are presented. The maximum value of the assets is represented by Bitcoin. Additionally, a more detailed version of the dispersion is illustrated with the help of a 25 % to 75 % interval. Here each group denotes each respective percentile. Calculating the difference between the largest and smallest percentiles, it is found that Bitcoin has the largest dispersion of returns.

Next, the higher order moments are presented. What stands out is that Bitcoin is the only asset which has a positive skewness. The rest of the assets are shown to have a negative skewness, with

[23]The data for CRIX is obtained from data.thecrix.de. However, the time period for CRIX is shorter and covers only 2014-07-31 to 2020-06-12.

[24]Note that CRIX only consists of 1532 observations.

Table 2: Descriptive statistics of all time series' returns.

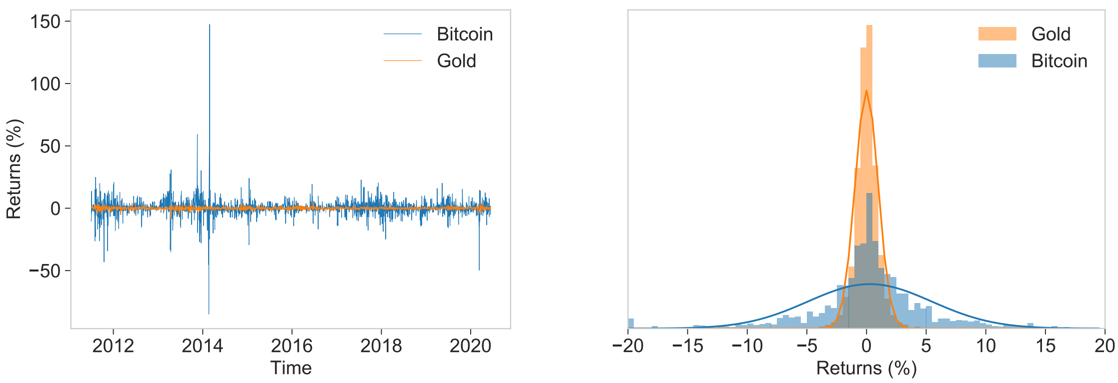
	S&P 500	MSCI World	FTSE 100	MSCI EM 50	Gold	Silver	WTI	Bitcoin
Observations	2336	2336	2336	2336	2336	2336	2336	2336
Mean	0.04	0.02	0.00	0.01	0.01	-0.03	-0.19	0.27
Std. dev.	1.10	0.95	1.02	1.01	0.97	1.67	7.40	6.81
Min.	-12.77	-10.44	-11.51	-6.39	-8.88	-13.53	-305.97	-84.88
25%	-0.31	-0.32	-0.45	-0.52	-0.48	-0.73	-1.09	-1.49
50%	0.03	0.05	0.02	0.06	0.01	0.00	0.00	0.14
75%	0.49	0.44	0.49	0.57	0.50	0.72	1.04	2.30
Max.	8.97	8.41	8.67	6.51	4.69	9.16	30.02	147.42
Skewness	-0.95	-1.26	-0.88	-0.40	-0.54	-0.84	-32.27	3.23
Kurtosis	19.73	19.61	12.73	3.80	6.10	7.65	1285.10	111.10
Jarque Bera	38056.34***	37889.75***	16007.48***	1460.13***	3718.34***	5942.40***	160462173.99***	1200271.85***
Ljung Box (25)	276.09***	158.86***	62.19***	107.66***	23.52	46.89***	318.69***	75.69***
ARCH (25)	992.95***	885.18***	648.37***	506.18***	172.61***	218.08***	61.03***	232.76***
ADF	-12.96***	-11.71***	-15.98***	-17.28***	-47.98***	-12.71***	-9.71***	-18.59***

The Jarque-Bera (JB) test will, by definition, have a value of zero if the returns are normal, hence if both skewness and excess kurtosis have a value equal to zero. The Ljung Box test tests for autocorrelation in the time series at the 25th lag. The ARCH test tests for heteoscedasticity in the volatility at the 25th lag. Finally, the ADF test tests for stationarity of the time series.

the WTI being identified as having the largest skewness in absolute value. In this respect, the value of -32.27 confirms that WTI has experienced extreme negative values. The highest kurtosis is observed in WTI with an extraordinary high value of 1285.10, followed by Bitcoin with a value of 111.10. The precious metals, gold and silver, do not show as high values as Bitcoin, or the two indices S&P 500 and MSCI World. These results indicate that the returns of Bitcoin do not follow a normal distribution. In fact, this finding of non-normal returns holds for all the assets. This observation is further confirmed by the Jarque-Bera test for normality. In order to test if the time series have the property of autocorrelation and conditional heteroscedasticity, formal tests are conducted. The Ljung Box test shows that there is a presence of autocorrelation in all the time series, except for gold, however this result is not significant. In addition, the ARCH test confirms that there is heteroscedasticity in the volatility of the series. These results suggest that ARCH models might be used. Finally, the Augmented Dickey Fuller (ADF) test is done in order to see if the data is stationary. The results are presented in table 2 and indicate that all the time series are stationary.

3.3 Preliminary analysis

The returns of Bitcoin and gold are presented in more detail in figures 2a and 2b. There are signs of the data being mean reverting, which implies that the financial time series of these two assets are stationary. As already mentioned, this observation is confirmed by the ADF test. In addition, volatility clustering is apparent from the figure. This characteristic seems to be present for both assets, even if it in the case of Bitcoin appears more elevated. Interestingly, expanding the data analysis by including a longer time period, shows that there is a sharp decrease in returns of Bitcoin in the first quarter of 2020. Moreover, it is seen that these returns have not suffered of a negative fall of this magnitude for many years. More specifically, Bitcoin is shown to only have reached a lower point than this in 2014. Furthermore, figure 2b shows that the returns



(a) Returns of bitcoin and gold over time. *(b) Histogram of the returns of bitcoin and gold.*

Figure 2: Returns of bitcoin and gold as a function time (left) and the corresponding histograms (right).

deviate from a normal distribution where the normal distribution is indicated by the solid lines. Figure 2b shows that Bitcoin has a leptokurtic distribution. This observation is confirmed by the high value of the kurtosis and indicates a higher possibility of extreme events compared to a normal distribution. In addition, figure 2b shows that the fat tails of the return distribution are more pronounced for Bitcoin. However, the return distribution of gold is shown to be more peaked, which is also an attribute of the excessive kurtosis compared to a normal distribution. In general, figure 2b illustrates the high kurtosis of both Bitcoin and gold. However, it is perhaps not as obvious when it comes to the skewness of these two time series. The results presented earlier show that gold has a slightly negative skewness, while Bitcoin is the only asset which shows a positive skewness. However, the values of the skewness, in absolute terms, of these two assets do not stand out in the same way as their respective values of kurtosis.

In accordance to the methodology by Klein, Thu, and Walther (2018), the correlation between the assets is presented in table 3. These results are presented in order to get a first glance of the correlation relationships between the different assets. In particular, Bitcoin has a small, positive, correlation with all the other assets. Bitcoin has the highest, respective lowest, correlation with MSCI World and silver, respectively. Interestingly, gold is the only asset which shows a negative correlation. Explicitly, this relation is shown between gold and the two indices, S&P 500 and FTSE 100. It should be noted that the correlation values in table 3 denote the average correlation over the whole time period. A more detailed analysis will be performed using the BEKK-GARCH model, which accounts for time varying specifics.

Table 3: Pairwise Pearsons correlation.

	S&P 500	MSCI World	FTSE 100	MSCI EM 50	Gold	Silver	WTI	Bitcoin
S&P 500	1.0000	0.9428	0.6291	0.5510	-0.0187	0.1216	0.1736	0.0857
MSCI World		1.0000	0.7730	0.6849	0.0360	0.2258	0.1786	0.0871
FTSE 100			1.0000	0.6359	-0.0091	0.1947	0.1295	0.0737
MSCI EM 50				1.0000	0.0403	0.2363	0.1290	0.0343
Gold					1.0000	0.6587	0.0239	0.0237
Silver						1.0000	0.0548	0.0148
WTI							1.0000	0.0262
Bitcoin								1.0000

4 Results and Analysis

This section presents the results and provides a corresponding analysis. First, as mentioned in the methodology section, I investigate the conditional volatility of the assets using different univariate ARCH models. This is followed by the BEKK-GARCH correlation analysis using a multivariate model. The section concludes with the construction of different portfolios and the evaluation of them in order to examine if Bitcoin or gold hold any hedging or safe haven capabilities during periods of market turmoil.

At first, the volatility is modelled using the models presented in section 2, i.e. GARCH(1,1), APARCH(1,1), FIGARCH(1,d,1) and FIAPARCH(1,d,1). The results of these models are presented in tables 4 to 7. The purpose of this analysis is to investigate the volatility behaviour of the assets, and in particular, to examine if Bitcoin can be classified as an established asset class based on its volatility structure. Table 4 shows the GARCH(1,1) results. These results include the estimated parameters of the model as well as several key test results. With this model, Bitcoin has the greatest ω value which denotes the intercept of the variance, compared to the other assets. In addition, the sum of α_1 and β_1 is the highest for Bitcoin which indicates a high degree of volatility persistence. This characteristic is illustrated in figure 2a and previously referred to as volatility clustering. Bouri et al. (2017b) suggest that the property of long memory results in an opportunity to forecast the volatility and hence, provides an important hedging advantage. It is evident that the corresponding values for the remaining assets also are close to one. However, the precious metals, silver and gold, together with the indices S&P 500 and MSCI World, have slightly higher values. The results involving a presence of persistence in Bitcoin and the precious metals is validated in related literature (Klein 2017; Capie, Mills, & Wood 2005; Chkili, Hammoudeh, & Nguyen 2014; Bouri et al. 2017b). The parameter denoted, ν, signifies the degrees of freedom of the t-distribution. Klein, Thu, and Walther (2018) assert that a low estimated value of ν correlates with a high kurtosis value for the returns. While this is true for Bitcoin in both data sets, we see that it does not completely hold for all assets. For instance, silver has a kurtosis of 7.65 and ν = 3.17 while the S&P 500 has a kurtosis of 19.73 and ν = 4.38.

Table 4: Estimation results for the GARCH model.

