Erik Bjørvik & Runar Tuflåt

Cryptocurrencies

DCC-GARCH, a time-varying correlation assessment of cryptocurrencies hedging, safe haven and diversification capabilities

Master's thesis in Economics and Business Administration
Supervisor: Hans Marius Eikseth
May 2022

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Abstract

This master thesis employs a dynamic conditional correlation (DCC) method in the interest of testing different cryptocurrencies and commodities capabilities to function as a hedge or safe haven, towards different stock indices across the globe. Additionally, it uses a portfolio analysis to contrast the practical significance these assets have on the risk return relationship when embedded into a portfolio. The dataset consists of the historical returns for five cryptocurrencies, one cryptocurrency index, gold, oil, an agriculture index, as well as 19 different stock indices across the globe. The time span of the sample stretches from the 6th of October 2014 to the 8th of December 2021. Comprehensively, the results show that only gold and Tether possess hedging capabilities, and that gold is superior when embedded into a portfolio. Likewise, the results reveal that Tether is the only asset that can function as a safe haven, but this holds mainly for the most extreme downdraws in the market. This reveals that the volatile cryptocurrencies[1] and the cryptocurrency index (CRIX) fails to be both a hedging and safe haven tool. These findings will provide meaningful information for investors with respect to optimal asset allocations during various market circumstances.

[1] Bitcoin, Ethereum, Litecoin, XRP

Sammendrag

Denne masteroppgaven bruker en dynamic conditional correlation (DCC) metode for å teste ulike kryptovaluta og råvarers evner til å fungere som en sikring eller trygg havn, mot ulike aksjeindekser i verden. I tillegg gjennomføres det en porteføljeanalyse for å kontrastere den praktiske betydningen disse aktivaene har på forholdet mellom risiko og avkastning når de blir inkludert i en portefølje. Datasettet består av den historiske avkastningen for fem kryptovalutaer, en kryptovalutaindeks, gull, olje, en landbruksindeks, samt 19 forskjellige aksjeindekser over hele kloden. Tidsrommet for vårt utvalg strekker seg fra 6. oktober 2014 til 8. desember 2021. Resultatene viser at bare gull og Tether egner seg som sikringsalternativer, men at gull er det overlegne aktiva i henhold til forholdet mellom risiko og avkastning når det inkluderes i en portefølje. Videre viser resultatene at Tether er det eneste aktiva som kan fungere som en trygg havn, men dette gjelder hovedsakelig kun under de aller mest urolige dagene i markedet. Dette viser at de volatile kryptovalutaene og kryptovalutaindeksen (CRIX) verken fungerer som en sikring eller en trygg havn. Våre funn vil gi nyttig informasjon for investorer med hensyn til optimal aktiva allokering under ulike markedsforhold.

Acknowledgements

With this thesis we mark the end of our master's degree in Economics and Business administration, with specialization in finance, at Norwegian University of Science and Technology (NTNU), Trondheim.

This thesis has put the theoretical and practical knowledge we have acquired through 5 years at NTNU to a test. We have treasured investigating the growing field of cryptocurrency, and it has been a challenging and rewarding process to explore the different cryptocurrencies capabilities to function as a hedge and safe haven.

We wish to express our sincere gratitude to our supervisor Hans Marius Eikseth for valuable guidance and feedback throughout the process. Additionally, we would like to thank Ranik Raaen Wahlstrøm for crucial contribution on retrieving data from Blockchain Research Center (BRC).

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Norges tekniske-naturvitenskapelige universitet (NTNU)

24.05.2022

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1. Introduction

In the recent years, the demand for cryptocurrencies have increased drastically which have led to large fluctuations in the cryptocurrency prices. Since the surge in the price of several cryptocurrencies in 2017 followed by a setback in the beginning of 2018, the price of various cryptocurrencies has had a steady growth until the covid-19 outbreak in 2020. The Covid-19 pandemic have caused another bull run in the digital currency market forcing the prices of the digital currencies to new peaks, and for the first time in history, the total market capitalization of the cryptocurrency market has reached two trillion dollars (Coinmarketcap, n.d.-a). This run in the cryptocurrency market have some similarities to the behavior of bond and gold prices during the financial crisis in 2007, where large investors and companies moved their funds from risky investments such as stocks to safer assets like gold and bonds, in order to reduce the risk of their portfolios. This parallel makes it interesting to investigate whether cryptocurrencies can play a significant role in a portfolio during turmoil periods.

