The search for safe haven assets in the time of a global pandemic

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Abstract

The global pandemic has initially negatively influenced the financial markets all over the world. As a consequence, the volatility in the stock markets increased and investors have experienced great monetary losses. In addition, the volatility spillover has increased between different markets and assets, which additionally amplifies the negative influence by the pandemic. This motivates the search for safe haven assets in the time of a global pandemic. The aim of this thesis is therefore to analyse if Bitcoin, Ethereum and Binance Coin have diversification benefits, hedging properties and most importantly, if they are able to act as safe haven assets against stock indices, namely MSCI World, MSCI EM 50 and S&P 500, during the global pandemic. In order to analyse this, a diagonal BEKK-GARCH model is used. First, I analyse the volatility spillover between cryptocurrencies and stock indices. Secondly, I perform a dynamic pairwise correlation analysis. Finally, minimum-variance portfolios are constructed and evaluated in order to additionally analyse the hedging capabilities and safe haven properties of the three cryptocurrencies. The results show that there is a presence of volatility spillover between these assets. Moreover, the results show that Bitcoin, Ethereum and Binance Coin have diversification benefits against all stock indices. In general, Bitcoin and Ethereum show hedging properties against stock indices. However, these properties are shown to be time-varying. The search for safe haven assets is of great importance in this time period. The correlation analysis shows that Bitcoin and Ethereum are able to act as save haven assets during the initial phase of the pandemic. This is confirmed by the portfolio analysis. In contrast, Binance Coin shows a high positive correlation with the stock indices, however, by using the possibility to short it, it yields the most favourable results in the portfolio analysis.

Contents

1 Introduction

The World Health Organization (WHO) declared the coronavirus disease (COVID-19) a global pandemic on March 11th, 2020 (WHO, 2021) . Today, more than two years has passed since the coronavirus was initially discovered, and on November 26th, 2021, a new variation of the virus, named Omicron, was identified (Karim & Karim, 2021). Indeed, the future of the global pandemic remains uncertain (OECD, 2021). The importance of realising that an epidemic can influence the economic and financial markets is discussed by the International Monetary Fund (IMF) (Bloom, Cadarette, & Sevilla, 2018). Additionally, parallels are drawn to natural disasters and armed conflicts which are previously observed to negatively influence financial markets. Evidently, the significance of these arguments are validated in the aftermath of the initial phase of the global pandemic.

The global pandemic has initially negatively influenced the financial markets all around the world[1] (Baker et al., 2020; Chevallier, 2020; Zhang, Hu, & Ji, 2020; Nguyen et al., 2021). Consequently, the impact of the global pandemic has been investigated profoundly. For instance, Goodell (2020) investigates the effect of the pandemic on financial markets and compares it to the impact of natural disasters, which is in line with Bloom, Cadarette, & Sevilla (2018). The results by Goodell (2020) imply that the current global pandemic will continue to influence the financial markets in the future. In addition, there is reason to believe that the pandemic will change the dynamics of the financial markets (Goodell, 2020). Therefore, it is suggested that past research should be replicated. Additionally, Goodell (2020) states that the next time there is an epidemic or pandemic, we should expect nothing less than a substantial reaction by the global financial markets. In accordance to this, Marani et al. (2021) analyse the global pandemic and compare it to historical epidemics in the world dating back to year 1600. The results indicate that the occurrence of extreme epidemics is going to increase in the future.

The negative influence on the financial markets, particularly between March and April 2020, is confirmed by research (Zhang, Hu, & Ji, 2020; Baker et al., 2020; Shehzad, Xiaoxing, & Kazouz, 2020; Ali, Alam, & Rizvi, 2020; Nguyen et al., 2021). The global pandemic has, among other things, resulted in an increased level of volatility in the stock markets[2] (Ambros et al., 2021; Baker et al., 2020; Uddin et al., 2021) and great monetary losses for investors (Zhang, Hu, & Ji, 2020) as the stock markets drastically dropped in value (Ali, Alam, & Rizvi, 2020). In addition, risk aversion in the stock market has increased as a

[1]It is worth mentioning that while new variants of the coronavirus have increased the volatility in the stock market, this increase has been shorter for every novel variant (Russel & Hadi, 2021). In addition, the volatility increase has been followed by a recovery to a new high in the stock market (Russel & Hadi, 2021; Turner, 2021).

[2]Interestingly, the increase in volatility caused by COVID-19 is greater than similar events in the past, such as SARS in 2003 and Ebola in 2015 (Baker et al., 2020). In fact, Baker et al. (2020) observe 18 volatility jumps in the U.S. stock market between 24th February and 24th March 2020, i.e. a total of 22 trading days, which is more than any other period in history.

result of the global pandemic (Papadamou et al., 2020)[3]. Indeed, the global pandemic had a greater negative impact on the stock markets than the Global Financial Crisis in 2008 (Shehzad, Xiaoxing, & Kazouz, 2020; Chevallier, 2020). Moreover, Baker et al. (2020) show that the impact is greater than the impact by any other infectious disease in the past[4].

However, the negative influence is heterogeneous for different assets and across markets. The negative impact is observed to differ for OECD-, developing and emerging markets (Chevallier, 2020) and is furthermore higher for stock markets in Europe and United States than for Asian stock markets (Shehzad, Xiaoxing, & Kazouz, 2020). In addition, Ambros et al. (2021) discover asymmetric volatility which is in line with the theory by Engle & Ng (1993) explaining that a negative shock increases the volatility to a greater extent than a positive shock. Moreover, the reaction and recovery rates of stock indices, bonds, precious metals and cryptocurrencies are heterogeneous (Yarovaya, Matkovskyy, & Jalan, 2021). Specifically, the degree of mean reversion is higher for stock indices compared to cryptocurrencies, which in turn have higher volatility persistence. This result implies that investments in stock indices include a lower risk compared to investments in cryptocurrencies (Yarovaya, Matkovskyy, & Jalan, 2022). This is not surprising, as Bitcoin is repeatedly shown to be more volatile than other assets, e.g. stocks (Baek & Elbeck, 2015), currencies (Blau, 2018) and commodities (Dwyer, 2015).

1.1 Motivation and Scope

The important concept of loss aversion is related to prospect theory (Kahneman & Tversky, 1979) and introduced by Tversky & Kahneman (1991). By definition, loss aversion implies that investors are more sensitive to losses than to gains of equal amounts. This implies that the negative influence of the global pandemic on stock markets, and the monetary losses mentioned in section 1, may be distinguished as greater than initially realised. In addition, the presence of volatility spillover between different markets and assets creates amplification of the negative influence (see section 2). This creates additional motivation to search for assets which have diversification abilities and hedging properties. Moreover, this motivates the search for safe haven assets in the time of a global pandemic. These potential properties, which are beneficial, are defined as follows. In order for an asset to have diversification abilities it must have a positive, but not perfect, correlation with other assets (Baur & Lucey, 2010). In addition, an asset which has hedging properties is either uncorrelated, or negatively correlated, with another asset (Baur & Lucey, 2010). Moreover, in order for an asset to be a safe haven, it must have the same properties as a hedge, but importantly they must hold during a time of market turmoil (Baur & Lucey, 2010). Hence, the asset must be uncorrelated or negatively correlated with other assets when the market

[3]This is considered to be an indirect effect of the pandemic, while the increase in volatility represents the direct effect (Papadamou et al., 2020).

[4]In this aspect, Baker et al. (2020) suggest that the government restrictions are partly the reason to why the global pandemic had such a large impact on the stock market.

is in distress. These definitions are used in the rest of this thesis.

The definitions by Baur & Lucey (2010) provide explanation to why the global pandemic is an essential time period to analyse and search for a safe haven asset. Importantly, the global pandemic represents the first time period in the lifetime of cryptocurrencies which is distinguished by market turmoil. This additionally provides motivation for this thesis. In general, these properties are shown to be time-varying (see section 2), which further motivates a repeated analysis. The aim of this thesis is therefore first to analyse whether cryptocurrencies, namely Bitcoin, Ethereum and Binance Coin, have diversification benefits and hedging properties against the three stock indices MSCI World, MSCI EM 50 and S&P 500. Secondly, this thesis investigates their ability to act as safe haven asset against stock indices during the global pandemic.

1.2 Thesis Outline

The outline of this thesis is as follows. Following the introduction in section 1, a review of related literature is presented in section 2. The methodology is explained in section 3 and more specifically, section 3.3 explains the diagonal BEKK-GARCH model, which is used in this thesis. Section 3 is followed by a preliminary data analysis in section 4. The results and analysis are presented in section 5 and finally, section 6 consists of the conclusions derived from the results in section 5.

2 Literature Review

This section consists of two main parts. The first part considers research with a focus on volatility spillover, while the second part includes research on properties of assets in terms of diversification, hedging and safe haven abilities. In addition, the second part consists of research regarding a correlation analysis between assets, as this is essential in order to determine the previously mentioned properties. Similarly, a portfolio analysis is also included in the second part. In general, characteristics of the investigated assets are observed to be time-varying and to show a different pattern during time periods with market turmoil. This creates additional motivation for this thesis, which is mentioned in section 1.

The higher degree of globalisation, together with an increased connection between different markets around the world, has resulted in more integrated global and financial markets (Erten et al., 2012). This interdependence is extensively analysed by researchers since it implies possible volatility spillovers between different markets and similarly, between different assets. In this aspect, multivariate conditional volatility models are frequently used. In particular, the BEKK-GARCH model is common, see e.g. (Katsiampa, Shaen, &

Lucey, 2019; Beneki et al., 2019; Erten et al., 2012).

The volatility spillover is frequently analysed in energy markets (Green et al., 2018). Their results indicate a presence of volatility spillover which varies with time and across commodities. This research area has also received attention in times of market turmoil, such as the global pandemic. For instance, Ghorbel & Jeribi (2021) analyse the volatility spillover between energy assets, stock indices, gold and Bitcoin. Their results show a high dynamic correlation between the energy assets and the stock indices, which implies that the global pandemic has resulted in contagion between these two markets. Furthermore, the results imply that Bitcoin is not a safe haven asset. Research shows that there is a significant volatility spillover between emerging markets during the Global Financial Crisis in 2008 (Erten et al., 2012). Furthermore, the volatility spillover is higher from developed to emerging markets than in the opposite direction. In the time of the global pandemic, the results similarly imply that developed markets are the main transmitters of risk, while emerging markets are the main risk receivers (Li, 2021). In addition, Li (2021) find that downside risk is transferred from developed stock markets to global financial markets. It is therefore essential to analyse the relationships between global stock markets in order to determine hedging possibilities and to create efficient portfolios (Erten et al., 2012).

The volatility spillover is also repeatedly analysed in the market of cryptocurrencies. Katsiampa, Shaen, & Lucey (2019) examine the pairwise conditional correlation and the conditional volatility between large cryptocurrencies and find a presence of volatility spillover between Bitcoin, Ethereum and Litecoin. The results by Katsiampa, Shaen, & Lucey (2019) imply a presence of integration and interdependence in the cryptocurrency market. Similarly, Katsiampa (2019) investigates the volatility dynamics of Bitcoin and Ethereum. The results are in line with the findings by Katsiampa, Shaen, & Lucey (2019). In addition, the conditional correlation and volatility of Bitcoin and Ethereum are responsive to major events. Furthermore, Beneki et al. (2019) discover that correlation and volatility spillover between Bitcoin and Ethereum is time-varying. Interestingly, Koutmos (2018) shows that Bitcoin is the main contributor of both return and volatility spillover[5]. Moreover, research shows that the spillover effect between cryptocurrencies has increased with time (Koutmos, 2018). As a result, this reveals an increased level of interdependence between cryptocurrencies and hence, a higher risk of contagion (Koutmos, 2018). Furthermore, the level of volatility spillover is also shown to increase in a time with market turmoil (Guo, Li, & Li, 2021; Li, 2021). Additionally, volatility spillover is generally found to be time-varying, asymmetric and crisis sensitive (Li, 2021; Yousfi et al., 2021). These characteristics provide motivation for analysing the volatility spillover between different markets and assets during the global pandemic. Moreover, a presence of volatility spillover is proposed to amplify the negative influence of the global pandemic on the stock markets and as a result lead to a higher risk of financial contagion.

[5]Koutmos (2018) analyses the spillover effect between the 18 largest cryptocurrencies based on market capitalisation.