	S&P 500	MSCI World	FTSE 100	MSCI EM 50	Gold	Silver	WTI	Bitcoin
θ_0	0.0855***	0.0616***	0.0375**	0.0378**	0.0140	0.0111	0.0338	0.2598***
θ_0	-0.0604***	0.0892***	0.0053	0.1716***	-0.0366**	-0.0455***	-0.0362*	-0.0096
ω	0.0252***	0.0147***	0.0272***	0.0227***	0.0077***	0.0123*	0.1780	1.0008
α_1	0.1972***	0.1562***	0.1381***	0.0756***	0.0373***	0.0209***	0.1388***	0.2168***
β_1	0.8009***	0.8361***	0.8406***	0.9002***	0.9554***	0.9776***	0.8399***	0.7832***
ν	4.3850***	5.0128***	5.5074***	10.0960***	4.4896***	3.1652***	4.1860***	2.9248***
LL	-2687.69	-2411.70	-2860.08	-3068.80	-2940.85	-4122.77	-4890.82	-6606.99
BIC	5421.90	4869.93	5766.69	6184.14	5928.23	8292.07	9828.17	13260.52
Jarque Bera	937.54***	740.55***	282.37***	59.66***	1313.57***	3042.49***	12925849.38***	7947.31***
Ljung Box (25)	26.37	27.66	23.12	25.14	33.23	41.85**	17.56	84.94***
ARCH (25)	20.22	20.15	26.00	23.82	46.33***	67.42***	0.13	24.18

*Statistically significant parameters are indicated with asterisk *, **, *** for 10 %, 5 % and 1 % level of significance.*

In addition to the estimated model parameters, I examine the model feasibility by inspecting the Ljung Box and Engle's ARCH test results. Both tests consider the standardized residuals of the model and in order for the model to be appropriate, the null hypothesis of both tests should not be rejected. The Ljung Box is a statistical test which tests for autocorrelation in the residuals and according to the test results, Bitcoin and silver are the only assets which reject the null hypothesis, hence the GARCH model may not be suitable. In contrast, Engle's ARCH test provides indication of autoregressive conditional heteroscedasticity. Neither this test rejects the null hypothesis for Bitcoin. In contrast to the Ljung Box test, the null hypothesis is not rejected for gold. Nevertheless, for all the other assets the GARCH model seems to be appropriate as the null hypothesis of either test is not rejected. Additionally, a test for normality is computed. The results suggest that a normal distribution remains rejected for every asset.

The estimated parameter values of APARCH(1,1) are presented in table 5. Here, special focus is placed on the parameter γ, which denotes the leverage effect, also called the asymmetric effect in the model. Asymmetric volatility of a time series, implies that negative returns are associated with an increase in conditional volatility, while positive returns are associated with a decrease in conditional volatility of an asset[25]. If γ is positive, then this indicates that negative shocks have a higher impact on the conditional volatility than positive shocks. Meanwhile, if γ is negative then positive shocks have a higher impact on the conditional volatility. For Bitcoin, silver, and gold γ is negative. However, these results are not statistically significant. Despite this, it is still interesting to note that Bitcoin and the precious metals share the same sign of γ, and hence that their conditional volatility is suggested to be influenced to a higher degree by positive shocks. This result demonstrates a preferable property in an investment asset considering a time period which is characterised by market turmoil, assuming that investors are risk averse. The reason being that the volatility, which is a proxy for risk, will not increase as much during a time period which is influenced by a negative market shock. Moreover, this property is referred to as an inverse leverage effect, and is shown to be an established property of gold and silver (Klein, Thu, & Walther 2018; Catania & Grassi 2017). In contrast, γ is positive and significant for the other assets, implying that their conditional volatility is profoundly influenced by negative shocks in the market. These results are in line with the ones found by Klein, Thu, and Walther (2018), with the exception that their results are significant for Bitcoin and silver. In contrast, Dyhrberg (2016b) presents results which do not show a significant asymmetry effect. Nevertheless, Chkili, Hammoudeh, and Nguyen (2014) and Klein (2017) find a presence of asymmetry in the volatility of gold, silver and oil. In this respect, Klein, Thu, and Walther (2018) argue that this difference in results is related to the choice of return distribution. Instead of using a normal distribution in accordance with Dyhrberg (2016b), Klein, Thu, and Walther (2018) use the Student's t-distribution, as is done in this paper, which is able to account for heavy tails. They conjecture that it is more appropriate to use a return distribution which better describes the returns of a certain time series in order to find a property, such asymmetry in the volatility of an

[25]In the stock market, asymmetric volatility is found to result from the leverage effect and the volatility feedback effect (Klein, Thu, & Walther 2018).

Table 5: Estimation results for the APARCH model.

	S&P 500	MSCI World	FTSE 100	MSCI EM 50	Gold	Silver	WTI	Bitcoin
θ_0	0.0521***	0.0336***	0.0109	0.0108	0.0171	0.0119	0.0081***	0.2613***
θ_1	-0.0481***	0.0976***	0.0148	0.1772***	-0.0364**	-0.0430**	-0.0489***	-0.0217***
ω	0.0308***	0.0220***	0.0276***	0.0247***	0.0095***	0.0256	0.0232***	0.0700***
α_1	0.0000	0.0000	0.0000	0.0000	0.0606***	0.0344	0.0199**	0.1627***
γ_1	0.2291***	0.1883***	0.1921***	0.1235***	-0.0207	-0.0158	0.0681***	-0.0069
β_1	0.8813***	0.9010***	0.8945***	0.9111***	0.9497***	0.9660***	0.9460***	0.8408***
δ	0.7984***	0.8478***	1.1433***	1.9180***	1.5221***	2.5413***	0.6516***	0.2500***
ν	5.3114***	5.9451***	6.5023***	13.5456***	4.5346***	3.0993***	4.4522***	2.2978***
LL	-2617.70	-2356.56	-2812.38	-3036.80	-2939.27	-4130.01	-4855.32	-6580.28
BIC	5297.44	4775.17	5686.80	6135.65	5940.58	8322.06	9772.69	13222.61
Jarque Bera	1190.32***	1922.07***	291.62***	32.63***	1842.89***	2924.83***	12023325.10***	29244.11***
Ljung Box (25)	24.91	24.05	22.65	23.22	33.70	41.31**	40.73**	72.32***
ARCH (25)	39.40**	21.19	32.48	27.07	64.55***	57.98***	2.24	18.36

*Statistically significant parameters are indicated with asterisk *, **, *** for 10 %, 5 % and 1 % level of significance.*

asset, if it is present. The power parameter δ is around 1.0 for S&P 500, MSCI World, and FTSE 100, which implies that the volatility is best modelled by the standard deviation. Moreover, Ding, Granger, and Engle (1993) show that δ close to 1.0 implies an indirect indication of long memory. That is because the autocorrelation of $|r_t|^\delta$ is larger and sustained longer. In contrast, MSCI EM 50, gold, and silver have values of δ closer to 2, which implies that the volatility of these assets is preferably modelled by the variance. Most interestingly, Bitcoin has an estimated δ of 0.25 which compared to the other assets is the absolute lowest[26]. This illustrates a dissimilarity in the volatility behaviour of Bitcoin and the established asset classes, and also highlights a disparity between Bitcoin and gold. Furthermore, it is in stark contrast to the estimated value which Klein, Thu, and Walther (2018) report, i.e. 2.31. The estimated values of ν are similar to the GARCH model, for the APARCH model. Finally, I consider this model's suitability. The null hypotheses for both the Ljung Box and Engle's ARCH tests are not rejected for MSCI World, MSCI EM 50, and FTSE 100. On the other hand, Bitcoin rejects the null hypothesis for the Ljung Box test on the 1 % significance level while WTI and silver do it on the 5 % level. The null hypothesis of Engle's ARCH test is rejected on the 1 % significance level by gold and silver while on the 5 % level by S&P 500. Accordingly, the model is not as suitable for these assets compared to the stock indices. This result illustrates a similarity between Bitcoin, the two metals and oil, together with simultaneously presenting a dissimilarity between Bitcoin and the volatility structure of the stock indices.

Next, we consider the FIGARCH model and the corresponding estimation results which table 6 presents. The d parameter is of particular interest as it facilitates the model's ability to directly capture long memory of a time series. The closer to zero d gets, the higher occurrence of long memory. We see that all time series experience some degree of long memory, although silver has the lowest d (0.165), albeit only significant at the 10 % level. Silver is followed by MSCI EM 50 at 0.352. Moreover, gold shows the highest d value. This is a surprising result as it puts silver and gold on opposite sides of d values. Bitcoin shows a more comparable degree of long memory with gold and WTI than with silver. Furthermore, the δ parameter is in an approximate

[26]When estimating the δ parameter, 0.25 was set as a lower bound.

Table 6: Estimation results for the FIGARCH model.

	S&P 500	MSCI World	FTSE 100	MSCI EM 50	Gold	Silver	WTI	Bitcoin
θ_0	0.0844***	0.0624***	0.0387***	0.0368**	0.0116***	0.0127	0.0294	0.2447***
θ_1	-0.0608***	0.0906***	0.0062	0.1705***	-0.0361***	-0.0439**	-0.0380**	-0.0206***
ω	0.0286	0.0282*	0.0405**	0.0596*	0.0231*	0.2856	0.1182**	0.1410***
ϕ	0.0000	0.0000	0.2120**	0.0319	0.0000	0.4175**	0.1078*	0.0961
d	0.5765***	0.5383***	0.5067***	0.3520***	0.9092***	0.1650*	0.7844***	0.7387***
β	0.4225***	0.4364***	0.5546***	0.3444**	0.9092***	0.5237**	0.8027***	0.6782***
δ	2.2041***	1.9614***	1.9396***	2.0631***	0.8036	2.8292***	1.0654***	0.2598***
ν	4.4326***	5.3154***	5.7243***	9.7867***	4.5216***	3.0314***	4.4225***	2.3480***
LL	-2678.92	-2401.59	-2855.10	-3066.57	-2937.60	-4130.43	-4871.67	-6580.04
BIC	5419.89	4865.22	5772.25	6195.19	5937.25	8322.91	9805.38	13222.12
Jarque Bera	962.88***	750.66***	275.70***	73.16***	4967.44***	1639.48***	22722852.09***	27193.69***
Ljung Box (25)	26.24	26.32	22.54	26.51	34.81*	37.60*	26.93	72.81***
ARCH (25)	22.48	25.61	27.64	21.97	78.55***	32.59	0.28	16.61

*Statistically significant parameters are indicated with asterisk *, **, *** for 10 %, 5 % and 1 % level of significance.*

range of value 2 and 3 for S&P 500, MSCI World, FTSE 100, MSCI EM 50, and silver. Similar to the APARCH model, Bitcoin has the lowest δ, and additionally it describes another difference to gold. When it comes to autocorrelation and autoregressive conditional heteroscedasticity of the standardized residuals, this model seems to do better than the GARCH and APARCH models. This is in agreement with the results by Chkili, Hammoudeh, and Nguyen (2014). In particular, the null hypothesis is only rejected by Bitcoin on the Ljung Box test and by gold on Engle's ARCH test. Concluding that the volatility structure of these two assets are not preferable to model with the FIGARCH model.

The FIAPARCH model is the last one I consider. The estimated parameters are presented in table 7. The estimated values of the long memory parameter, d, suggest that all time series display some long memory which is in correspondence with the FIGARCH model results. The assets having the highest degree of persistence, albeit not significant, are MSCI EM 50 and silver. Nonetheless, the FTSE 100 has the lowest, significant, d value. Once again, silver and gold are on the opposite sides of the d value range (0.0767 and 0.9213), while Bitcoin is in between (0.6493). Like for the APARCH model, γ is negative for gold, silver, and Bitcoin, even though it is still not a significant result. The rest of the assets also show asymmetric behaviour, however the value of γ is positive and highly significant for all assets. The Ljung Box and Engle's ARCH test hypotheses are not rejected for S&P 500, MSCI World, MSCI EM 50, and WTI at the 10 % level. In contrast, the Ljung Box test hypothesis is rejected for gold, silver and Bitcoin on the 10 %, 5 % and 1 % level respectively. It follows that neither this model is fully appropriate for these assets. However, it is recognised that Bitcoin, gold and silver share this particular characteristic, suggesting a comparability in the volatility structure. Moreover, Engle's ARCH test hypothesis is rejected for FTSE 100, gold, and silver on the 5 %, 1 % and 1 % level respectively.