As a result of the increasing demand for cryptocurrencies and large market capitalization, institutional investors as well as governments have recently opened their eyes for the cryptocurrency market and started to include cryptocurrencies in their business strategy (Areddy, 2021). In February 2021 Tesla bought 1.5 billion dollars' worth of Bitcoin so they could accept payments in Bitcoin (Kovach, 2021). Previously, investing in cryptocurrencies were considered as a speculative investment made by small investors, but in the later years as institutional investors and large companies are starting to accumulate Bitcoin and other digital currencies it indicates that such digital currencies have some important characteristics and has come to stay.

Since Bitcoins establishment in 2008 as the first Peer-to-Peer Electronic Cash System (Nakamoto, 2008), numerous of different cryptocurrencies have been introduced. Each with the purpose to either cover and refine Bitcoins social and technical limitation, or with the aim of creating financial gain (Tarasiewicz & Newman, 2015). Unlike fiat currencies that are controlled by the authorities, most of the cryptocurrencies are decentralized. Furthermore, most of the cryptocurrencies are created with a mechanism to maintain scarcity, as for gold is given by its limited natural supply by being a rare physical resource. This is one of the reasons why Bitcoin is often referred to as the digital gold, as both are decentralized and scarce assets (Popper, 2015). Since previous research recognizes gold as a functional hedging and safe haven tool (Baur & Lucey, 2010; Baur & McDermott, 2010; Beckmann et al., 2015), these similarities may allow cryptocurrencies to possess the same hedging and safe haven capabilities.

Thus, the purpose of this paper is to find out if the most popular cryptocurrencies can effectively reduce the risk of a portfolio by examining the relationship between cryptocurrencies and various stock indices in the world and evaluate how well these risk reducing capabilities are compared to more established assets. We have thus chosen the following as our main research question:

With the introduction of cryptocurrencies, which is the superior hedging and safe haven tool?

In line with this, we seek to answer the following related questions:

RQ 1. Do the cryptocurrencies possess hedging and safe haven capabilities?

RQ 2. If so, compared to other assets showing to have these capabilities, which performs the best embedded into a portfolio.

Moreover, there are several different studies that deal with cryptocurrencies, especially Bitcoin, and their hedging and safe haven properties, and the results are inconsistent (Stensås et al., 2019; Bouri et al., 2020; Shahzad et al., 2020; Lavelle et al., 2021, Meshcheryakov & Ivanov, 2020; Klein et al., 2018). This signifies that there is little evidence of whether one benefits from replacing gold and other commodities with Bitcoin and other cryptocurrencies, the so-called altcoins, with the purpose of hedging. Our article supplements previous findings by including Bitcoin and several different altcoins, and test their hedging and safe haven capabilities against various indices in the world. In addition, to the best of our knowledge, we differ from previous literature by testing the hedge effectiveness of the cryptocurrencies when embedded into a portfolio.

From an investors perspective including an asset into the portfolio will reduce the risk significantly, if the asset is negatively correlated with the other assets in the portfolio (Bouri et al., 2017). In this paper we differentiate between a hedge, safe haven and diversifier in order to get a deeper understanding of the risk reducing capabilities of different cryptocurrencies. A safe haven is defined as a place of protection and a shelter against "stormy weather", i.e., a place for investors to retreat their wealth and protect them from big losses during market turmoil (Baur and McDermott, 2010). An asset with these capabilities will be utilized differently by investors, compared to an asset that possess hedging or diversification capabilities. To investigate RQ 1, we have in this paper employed Baur and

McDermotts definitions to properly distinguish between these three capabilities. They present these as follows:

A diversifier is defined as an asset that is positively (but not perfectly correlated) with another asset or portfolio on average.

A strong (weak) hedge is defined as an asset that is negatively correlated (uncorrelated) with another asset or portfolio on average.