Chevallier (2020) analyses the contagion, i.e. the increase in correlation, caused by the global pandemic on the financial markets. The results indicate a high correlation between international equities and Chevallier (2020) argues that this additionally increases the risk of financial contagion. Similarly, Guo, Li, & Li (2021) present results which confirm a higher degree of tail risk contagion between financial markets during the global pandemic. In addition, the contagion increases more between financial firms than between non-financial firms (Akhtaruzzaman et al., 2021)[6]. The financial contagion is furthermore investigated by Yarovaya et al. (2020). In accordance to these results, a significant increase in financial contagion and presence of a weak volatility spillover effect is observed between the U.S. and Chinese stock markets (Nguyen et al., 2021). Similar results are presented by Yousfi et al. (2021). In line with these findings, a presence of asymmetry in volatility spillovers is moreover observed by Li (2021). In addition, Li (2021) shows that volatility spillover displays time-varying and asymmetric characteristics. The volatility spillover between stock markets is high during the global pandemic[7]. For instance, Samitas, Kampouris, & Polyzos (2022) discover a presence of volatility spillover and risk of contagion between 51 stock markets around the world, which include both developed and emerging markets. In accordance with these results, Malik, Sharma, & Kaur (2021) observe volatility spillover and a presence of contagion, caused by the global pandemic, between the stock markets in the BRIC countries.

The motivation for analysing volatility spillover during the global pandemic applies for the market of cryptocurrencies as well. Corbet et al. (2021) find that stock markets have an impact on the volatility of Bitcoin. However, the results presented by Jiang et al. (2022) imply that the opposite direction of volatility spillover also holds. Corbet, Larkin, & Lucey (2020) investigate whether cryptocurrencies are able to provide diversification benefits. The results show that the correlation between cryptocurrencies and stock markets has significantly increased during the global pandemic (Corbet, Larkin, & Lucey, 2020). Moreover, Corbet, Larkin, & Lucey (2020) conclude that Bitcoin does not act as a safe haven in this period. Indeed, Bitcoin is shown to amplify the financial contagion (Corbet, Larkin, & Lucey, 2020). Nevertheless, Bitcoin is able to act as a safe haven asset against traditional currencies during the global pandemic (Hsu, Sheu, & Yoon, 2021). The volatility spillover between cryptocurrencies and other assets is also observed to be asymmetric, and increasingly so during the global pandemic (Hsu, Sheu, & Yoon, 2021). It is important to note that the properties of cryptocurrencies, i.e. their ability to show diversification, hedging and safe haven abilities, are time-varying, and moreover shows significantly different properties in times of market turmoil as compared to normal times (Hsu, Sheu, & Yoon, 2021). This provides motivation for further investigation of volatility spillover between different assets. This thesis will include an analysis of volatility spillover between

[6]Moreover, the results show that a financial contagion is not necessarily caused by a financial crisis, but rather a health crisis in this case (Akhtaruzzaman et al., 2021). This is in line with Bloom, Cadarette, & Sevilla (2018).

[7]Li (2021) analyse the stock markets in U.S., Japan, Germany, UK, France, Italy, Canada, China, India and Brazil.

cryptocurrencies and stock indices during the global pandemic.

A significant amount of research has been done with the motivation of finding safe haven assets. The negative influence on financial markets, mentioned in section 1, contributes to the importance of finding safe haven assets and to repeatedly analyse the safe haven properties of these assets (Ji, Dayong, & Zhao, 2020). In this aspect, gold is known as a traditional safe asset. This follows from that gold is repeatedly shown to be uncorrelated with other assets (Baur & Lucey, 2010). This characteristic is essential for an asset to be able to act as a hedge or a safe haven (Baur & Lucey, 2010). Consequently, these properties of gold have been investigated over the years (Baur & Lucey, 2010; Capie, Mills, & Wood, 2005; Baur & McDermott, 2010; Dyhrberg, 2016b; Klein, 2017)[8]. Interestingly, Klein, Thu, & Walther (2018) state that Bitcoin is considered to be the new gold in the aspect. As a result, the ability of cryptocurrencies to have these properties, namely to be able to diversify, hedge and act as a safe haven against other assets, are repeatedly analysed.

Analysing the correlation between cryptocurrencies and other assets is essential in order to determine possible diversification benefits, hedging capabilities and additionally the ability of cryptocurrencies to act as safe havens. The hedging capabilities of Bitcoin are investigated by Dyhrberg (2016b). The results show that Bitcoin acts as a hedge against stocks and currencies. Moreover, Dyhrberg (2016b) suggests that Bitcoin, based on a volatility and correlation analysis, is defined as something between a traditional currency and a commodity [9]. In contrast to these results, Baur, Dimpfl, & Kuck (2018) replicate the study by Dyhrberg (2016b) and argue that Bitcoin does not have these properties. Nevertheless, Bitcoin has diversification benefits (Baur, Dimpfl, & Kuck, 2018). Despite that cryptocurrencies generally have a positive correlation with other cryptocurrencies, they tend to have a low correlation with other assets (Härdle, Harvey, & Reule, 2019). This implies diversification benefits and is confirmed by research, see e.g. (Dyhrberg, 2016a; Corbet et al., 2018; Smales, 2019). In fact, Guesmi et al. (2019) illustrate that Bitcoin is able to provide diversification and hedging benefits by reducing the downside risk in a portfolio[10]. In accordance to this, Bouri et al. (2017b) have similar results and additionally find that Bitcoin is a safe haven asset against stock indices. However, this characteristic varies with time and across different markets (Bouri et al., 2017b; Bouri, Lucey, & Roubaud, 2020; Bouri, Shahzad, & Roubaud, 2020), which represents a motivation for revisiting this research question repeatedly. For instance, Bouri, Shahzad, & Roubaud (2020) show that Bitcoin, Ethereum and Litecoin have time-varying hedging capabilities against the stock indices in Asia and Japan. In addition, Bouri, Shahzad, & Roubaud (2020) find that

[8]For instance, research shows that gold is able to act as a hedge (Baur & Lucey, 2010; Capie, Mills, & Wood, 2005) and safe haven (Baur & Lucey, 2010; Klein, 2017) against stock indices, however this property is time-varying.

[9]Researchers have studied the volatility of cryptocurrencies, especially in the case of Bitcoin, over the years (Bariviera et al., 2017; Conrad, Custovic, & Ghysels, 2018). While several different GARCH models have been used (Bouri et al., 2017b; Katsiampa, 2017; Chu et al., 2017; Catania & Grassi, 2017), a simple GARCH(1,1) model is repeatedly shown to be a good fit (Conrad, Custovic, & Ghysels, 2018).

[10]The portfolio consists of stocks, gold and oil in this case (Guesmi et al., 2019).

cryptocurrencies have diversification benefits, which is in line with Corbet et al. (2018). Interestingly, Stensås et al. (2019) find that Bitcoin has hedging properties against developed stock markets, but only diversification benefits against emerging markets[11]. While there is not one cryptocurrency which is a consistent hedge against stock indices, Susilo et al. (2020) show that an equally weighted portfolio which consists of five cryptocurrencies is able to provide greater hedging benefits. In contrast to the findings by Bouri, Shahzad, & Roubaud (2020), Klein, Thu, & Walther (2018) show that Bitcoin does not have hedging capabilities against developed markets. An extensive analysis is presented by Wang et al. (2019). Specifically, Wang et al. (2019) analyse a total of 973 cryptocurrencies and 30 stock indices in order to investigate possible hedging properties and safe haven abilities. In general, the results show that cryptocurrencies do not have hedging capabilities against stock indices. However, cryptocurrencies are able to act as safe haven assets. This property is moreover positively correlated with the market capitalisation of the cryptocurrency and thus indicates that Bitcoin is the best safe haven (Wang et al., 2019). Additionally, Urquhart (2016) shows that Bitcoin is a safe haven for currencies. However, the results by Bouri et al. (2017a), Kristoufek (2015), Smales (2019) and Klein, Thu, & Walther (2018) show that Bitcoin is not able to act as a safe haven asset.

As observed, a great amount of previous research has focused on these properties of cryptocurrencies. However, it is important to note that the global pandemic represents the first time period, since Bitcoin was introduced by Nakamoto (2008), which is influenced by a market turmoil. This specific time period is essential, by definition (Baur & Lucey, 2010), in order to analyse whether cryptocurrencies are able to act as safe haven assets. Therefore, it is not surprising that an extensive amount of research has been done in this aspect. Conlon & McGee (2020) show that Bitcoin is not a safe haven asset during the global pandemic. In contrast to a safe haven asset, Bitcoin increases the downside risk of a portfolio (Conlon & McGee, 2020)[12]. In general, the ability of an asset to act as a safe haven is time-varying (Cheema, Faff, & Szulczuk, 2020)[13]. While Bitcoin is not a safe haven during the global pandemic, results show that Tether is a safe haven in this time period (Cheema, Faff, & Szulczuk, 2020). These result are consistent with Conlon, Corbet, & McGee (2020). Specifically, Conlon, Corbet, & McGee (2020) investigate the safe haven properties of Bitcoin, Ethereum and Tether by analysing the downside risk and calculating the Value at Risk of portfolios which consist of different stock indices[14] and one cryptocurrency. Their results show that while Bitcoin and Ethereum are not safe haven assets in general[15], Tether is able to act as a safe haven asset against all stock indices[16].

[11]In this aspect, commodities are shown to have better hedging abilities against emerging markets (Susilo et al., 2020).

[12]However, the time period considered by Conlon & McGee (2020) is rather short as it only includes data until 20th March, 2020.

[13]For instance, while gold acts as a safe haven asset during the Global Financial Crisis in 2008, it does not show this ability during the global pandemic (Cheema, Faff, & Szulczuk, 2020).

[14]Namely, MSCI World, S&P 500, FTSE 100, FTSE MIB, IBEX and CSI 300.

[15]They act as safe haven assets against the stock index CSI 300.

[16]Note that Tether is pegged to the US dollar.

This implies that the safe haven property of cryptocurrencies varies internationally. These results are confirmed by Bouri, Lucey, & Roubaud (2020) as Bitcoin is shown to be a weak diversifier against the stock markets in Europe and Ethereum is shown to be a hedge against Asian and Japanese stock markets. However, Ethereum only has diversification benefits against stock markets in Europe and the U.S. Interestingly, Stellar has diversification benefits against all stock indices. Indeed, the results by Bouri, Lucey, & Roubaud (2020) indicate that no cryptocurrency is able to act as a safe haven asset. Similarly, Caferra & Vidal-Tomás (2021) suggest that Bitcoin and Ethereum may have possible diversification and hedging capabilities against stock indices[17]. In contrast to these findings, Ji, Dayong, & Zhao (2020) analyse the downside risk of portfolios and show that the only assets which are able to act as safe havens during the global pandemic are gold and soybean commodity. In contrast to these results, Mariana, Ekaputra, & Husodo (2021) observes a negative correlation between Bitcoin and Ethereum against S&P 500, which implies that these cryptocurrencies are safe haven assets. In addition, Mariana, Ekaputra, & Husodo (2021) suggest that Ethereum is a better safe haven asset, although it is more volatile than Bitcoin. Goodell & Goutte (2021) observe an increased correlation between cryptocurrencies and stock indices during the global pandemic. Furthermore, the results by Goodell & Goutte (2021) show that Tether is a safe haven asset. Nevertheless, Corbet, Larkin, & Lucey (2020) present evidence which indicate that cryptocurrencies neither have hedging benefits nor act as safe haven assets during the global pandemic, instead they amplify the risk of financial contagion. This is in accordance with the results by Conlon & McGee (2020). However, as previous research has presented inconsistent results and therefore also derived different conclusions in this matter, further research is motivated.

[17]This conclusion is based on that the cryptocurrencies made faster recoveries during the global pandemic (Caferra & Vidal-Tomás, 2021).

3 Methodology

This section describes the method employed in this thesis. Particularly, the aim of this section is to explain and motivate the three separate parts which constitute the methodology. Furthermore, it explains the chosen model used to perform the analysis.

3.1 Method

The analysis performed in this thesis is threefold. To begin with, the volatility spillover is analysed. The main focus is to investigate whether there is any volatility spillover present between different cryptocurrencies, and moreover, to see if there exists any volatility spillover between cryptocurrencies and stock indices, i.e. the stock market. There are two motivational reasons considered in the first part of my analysis. First, presence of volatility spillover between different markets illustrates that they are connected. Secondly, the results from this analysis are able to indicate if it is possible to discover any hedging properties. This is the case if the volatility spillover between cryptocurrencies and stock indices is smaller compared to among two assets within the same market.

Following, I calculate and illustrate the conditional correlation between the three cryptocurrencies and three stock indices. This is done pairwise, i.e. the conditional correlation is computed sequentially for every cryptocurrency and every stock index. This part of the analysis is particularly important when determining whether cryptocurrencies have diversification benefits, hedging properties, and more interestingly, if they act as safe haven assets.