In order to select the best model for every asset, I consider the Bayesian selection criterion (BIC). The reason to why I study every asset using all the models is twofold. First, I wish to compare the assets within each model respectively. Secondly, as this foremost is a replication, I want to compare my results with the ones presented by Klein, Thu, and Walther (2018). However, studying the BIC, I can determine that the FIAPARCH model is best for S&P 500, MSCI World,

Table 7: Estimation results for the FIAPARCH.

	S&P 500	MSCI World	FTSE 100	MSCI EM 50	Gold	Silver	WTI	Bitcoin
θ_0	0.0518***	0.0359***	0.0106	0.0106	0.0159	0.0151*	0.0063	0.2453***
θ_1	-0.0353*	0.1036***	0.0150	0.1812***	-0.0374**	-0.0475***	-0.0374*	-0.0161
ω	0.1708***	0.1837***	0.2322***	0.4631**	0.0213***	0.3833	0.1679	0.5431***
ϕ	0.2583***	0.2381***	0.3877***	0.2780**	0.0000	0.4617	0.2768***	0.1472**
d	0.2886***	0.2525***	0.1686***	0.0723	0.9213***	0.0767	0.4464*	0.6493***
β	0.4651***	0.4354***	0.5062***	0.3299**	0.9213***	0.5194	0.6627***	0.6091***
γ	0.7678***	0.7035***	0.7800***	0.6392***	-0.0885*	-0.0432	0.2638***	-0.0215
δ	0.7260***	0.6725***	0.5369***	0.3497	0.8870***	0.3463	0.8999***	0.7782***
ν	5.4486***	6.2034***	6.7836***	13.3344***	4.3785***	3.0311***	4.5727***	2.3223***
LL	-2604.42	-2341.89	-2796.23	-3039.22	-2935.12	-4133.26	-4858.18	-6578.30
BIC	5278.63	4753.59	5662.27	6148.24	5940.04	8336.31	9786.15	13226.40
Jarque Bera	1125.99***	2916.24***	296.15***	33.88***	6438.38***	2233.40***	10076027.29***	15286.78***
Ljung Box (25)	25.17	23.42	22.07	22.67	35.58*	42.00**	22.08	87.31***
ARCH (25)	21.47	14.05	39.36**	28.40	90.71***	70.80***	0.26	19.11

*Statistically significant parameters are indicated with asterisk *, **, *** for 10 %, 5 % and 1 % level of significance.*

and FTSE 100, the APARCH model is best for MSCI EM 50 and WTI, the GARCH model is best for gold and silver and the FIGARCH model is best for Bitcoin. This adds to the differences comparing gold and silver with Bitcoin. Nevertheless, the GARCH model might not be suitable for silver as the hypotheses of the Ljung Box and Engle's ARCH test were rejected. This was not the case with the FIGARCH model. For gold, we cannot make the same suggestion as there was no difference in test results (the Ljung Box test was rejected for all models). By comparison, Chkili, Hammoudeh, and Nguyen (2014) find that no model outperforms the rest for all assets considered, however the FIGARCH and FIAPARCH models are, similarly to this paper, found to be better suited to model the variance of these assets.

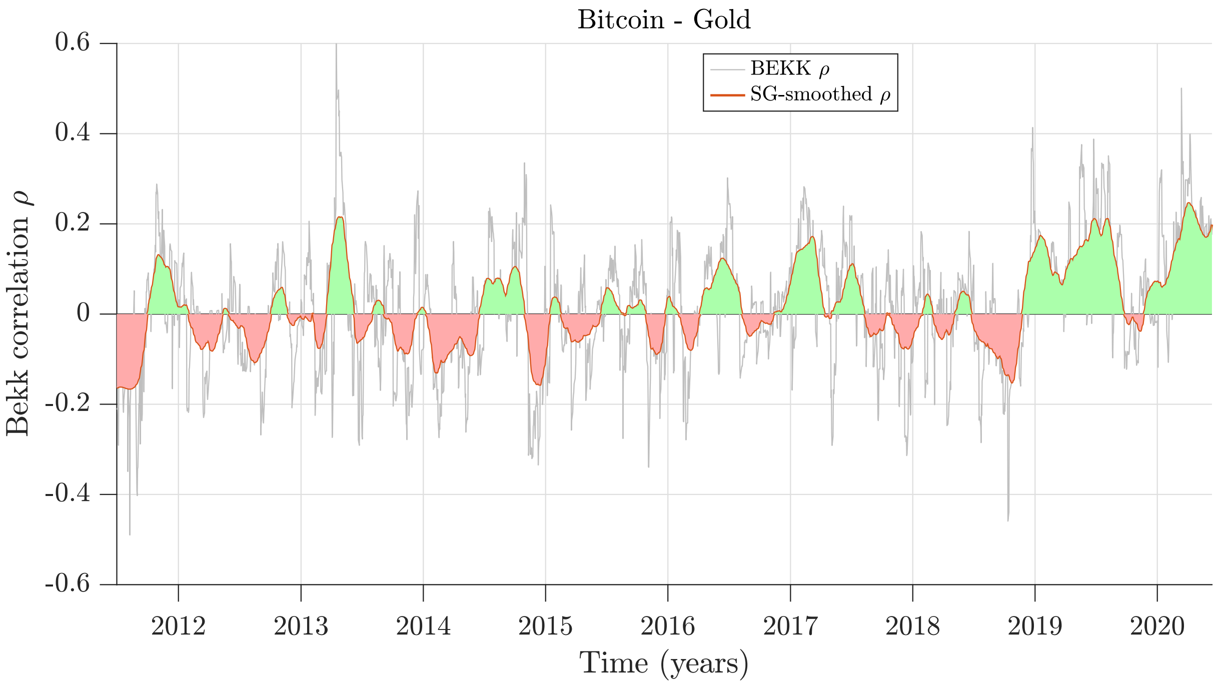
In order to determine if Bitcoin can be classified as an established asset class based on its volatility behaviour, a short summary of the presented results above is revisited. Bitcoin and gold share a few similarities in their volatility structure. For instance, they have a similar asymmetric behaviour in their volatility structure, i.e. the leverage parameter shows similar values. It further indicates a closer resemblance of Bitcoin and the two precious metals than to the stock indices and commodities such as oil. In terms of long memory, Bitcoin and gold do not show as high volatility persistence as silver. Despite these similarities, the BIC suggests that Bitcoin and gold are preferably modelled with different models. Therefore, these results are considered to be rather inconclusive and I am not able to classify Bitcoin in an already established asset class based on these findings only.

In the next part of this analysis, results from the dynamic correlation analysis are presented. First, a BEKK-GARCH correlation between Bitcoin and gold is presented in figure 3, which illustrates that the correlation between these assets unfolds from negative to positive. The red area, which implies a negative correlation between the assets, is more frequently observed up until 2016. Then, it appears that there is a time period where there is a more positive correlation present between the assets. However, this correlation reduces again after mid 2017 and continues to mainly show a negative relationship until the end of 2018. A turning point is observed during the last quarter of 2018, when the correlation between Bitcoin and gold yet again becomes positive.

This is, in particular, true for the last time period studied. The year of 2020 is partly characterised by a time period of market turmoil and likewise a financial crisis, which is caused by the Covid-19 pandemic. Certainly, the last period covered in this paper is of special importance as it includes the first time period in the history of Bitcoin which is characterised by market distress. Indeed, it is interesting to note that Bitcoin and gold experience a positive correlation during the entire time period consisting of the first half of 2020. Hence, they show a similarity in their behaviour at this specific time. In addition, figure 3 illustrates mostly a positive correlation between Bitcoin and gold from the beginning of 2019. This portrays an interesting change in behaviour regarding the correlation between these assets. More importantly, Bitcoin and gold are showing a more stable correlation as a result of the established similarity in behaviour. Exploring the whole time period leads to the conclusion that gold and Bitcoin have the highest positive correlation in 2020. The opposite is true in the past time periods, when the correlation is dominated by shifts from a positive to a negative one, which is more frequently detected.

Secondly, figure 4 illustrates the correlation between Bitcoin and S&P 500. As already distinguished, the recent time period signifies an interval of the first case of market turmoil during the lifetime of Bitcoin. Therefore, the last segment in figure 4 is of particular interest. The essential requirement, by definition, for an asset to provide hedging benefits, is for it to be either uncorrelated or negatively correlated with other assets (Baur & Lucey 2010). It follows that for an asset to be considered as a safe haven, it must possess the same properties during a period of market turmoil (Baur & Lucey 2010). In this regard, figure 4 shows that the correlation between Bitcoin and S&P 500 is negative at the very beginning of 2020, and then shows a historic positive

Figure 3: BEKK-GARCH correlation of Bitcoin and gold.

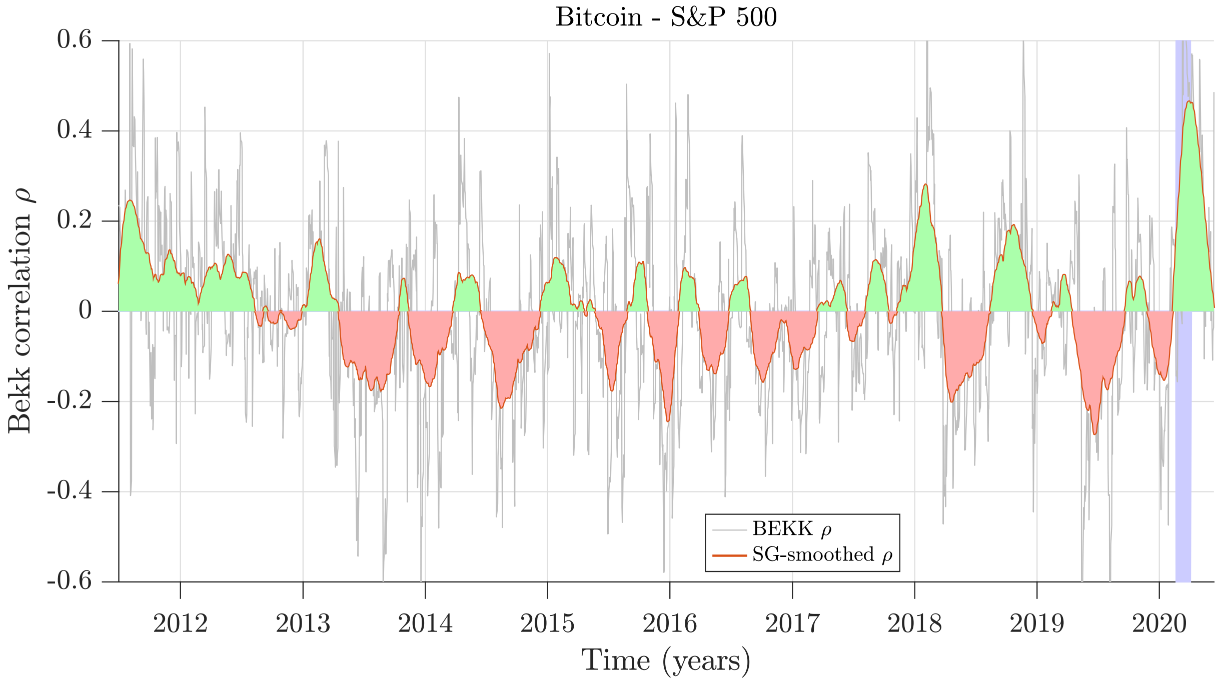


A Savitzky-Golay filter is applied and represented by the solid line.

peak, i.e. it reaches a record high level of positive correlation between the assets. This indicates that Bitcoin fails to act as a hedge, or safe haven, against S&P 500 in the current time period. Nevertheless, Bitcoin ensures diversification benefits at this time. Similar results are found in preceding literature (Baur, Dimpfl, & Kuck 2018; Bouri et al. 2017b; Corbet et al. 2018; Smales 2019), however, Bouri et al. (2017b) find that the diversification is time variant. While, Dyhrberg (2016a) observes that Bitcoin acts as a hedge over short time intervals, Bouri et al. (2017b) and Klein, Thu, and Walther (2018) conclude that Bitcoin does not meet the requirements of a safe haven asset and, in addition, Smales (2019) confirms this result. Yet, neither one of these research papers include a time period which is characterised by market turmoil, which, as previously mentioned, adds to the contribution of this analysis. In this aspect, Klein, Thu, and Walther (2018) identify time periods which are influenced by the market downturn, defined by a downturn in the S&P 500 index, and consider these to be an indication of periods with market distress. The results illustrate a negative correlation which gradually moves towards becoming positive, which demonstrates that Bitcoin moves in tandem with the market (Klein, Thu, & Walther 2018). These results do not differ from the conclusion made here. In addition to an analysis involving the most recent time period, figure 4 reveals that Bitcoin has a shifting correlation with the S&P 500 index. This observation signifies that Bitcoin has the property of a diversifier in some time periods and has the ability to act as a hedge in other periods. Interestingly, neither one of these time interval has the propensity to be long lasting.