A strong (weak) safe haven is defined as an asset that is negatively correlated (uncorrelated) with another asset or portfolio in certain periods only, e.g., in times of falling stock markets.

To assess these three capabilities, we adapt the regression framework proposed by Ratner and Chiu (2013) which avail itself of the DCC-GARCH model proposed by Engle (2002). This is an approach that is widely used in earlier studies on the hedging and safe haven capabilities of gold and other commodities, and later on used to assess Bitcoin's capabilities. This method allows us to extract the time-varying correlation, as further is applied in our main regression model[2]. Following the estimated results of the hedging, safe haven and diversification capabilities, we conduct a descriptive portfolio analysis in order to answer RQ 2. This will highlight the practical significance of including the potential hedge assets into a portfolio and elucidate which asset might serve as the superior hedge in our sample. The three descriptive measures used in our portfolio analysis are expected return, standard deviation and value at risk.

The dataset includes 19 of the largest stock indices across all the continents in the world, in order to get a broad sample of different developed and developing economies. Furthermore, the dataset consists of four of the highly known, liquid and highest market capitalized cryptocurrencies, Bitcoin, Ethereum, XRP and Litecoin. To broaden the sample of cryptocurrencies in our study, we have chosen to include the well-known stablecoin Tether, as well as the CRIX index in order to represent the cryptocurrency market as a whole. As comparable commodities gold, oil and the agriculture index are included in our study. The timespan of our sample stretches from the 6th of October 2014 to the 8th of December 2021.

Our paper finds evidence of gold and Tether being a strong hedge against most of the indices, while the rest of the cryptocurrencies and the commodities only functioned as an effective diversifier. In addition, Tether was the only one showing statistical proof of functioning as a

[2] See equation (5)

safe haven, but only on the most severe days. Regarding the hedging capabilities, the portfolio analysis revealed that only gold was an effective hedge when embedded into a portfolio.

Further in this chapter we will give a brief introduction of the cryptocurrency market, as well as the chosen cryptocurrencies included in this paper. Chapter 2 presents previous literature on the hedge, safe haven and cryptocurrency topic, while chapter 3 exhibit our dataset and provide a brief overview of some key descriptive statistics. Chapter 4 outlines the DCC-GARCH method and give the regression framework used to test the hedging, safe haven and diversification capabilities, in addition to give a tangible definition of these key properties. Chapter 5 presents the results from the main regression model in order to answer RQ 1, along with a portfolio analysis which will shed light on RQ 2. In chapter 6 we compile our results of the hedging and safe haven properties, in addition to the portfolio analysis, and utilize this to discuss the connotation this have on our research question. Finally, chapter 7 concludes.

1.1 Cryptocurrencies

In this section we will introduce the concept of cryptocurrencies and give an overview of their market, as well as giving a brief rundown of the cryptocurrencies in our paper.

A cryptocurrency is a digital asset that is decentralized, based on blockchain technology and designed to work as a medium of exchange. Because a cryptocurrency is decentralized there is no central authorities such as government or bank that can manage the supply or the value of the digital currencies. Rather, the supply of the digital currencies is managed through a peer-to-peer network where anyone could participate by mining coins (Ashford & Schmidt, 2022).

As for many other assets, scarcity is also a key part for the value of the cryptocurrencies. Among cryptocurrencies there are several contrasting mechanisms to maintain scarcity. Some cryptocurrencies have limited supply, some are controlled by central firms and cannot be mined, while others have a built-in burning mechanism to reduce the fraction of coins in circulation (DeMatteo, 2021).

The cryptocurrency market has in the recent years undergone a strong growth and many have considered cryptocurrencies as a new investment class. Bitcoin was the first cryptocurrency to be established, and since its launch in 2009, several cryptocurrencies have emerged. In total, there are 17,791 different cryptocurrencies as of February 2022 (Coinmarketcap, n.d.-b).

1.1.1 Bitcoin (BTC):

Bitcoin is the first cryptocurrency to be launched and was established in 2008 by a person or a group of people under the pseudonym Satoshi Nakamoto (Nakamoto, 2008). Bitcoin has since its origin been the most popular and dominating cryptocurrency, covering 42% of the total cryptocurrency market capitalization as of April 2022 (Coinmarketcap, n.d.-c). However, as other cryptocurrencies have been launched, the proportion that Bitcoin accounts for in the total cryptocurrency market have decreased the recent years.