The final part of the methodology is performed with the aim to further investigate the hedging capabilities of the cryptocurrencies. In order to do this, I create different minimum-variance portfolios. The first group consists entirely of a stock indices and constitute the benchmark in the analysis. Subsequentially, I construct portfolios of two components, namely, one cryptocurrency and one stock index. The combination of these two assets are based on time-varying weights[18]. Next, Value-at-Risk (VaR) and mean returns are computed in order to investigate portfolio performance. These values are compared between each two portfolio counterparts, i.e. the portfolios which contain the same stock index. In this regard, a lower VaR number in a portfolio which has a positive weight placed on a cryptocurrency shows evidence of hedging capabilities. Furthermore, to gain further insight, an additional analysis is performed which focuses more in detail on the recent time period, i.e. it covers only the year 2020. Hence, this provides information of whether the cryptocurrencies have safe haven properties.

[18]This is done in accordance with the minimum-variance criterion.

3.2 Conditional Volatility Models

In this section, an introduction of the model used in this thesis is given. This model is used for all three parts of the method in this thesis. That is, after the parameters are estimated, they are used to calculate the time-varying correlations and additionally to create the minimum-variance portfolios to investigate potential hedging and safe haven properties.

A common approach when it comes to modelling the volatility of a financial time series is to use univariate models. It is important to model the conditional variance since the returns of a time series often are unpredictable and therefore not suitable when computing estimations and forecasts. In addition, financial time series often display heteroscedasticity, i.e the variance is time-variant. This characteristic is illustrated by volatility clustering and implies that the variance of a time series is a function of past shocks. Furthermore, this indicates that there is structure in the variance and therefore that there is available information to make use of. In fact, this is precisely the reason to why the conditional variance is considered[19]. This is done by including information sets in the analysis.

The interest in modelling the conditional variance of assets has given rise to many new variations of univariate volatility models being developed since Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model. For instance, Bollerslev (1986) extends the model to a Generalised ARCH (GARCH) model. Similarly, numerous models with different modifications and alternations have been presented, see e.g. (Ding, Granger, & Engle, 1993; Baillie, Bollerslev, & Mikkelsen, 1996; Tse, 1998). An extensive amount of research focus on the univariate models. However, it is also important to understand the co-movements of asset returns, which is determined by implementing multivariate volatility modelling.

Bollerslev, Engle, & Wooldridge (1988) suggest that the importance of considering multivariate models is attributed to the advantage of being able to study the covariance of assets. Engle & Kroner (1995) extend the model by Bollerslev, Engle, & Wooldridge (1988) into a multivariate GARCH specification, which is explained more in detail in section 3.3. Recently, the interest of studying covariances and correlations between assets has increased together with the higher degree of market integration. In fact, multivariate GARCH models are commonly used in contemporary literature to investigate volatility spillover effects and the dynamic correlations between assets.

[19]By considering the conditional variance, as opposed to the unconditional variance, the variance is conditioned on the past.

3.3 The diagonal BEKK model

The diagonal BEKK model is defined in the following way (Engle & Kroner, 1995). Let $\boldsymbol{\varepsilon}_t$ denote the vector of error terms, $\boldsymbol{\mathcal{F}}_t$ denotes the information set and $\boldsymbol{H}_t$ is the conditional covariance matrix. The mean equation is defined according to equation (1),

$$\boldsymbol{r}_t = \boldsymbol{\mu}_t + \boldsymbol{\varepsilon}_t \tag{1}$$

$$\boldsymbol{\varepsilon}_t | \mathcal{F}_t \sim N(0, \boldsymbol{H}_t) \tag{2}$$

where $\boldsymbol{r}_t$ is an $n \times 1$ vector of n returns at time t, $\boldsymbol{\mu}_t$ is an $n \times 1$ vector, and $\boldsymbol{\varepsilon}_t$ is an $n \times 1$ vector of error terms. I use the model expressed in equation (3) to calculate the conditional covariance matrix, $\boldsymbol{H}_t$.

$$\boldsymbol{H}_t = \boldsymbol{C}^T \boldsymbol{C} + \boldsymbol{A}^T \varepsilon_{t-1} \varepsilon_{t-1}^T \boldsymbol{A} + \boldsymbol{B}^T \boldsymbol{H}_{t-1} \boldsymbol{B} \tag{3}$$

In equation (3) $\boldsymbol{A}$, $\boldsymbol{B}$ and $\boldsymbol{C}$ are $n \times n$ matrices containing parameters, $\boldsymbol{\varepsilon}_{t-1}$ is an $n \times 1$ vector of error terms. More specifically, $\boldsymbol{C}$ is a lower triangular matrix, which means that $\boldsymbol{C}^T \boldsymbol{C}$ is positive semi-definite by definition. The $\boldsymbol{A}$ and $\boldsymbol{B}$ matrices are, apart from identifiability conditions, unrestricted. In order to eliminate equivalent structures, we restrict the values of one of the diagonal parameters in the matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ to be positive, together with the diagonal elements in the $\boldsymbol{C}$ matrix, i.e. a_{11}, b_{11} and c_{ii} are positive, in accordance with Engle and Kroner (1995). In addition, the $\boldsymbol{C}$ matrix consists of constants, while the $\boldsymbol{A}$ and $\boldsymbol{B}$ matrices include parameters which have the interpretation of volatility spillover effects.

This model is simple to illustrate in the bivariate case,

$$\begin{aligned} \boldsymbol{H}_t = \boldsymbol{C}^T \boldsymbol{C} + &\begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \\ &+ \begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix} \boldsymbol{H}_{t-1} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \end{aligned} \tag{4}$$

Furthermore, the $\boldsymbol{H}_t$ is defined according to

$$\boldsymbol{H}_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} \tag{5}$$

where $h_{ii,t}$ denotes the conditional variance of asset i at time t and h_{ij} denotes the conditional covariance between asset i and asset j at time t, where $i \neq j$. The construction of the model imposes positivity on $\boldsymbol{H}_t$. In this model, $\boldsymbol{H}_t$ is positive definite by definition, i.e. the positivity is satisfied without imposing any restrictions. In addition, an advantage of this model is that the conditional covariance matrix is modelled directly, in contrast to other multivariate conditional volatility models (Caporin & Mcaleer, 2012; Silvennoinen & Teräsvirta, 2009). Furthermore, the estimation of the parameters in the full BEKK model might be difficult due to the curse of dimensionality (Caporin & Mcaleer, 2012). However, it is simple to illustrate that the number of parameters are decreased in the diagonal version of the model, see equation (6)[20].

The diagonal BEKK model is presented in equation (6), where the $\boldsymbol{A}$ and $\boldsymbol{B}$ matrices are diagonal.

$$\begin{aligned}\boldsymbol{H}_t = \boldsymbol{C}^T\boldsymbol{C} &+ \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix} \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix} \\ &+ \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix} \boldsymbol{H}_{t-1} \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}\end{aligned} \tag{6}$$

The estimation of the model is done in the following way. Let $\boldsymbol{\theta}$ be the vector of all the parameters in the model. We assume a multivariate normal distribution. Accordingly, we maximise the likelihood function in equation (7).

$$\ln L(\boldsymbol{\theta}) = \sum_{t=1}^{T} \left(-\frac{1}{2} \ln |\boldsymbol{H}_t| - \frac{1}{2} \boldsymbol{\eta}_t' \boldsymbol{H}_t^{-1} \boldsymbol{\eta}_t \right) \tag{7}$$

The equations of the conditional variances, $h_{ii,t}$, and covariances, $h_{ij,t}$, are extended for all six time series according to equations (8) to (28), where Ω is equivalent to $\boldsymbol{C}^T\boldsymbol{C}$ from equation (6).

[20]In addition, estimation biases and limitations of the full BEKK model are discussed by Allen & McAleer (2018). Although this is out of the scope of this thesis, it is still interesting to mention that these limitations do not apply to the the diagonal BEKK model. Moreover, the quasi maximum likelihood estimation of the parameters in the diagonal BEKK model are shown to be consistent and asymptotically normal which implies that statistical inference for testing a hypothesis is valid (Allen & McAleer, 2018).

$$h_{11,t} = \Omega_{11} + a_{11}^2 \varepsilon_{1,t-1}^2 + b_{11}^2 h_{11,t-1} \tag{8}$$

$$h_{12,t} = \Omega_{12} + a_{11} a_{22} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + b_{11} b_{22} h_{12,t-1} \tag{9}$$

$$h_{13,t} = \Omega_{13} + a_{11} a_{33} \varepsilon_{1,t-1} \varepsilon_{3,t-1} + b_{11} b_{33} h_{13,t-1} \tag{10}$$

$$h_{14,t} = \Omega_{14} + a_{11} a_{44} \varepsilon_{1,t-1} \varepsilon_{4,t-1} + b_{11} b_{44} h_{14,t-1} \tag{11}$$

$$h_{15,t} = \Omega_{15} + a_{11} a_{55} \varepsilon_{1,t-1} \varepsilon_{5,t-1} + b_{11} b_{55} h_{15,t-1} \tag{12}$$

$$h_{16,t} = \Omega_{16} + a_{11} a_{66} \varepsilon_{1,t-1} \varepsilon_{6,t-1} + b_{11} b_{66} h_{16,t-1} \tag{13}$$

$$h_{22,t} = \Omega_{22} + a_{22}^2 \varepsilon_{2,t-1}^2 + b_{22}^2 h_{22,t-1} \tag{14}$$

$$h_{23,t} = \Omega_{23} + a_{22} a_{33} \varepsilon_{2,t-1} \varepsilon_{3,t-1} + b_{22} b_{33} h_{23,t-1} \tag{15}$$

$$h_{24,t} = \Omega_{24} + a_{22} a_{44} \varepsilon_{2,t-1} \varepsilon_{4,t-1} + b_{22} b_{44} h_{24,t-1} \tag{16}$$

$$h_{25,t} = \Omega_{25} + a_{22} a_{55} \varepsilon_{2,t-1} \varepsilon_{5,t-1} + b_{22} b_{55} h_{25,t-1} \tag{17}$$

$$h_{26,t} = \Omega_{26} + a_{22} a_{66} \varepsilon_{2,t-1} \varepsilon_{6,t-1} + b_{22} b_{66} h_{26,t-1} \tag{18}$$

$$h_{33,t} = \Omega_{33} + a_{33}^2 \varepsilon_{3,t-1}^2 + b_{33}^2 h_{33,t-1} \tag{19}$$

$$h_{34,t} = \Omega_{34} + a_{33} a_{44} \varepsilon_{3,t-1} \varepsilon_{4,t-1} + b_{33} b_{44} h_{34,t-1} \tag{20}$$

$$h_{35,t} = \Omega_{35} + a_{33} a_{55} \varepsilon_{3,t-1} \varepsilon_{5,t-1} + b_{33} b_{55} h_{35,t-1} \tag{21}$$

$$h_{36,t} = \Omega_{36} + a_{33} a_{66} \varepsilon_{3,t-1} \varepsilon_{6,t-1} + b_{33} b_{66} h_{36,t-1} \tag{22}$$

$$h_{44,t} = \Omega_{44} + a_{44}^2 \varepsilon_{4,t-1}^2 + b_{44}^2 h_{44,t-1} \tag{23}$$

$$h_{45,t} = \Omega_{45} + a_{44} a_{55} \varepsilon_{4,t-1} \varepsilon_{5,t-1} + b_{44} b_{55} h_{45,t-1} \tag{24}$$

$$h_{46,t} = \Omega_{46} + a_{44} a_{66} \varepsilon_{4,t-1} \varepsilon_{6,t-1} + b_{44} b_{66} h_{46,t-1} \tag{25}$$

$$h_{55,t} = \Omega_{55} + a_{55}^2 \varepsilon_{5,t-1}^2 + b_{55}^2 h_{55,t-1} \tag{26}$$

$$h_{56,t} = \Omega_{56} + a_{55} a_{66} \varepsilon_{5,t-1} \varepsilon_{6,t-1} + b_{55} b_{66} h_{56,t-1} \tag{27}$$

$$h_{66,t} = \Omega_{66} + a_{66}^2 \varepsilon_{6,t-1}^2 + b_{66}^2 h_{66,t-1} \tag{28}$$

After the parameters are estimated, the time-varying correlations are calculated. Specifically, the correlation between time series i and j is calculated according to equation (29).

$$\rho = \frac{h_{ij,t}}{\sqrt{h_{ii,t} h_{jj,t}}} \tag{29}$$

The estimated time-varying correlations are used to create the minimum variance portfolios. The weights of each respective cryptocurrency in the three stock indices are re-weighted daily.