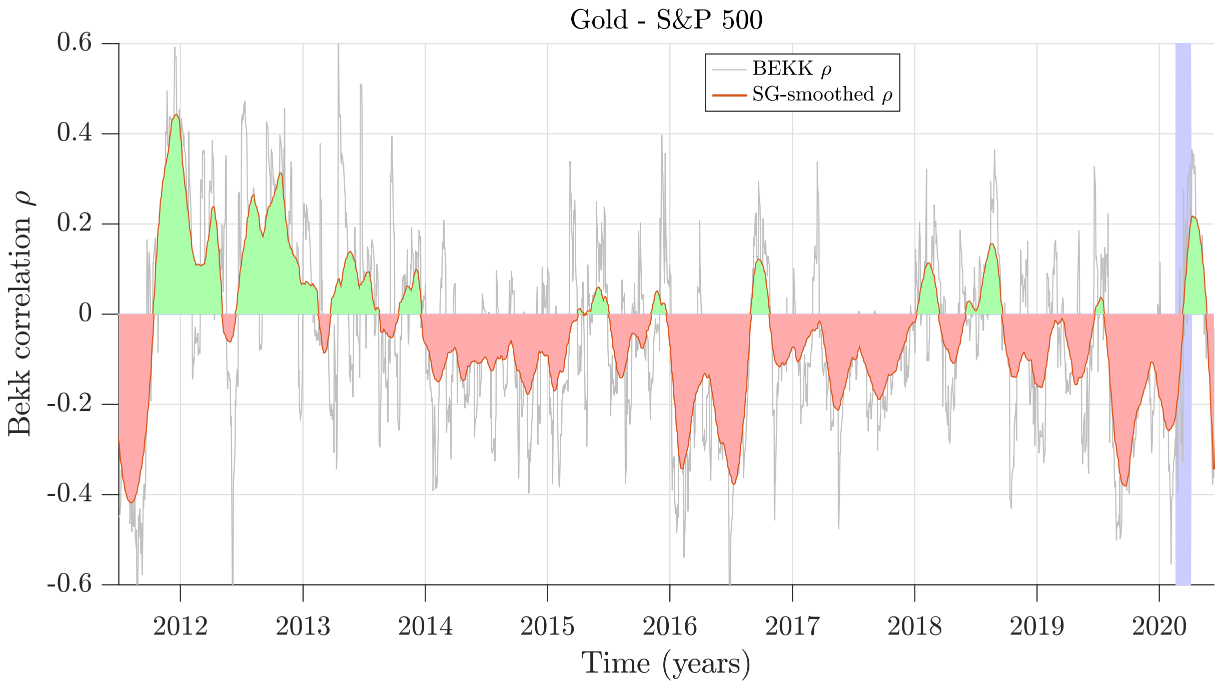
Figure 5 presents the correlation between gold and S&P 500. In general, gold is seen to be

Figure 4: BEKK-GARCH correlation of Bitcoin and S&P500.



A Savitzky-Golay filter is applied and represented by the solid line. Times of market distress is highlighted in purple.

Figure 5: BEKK-GARCH correlation of gold and S&P 500.

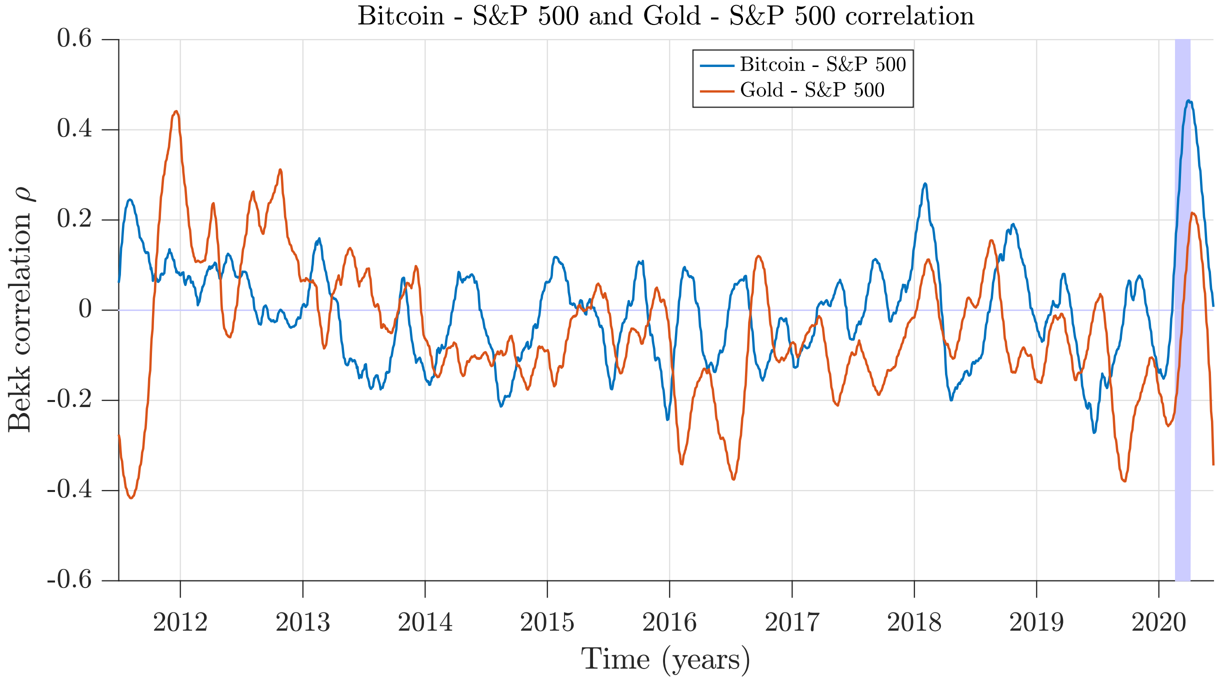


A Savitzky-Golay filter is applied and represented by the solid line. Times of market distress is highlighted in purple.

mainly negatively correlated with S&P 500 after 2013. This observation suggests that gold has moved from depicting mainly diversification benefits, to acting more as a potential hedge as a negative correlation is more frequently illustrated in the later years. This is in line with previous findings, e.g. Capie, Mills, and Wood (2005) show that the hedging capabilities of gold are time variant. Focusing on the recent time period, the previous analysis highlights a difference in the behaviour of the two assets. Gold is seen to have a negative correlation in the first part of the time period defined by market distress. This suggest a potential for gold to act as a safe haven during the recent financial crisis. This is not surprising, as gold is typically considered to represent a hedge and safe haven asset (Baur & Lucey 2010; Baur & McDermott 2016; Klein 2017; Smales 2019). For instance, Baur and McDermott (2016) discover that gold functions as a safe haven asset during black swan events. Klein (2017) finds that gold is able to act like a safe haven asset during the financial crisis in 2008, however, the correlation turns positive a year after the market turmoil. Even if the particular time period is not as long in this case, the same pattern is still observed. Besides this, Baur and Lucey (2010) provide a definition of a safe haven asset in the sense of it not needing to last long, except for when the market is in distress.

In comparison to these findings, Klein, Thu, and Walther (2018) observe that the correlation between gold and S&P 500 turns negative in periods when the market is in distress. Namely, this change in correlation is illustrated in the second period, where the correlation shows a significant decrease as a response to the market downturn in a short period of time. While, in the first interval considered there exists a negative correlation over the whole period influenced by a

Figure 6: BEKK-GARCH correlation of Bitcoin and S&P 500 and gold and S&P 500.



Times of market distress is highlighted in purple.

market downturn. Consequently, Klein, Thu, and Walther (2018) assert that this shows a safe haven property of gold, and further argue that this confirms the flight-to-quality hypothesis.

In addition, to further distinguish the correlations between these two assets and the S&P 500 respectively figure 6 presents the correlations of both assets simultaneously. A general observation is that the two correlations appear to move in opposite directions in the initial time period. Then, they reach a turning point around mid 2014, and begin to move increasingly in tandem with each other. There are a few exceptions present, see for instance the period in the first half of 2016 and mid 2017. Again, focusing on the most recent time period, figure 6 highlights that the correlations are moving in a highly similar direction. However, the red line, which denotes the correlation between gold and S&P 500, is slightly lagging behind. This observation is also detected in previous figures, as figure 5 displays a slightly later occurrence of the correlation showing a positive value when considering the most recent time period, as compared to figure 4, which illustrates the correlation between Bitcoin and S&P 500.

In accordance with the paper by Klein, Thu, and Walther (2018), additional dynamic correlation analyses are performed and presented in section 5. A few key points to make note of are the following. First, considering the correlation between gold and the MSCI World index, figure 8 shows that there is a similar correlation as was previously identified between gold and the S&P 500 index. In general, there appears to be a higher degree of positive correlation as opposed to between gold and S&P 500. Likewise, figure 9 illustrates a similar correlation between Bitcoin and MSCI World during the most recent time period as figure 4 shows. This indicates that Bitcoin is not acting as a safe haven against the MSCI World index during the previous market turmoil either. The overall correlation shifts from positive to negative frequently and therefore applies to the same reasoning as mentioned previously. Moreover, figure 10 and figure 11 illustrate a similar behaviour for the two assets as is formerly discussed regarding the observations in figure 6. On the other hand, figure 12 depicts a slightly different correlation than the two assets have with previously presented indices. Here, the correlations are a rather good mirror image of each other in the beginning of the time period. However, along the way, they begin to move more closely with one another, although some lagging is observed. Interestingly, while Bitcoin shows a positive correlation during the recent period with market distress, gold actually depicts a shift from a positive correlation to a negative one, as soon as the period begins. This behaviour implies that gold, to some extent, has an ability to act as a safe haven for investments in WTI, while the opposite is true for Bitcoin. Thus, holding a portfolio of WTI and gold is preferred to holding one which consists of Bitcoin and WTI, at least for a risk averse individual, during the recent time period.