As of April 2022, the total supply of Bitcoin is approximately 19 million, and the total number of Bitcoins that can be mined are limited to 21 million (Coinmarketcap, n.d.-c).

The main advantage of Bitcoin compared to fiat currencies as a payment method is the peer-to-peer network, which eliminates the need of any intermediaries. In other words, the open-source network used in Bitcoin makes the transactions happen directly between independent network participants without having a financial institution to permit or facilitate these transactions (Coinmarketcap, n.d.-c). However, Bitcoin has a disadvantage when it comes to transaction time. According to CoinMarketCap, the average confirmation time for a payment in Bitcoin is about 10 minutes. Taking this into consideration one might at this time consider Bitcoin more of an investment alternative rather than a medium of exchange.

1.1.2 Ethereum (ETH)

Ethereum was founded in 2013 and is the second largest cryptocurrency by market capitalization with a market dominance of about 19%. In contrast to Bitcoin, Ethereum has extended the utility of cryptocurrencies and are aiming towards the use of smart contracts and digital apps, in addition to working as a medium of exchange (Coindesk, n.d.-a).

By contrast to Bitcoin where the supply is limited to 21 million, Ethereum do not have a limit but rather a fee-burning mechanism to maintain its scarcity (Coinmarketcap, n.d.-d).

1.1.3 Ripple (XRP)

XRP is a digital coin controlled by the fintech company Ripple, which launched in 2012, and it is a payment system designed to facilitate cheaper and faster payments. As of April 2022, XRP is the sixth largest cryptocurrency with a market dominance of about 2% (Coinmarketcap, n.d.-e).

Unlike other mined cryptocurrencies, where coins enter the circulation through a mining process, Ripple has another procedure which do not involve mining. Instead, new coins enter the circulation whenever Ripple choose to sell coins from its pre-mined stack of 100 000 000 000 XRP coins (Coindesk, n.d.-b). When XRP coins enter the circulation, they can be traded as other cryptocurrencies.

1.1.4 Litecoin (LTC)

Litecoin were developed in 2011 and it is the 21 largest cryptocurrency ranked by market capitalization, with a market dominance of about 0,5% (Coinmarketcap, n.d.-f). Litecoin is built on the same code as Bitcoin, and it was created to increase the transaction speed as well as decrease the transaction fees for smaller payments (Coindesk, n.d.-c).

Today over 2000 merchants and stores accepts payments in Litecoin which makes it one of the most widely accepted cryptocurrencies. The supply is limited to 84 million and as of April 2022 there are about 70 million Litecoin's in circulation (Coinmarketcap, n.d.-f).

1.1.5 Tether (USDT)

USDT was launched in 2014 by the Hong Kong based company Tether. By contrast to other cryptocurrencies that are extremely volatile, USDT has less fluctuations and since it tracks the US dollar it is commonly known as a stablecoin. As of April 2022, USDT is the largest stablecoin and the third largest cryptocurrency with a market dominance of about 3,8% (Coinmarketcap, n.d.-g).

Compared to other volatile cryptocurrencies, stablecoins are often considered a better store of value as they are protected against the large fluctuations in the cryptocurrency market. Furthermore, stablecoins have in recent years been used as an inflation hedge and is often used in order to buy and sell different cryptocurrencies (Coindesk, n.d.-d).

There is no maximum supply of USDT and whenever Tether issues new USDT tokens it allocates the same amount in US dollar to provide that USDT is fully backed by cash and cash equivalents (Coinmarketcap, n.d.-g).

1.1.6 Cryptocurrency index (CRIX)

The Royalton CRIX was created in 2021 and is a cryptocurrency index that contains eight different cryptocurrencies. It was developed to be a benchmark for the cryptocurrency market and the index is calculated by S&P Global (Royalton CRIX Index, n.d.).