4 Preliminary Data Analysis

4.1 Data sample

The data used for the analysis in this thesis consists of six different time series. These include three cryptocurrencies: Bitcoin (BTC), Ethereum (ETH) and Binance Coin (BNB) and three indices: MSCI World, MSCI EM 50 and S&P 500[21], see table 1 for number reference. The data for the cryptocurrencies is obtained from coindesk.com, while the data for the stock indices is obtained from Datastream, all of which have a GMT timestamp.

Table 1: Definition of each asset.

Number	Name of asset
1	MSCI World
2	MSCI EM 50
3	S&P 500
4	Bitcoin
5	Ethereum
6	Binance Coin

The choice of cryptocurrencies is based on the largest market capitalisation[22]. The indices provide a global perspective. In particular, the MSCI World index represents developed markets, the MSCI EM 50 represents emerging markets and S&P 500 constitutes a benchmark. Interestingly, this allows us to analyse whether the three potential properties of cryptocurrencies, namely diversification, hedging and safe haven abilities, are disparate against the different stock indices.

The time period covered is between 2017-07-25 and 2021-10-02. The shorter time period depends on data availability. This is not considered to be a disadvantage as the primary focus is the recent time period which is influenced by the global pandemic. In particular, it is interesting to analyse the period which takes place after WHO declared COVID-19 as a global pandemic. Therefore, an essential part of the analysis is performed around this threshold. In total, there are 1085 observations included for every time series.

The closing prices are considered, which is important to note, especially since the cryptocurrencies are traded continuously. Furthermore, only the prices on working days 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 (30) where r_t is the return at day t, P_t is the price at day t and P_{t-1} is the price at the previous day.

$$r_t = 100 \cdot \log \frac{P_t}{P_{t-1}} \tag{30}$$

[21] All prices are in USD.

[22] The data was collected on 2021-10-02.

4.2 Descriptive statistics

The descriptive statistics of the asset returns are presented in table 2. We observe that Binance Coin has the highest mean return (0.75 %). This value is substantially higher than the mean return for the stock indices, which range between 0.02 % and 0.05 %. Additionally, the mean return of Binance Coin is higher than the one of Bitcoin (0.25 %) and Ethereum (0.24 %). In general, we find that the mean return of cryptocurrencies are larger than the mean return for the stock indices. A similar pattern is present for the standard deviations. Namely, the highest standard deviation is found in the returns of Binance Coin (9.25 %), followed by Ethereum (6.29 %) and Bitcoin (4.91 %). Conversely, the standard deviations for the stock indices are substantially lower and range from 1.07 % to 1.28 %.

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

	MSCI World	MSCI EM 50	S&P 500	Bitcoin	Ethereum	Binance Coin
Observations	1085	1085	1085	1085	1085	1085
Mean	0.04	0.02	0.05	0.25	0.24	0.75
Std. dev.	1.07	1.16	1.28	4.91	6.29	9.25
Min.	-10.44	-6.39	-12.77	-31.59	-42.36	-82.05
25%	-0.29	-0.58	-0.31	-1.82	-2.57	-2.92
50%	0.08	0.06	0.08	0.10	0.21	0.30
75%	0.48	0.68	0.58	2.70	3.29	3.67
Max.	8.41	6.51	8.97	24.99	27.62	119.40
Skewness	-1.59	-0.39	-1.12	-0.46	-0.59	1.69
Kurtosis	24.17	3.41	20.57	4.79	5.02	35.20
Jarque Bera	26614.35***	546.82***	19162.51***	1063.30***	1191.09***	56009.72***
Ljung Box (25)	276.91***	51.08***	385.79***	28.84	46.27***	94.81***
ARCH (25)	441.19***	266.67***	468.97***	47.38***	55.64***	463.20***
ADF	-7.52***	-11.96***	-7.50***	-22.17***	-13.02***	-10.78***

The Jarque-Bera test tests for a normal distribution. The Ljung Box tests for autocorrelation and the ARCH test tests for hetereoscedasticty in the volatility, both at the 25th lag. Finally, the ADF test tests for stationarity.

Following, the minimum and maximum values of all the assets are presented. Here we observe that both the minimum and maximum value, compared across all assets, is represented by Binance Coin. This implies a higher dispersion of returns compared to the other assets. Yet again, Bitcoin and Ethereum have larger absolute values than the stock indices. However, Binance Coin outperforms the other cryptocurrencies in this regard. Additionally, a more detailed version of the dispersion is illustrated with the help of an interval between 25 % and 75 %. Here each group, i.e. 25 %, 50 % and 75 %, denotes that respective percentile. By calculating the difference between the highest and the smallest percentile for each asset, we conclude that Binance Coin shows the largest dispersion of returns.

Next, the higher order moments are presented. Interestingly, Binance Coin is the only asset with a positive skewness. In addition, Binance Coin has the highest value of skewness (1.69), followed by MSCI World (-1.59), in absolute terms. The highest kurtosis is observed in Binance Coin. The kurtosis for Bitcoin and Ethereum are substantially lower. Moreover, MSCI World and S&P 500 are more similar to Binance Coin in terms of kurtosis as the respective values are substantially higher than for MSCI EM 50, Bitcoin and Ethereum.

These findings suggest that the returns of all time series do not follow a normal distribution. By definition, a normal distribution has a skewness equal to zero and a kurtosis equal to three. In this respect, MSCI EM 50 is the asset which is closest to resemble a normal distribution when observing the higher order moments. Furthermore, the Jarque-Bera test for normality is performed and presented in table 2. It will, by definition, have a value of zero if the returns are normal. Since it is a joint test, it means that both skewness and excess kurtosis must have a value equal to zero for this result to hold. Thus, in this case, the test confirms that the asset returns are non-normal.

Following, in order to test for autocorrelation and conditional heteroscedasticity, the Ljung Box test and the ARCH test are computed. The test statistic of these tests are presented in table 2. The result from the Ljung Box test shows that there is a presence of autocorrelation in all time series, except for Bitcoin. In addition, the ARCH test confirms that there is heteroscedasticity in the volatility of the time series. These results suggest that GARCH models preferably can be used to model the time series. Finally, the Augmented Dickey Fuller (ADF) test is done in order to test for a unit root, i.e. to see if the data is stationary. The results are presented in table 2 and indicate that all the time series are stationary.

4.3 Preliminary analysis

The level data of every time series is presented in figure 1. The focus of this final part of the preliminary data analysis is threefold. First, an overall observation of the time series' is considered. Secondly, attention is placed on the time when COVID-19 was declared a pandemic. Finally, we focus on the time period following this specific point in time and up until the present time period.

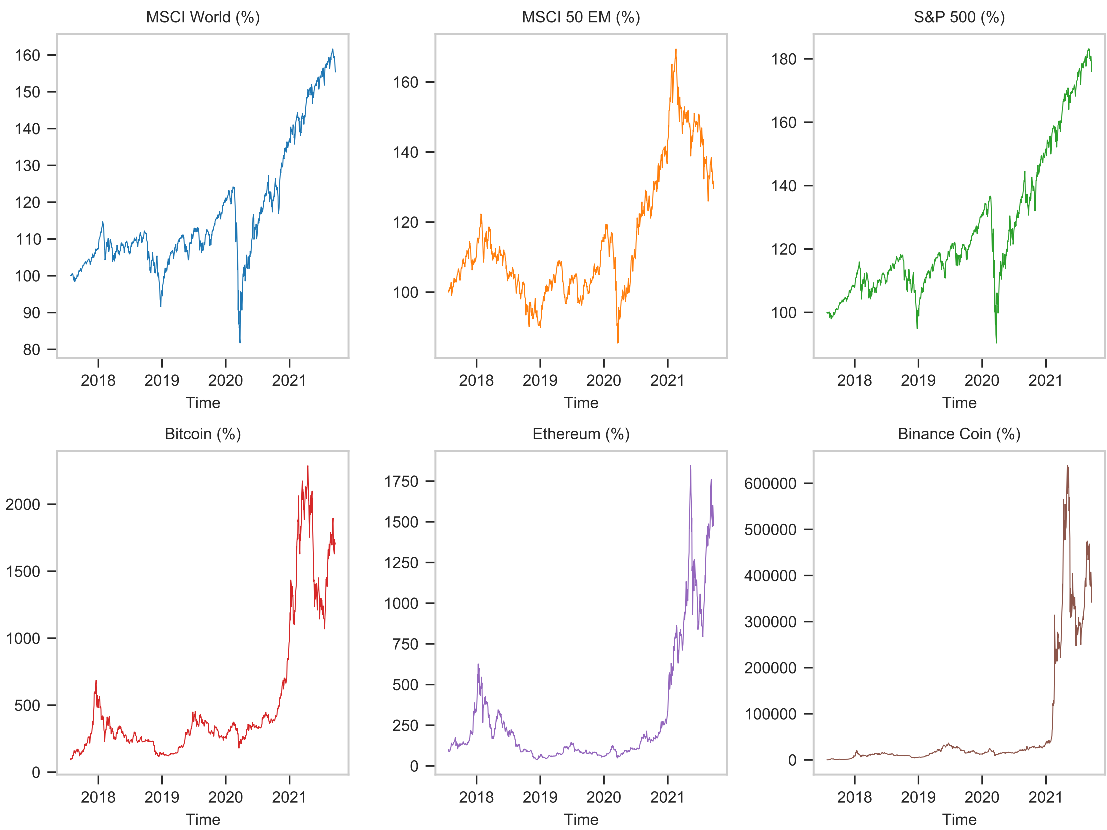
In general, an increasing trend is evident in figure 1. The increase in the level data for the stock indices does not compare to the increase of the cryptocurrencies. More specifically, it is observed that Bitcoin, Ethereum and Binance Coin show a tremendous price increase in the end of 2020 and first half of 2021. In particular, Binance Coin shows the most sharp increase in price.

The level data illustrates a sharp decrease for all the time series at the start of the pandemic[23]. Consequently, the pandemic shows a negative effect on the financial market as all assets drop drastically. However, since then the prices of all time series show an increasing trend. While there are periods with decrease present in 2020, all assets are currently beyond the price levels at which they were before the pandemic.

The returns of all the assets are illustrated in figure 2. We can observe a presence of

[23]Pay attention to that the y-axis differs for the the assets.

Figure 1: Level data of all assets over time.

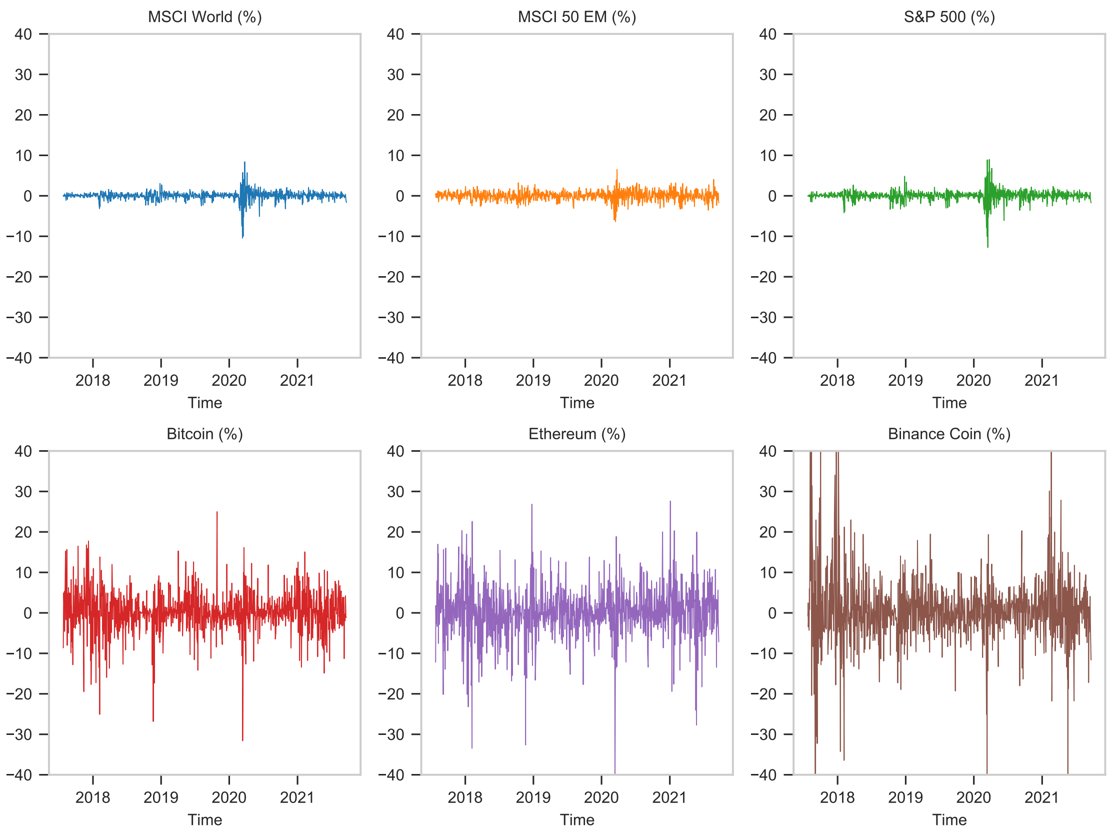


Level data of MSCI World, MSCI 50 EM, S&P 500, Bitcoin, Ethereum and Binance Coin over time.

mean reversion in the time series, which implies that the returns are stationary. This observation is previously implied by the ADF test in table 2. Hence, we can conclude that the stationarity condition holds. In addition, we observe volatility clustering in figure 2. This characteristic is present for all time series, but the volatility clustering is more elevated in the case of Bitcoin, Ethereum and Binance Coin. Note that the three cryptocurrencies show a substantially higher volatility of their returns compared to the stock indices. In addition, we observe a similar pattern as in figure 1, namely a sharp decrease in returns right at the start of the pandemic.