In summary, the findings surrounding Bitcoin appear to be rather inconclusive. The reason behind this is that there exists no clear evidence which determines when Bitcoin has the property of a hedge, and when the asset only shows diversification benefits. It is, however, confirmed that Bitcoin does not have the property of a safe haven. This conveys a difference between Bitcoin and gold, which is ordinarily defined as the traditional safe haven asset see e.g. (Baur & Lucey 2010; Klein 2017; Baur & McDermott 2016). Meanwhile, gold once again shows a tendency to act both as a hedge and safe haven, albeit the latter property only covers a short time period.

The final part of the analysis concerns a portfolio evaluation where the aim is to investigate possible hedging properties of Bitcoin and gold. This is done by constructing minimum-variance portfolios, where each portfolio consists of an index, S&P 500, MSCI World or MSCI EM50, and additionally by either Bitcoin or gold. Thus, the portfolios consist of two components. Table 8 presents the descriptive statistics of the weights in these portfolios. Furthermore, figure 7 illustrates the minimum variance composition, i.e. the weights which are time varying. Gold has the highest mean weight in all the portfolios, i.e. 44.71 % combined with S&P 500, 38.87 % in the case of MSCI World and 51.44 % when combined with MSCI EM50. In respect of Bitcoin, the weights correspond to 3.98 % for S&P 500, 2.99 % for MSCI World and 4.64 % for MSCI EM50. Thus, the weights of Bitcoin are considerably much lower than for gold. The result, regarding the time varying weights of Bitcoin, is in line with Guesmi et al. (2019). The standard

Table 8: Descriptive statistics of the portfolio weights.

	S&P 500		MSCI World		MSCI EM50	
	Bitcoin	Gold	Bitcoin	Gold	Bitcoin	Gold
Mean	0.0398	0.4471	0.0299	0.3887	0.0464	0.5144
St. dev.	0.0502	0.1709	0.0422	0.1711	0.0433	0.1393
Min.	-0.2060	-0.0990	-0.2250	-0.1110	-0.1220	-0.092
Max.	0.3840	1.0000	0.2541	1.000	0.1980	0.955

deviation of the portfolio weights is higher for gold which suggests that the variation in weights of gold differs to a larger extent. This characteristic is furthermore illustrated in figure 7, where we see that the time varying weight of gold, denoted by the red line, depicts a higher volatility. Interestingly, gold is the only asset which reaches a weight equal to one, meaning that the entire portfolio is composed of gold. In addition, there are instances of short positions in both gold and Bitcoin. These are defined both by the negative minimum values in table 8 and by the red and blue lines dropping below the black dotted line in figure 7.

Next, table 9 presents the Value-at-Risk (VaR) measures for the three indices. It appears that VaR measures regarding the S&P 500 index are larger, in absolute value, than for the MSCI World. The MSCI EM50 has the highest negative value for 5 % and 10 % VaR measures. However, it is S&P 500 which has the most negative VaR value at 1 %. These results are corresponding to the ones which Klein, Thu, and Walther (2018) present. These results are subsequently used as an indication of when the market is characterised as being in distress. Since a time period including a market turmoil is essential for studying hedging properties of assets, these measures are used in order to evaluate the average return of the constructed portfolios during times of market distress. Table 10 presents the results which are needed to evaluate the different portfolios, i.e. the mean returns, the volatilities, higher order moments and the mean return in a period identified as market turmoil. Portfolios which consist solely of each respective index are included as a point of reference for comparison.

At first glance, we can see that it is only when the portfolio consists of MSCI EM50 and one of the assets that the mean return is higher, compared to a portfolio made up entirely of an index.

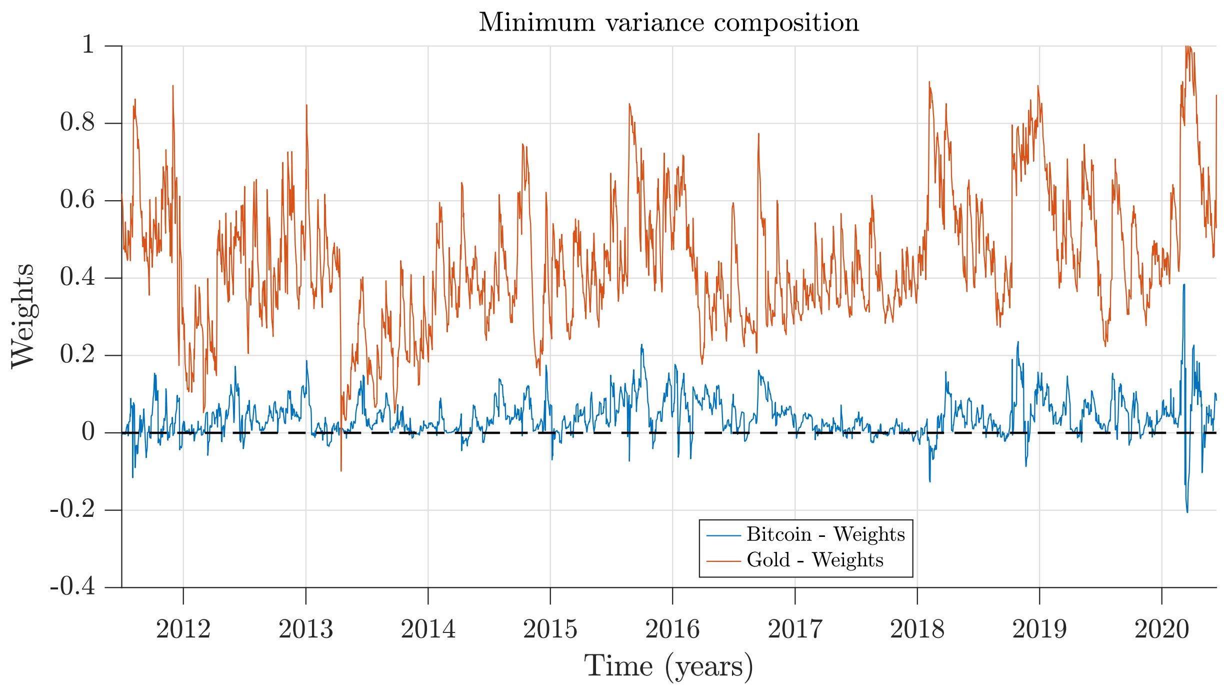


Figure 7: Time-varying weights of minimum-variance portfolios for Gold–S&P 500 and Bitcoin–S&P 500 based on BEKK correlations.

Table 9: Value at risk measures.

	S&P 500	MSCI World	MSCI EM50
$VaR_{0.01}$	-3.2403	-2.9294	-2.7287
$VaR_{0.05}$	-1.6083	-1.3903	-1.6392
$VaR_{0.10}$	-0.9477	-0.8733	-1.1750

Hence, in the case of S&P 500 and MSCI World, the portfolio furthest to the left has the highest mean. Including Bitcoin in one of the first two portfolios results in an increase of volatility, measured by standard deviation, of the portfolio. The MSCI EM50 index is an exception in this respect. This result is further able to distinguish Bitcoin from gold. This is due to that a positive weight of gold, in any of the three indices, contributes to a decrease in volatility. This characteristic presents an advantage in terms of minimising the portfolio risk and is preferred by risk-averse individuals. The portfolio which consists of a combination of both S&P 500 and Bitcoin shows the largest dispersion in min- and max value. This is an implication of the high volatility of Bitcoin. Moreover, the same result holds for MSCI EM50. However, the portfolio which only consists of the MSCI EM50 index shows the highest maximum value. Yet again, including Bitcoin in the portfolio results in the lowest minimum value. The values of kurtosis show different effects. While a combination of S&P 500 and Bitcoin represents the highest value by far (38.25), for MSCI World, the highest kurtosis is caused by the index itself. Interestingly, gold contributes to the highest kurtosis when paired with MSCI EM50. Negative skewness is the highest for the portfolios which include Bitcoin, in the case of S&P 500 and MSCI World, while again it is the MSCI EM50 index which causes the highest negative skewness.

Finally, the mean return of the portfolios in periods when the return of each respective index is below the VaR for that portfolio (see table 9). Table 10 presents a striking result when considering the returns of portfolios which include Bitcoin. In particular, these results imply that Bitcoin adds to the downside risk of every portfolio, for all different VaR levels, except one case (see MSCI EM50, VaR 1 %). Conlon and McGee (2020) find a similar results regarding that Bitcoin contributes to downside risk of a portfolio. Therefore, the mean returns are lower when considering the portfolios which include a combination of an index and Bitcoin. Certainly, in the reasoning as an risk-averse individual this is not a preferred property of an asset, especially not during market turmoil. This further shows that Bitcoin is not able to act as neither a hedge nor a

Table 10: Hedging properties.

1st component	S&P 500			MSCI World			MSCI EM50		
2nd component	S&P 500	Bitcoin	Gold	MSCI World	Bitcoin	Gold	MSCI EM50	Bitcoin	Gold
Mean	0.0351	0.0294	0.0243	0.0204	0.0185	0.0196	0.0091	0.0178	0.0104
St. dev.	1.0982	1.1583	0.6474	0.9529	0.9760	0.6337	1.0140	1.0099	0.6931
Min.	-12.7652	-16.6299	-4.2913	-10.4412	-9.9052	-4.4758	-6.3863	-6.9676	-4.1861
Max.	8.9683	9.2704	4.7214	8.4063	8.9143	4.6867	6.5105	6.6016	4.6726
Kurtosis	22.6812	38.2499	9.1437	22.5697	21.8572	9.8260	6.7926	7.3040	7.4063
Skewness	-0.9538	-2.2335	-0.3816	-1.2599	-1.2903	-0.3977	-0.4024	-0.3940	-0.3022
Return|$VaR_{0.01}$	-5.0414	-5.7817	-2.7042	-4.5189	-4.8138	-2.6785	-3.7890	-3.7894	-2.7136
Return|$VaR_{0.05}$	-2.7699	-2.9161	-1.5995	-2.4247	-2.5015	-1.5607	-2.3957	-2.3758	-1.6428
Return|$VaR_{0.10}$	-2.0120	-2.0746	-1.1872	-1.7677	-1.8111	-1.1590	-1.8899	-1.8621	-1.2732

safe haven asset. Gold, on the other hand, manages to reduce the downside risk of the portfolios and hence, appears to have hedging and possibly even safe haven properties. These results are moreover found by Klein, Thu, and Walther (2018).

The final calculations done in this paper consider a robustness check. In order to do this, the CRIX is used instead of data of Bitcoin. The methodology applied is explained in section 2. The results are presented in section 5. The overall finding is that the results are dissimilar to some extent, for e.g. see table 12. However, it can be argued that the differences depend on the shorter time period studied.

5 Conclusion

The first objective of this paper was to investigate the volatility structure of Bitcoin and compare it to the volatility behaviour of gold, as well as to the other asset classes. The methodology of investigating this was by using different ARCH models. This part of the analysis, together with the remaining objectives, was done according to the method by Klein, Thu, and Walther (2018). The second objective was to study the correlations of Bitcoin against the other assets. Specifically, it was interesting to compare the correlation of Bitcoin to the corresponding correlation of gold. The third objective of this paper was to investigate if Bitcoin or gold possess hedging and safe haven properties during a time period characterised by market distress. The aim of these objectives was to examine if Bitcoin behaves similarly to gold and hence, can be named the new gold.