The composition of cryptocurrencies in the index is 58% allocated in Bitcoin, 25.9% in Ethereum, 4.8% in Binance Coin, 2.9% in Ripple, 2.6% in Cardano, 2.5% in Solana Token, 1.7% in Polkadot and 1.6% in Luna (Royalton CRIX Index, n.d.).

2. Literature Review

There is various research conducted on the topic safe haven and hedge. Baur and Lucey (2010) investigated the hedging properties of gold against the U.K., U.S. and German bond and stock market. They find evidence that gold is a hedge on average as well as a safe haven in extreme market turmoil. Furthermore, Baur and McDermott (2010) extended the study conducted by Baur and Lucy (2010), by exploring golds ability to serve as a hedge and safe haven in developed and emerging markets across the globe. They argue that gold is both a hedge and safe haven for European and U.S. stock markets, while for the large emerging markets such as BRIC countries as well as Australia, Japan and Canada gold is no more than a diversifier. Their analysis also reveals that gold is a strong safe haven during the financial crisis in 2007 for most of the developed markets.

Due to the growing interest of the cryptocurrency market, several researchers have investigated the topic cryptocurrency. Bouri et al. (2019) investigates the role of trading volume among cryptocurrencies in order to predict the return and volatility in the cryptocurrency market. Nygren (2018) fixate on the price determinants of the six largest minable cryptocurrencies. Dyhrberg (2016) explored the financial asset capabilities of Bitcoin and argues that Bitcoin have several similarities to both gold and the dollar regarding the hedging capabilities, in addition to working as a medium of exchange. Contrastingly, Baur et al. (2018) situates that Bitcoin are more a speculative investment and can neither be classified as an alternative currency nor a medium of exchange.

While there are a lot of evidence that gold can serve as both a hedge and safe haven against numerous stock markets, cryptocurrencies are a less explored topic on this field, and the results are incongruous. Stensås et al. (2019) investigated the dynamic conditional correlation (DCC) between Bitcoin and seven developed countries, six developing countries, five regional indices and 10 commodities to explore whether Bitcoin can act as a diversifier, safe haven or hedging tool. They find proof that Bitcoin can serve as a hedge against most of the emerging markets, which includes Brazil, Russia, India and South Korea. Meanwhile, for the developed markets, the regional indices and the commodities, Bitcoin is no more than a diversifier. However, the paper does not find any evidence of Bitcoin being a strong safe have during extreme market conditions, but when isolating specific crisis periods, they do find evidence of Bitcoin being either a strong or weak safe haven (Stensås et al., 2019). Investigating the same sample period as Stensås et al. (2019), Smales (2019) finds proof of

Bitcoin being a weak hedge against all the chosen assets[3] in their paper, as Bitcoin and the assets are uncorrelated. Regarding the safe haven capabilities, Smales (2019) argue that Bitcoin should not be considered a safe haven, as a consequence of the high volatility and low liquidity at that time. While Smales (2019) based their analysis on the sub sample periods covering the three time periods 2011-2013, 2014-2016 and 2017-2018, Stensås et al. (2019), based their investigation of Bitcoin as a safe haven tool on global events such as BREXIT, the U.S. president election and Chinese stock market turbulence.

Bouri et al. (2020) took a broader view by including eight different cryptocurrencies to test their abilities to act as a hedge and safe haven against the S&P 500 and its 10 equity sectors. Their results show that Bitcoin, Stellar and Ripple are safe havens for all the indices in the U.S. equity market. Additionally, they argue that Litecoin and Monero are safe havens for the aggerate U.S. equity index as well as for selected sectors. Ethereum, Dash and Nem were all found to be hedges for few equity sectors (Bouri et al., 2020).

Contrastingly, other researchers provide evidence of Bitcoin being a poor hedge and only suitable for diversification (Bouri et al., 2017; Klein et al., 2018). They create a more mixed view on whether cryptocurrencies have the properties to be a hedging or safe haven tool. More specifically, Klein et al. (2018) conducted an analysis where they compared the conditional variance of both Bitcoin and gold as well as performing a portfolio analysis. The paper concludes that Bitcoin is positively correlated with dipping markets while gold is negatively correlated, which indicates that Bitcoin neither can be a hedge or safe haven. Furthermore, the portfolio analysis states that an inclusion of Bitcoin versus gold in a portfolio has a fundamentality different linkage to the equity markets, which is in line with the results showing that the price of Bitcoin and gold move opposite in falling equity markets. The paper also finds evidence that the results are valid for the Cryptocurrency index (CRIX), as a result of Bitcoin being the largest component in the CRIX index.