Furthermore, the returns are presented in figure 3. The solid line represents a normal distribution. Here we can observe deviations from a normal distributions for all the assets. Specifically, the fat tails of the return distributions are more pronounced than what is the case for a normal distribution. Moreover, the return distributions are more peaked, which is also an attribute of the presence of excess kurtosis. These findings confirms the previously presented results in table 2. Namely, Binance Coin, MSCI World and S&P 500 are the assets which have most peaked distributions and have most outliers and we have previously seen that these assets have the highest kurtosis. In particular, Bitcoin, Ethereum and Binance Coin have a leptokurtic distribution. This implies a greater probability of extreme events and is illustrated as fatter tails in the distribution. This result is in line with

Figure 2: Returns of all assets expressed in %.



Returns of MSCI World, MSCI 50 EM, S&P 500, Bitcoin, Ethereum and Binance Coin over time.

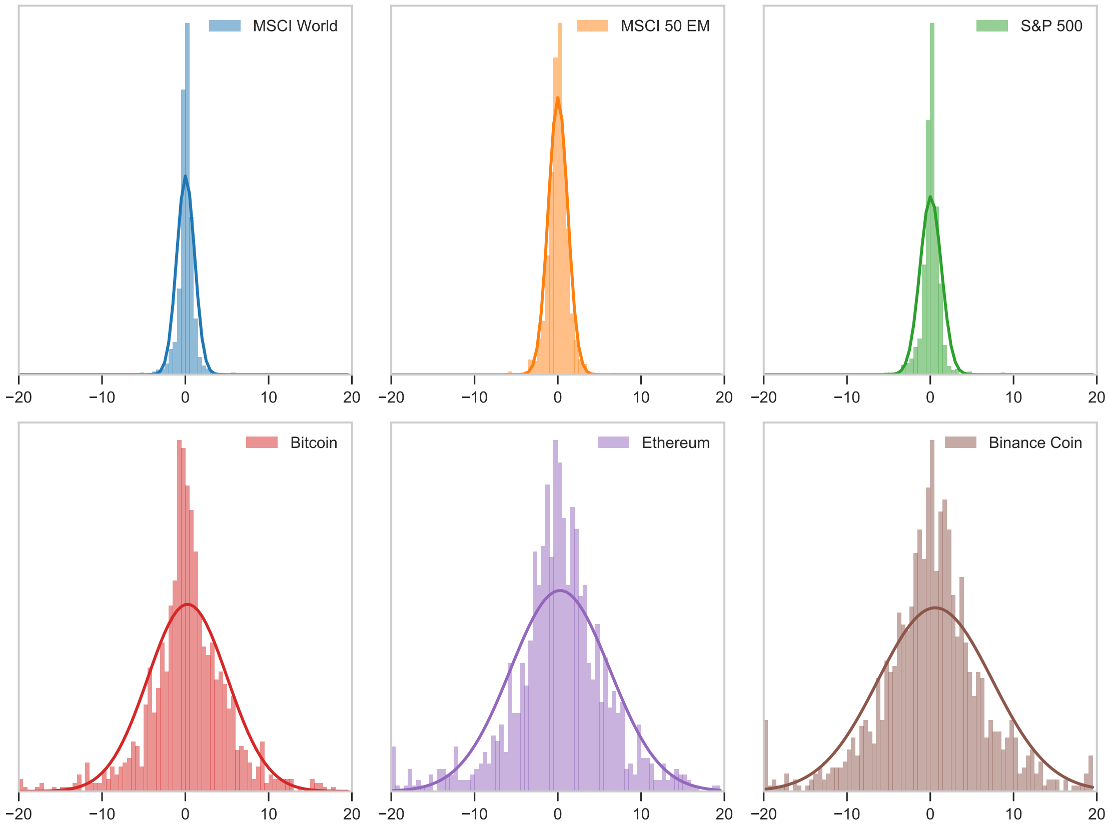
the one in figure 2, where the cryptocurrencies show a higher level of volatility, and the larger dispersion values in table 2.

Next, the correlations between the assets are presented in table 3. It is important to note that these correlations are calculated over the whole time period and therefore represent an average value. Time-varying correlations between all assets is presented subsequently. However, the results in table 3 are presented in order to get a first glance of the correlation between the assets. To begin with, a general observation is that the stock indices have a high positive correlation among each other. In particular, MSCI World and S&P 500 are the two stock indices with the highest correlation (0.97), followed by MSCI World and MSCI EM 50 (0.62) and finally, MSCI EM 50 and S&P 500 (0.53). This high positive

Table 3: Pairwise Pearsons correlation.

	MSCI World	MSCI EM 50	S&P 500	Bitcoin	Ethereum	Binance Coin
MSCI World	1.0000	0.6182	0.9686	-0.0005	0.0027	0.1896
MSCI EM 50		1.0000	0.5275	0.0724	0.1017	0.1236
S&P 500			1.0000	-0.0418	-0.0507	0.1740
Bitcoin				1.0000	0.7453	0.1526
Ethereum					1.0000	0.1305
Binance Coin						1.0000

Figure 3: Returns (%)



Histogram of the returns of MSCI World, MSCI 50 EM, S&P 500, Bitcoin, Ethereum and Binance Coin.

correlation does not hold between stock indices and cryptocurrencies. In contrast, there is a low correlation between assets from these two groups. In addition, we observe a negative correlation between several cryptocurrencies and stock indices (Bitcoin and MSCI World, Bitcoin and S&P 500, Ethereum and S&P 500). While Ethereum also has a low correlation with the stock indices, and a negative correlation with S&P 500, Binance Coin has a slightly higher positive correlation with the stock indices. Furthermore, this distinction is also observed in the correlations between the cryptocurrencies. While the correlation between Bitcoin and Ethereum is high (0.75), the correlation between each cryptocurrency and Binance Coin is substantially lower, with values of 0.15 and 0.13, respectively.

5 Results and Analysis

In this section, I present the results and provide an analysis based on the most important implications of them. First, the volatility spillover is analysed in section 5.1. Secondly, the pairwise correlation between the cryptocurrencies and stock indices is illustrated in section 5.2. Finally, the portfolio analysis is presented in section 5.3.

5.1 Volatility Spillover

First, the estimated parameters from the diagonal BEKK-GARCH model are presented in table 4. All the estimated parameters in the two matrices ***A*** and ***B*** are statistically significant at the 1 % level[24]. This is important to note, as all the following calculations in this thesis include the estimation of these parameters.

*Table 4: Estimated parameters from the diagonal BEKK-GARCH model. Statistically significant parameters are denoted with asterisk, *, **, *** for 10%, 5% and 1% level of significance. The standard error (SE) is expressed in brackets.*

a_{11}	0.1728***										
	(0.0514)										
		a_{22}	0.1669***								
			(0.0473)								
				a_{33}	0.2987***						
					(0.1051)						
						a_{44}	0.3221***				
							(0.0420)				
								a_{55}	0.1588***		
									(0.0229)		
										a_{66}	0.2879***
											(0.0305)
b_{11}	0.9690***										
	(0.0153)										
		b_{22}	0.9643***								
			(0.0197)								
				b_{33}	0.9453***						
					(0.0262)						
						b_{44}	0.9241***				
							(0.0209)				
								b_{55}	0.9778***		
									(0.0072)		
										b_{66}	0.9374***
											(0.0135)
c_{11}	0.8846***										
	(0.2299)										
c_{21}	1.0814***	c_{22}	0.7383***								
	(0.3583)		(0.2108)								
c_{31}	0.2433	c_{32}	0.1591	c_{33}	1.1682***						
	(0.2327)		(0.1012)		(0.2409)						
c_{41}	0.0033	c_{42}	-0.0031	c_{43}	0.0286	c_{44}	0.2030***				
	(0.0222)		(0.0039)		(0.0452)		(0.0416)				
c_{51}	0.0111	c_{52}	0.0084	c_{53}	0.0140	c_{54}	0.1088***	c_{55}	0.1094***		
	(0.0071)		(0.0145)		(0.0315)		(0.0227)		(0.0371)		
c_{61}	0.0100	c_{62}	0.0049	c_{63}	0.0248	c_{64}	0.1524***	c_{65}	0.0249**	c_{66}	0.0390***
	(0.0139)		(0.0074)		(0.0355)		(0.0275)		(0.0104)		(0.0062)

[24]While not all the parameters in the ***C*** matrix are statistically significant, this does not have a negative influence the analysis as this matrix only contains constants.

The parameters from table 4 are inserted in equations (8) to (28) in order to calculate the conditional variances and conditional covariances. The results are shown in equations (31) to (51). The analysis of these equations are done in two parts. To begin with, I focus on the parameters in the $\boldsymbol{A}$ matrix which constitute the ARCH coefficients in equations (31) to (51). First, I analyse the conditional variance of every asset (see equation (31), equation (37), equation (42), equation (46), equation (49) and equation (51).)

In this part of the analysis, the ARCH effect represents the assets' own volatility spillover effect. The results indicate that, while the own volatility spillover effect is similar for MSCI World (0.0299) and MSCI EM 50 (0.0279), it differs, and perhaps more importantly, is higher for the S&P 500 index (0.0892). Furthermore, Bitcoin has the highest own volatility spillover effect (0.1037) compared to all assets. This is followed by S&P 500 (0.0892) and Binance Coin (0.0829). Interestingly, Ethereum shows a lower own volatility spillover effect (0.0252) and is in this respect more similar to the two MSCI indices.

$$h_{11,t} = 2.0114 + 0.0299\varepsilon^2_{1,t-1} + 0.9390h_{11,t-1} \tag{31}$$
$$h_{12,t} = 0.8372 + 0.0288\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.9344h_{12,t-1} \tag{32}$$
$$h_{13,t} = 0.2847 + 0.0516\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 0.9160h_{13,t-1} \tag{33}$$
$$h_{14,t} = 0.0034 + 0.0557\varepsilon_{1,t-1}\varepsilon_{4,t-1} + 0.8955h_{14,t-1} \tag{34}$$
$$h_{15,t} = 0.0015 + 0.0274\varepsilon_{1,t-1}\varepsilon_{5,t-1} + 0.9475h_{15,t-1} \tag{35}$$
$$h_{16,t} = 0.0004 + 0.0497\varepsilon_{1,t-1}\varepsilon_{6,t-1} + 0.9083h_{16,t-1} \tag{36}$$
$$h_{22,t} = 0.5705 + 0.0279\varepsilon^2_{2,t-1} + 0.9299h_{22,t-1} \tag{37}$$
$$h_{23,t} = 0.1860 + 0.0499\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.9115h_{23,t-1} \tag{38}$$
$$h_{24,t} = 0.0010 + 0.0538\varepsilon_{2,t-1}\varepsilon_{4,t-1} + 0.8911h_{24,t-1} \tag{39}$$
$$h_{25,t} = 0.0010 + 0.0265\varepsilon_{2,t-1}\varepsilon_{5,t-1} + 0.9429h_{25,t-1} \tag{40}$$
$$h_{26,t} = 0.0002 + 0.0481\varepsilon_{2,t-1}\varepsilon_{6,t-1} + 0.9039h_{26,t-1} \tag{41}$$
$$h_{33,t} = 1.3663 + 0.0892\varepsilon^2_{3,t-1} + 0.8936h_{33,t-1} \tag{42}$$
$$h_{34,t} = 0.0111 + 0.0962\varepsilon_{3,t-1}\varepsilon_{4,t-1} + 0.8736h_{34,t-1} \tag{43}$$
$$h_{35,t} = 0.0021 + 0.0474\varepsilon_{3,t-1}\varepsilon_{5,t-1} + 0.9243h_{35,t-1} \tag{44}$$
$$h_{36,t} = 0.0010 + 0.0860\varepsilon_{3,t-1}\varepsilon_{6,t-1} + 0.8861h_{36,t-1} \tag{45}$$
$$h_{44,t} = 0.0763 + 0.1037\varepsilon^2_{4,t-1} + 0.8540h_{44,t-1} \tag{46}$$
$$h_{45,t} = 0.0157 + 0.0511\varepsilon_{4,t-1}\varepsilon_{5,t-1} + 0.9036h_{45,t-1} \tag{47}$$
$$h_{46,t} = 0.0059 + 0.0927\varepsilon_{4,t-1}\varepsilon_{6,t-1} + 0.8663h_{46,t-1} \tag{48}$$
$$h_{55,t} = 0.0126 + 0.0252\varepsilon^2_{5,t-1} + 0.9561h_{55,t-1} \tag{49}$$
$$h_{56,t} = 0.0010 + 0.0457\varepsilon_{5,t-1}\varepsilon_{6,t-1} + 0.9166h_{56,t-1} \tag{50}$$
$$h_{66,t} = 0.0015 + 0.0829\varepsilon^2_{6,t-1} + 0.8787h_{66,t-1} \tag{51}$$