The results show that Bitcoin has a similar asymmetry behaviour with the precious metals, i.e. gold and silver. Their leverage parameter was shown to be negative which indicates that positive shocks have a higher impact on their conditional volatility. These results were however not statistically significant. The opposite was found to be true for the remaining assets. This result implies that the volatility behaviour of Bitcoin is more similar to gold, than to the stock indices or commodities such as oil. Moreover, it suggests that both Bitcoin and gold hold a preferable property during a time period of market distress. However, a disparity is highlighted between Bitcoin and gold as the value of the δ parameter indicates that gold is preferable modelled by variance while this is not the case for Bitcoin. In addition, Bitcoin has a similar degree of long memory in its volatility as gold and WTI do. Despite these similarities, the BIC suggests that Bitcoin and gold are preferably modelled with different models. Therefore, these results are considered to be rather inconclusive and I am not able to classify Bitcoin in an already established asset class based on these findings only. Neither one of the used models are found to be entirely suitable for modelling the conditional volatility of Bitcoin and gold (nor silver). At the same time as this suggests similar characteristics of these assets, the BIC suggests that the GARCH model is best for gold and silver while the FIGARCH model is best for Bitcoin. In general, the volatility analysis suggests a closer resemblance of Bitcoin and the precious metals than to the rest of the assets. Moreover, based on the Ljung Box test and the ARCH test, Bitcoin and the precious metals are not suitable to model with the models which were used in this paper. A general conclusion regarding the volatility behaviour of the assets is that Bitcoin is more similar to gold, silver and oil in some cases, than to stock indices.

The results form the dynamic correlation analysis show that Bitcoin does not act as a hedge, or a safe haven during the recent market distress. Bitcoin does however show a presence of diversification benefits. These results are in line with the findings by e.g. Klein, Thu, and Walther (2018) and Bouri et al. (2017b). Gold is able to act as a hedge during the recent market turmoil and hence possesses the property of a safe haven asset. However, this characteristic is only observed for a rather short time period. Considering the whole time period shows that Bitcoin does show some presence of acting as a hedge, however, the results of when this holds are ambiguous and can not be confirmed in general. Hence, the results show that gold can be considered as the traditional safe haven, as it is known for while Bitcoin can not be considered to be the new gold.

In the final part of this investigation, I constructed minimum-variance portfolios and then evaluated them during periods of market distress in order to investigate possible hedging properties. First, the included weights of Bitcoin were small compared to gold, and the time varying weights of gold had a higher volatility. In addition, it was only gold which was found to add up to a weight of 100 percent in a portfolio. Thus, we can conclude that there is a disparity between the two assets. More crucial, however, is that the inclusion of Bitcoin in a portfolio resulted in an increase of the volatility and an increase in the downside risk of the portfolio. In contrast, adding gold to a portfolio contributed to a decrease in the volatility. The results showing that Bitcoin contributes to the downside risk of a portfolio during market distress imply that Bitcoin does not provide any hedging possibilities, nor can be classified as a safe haven. Gold on the other hand is found to have hedging properties and additionally, still possesses the property of being a safe haven asset, albeit for a short time period. In conclusion, Bitcoin and gold are found to have some similar properties, concerning their volatility behaviour, but based on the overall findings in this paper, Bitcoin can not be named the new gold as it does not hold the same essential properties.

The limitations of this paper are the following. The data availability is limited as the cryptocurrency market is still young. The results are not robust when investigating the CRIX instead of Bitcoin. This is suggested to depend on the different time period considered. Moreover, there was not a single model which was found to be appropriate for studying the volatility structure of Bitcoin, gold and silver. A few recommendations for further research can be to test more models, as well as include more lags, and try to find a suitable model for each asset based on information criteria. Furthermore, instead of using the CRIX to conduct a robust check, a possibility is to include several cryptocurrencies.

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Appendices

Table 11: Descriptive statistics of all time series' returns with CRIX.

	S&P 500	MSCI World	FTSE 100	MSCI EM 50	Gold	Silver	WTI	CRIX
Observations	1532	1532	1532	1532	1532	1532	1532	1532
Mean	0.03	0.01	-0.01	0.01	0.02	-0.01	-0.30	0.21
Std. dev.	1.14	0.97	1.05	1.03	0.84	1.46	9.07	4.57
Min.	-12.77	-10.44	-11.51	-6.39	-3.61	-13.53	-305.97	-44.66
25 %	-0.29	-0.30	-0.45	-0.54	-0.44	-0.64	-1.34	-1.40
50 %	0.03	0.05	0.02	0.06	0.01	0.00	0.00	0.23
75 %	0.47	0.41	0.49	0.59	0.46	0.70	1.21	2.18
Max.	8.97	8.41	8.67	6.51	4.69	8.48	30.02	22.03
Skewness	-1.07	-1.57	-1.11	-0.50	0.16	-0.78	-26.69	-0.94
Kurtosis	23.51	26.05	16.10	4.35	2.99	8.31	866.56	9.78
Jarque Bera	35331.22***	43659.33***	16743.07***	1260.79***	570.23***	4530.12***	47803181.25***	6289.98***
Ljung Box (25)	361.30***	226.79***	75.48***	63.64***	32.23	56.43***	216.42***	36.36*
ARCH (25)	676.88***	616.85***	463.67***	409.68***	147.83***	166.18***	39.62**	36.99*
ADF	-8.82***	-8.83***	-8.49***	-13.82***	-39.65***	-25.21***	-8.31***	-17.81***

Table 12: Pairwise Pearsons correlation with crix.

	S&P 500	MSCI World	FTSE 100	MSCI EM 50	Gold	Silver	WTI	CRIX
S&P 500	1.0000	0.9546	0.6172	0.5573	-0.0658	0.1343	0.1701	-0.0540
MSCI World		1.0000	0.7502	0.6727	-0.0252	0.2098	0.1747	-0.0211
FTSE 100			1.0000	0.6287	-0.0582	0.1574	0.1203	0.0331
MSCI EM 50				1.0000	-0.0256	0.1900	0.1239	0.0153
Gold					1.0000	0.6264	0.0069	0.0383
Silver						1.0000	0.0463	0.0411
WTI							1.0000	0.0207
CRIX								1.0000

Table 13: Estimation results for the GARCH model with CRIX.

	S&P 500	MSCI World	FTSE 100	MSCI EM 50	Gold	Silver	WTI	CRIX
θ_0	0.0831***	0.0590***	0.0336*	0.0454**	0.0143	0.0171	0.0112	0.2535***
θ_1	-0.0618**	0.0939***	0.0265	0.1853***	-0.0387*	-0.0234	-0.0390	-0.0070
ω	0.0250***	0.0171***	0.0350***	0.0324**	0.0095**	0.0262	0.5604***	0.5819
α_1	0.2239***	0.1952***	0.1632***	0.0867***	0.0409***	0.0302*	0.1572***	0.1663***
β_1	0.7761***	0.7987***	0.8111***	0.8793***	0.9472***	0.9646***	0.7816***	0.8337***
ν	4.4434***	5.0694***	5.2613***	11.0875***	5.1773***	3.1156***	3.8235***	3.0598***
LL	-1707.73	-1498.81	-1866.05	-2028.78	-1772.14	-2528.73	-3485.16	-4158.75
BIC	3459.46	3041.63	3776.11	4101.56	3588.29	5101.47	7014.32	8361.51
Jarque Bera	999.04***	560.49***	245.28***	37.43***	246.73***	963.30***	15995547.38***	6073.93***
Ljung Box (25)	24.07	29.60	19.18	22.22	33.06	33.34	14.89	58.55***
ARCH (25)	15.74	18.43	22.21	20.12	22.08	54.72***	0.07	11.60

*Statistically significant parameters are indicated with asterisk *, **, *** for 10 %, 5 % and 1 % level of significance.*

Table 14: Estimation results for the APARCH model with CRIX.

	S&P 500	MSCI World	FTSE 100	MSCI EM 50	Gold	Silver	WTI	CRIX
θ_0	0.0502***	0.0317***	0.0040	0.0174	0.0184	0.0170	0.0060	0.2603***
θ_1	-0.0500***	0.1011***	0.0392	0.1975***	-0.0393*	-0.0243	-0.0551**	-0.0292***
ω	0.0322***	0.0246***	0.0296***	0.0365***	0.0124**	0.0603	0.0278***	0.0517*
α_1	0.0000	0.0000	0.0000	0.0000	0.0694***	0.0347	0.0000	0.1277**
γ_1	0.2526***	0.2213***	0.1972***	0.1381***	-0.0357*	-0.0197	0.0761***	-0.0007
β_1	0.8713***	0.8835***	0.8925***	0.8866***	0.9429***	0.9488***	0.9563***	0.8726***
δ	0.8057***	0.9251***	1.0157***	2.0670**	1.4962***	2.9904***	0.5949***	0.2839
ν	5.0136***	5.8695***	6.2312***	15.4158***	5.0601***	3.1229***	4.0080***	2.5393***
LL	-1664.23	-1461.93	-1833.40	-2010.60	-1769.79	-2527.83	-3456.62	-4138.87
BIC	3387.13	2982.53	3725.46	4079.87	3598.25	5114.33	6971.90	8336.41
Jarque Bera	1442.92***	2685.43***	198.09***	20.91***	290.66***	974.54***	8909156.84***	10281.74***
Ljung Box (25)	23.16	25.80	22.63	22.19	33.65	33.17	46.30***	51.77***
ARCH (25)	49.26***	22.90	21.63	22.43	24.25	48.86***	2.67	12.22

*Statistically significant parameters are indicated with asterisk *, **, *** for 10 %, 5 % and 1 % level of significance.*

Table 15: Estimation results for the FIGARCH model with CRIX.