However, while many researchers reject Bitcoin and other cryptocurrencies as a hedge or safe haven, Conlon et al. (2020) finds proof that Tether, which is a stablecoin, has the properties to act as a hedge and safe haven. They argue that Tether maintained its link to the US dollar during the market turmoil caused by the COVID-19 pandemic, and consequently fulfill the characteristics of being a safe haven. These results of Tether successfully being a safe haven have been confirmed by Vukovic et al. (2021). According to their research, Tether where

[3] S&P 500, Nasdaq, Apple, Twitter, gold and 10-year treasury note

negatively correlated with S&P 500 during times of market turmoil, providing evidence of Tether being a safe haven, while the rest of the four cryptocurrencies[4] used in their analysis moved together with S&P 500.

Looking at volatility, cryptocurrencies are known to be extremely volatile (Vejačka, 2014; Salamat et al., 2020; Bouoiyour & Selmi, 2015). However, despite being volatile assets, several studies have found proof of the benefits of including cryptocurrencies in a portfolio (Kyriazis, 2021; Chuen et al., 2018). More specifically, Chuen et al. (2018) provides evidence that cryptocurrencies and traditional assets are low correlated, implying that cryptocurrencies would effectively reduce the risk of a portfolio. Additionally, the study reveals that the average return of the cryptocurrencies are higher than the traditional assets, which increases the risk-reward performance of the portfolio.

[4] Bitcoin, Ethereum, XRP and Bitcoin Cash

3. Data

In this section we will give a brief presentation of the dataset before examining it further by presenting some key descriptive statistics.

Our dataset consists of 19 different major stock indices covering each continent, as well as Scandinavia. This allows us to broader investigate the hedging and safe haven capabilities of the different cryptocurrencies, by getting a dataset that involves various developed and developing markets. The four cryptocurrencies Bitcoin, Ethereum, XRP and Litecoin are chosen based on their market capitalization, trading volume and launch date. Furthermore, due to high market capitalization and being the largest stablecoin, Tether is included in our study. As comparable commodities, we have chosen gold due to previous literatures findings of gold as the superior hedging alternative, oil being the largest traded commodity and the agriculture index to cover the rest of the soft commodities. We will later in this paper refer to the five cryptocurrencies, the CRIX index and the three abovementioned commodities under the common name assets.

We have, due to the short lifetime of the cryptocurrency market, obtained daily closing spot prices of all the stock indices as well as the chosen assets under study, in order to get a big enough sample. The price history of all the stock indices, gold and brent crude oil are downloaded from Thomson Reuters Eikon Datastream. Similarly, we have downloaded the price history of the agriculture index from S&P Dow Jones Indices. We have for four of the cryptocurrencies and the CRIX index received the price history from a database obtained by Blockchain Research Center (BRC)[5], while for Tether we have obtained the price history from Yahoo Finance. The return series are calculated by taking the first difference of the natural logarithm of the closing prices[6].

As a benchmark for the economy in the U.K., Germany, France, Italy, Switzerland, Russia, Norway, Sweden, Denmark, Canada, Brazil, Australia, South Africa, Japan, India and China, are correspondingly, FTSE 100, DAX 30, CAC 40, FTSE MIB, SMI, MOEX, OSEBX, OMXSPI, OMXC20, Toronto Composite Index, Ibovespa, ASX 200, FTSE JSE, Nikkei 225, Sensex and Shanghai Composite Index used. For the USA we have included the two major indices S&P 500 and NASDAQ. Finally, as a proxy for the world index we have used the MSCI world index.