In the second part of this analysis I consider the conditional covariances of all time series. Namely, I analyse the ARCH effects between the six assets. More specifically, this denotes the pairwise cross-volatility spillover effect. This analysis is performed subsequentially for all the assets and follows the order presented in table 1.

To begin with, the cross-volatility spillover effect between MSCI World and the remaining assets is analysed (see equations (32) to (36)). The results indicate that the greatest influence is present between MSCI World and Bitcoin (0.0557). This is followed by the influence present between MSCI World and S&P 500 (0.0516) and additionally with Binance Coin (0.0497). Next, we analyse the ARCH effect between MSCI 50 EM and the remaining assets (see equation (32) and equations (38) to (41)). The results show that the greatest influence exists between MSCI 50 EM and Bitcoin (0.0538), followed by Binance Coin (0.0481). Similarly, in respect of the cross-volatility spillover effect between S&P 500 and the remaining assets (see equation (33), equation (38) and equations (43) to (45)), the following results are obtained. The greatest influence is between S&P 500 and Bitcoin (0.0962), followed by S&P 500 and Binance Coin (0.0860).

Interestingly, in respect of the ARCH effect between the three stock indices, the results imply that S&P 500 has the most influence on its own volatility spillover effect (0.0892), i.e. compared to pairwise cross-volatility spillover with MSCI World (0.0516) and MSCI EM 50 (0.0499), respectively. For instance, compare the ARCH coefficient in equation (42) and equation (33). However, if we consider all six assets, we find a higher influence of the ARCH effect imposed by Bitcoin (0.0962) and Binance Coin (0.0860) on the S&P 500 index. In addition, the influence between Ethereum and S&P 500 (0.0474) is lower and more similar to the relationship with the two MSCI indices.

Finally, we consider the ARCH effect between the cryptocurrencies Bitcoin, Ethereum and Binance Coin. As already mentioned, Bitcoin has the highest own volatility spillover effect (0.1037) compared to all other assets. In addition, the results show that the cross volatility spillovers are smaller than the own volatility spillover effect for Bitcoin. Indeed, the ARCH coefficients in equation (47) and equation (48), representing the influence of Ethereum and Binance Coin respectively, have lower values. This comparison is especially true in the former case. Next, the highest cross volatility spillover effect for Ethereum is influenced by Bitcoin (0.0511), followed by S&P 500 (0.4744) and Binance Coin (0.0457) (see equation (44), equation (47) and equation (50)). Similarly, by investigating the ARCH coefficient for Binance Coin (see equation (48)), the results suggest that the highest influence is present between Binance Coin and Bitcoin (0.0927).

In summary, Bitcoin is the asset which has the highest cross-volatility spillover effect with other assets. Furthermore, Bitcoin has the highest own volatility spillover effect compared to all assets. In fact, investigating the ARCH effect, we see that S&P 500 is more influenced by the volatility of Bitcoin than by the two MSCI indices. In addition, the results show that Bitcoin has the greatest influence on its own volatility, which implies that the cross-volatility spillover of all other assets in relation to Bitcoin are smaller than Bitcoins own volatility spillover effect. In general, the two cryptocurrencies Bitcoin and Binance

Coin, together with the S&P 500 index, have a higher cross-volatility effect with other assets. These results imply an existence of volatility spillovers between different markets. Interestingly, the influence between the two MSCI indices, which consist of developed and emerging markets, and Bitcoin and S&P 500, which represent the two assets with the highest degree of cross-volatility spillover, do not show a large difference in the ARCH coefficients (see equation (34) and equation (39)). This implies that there is no essential difference between developed and emerging markets in aspect of the ARCH effect.

Secondly, I focus on the parameters in the ***B*** matrix which constitute the GARCH coefficients in equations (31) to (51). This part of the volatility analysis considers the GARCH parameter, which denotes the persistence, of the assets. Specifically, the degree of volatility persistence is illustrated as volatility clustering and is previously observed in figure 2. First, I analyse the conditional variance of each asset (see equation (31), equation (37), equation (42), equation (46), equation (49) and equation (51)). This part of the analysis includes the estimated parameters in the ***B*** matrix. In particular, the diagonal parameters in matrix ***B*** capture the own GARCH effect of each asset. The results indicate that Ethereum (0.9561) has the highest own GARCH coefficient (see equation (49). This result is in line with the results illustrated in figure 2. The remaining GARCH coefficients, in a descending order, are as follows, MSCI World (0.9390) (see equation (31)), MSCI EM 50 (0.9299) (see equation (37)), S&P 500 (0.936) (see equation (42)), Binance Coin (0.8787) (see equation (51)) and Bitcoin (0.8540) (see equation (46)). It is interesting to note that Ethereum is more similar with the stock indices in terms of the degree of volatility persistence than with Bitcoin and Binance Coin. This is particularly true for the dissimilar level of volatility persistence of Ethereum and Bitcoin.

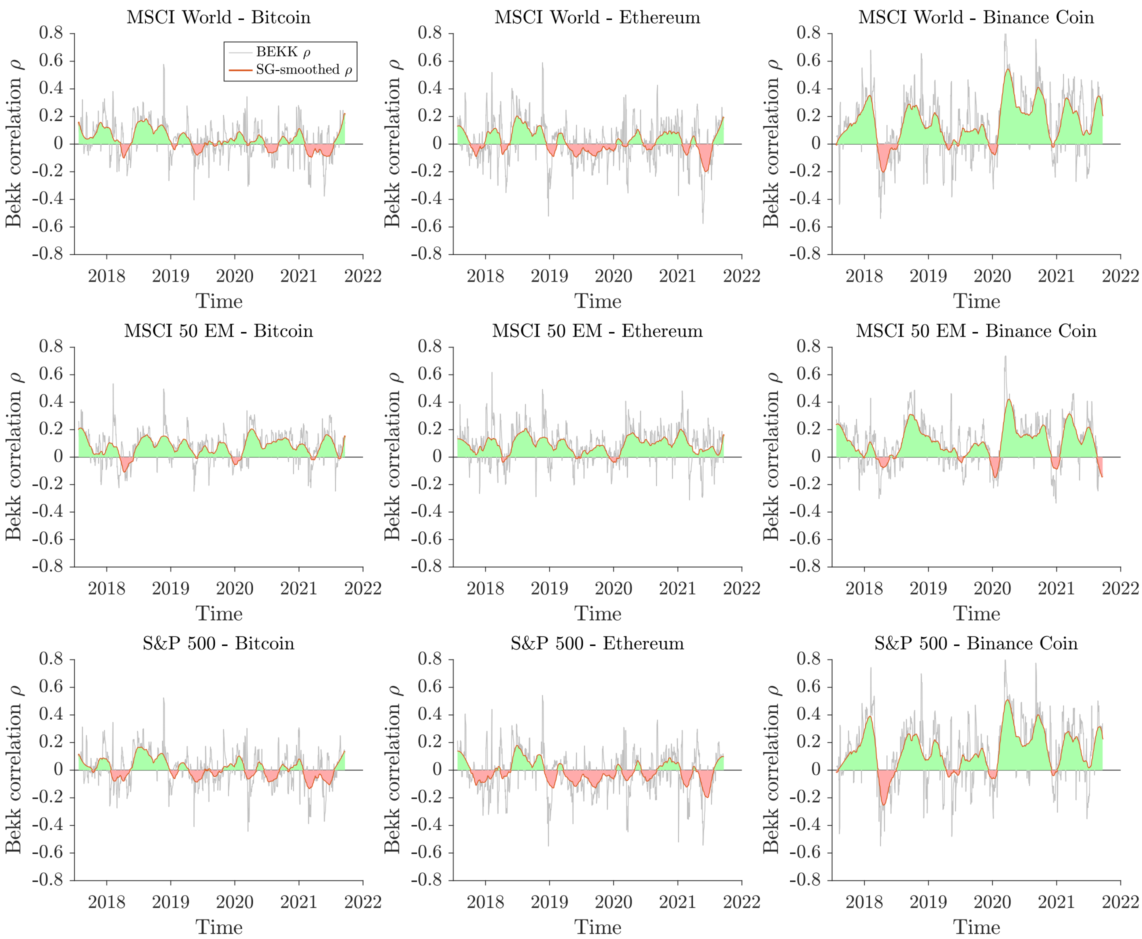
Subsequently, I analyse the cross volatility spillover of the GARCH effect between different assets. Interestingly, the results show that Ethereum (0.9475) is the only asset which has a greater influence in terms of persistence with MSCI World than the index has on its own (0.9390). Similarly, the same relationship holds for Ethereum and MSCI 50 EM (0.9429) and for Ethereum and S&P 500 (0.9429). Additionally, the GARCH coefficient is highest between Bitcoin and Ethereum (0.9036). Finally, the same pattern is found for Binance Coin (0.9166). Therefore it is not a surprise that the own GARCH effect of Ethereum has the highest influence on its own (0.9561). This GARCH effect is compared to all other cross volatility persistence effects, which range from Bitcoin (0.9036) to MSCI World (0.9475). The conclusion derived from these results is that Ethereum has the highest own GARCH effect, i.e. highest volatility persistence. Moreover, Ethereum is the asset which has the highest degree of influence with all remaining assets in terms of the GARCH effect. These findings are in line with the results by Beneki et al. (2019).

5.2 Correlation Analysis

The second part of the methodology comprises a dynamic correlation analysis where the time-varying correlations for all six assets are calculated according to equation (29). The results of the pairwise correlations are illustrated in figure 4. In addition, a Savitzky-Golay filter is applied on the pairwise correlations to better illustrate negative and positive correlation. The following analysis will first explore the behaviour of Bitcoin, Ethereum and Binance Coin against all stock indices overall, i.e. taking the whole time period into account. Secondly, the analysis will focus on the time period of the pandemic. This is done in order to see if the cryptocurrencies act as safe haven assets during the pandemic. Here, we search for a negative correlation between two assets, more specifically between a cryptocurrency and a stock index, at the start of the pandemic. Thirdly, we investigate if the correlation pattern between these assets have changed after the pandemic. The following correlation analysis is based on the definitions by Baur & Lucey (2010) introduced in section 1.

The results in figure 4 illustrate that the time-varying correlation between Bitcoin and

Figure 4: Diagonal BEKK-GARCH pairwise correlations for all six assets.



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

MSCI World fluctuates between a positive and a negative correlation. Similar evidence is repeatedly presented in research, see Bouri et al. (2017a), Bouri, Lucey, & Roubaud (2020), and Bouri, Shahzad, & Roubaud (2020). This result implies diversification benefits and hedging properties of Bitcoin. Additionally, similar results are observed when exploring the correlation between Bitcoin and S&P 500. However, the positive correlation between Bitcoin and MSCI 50 EM is higher compared to the correlation with MSCI World and S&P 500. Moreover, Bitcoin manages to more frequently display a negative correlation with MSCI World and S&P 500. Indeed, the occurrence of a negative correlation, and therefore a hedging capability, is most commonly seen between Bitcoin and S&P 500. These results suggest that Bitcoin is able to act as a diversifier and hedge against all stock indices. The results which imply that Bitcoin has diversification benefits are in line with the results by Bouri et al. (2017a), Baur, Dimpfl, & Kuck (2018), and Corbet et al. (2018). In addition, the ability of Bitcoin to act as a hedge against stock indices is also found by Bouri, Shahzad, & Roubaud (2020) and Dyhrberg (2016b). Interestingly, while diversification benefits are more common for MSCI 50 EM, the hedging capability is more frequently observed for MSCI World and, in particular, for S&P 500. This illustration is comparable to the results by Stensås et al. (2019).