	S&P 500	MSCI World	FTSE 100	MSCI EM 50	Gold	Silver	WTI	CRIX
θ_0	0.0809***	0.0601***	0.0354**	0.0468**	0.0139	0.0166	0.0311	0.2512***
θ_1	-0.0633**	0.0937***	0.0277	0.1837***	-0.0356	-0.0263	-0.0449	-0.0335***
ω	0.0182	0.0236*	0.0417*	0.0655	0.0238**	0.3305	0.1690***	0.0727
ϕ	0.0000	0.0000	0.2373**	0.0000	0.0220	0.4346	0.1141*	0.0000
d	0.6755***	0.6188***	0.5254***	0.3113***	0.8696***	0.1308	0.7718***	0.9359***
β	0.4620***	0.4593***	0.5537***	0.2589	0.8916***	0.5208	0.7876***	0.8305***
δ	2.5379***	2.1019***	2.0331***	2.1906***	0.9817*	3.0128***	1.0199***	0.3027***
ν	4.0892***	5.1468***	5.2811***	10.8331***	5.2265***	3.0591***	3.9243***	2.5655***
LL	-1700.91	-1494.41	-1862.92	-2025.89	-1768.31	-2527.17	-3472.93	-4138.91
BIC	3460.48	3047.49	3784.52	4110.46	3595.30	5113.01	7004.52	8336.48
Jarque Bera	1034.57***	514.34***	258.26***	41.52***	274.75***	936.32***	14708149.25***	9456.89***
Ljung Box (25)	24.11	28.34	18.43	22.94	34.99*	30.45	24.46	52.64***
ARCH (25)	16.71	22.35	23.06	21.87	22.23	38.22**	0.19	12.36

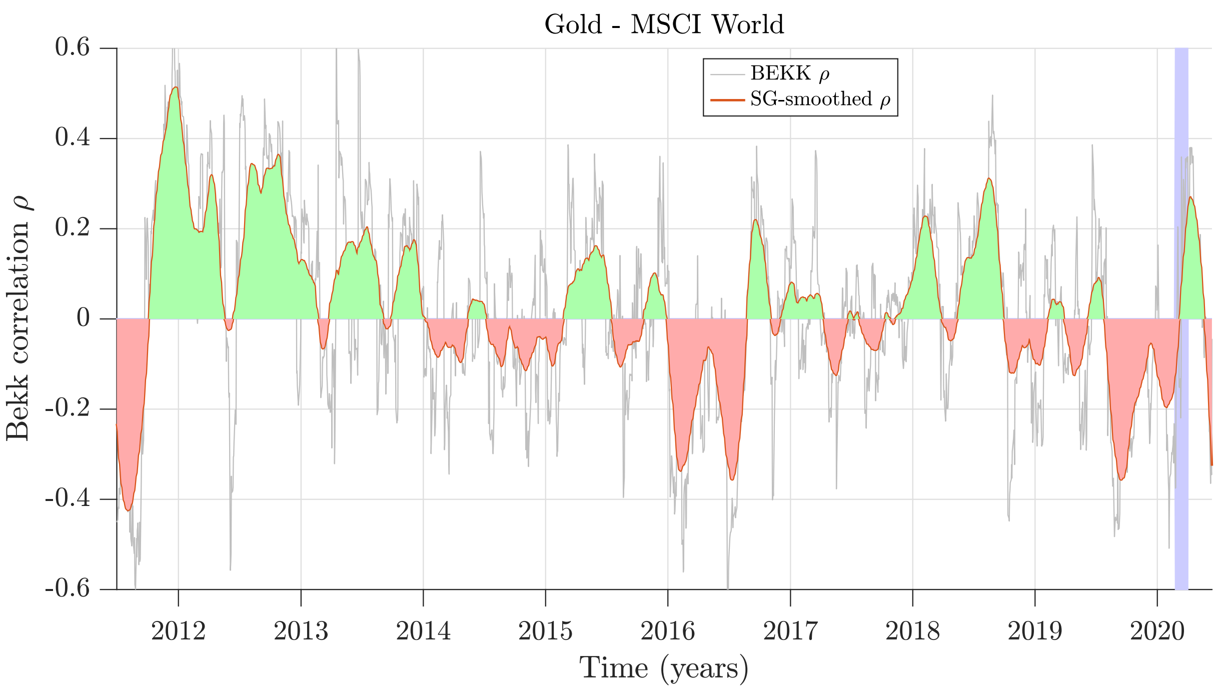
*Statistically significant parameters are indicated with asterisk *, **, *** for 10 %, 5 % and 1 % level of significance.*

Table 16: Estimation results for the FIAPARCH model with CRIX.

	S&P 500	MSCI World	FTSE 100	MSCI EM 50	Gold	Silver	WTI	CRIX
θ_0	0.0529***	0.0340***	0.0050	0.0199	0.0181	0.0248	0.0103	0.2493***
θ_1	-0.0448*	0.1110***	0.0399	0.1963***	-0.0369*	-0.0278	-0.0449	-0.0217
ω	0.1582***	0.1810***	0.2132***	0.6655***	0.0257***	0.3780	0.1623**	0.4913***
ϕ	0.2080***	0.1948***	0.3956***	0.1170	0.0413	0.4562	0.1560	0.1466
d	0.3452***	0.2811***	0.1904***	0.0463	0.8454***	0.0876	0.6880***	0.4141***
β	0.4604***	0.4094***	0.5295***	0.1490	0.8867***	0.5164	0.7811***	0.4531**
γ	0.6663***	0.6672***	0.7882***	0.5960***	-0.1152	-0.0468	0.2806***	-0.0098
δ	0.7507***	0.6914***	0.5594***	0.2500	0.9756***	0.3734	1.0073***	0.7598***
ν	5.0580***	6.0530***	6.4722***	15.0034***	5.1280***	2.9882***	4.1112***	2.5558***
LL	-1656.88	-1454.19	-1822.76	-2008.00	-1766.42	-2533.64	-3464.90	-4139.71
BIC	3379.77	2974.38	3711.52	4082.00	3598.84	5133.28	6995.79	8345.42
Jarque Bera	1156.53***	3565.16***	207.50***	24.01***	307.25***	1184.11***	9705055.41***	10860.14***
Ljung Box (25)	23.56	24.22	22.10	23.30	35.63*	34.16	22.56	58.06***
ARCH (25)	21.98	12.10	24.35	22.16	23.90	55.42***	0.23	14.97

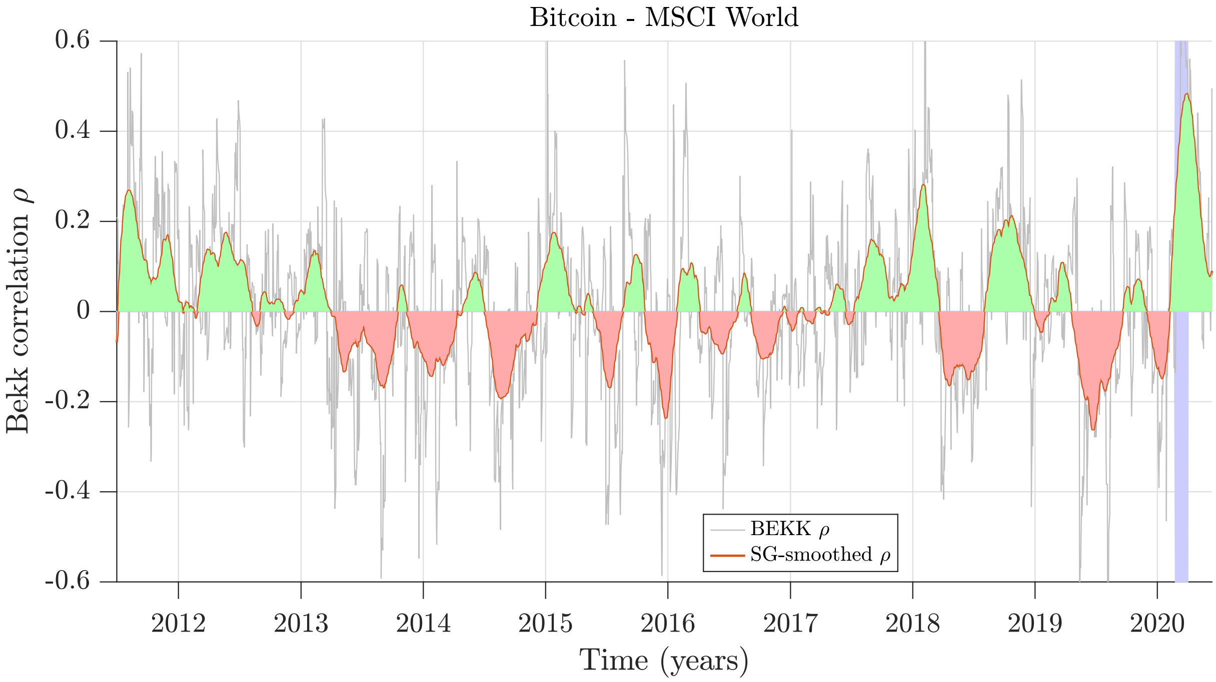
*Statistically significant parameters are indicated with asterisk *, **, *** for 10 %, 5 % and 1 % level of significance.*

Figure 8: BEKK-GARCH correlation of gold and MSCI World.



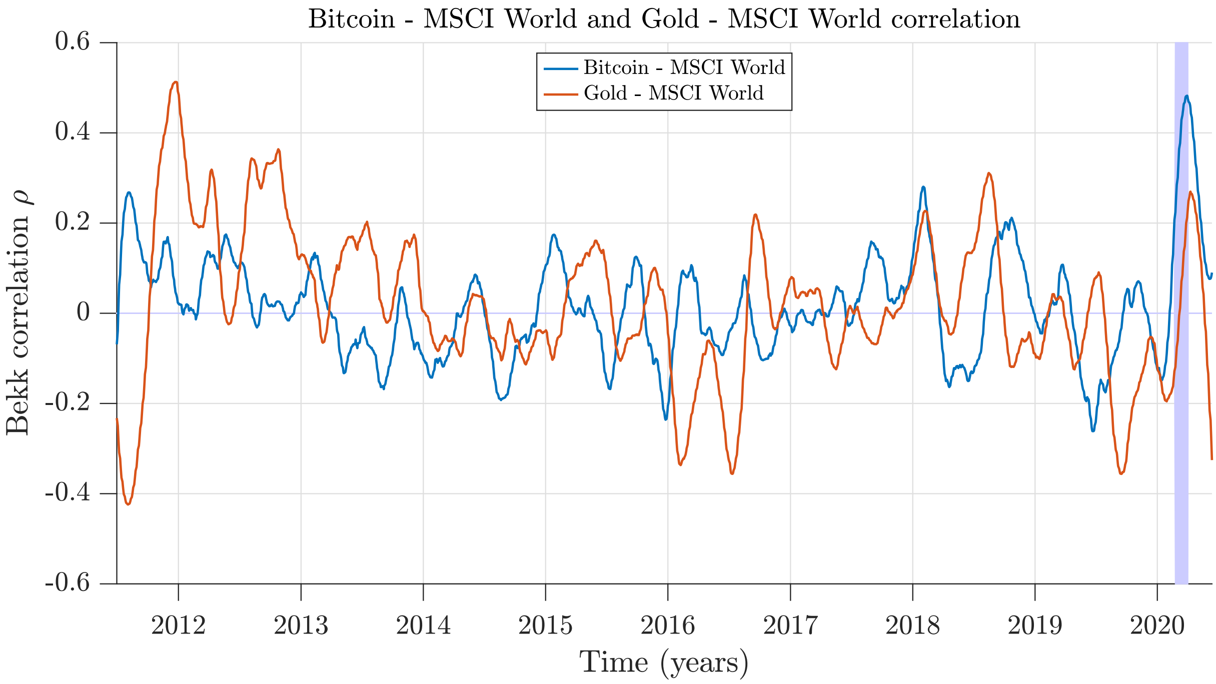
A Savitzky-Golay filter is applied and represented by the solid line. Times of market distress is highlighted in purple.

Figure 9: BEKK-GARCH correlation of Bitcoin and MSCI World.



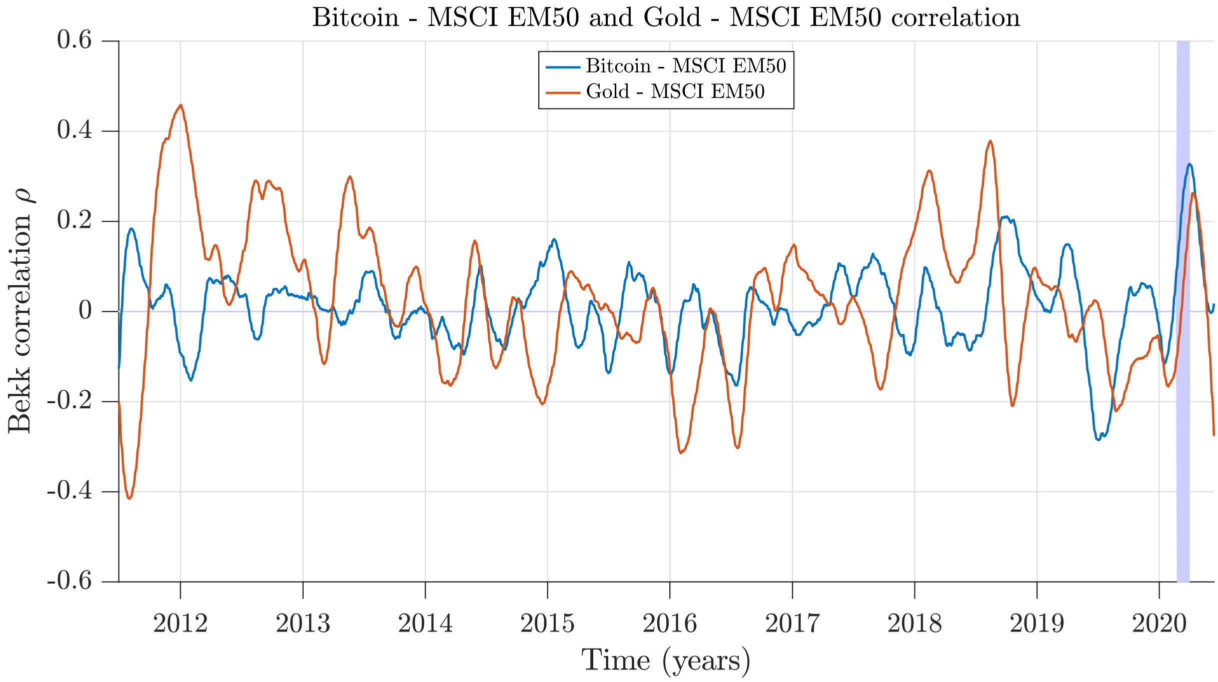
A Savitzky-Golay filter is applied and represented by the solid line. Times of market distress is highlighted in purple.

Figure 10: BEKK-GARCH correlation of Bitcoin and MSCI World and gold and MSCI World.



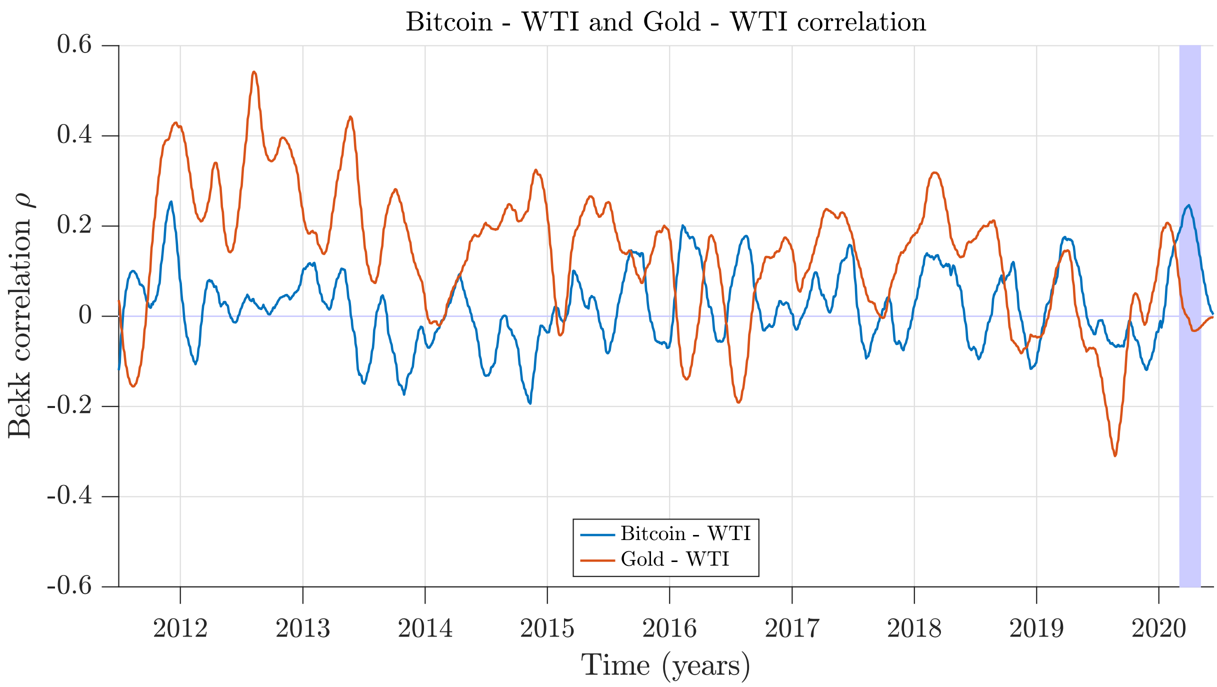
A Savitzky-Golay filter is applied and represented by the solid line. Times of market distress is highlighted in purple.

Figure 11: BEKK-GARCH correlation of Bitcoin and MSCI EM50 and gold and MSCI EM50.



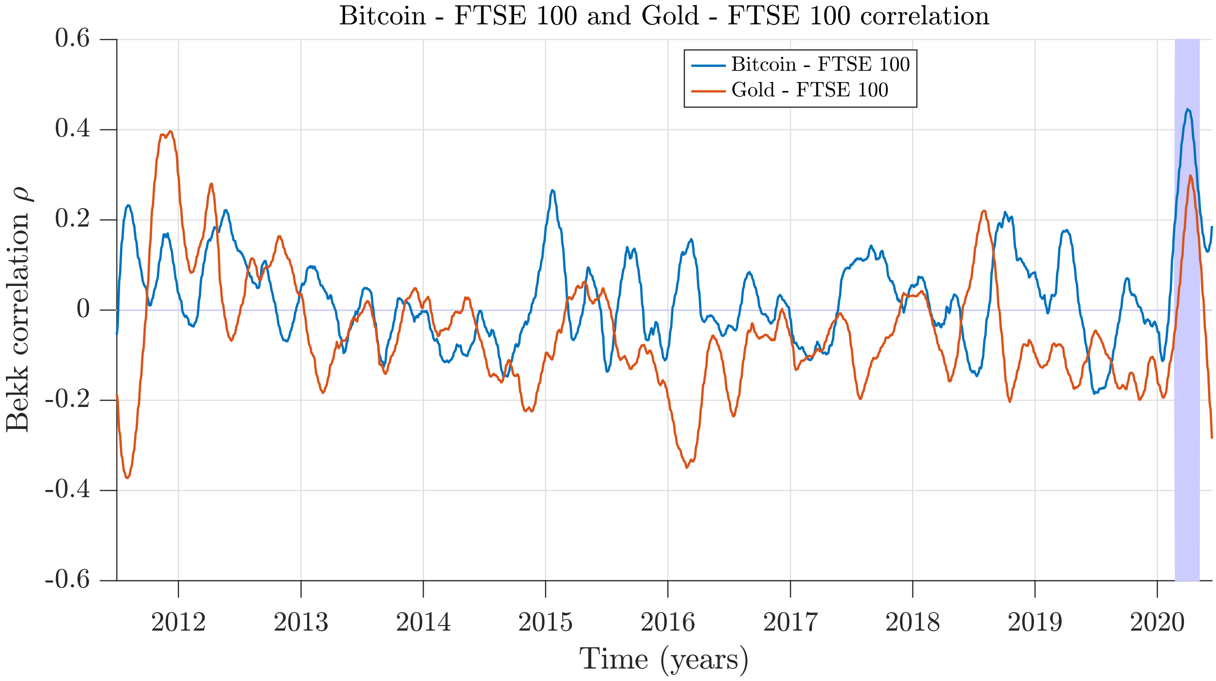
A Savitzky-Golay filter is applied and represented by the solid line. Times of market distress is highlighted in purple.

Figure 12: BEKK-GARCH correlation of Bitcoin and WTI and gold and WTI.



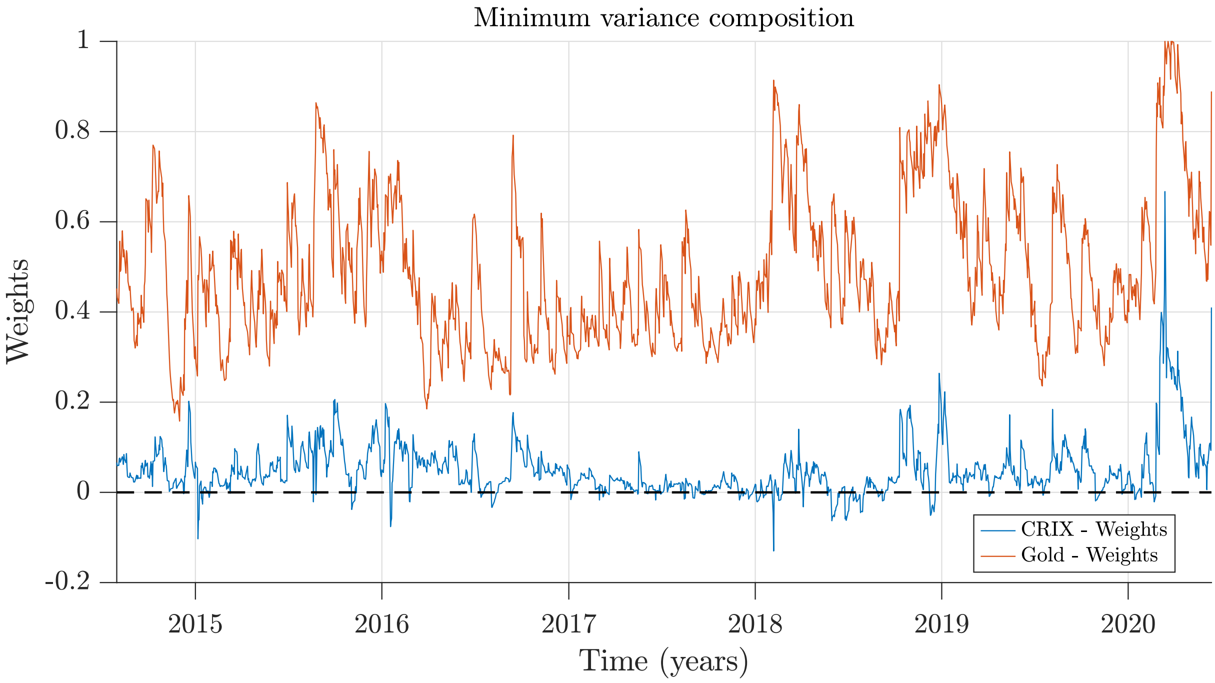
A Savitzky-Golay filter is applied and represented by the solid line. Times of market distress is highlighted in purple.

Figure 13: BEKK-GARCH correlation of Bitcoin and FTSE 100 and gold and FTSE 100.



A Savitzky-Golay filter is applied and represented by the solid line. Times of market distress is highlighted in purple.

Figure 14: Time-varying weights of minimum-variance portfolios for gold – S&P 500 and CRIX – S&P 500 based on BEKK correlations.



A Savitzky-Golay filter is applied and represented by the solid line.