Following, I investigate the correlation between Ethereum and the three stock indices. In general, the results for Ethereum are similar to the already presented results for Bitcoin. For instance, the correlation between Ethereum and MSCI World oscillates between a positive and a negative correlation. Additionally, the correlations between Ethereum and the two stock indices, MSCI World and S&P 500, are more similar compared to the correlation between Ethereum and MSCI 50 EM. Moreover, we illustrate a mostly positive correlation between Ethereum and MSCI 50 EM, which is in accordance to the results by Stensås et al. (2019). In contrast, the correlation between Ethereum and S&P 500 frequently shows a negative correlation which indicates a hedging capability. These results are consistent with Bouri, Shahzad, & Roubaud (2020) and Caferra & Vidal-Tomás (2021). The results imply that Ethereum has diversification benefits against stock indices. In addition, this characteristic is more pronounced for the MSCI 50 EM index. Furthermore, the results indicate that Ethereum has hedging properties, especially against S&P 500 and MSCI World. Interestingly, the hedging capability is more pronounced in the case of Ethereum than for Bitcoin, see e.g. the negative correlation between Ethereum and S&P 500 compared to the correlation between Bitcoin and S&P 500. This finding is along the lines of the results by Mariana, Ekaputra, & Husodo (2021). In similarity to Bitcoin, the hedging capabilities against MSCI 50 EM are limited.

Finally, I illustrate the pairwise correlations with Binance Coin. Interestingly, in the aspect of correlation with the stock indices, Binance Coin differs from Bitcoin and Ethereum. For instance, Binance Coin has mostly a positive correlation with all three stock indices. This is especially true after the pandemic. Nevertheless, the hedging possibility of Binance Coin against the MSCI 50 EM index increases after the pandemic. Interestingly, the opposite relationship is illustrated for Bitcoin and Ethereum, which only show diversification benefits at this time period. In addition, the positive correlation between Binance Coin and the three stock indices is substantially higher than the respective correlations between Bitcoin and Ethereum with these stock indices. Importantly, this high correlation requires caution since the definition of a diversifier states that it is essential that assets are not perfectly correlated with each other (Baur & Lucey, 2010). In this respect, it can be discussed whether Binance Coin displays a too high correlation at any point in time. A second distinction follows from that Binance Coin has a similar correlation with all stock indices. In contrast, this is not the case for Bitcoin and Ethereum, which in general illustrate a more positive correlation with MSCI 50 EM than with MSCI World and S&P 500. The conclusion from these results is that Binance Coin shows both hedging capabilities and diversification benefits, both of which are larger, in absolute value, compared to the other two cryptocurrencies.

In the aspect of diversification benefits, figure 4 illustrates that Bitcoin acts as a diversifier against all stock indices. In fact, the same result holds for Ethereum and Binance Coin. In addition, Bitcoin and Ethereum show an increasing ability to act as hedging assets against MSCI World and S&P 500. However, the dynamic pairwise correlations illustrate that Bitcoin and Ethereum only have diversification benefits against MSCI 50 EM after the initial phase of the global pandemic. These results indicate that the correlation between cryptocurrencies, namely Bitcoin and Ethereum, differ against developed and emerging markets. Importantly, the results in figure 4 provide evidence of that Binance Coin displays a different correlation pattern with the stock indices compared to Bitcoin and Ethereum. For instance, Binance Coin shows a higher positive correlation with all stock indices, and additionally has an increasing ability to hedge against MSCI 50 EM since 2020. In contrast to this, Bitcoin and Ethereum illustrate the opposite relationship. Finally, the correlation of Binance Coin with all three stock indices is more similar across indices, i.e. moves in tandem to a higher extent, than Bitcoin and Ethereum do with the respective stock indices.

Following, a more detailed analysis of the ability of the three cryptocurrencies to behave as safe haven assets during the initial phase of the global pandemic is presented. Specifically, I focus on beginning of the global pandemic and the time period shortly after, which is based on that research shows that the global pandemic initially negatively influenced the financial markets during March and April, 2020 (Baker et al., 2020; Nguyen et al., 2021; Zhang, Hu, & Ji, 2020). The data reveals that the pairwise correlation start to react to the influence of the global pandemic three days after the announcement is made by WHO (WHO, 2021). In particular, both Bitcoin and Ethereum show a negative correlation with MSCI World for a week. This is followed by a few days with positive correlation before it unfolds to a negative correlation again. However, eventually this negative correlation unfolds into a positive correlation after a month. Nevertheless, Bitcoin and Ethereum only have a negative correlation with MSCI EM 50 for a week before the correlation becomes positive. As a result, the time period with a negative correlation, as a response to the global pandemic, is shorter compared to the correlation against MSCI World. Here, it can be discussed whether this rather short time period with a negative correlation can imply a safe haven property, however a very short one, of Bitcoin and Ethereum against the MSCI indices.

Next, I investigate the pairwise correlation between the cryptocurrencies and S&P 500 in the beginning of the global pandemic. The results show that Bitcoin and Ethereum are both able to display a negative correlation with S&P 500 for an entire month. Additionally, in this case the correlation does not temporarily unfold to a positive correlation but remains negative for the entire time period. Indeed, this implies a greater ability of Bitcoin and Ethereum to act as safe haven assets against S&P 500 than against the already mentioned MSCI indices. Interestingly, there is no exact number of days, months or years, of which a safe haven asset must have a negative correlation during market turmoil. However, this question is discussed by Baur & Lucey (2010) and Klein (2017). Indeed, Bitcoin and Ethereum are suggested to act as safe haven assets during the initial negative influence by the global pandemic with the motivation that the financial markets had the greatest negative influence during March and April, 2020 (Zhang & Broadstock, 2020; Shehzad, Xiaoxing, & Kazouz, 2020; Ali, Alam, & Rizvi, 2020). Therefore, this time period with a negative correlation may be enough. However, it is important to note that the safe haven properties of assets are previously found to be time-varying (Bouri, Lucey, & Roubaud, 2020; Hsu, Sheu, & Yoon, 2021).

As already mentioned, the pairwise correlations in figure 4 illustrate that Binance Coin shows a different behaviour than Bitcoin and Ethereum in terms of the correlation with stock indices. Similarly, this difference is observed in the beginning of the global pandemic. Specifically, Binance Coin has a positive correlation with all three stock indices over this entire time period. As a result, this implies that Binance Coin only has diversification benefits against stock indices. However, note that the positive correlation occasionally is rather high. The derived conclusion from these results is that Binance Coin is not a safe haven asset during the global pandemic.

Finally, I observe the correlations after this initial phase of the global pandemic and notice an interesting trend. First, the hedging capabilities of Bitcoin against MSCI World and S&P 500 becomes more apparent in 2021. While Ethereum displays a negative correlation with these two stock indices, it tends to be larger, in absolute terms, during 2021. In contrast to this, the correlation between Bitcoin and Ethereum with MSCI 50 EM, respectively, is more frequently positive after the beginning of the global pandemic. In contrast to this, Binance Coin repeatedly is observed to behave different to Bitcoin and Ethereum. In fact, the opposite trend of the pairwise correlation with stock indices is observed for Binance Coin.

5.3 Portfolio Analysis

The final part of the methodology consists of creating and evaluating minimum-variance portfolios. This is done with the aim to investigate if the cryptocurrencies show possible hedging properties against the three stock indices. Moreover, in order to get additional insight into the safe haven abilities of the cryptocurrencies, a subsample which only consists of data for 2020 is examined. Note that this final part of the methodology is also based on the estimated parameters in table 4.

The constructed portfolios compose two different groups of portfolios. First, a portfolio which consists entirely of one respective stock index is created and used as a comparison portfolio. Secondly, the other group composes of one stock index and additionally one cryptocurrency, where the latter has a time-varying weight based on the minimum-variance composition, see figure 5. The descriptive statistics for the portfolio weights are presented in table 5. Interestingly, we can observe that Bitcoin has the highest mean weight for all the portfolios which consist of a stock index and one cryptocurrency. In addition, the maximum weight of Bitcoin is observed for S&P 500. Interestingly, Binance Coin has the largest minimum weight in absolute value for all the stock indices. This is moreover illustrated in figure 5 which presents the optimal time-varying weights based on a minimum-variance composition of the constructed portfolios. It is interesting to note that the time-varying weights for Bitcoin and Ethereum move in tandem while the time-varying weights for Binance Coin repeatedly show the opposite pattern. For instance, see the time period in the first quarter of year 2020, i.e. the start of the global pandemic. Here it is evident that the minimum-variance composition suggests that investors should hold a short position in Binance Coin. Therefore, while we can observe an increase in the time-varying weights for Bitcoin and Ethereum, figure 5 illustrates a sharp decline in the time-varying weight

Table 5: Descriptive statistics of the portfolio weights.

	MSCI World			MSCI 50 EM			S&P 500		
	Bitcoin	Ethereum	Binance Coin	Bitcoin	Ethereum	Binance Coin	Bitcoin	Ethereum	Binance Coin
Mean	0.0331	0.0205	-0.0031	0.0392	0.0193	0.0158	0.0500	0.0336	0.0053
St. dev.	0.0597	0.0412	0.0350	0.0350	0.0248	0.0325	0.0767	0.0553	0.0408
Min.	-0.0830	-0.0740	-0.2700	-0.0750	-0.0570	-0.1100	-0.0820	-0.0700	-0.2520
Max.	0.6460	0.4550	0.1190	0.2500	0.1190	0.1090	0.6870	0.5340	0.2190

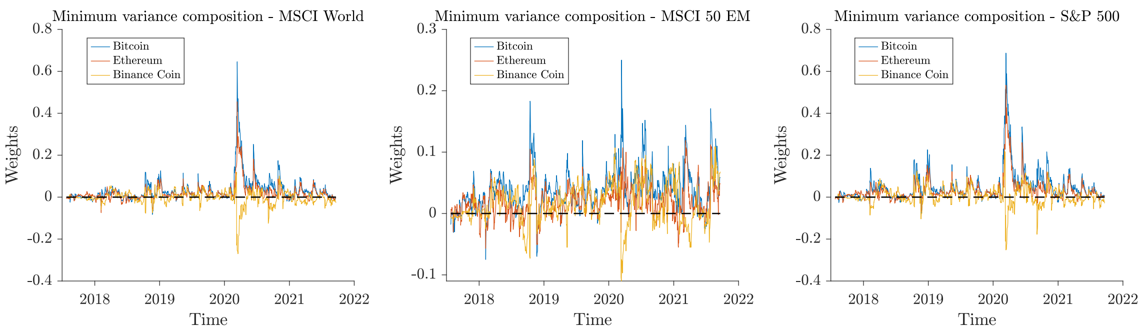


Figure 5: Time-varying weights of minimum-variance portfolios based on BEKK correlations.

Table 6: Value at risk measures.

	MSCI World	MSCI 50 EM	S&P 500	Bitcoin	Ethereum	Binance Coin
$VaR_{0.01}$	-3.1471	-3.1572	-3.8259	-13.6695	-17.8997	-20.3942
$VaR_{0.05}$	-1.5149	-1.9323	-1.8065	-7.4886	-9.6309	-10.0301
$VaR_{0.10}$	-0.8712	-1.3023	-0.9618	-4.6487	-6.2319	-7.1357

of Binance Coin. This pattern is more pronounced for the portfolios which additionally consist of MSCI World and S&P 500.

Subsequently, the Value at Risk (VaR) measure is computed for all six assets and presented in table 6. The MSCI World index has the smallest absolute value for VaR at 1%, 5% and 10%. In contrast, Binance Coin shows the largest negative value of VaR, especially at the 1% level (-20.39). In general, we observe higher VaR for the cryptocurrencies, which implies a higher potential of loss compared to the stock indices which have substantially lower value of VaR. This is not entirely surprising as the results in table 2 show that cryptocurrencies in general have a higher standard deviation and a larger dispersion of returns than the stock indices.

The descriptive statistics of the constructed minimum-variance portfolios are presented in table 7. These results are meaningful as they are able to help us determine whether Bitcoin, Ethereum or Binance Coin show possible hedging properties. In addition, the descriptive data of the portfolios for the subsample, which only covers year 2020, is presented in table 8. This part of the analysis has the aim to investigate if these cryptocurrencies act as safe haven assets during the global pandemic. Indeed, the conclusions derived from the results presented in table 8 are essential, by definition Baur & Lucey (2010), in the search for save haven assets during the global pandemic. The results presented in table 7 show that Binance Coin is the only cryptocurrency which is able to decrease the VaR value in the portfolio with MSCI World as the first component. However, the decrease is modest

Table 7: Hedging properties.

1st component	MSCI World				MSCI 50 EM				S&P 500			
2nd component	MSCI World	Bitcoin	Ethereum	Binance Coin	MSCI 50 EM	Bitcoin	Ethereum	Binance Coin	S&P 500	Bitcoin	Ethereum	Binance Coin
Mean	0.0406	0.0343	0.0366	0.0364	0.0239	0.0332	0.0323	0.0274	0.0521	0.0464	0.0472	0.0453
St. dev.	1.0661	1.1312	1.1222	1.0601	1.1631	1.1739	1.1712	1.1683	1.2824	1.2652	1.2838	1.3092
Min.	-10.4412	-18.3751	-16.1395	-9.5341	-6.3863	-6.6672	-6.3814	-7.1792	-12.7652	-18.9257	-18.4802	-12.3752
Max.	8.4063	8.6711	8.3267	9.3813	6.5105	6.7610	6.5316	6.7372	8.9683	9.0839	8.6976	9.7737
Kurtosis	27.0531	78.0106	55.0589	22.7490	6.3924	7.3825	6.4862	6.6967	23.4665	58.7366	51.3551	23.3752
Skewness	-1.5914	-4.7223	-3.7903	-1.0664	-0.3844	-0.3823	-0.2838	-0.3317	-1.1167	-3.8707	-3.6044	-1.1924
$Return \vert VaR_{0.01}$	-5.3932	-6.1681	-6.2624	-5.1835	-4.2862	-4.4992	-4.2667	-4.1792	-6.2312	-6.5843	-6.9191	-6.4587
$Return \vert VaR_{0.05}$	-2.7153	-2.7861	-2.8192	-2.7238	-2.7528	-2.7183	-2.7185	-2.7487	-3.3089	-3.2242	-3.3087	-3.4156
$Return \vert VaR_{0.10}$	-1.9293	-1.9508	-1.9556	-1.9592	-2.1639	-2.1446	-2.1455	-2.1663	-2.3555	-2.2823	-2.3183	-2.4033

Table 8: Safe haven properties. Time period covered is year 2020.

1st component	MSCI World				MSCI 50 EM				S&P 500			
2nd component	MSCI World	Bitcoin	Ethereum	Binance Coin	MSCI 50 EM	Bitcoin	Ethereum	Binance Coin	S&P 500	Bitcoin	Ethereum	Binance Coin
Mean	-0.0680	-0.1664	-0.2549	0.2421	-0.0947	-0,1195	-0.2465	0.0870	-0.0059	-0.1569	-0.2279	0.3347
St. dev.	4.1813	3.5165	3.6140	3.5933	2.8404	2.8219	2.8210	2.5017	4.9093	3.7448	3.8532	4.4092
Min.	-10.4412	-9.4845	-9.2586	-9.2482	-6.3863	-6.5556	-6.0954	-6.0365	-12.7652	-11.2827	-10.1628	-12.5482
Max.	8.4063	8.6179	8.3294	8.4185	6.5105	6.7307	6.5921	6.0739	8.9683	9.0600	8.7156	8.3427
Kurtosis	3.6205	4.2888	3.9618	3.5999	3.3630	3.4658	3.3671	3.6885	3.4507	4.7849	3.9153	4.0396
Skewness	-0.5340	-0.3985	-0.4285	-0.1924	-0.3261	0.0432	0.0687	-0.32405	-0.3640	-0.5387	-0.4689	-0.3600
$Return \vert VaR_{0.01}$	-10.4412	-9.4845	-9.2586	-9.2482	-6.3863	-6.5556	-6.0954	-6.03647	-12.7652	-11.2827	-10.1628	-12.5482
$Return \vert VaR_{0.05}$	-10.2145	-8.6587	-8.9038	-7.5042	-6.1410	-5.9069	-5.9347	-5.5976	-11.3798	-9.0822	-9.3652	-9.0041
$Return \vert VaR_{0.10}$	-8.5597	-7.0920	-7.6303	-6.1736	-5.8418	-5.3014	-5.4315	-4.8577	-9.3606	-7.4469	-8.1573	-7.4661

and only detected at the 1% level. Nevertheless, the VaR measure is increased in all other instances. In this aspect, the results indicate that both Bitcoin and Ethereum increase the downside risk. In contrast, when it comes to the portfolios which include S&P 500 as the first component, Binance Coin is not showing any hedging properties. However, Bitcoin and Ethereum present modest decreases in VaR at the 5% and 10% levels. Interestingly, all three cryptocurrencies show possible hedging abilities against MSCI 50 EM. Indeed, we can observe that the VaR measure is decreased for all but two cases, which consists of Bitcoin at the 1% level and Binance Coin at the 10% level. These results indicate that while hedging properties are present in Bitcoin, Ethereum and Binance Coin, the abilities to hedge against stock indices varies across the cryptocurrencies. This is in line with research, see e.g. Bouri et al. (2017b). Specifically, Bitcoin and Ethereum are able to hedge against S&P 500 while Binance Coin is not. Conversely, the opposite relationships holds for MSCI World. Finally, the hedging ability against MSCI 50 EM is present in all three cryptocurrencies.

In the aspect of possible safe haven properties, we analyse the results presented in table 8. First, note that the subsample only consists of data during the year 2020 and therefore comprises the beginning of the global pandemic. Hence, this time period also includes a sharp decline in the stock market, as mentioned in section 1. In table 8 we can generally observe a more pronounced ability of Bitcoin, Ethereum and Binance Coin to reduce the VaR measure. In a way, these results are more important than the results in table 7, as the results in table 8 are used to determine whether the cryptocurrencies have hedging abilities during market turmoil, i.e. can act as safe haven assets. In table 8 we can illustrate that all three cryptocurrencies are able to decrease the VaR against MSCI World. This holds at the 1%, 5% and 10% VaR. Importantly, while Binance Coin shows the greatest ability to act as a safe haven asset, it is important to note that no restrictions are imposed in terms of holding a short position. For instance, notice that the optimal time-varying weight of Binance Coin is negative at the start of the pandemic in figure 5. In the aspect of MSCI 50 EM, we observe that the cryptocurrencies show safe haven abilities in all cases except for Bitcoin at the 1% level. Similarly, all three cryptocurrencies are able to decrease the VaR measures of S&P 500. In addition, we observe that Bitcoin, Ethereum and Binance Coin are able to decrease the VaR values, in particular at the 5% and 10% levels.

The results based on this portfolio analysis can be summarised as follows. First, the hedging and safe haven abilities vary with different cryptocurrencies. This is in line with the research presented in section 2. Moreover, the ability to reduce downside risk is more pronounced in the subsample, i.e. 2020, which includes the start of the global pandemic and therefore includes a period with market turmoil. Finally, no restriction is imposed in the aspect of allowing investors to hold a short position. Interestingly, this implies that the positive correlation between Binance Coin and the stock indices, which is illustrated in figure 4, provides a benefit for investors who hold a short position of this cryptocurrency during a time with market turmoil.

6 Conclusion

The aim of this thesis was to investigate whether cryptocurrencies were able to act as save haven assets during a global pandemic and to estimate the spillover effects between markets. In addition, diversification benefits and hedging capabilities of cryptocurrencies were investigated. The methodology in this thesis consisted of three different parts, as explained in section 3. The diagonal BEKK model was used in order to perform the analysis. The results showed that the estimated parameters were statistically significant at the 1% level[25]. First, the volatility spillover between the assets was analysed. The results showed that there was a presence of volatility spillover between the cryptocurrencies and stock indices. In general, the results showed that cryptocurrencies had a higher degree of volatility spillover than the stock indices. Specifically, Bitcoin had the highest own volatility spillover and similarly, the highest cross-volatility spillover effect with regards to the ARCH effect. Moreover, the results showed that Ethereum was the asset which had the highest degree of volatility persistence and additionally that Ethereum had the highest cross-volatility GARCH effect.

The second part of the methodology consisted of analysing the dynamic pairwise correlations between cryptocurrencies and stock indices. This was done in order to investigate whether the cryptocurrencies had diversification benefits, hedging abilities and if they were able to act as safe haven assets. In general, the results showed that these properties were time-varying. Specifically, the results showed that all three cryptocurrencies had diversification benefits against all the stock indices. However, the hedging abilities differed across cryptocurrencies. Moreover, Bitcoin and Ethereum showed an increased ability to hedge against MSCI World and S&P 500. In contrast, their properties against the MSCI 50 EM index consisted only of diversification benefits, especially after the initial phase of the global pandemic. In addition, the correlation pattern between Bitcoin and Ethereum was heterogeneous against developed and emerging markets.

Based on the correlation analysis, the results showed that Binance Coin displayed a different correlation with stock indices than Bitcoin and Ethereum. Indeed, Binance Coin had a higher positive correlation with the stock indices. The derived conclusion from these results was that Bitcoin and Ethereum had time-varying properties in terms of diversification benefits and hedging capabilities. In contrast, Binance Coin showed a positive correlation and therefore was classified as an asset with diversification benefits. Finally, in the aspect of safe haven abilities the results showed that Bitcoin and Ethereum were able to act as safe haven assets. This was in particular true against the S&P 500 index. However, it is worth mentioning that this property was only present for a short time period. Nevertheless, this short time period may have been adequate based on the results in section 2, which showed that the greatest initial negative influence on the financial markets took place between

[25]As mentioned in section 5, the statistical significance did hold for all parameters in the matrix with constants. However, this does not affect the analysis.

March and April, 2020. In contrast, the results showed that Binance Coin was not able to act as a safe haven asset. Indeed, Binance Coin only had diversification benefits.

The final part of the methodology consisted of a portfolio analysis where the portfolios were constructed based on the minimum-variance criterion. This was done in order to investigate if the cryptocurrencies showed hedging properties and safe haven abilities. Bitcoin had the highest mean weight in all constructed portfolios, in particular in the portfolio which additionally consisted of S&P 500. This was not surprising, as the results showed that Bitcoin acted as a hedge and safe haven asset against S&P 500. In contrast, Binance Coin had the largest minimum weight, in absolute value, in all portfolios. Similarly, this corresponded to the results derived from the correlation analysis. While the minimum variance weights of Bitcoin and Ethereum were similar, the corresponding weights of Binance Coin differed. In addition, the minimum variance composition of MSCI 50 EM was different than the ones for MSCI World and S&P 500, which implied a difference between developed and emerging markets. Importantly, the results suggested that investors should hold a short position in Binance Coin, especially during the first quarter of 2020, i.e. the beginning of the pandemic. In general, the results indicated that the properties of cryptocurrencies were time-varying, which was in line with the results presented in section 2. Furthermore, the ability of Bitcoin, Ethereum and Binance Coin to reduce the downside risk in the constructed portfolios was modest. However, this effect was more pronounced when we only included data from 2020. The main result was that these properties varied across the cryptocurrencies and stock indices. For instance, all cryptocurrencies were able to decrease the downside risk of the portfolios which consisted of MSCI EM 50, while only Bitcoin and Ethereum could hedge against S&P 500. In general, the portfolio analysis showed that modest hedging capabilities and safe haven abilities were detected in cryptocurrencies.

6.1 Further Research

A recommendation for further research is to investigate whether an equally weighted portfolio consisting of these cryptocurrencies would provide an increased ability to hedge and to act as a safe haven asset[26]. Another suggestion would be to divide the data into several subsamples and analyse if the time-varying properties of these cryptocurrencies differ in time periods when different variations of the corona virus were discovered[27]. Furthermore, it will be interesting to repeatedly analyse the properties of cryptocurrencies as they are time-varying. Specifically, if there is time period in the future which is influenced by a pandemic or epidemic. This is based on the results by Marani et al. (2021) and Goodell (2020) which show that these time periods will occur more often. Another interesting extension could be to include more cryptocurrencies in the diagonal BEKK model.

[26]This is based on the result by (Susilo et al., 2020) which is mentioned in section 2.
[27]This is based on inspiration from the presented results by Russel & Hadi (2021).

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