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[5] Bitcoin, Ethereum, Litecoin, XRP

[6] $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$

Our time horizon spans from (limited by Ethereum[7]) the 6th of October 2014, to the 8th of December 2021, as we only received data for the CRIX index until this date. For each index we match the correspondingly observation of each asset, and thereby eliminate the dates where either the index or the asset has a missing value. This gives us 19 different times series, one for each stock index, with lengths ranging from 1662 to 1772 observations. Even though we got time series with differing lengths, the dataset is still in line with our research question, as we are only going to compare each asset, and therefore we need matching dates at each time series and not between each time series. Regarding Tether we could only obtain data from the 9th of November 2017. Consequently, we created a dataset where we matched only Tether against each of the indices. This left us with a dataset consisting of 19 pairs of return series ranging from 989 to 1060.

3.1 Descriptive Statistics

Descriptive statistics of our chosen indices and assets are provided in table 1. The returns for each time series are obtained by daily data, and the table carries out information about the mean, median, maximum and minimum of the return series for each of the 19 indices as well as the nine assets. Furthermore, the table contains the standard deviation, skewness, kurtosis and a sktest, which reveal if the data are normally distributed or not. Not surprisingly the standard deviation, which is a measure of volatility, are far higher for the chosen cryptocurrencies than the indices, with Tether as an exception. Among the commodities both gold and the agriculture index have a standard deviation close to all of the indices, while crude oil exhibit slightly higher values. However, as the four cryptocurrencies Bitcoin, Ethereum, Litecoin and XRP as well as the CRIX index are more volatile, they also provide a greater average return than the 19 indices. These results are likewise revealed in the maximum and minimum values of the return series, where the volatile cryptocurrencies are subject to more extreme daily movements, providing greater absolute values for these two measures. All the indices in our data as well as gold, Bitcoin, Ethereum and CRIX are negatively skewed. In addition, all indices and assets are leptokurtic as they suffer from high values of kurtosis. To get a better understanding of the distribution for each return series, a sktest are executed, revealing that none of our return series are normally distributed.

[7] For instance, without Ethereum, our time horizon would have been limited by XRP, and the sample would have started 5th of August 2013.

Table 1: Descriptive statistics

Descriptive statistics of the return series for all the 19 indices and the 9 assets. The sample period span from 6th of October 2014 to 8th of December 2021, except for Tether where the time horizon is 9th of November 2017 to 8th of December 2021. Sktest denotes Skewness and kurtosis test for normality. *** Significant at the 0.1% level.

	Mean	Median	Maximum	Minimum	Std.Dev.	Skewness	Kurtosis	Sktest
Indices:								
MSCI World	0.0003	0.0006	0.0841	-0.1044	0.0094	-1.4807	26.8957	692.74***
FTSE 100	0.0001	0.0005	0.0867	-0.1151	0.0106	-0.9246	16.4096	448.37***
DAX	0.0003	0.0008	0.1041	-0.1305	0.0128	-0.7505	14.1198	379.04***
CAC	0.0003	0.0008	0.0806	-0.1310	0.0124	-1.0411	15.3174	470.24***
MIB	0.0002	0.0008	0.0855	-0.1854	0.0150	-1.7372	22.6928	710.49***
SMI	0.0002	0.0006	0.0678	-0.1013	0.0101	-1.2095	15.7464	509.08***
MOEX	0.0005	0.0007	0.0743	-0.0871	0.0112	-0.6767	11.3840	321.36***
OSEBX	0.0004	0.0006	0.0546	-0.0918	0.0112	-0.8174	9.6602	321.04***
OMXSPI	0.0005	0.0009	0.0701	-0.1181	0.0111	-1.1563	14.3004	478.41***
OMXC20	0.0005	0.0009	0.0514	-0.0782	0.0114	-0.4410	6.0574	149.72***
NASDAQ	0.0007	0.0012	0.0893	-0.1315	0.0128	-0.9146	15.9046	438.18***
S&P 500	0.0005	0.0007	0.0897	-0.1277	0.0113	-1.0325	23.9421	537.31***
Toronto	0.0002	0.0008	0.1129	-0.1318	0.0101	-1.8359	47.3187	838.47***
Ibovespa	-0.0001	0.0007	0.1163	-0.1788	0.0246	-0.7310	9.0181	281.34***
ASX 200	0.0002	0.0007	0.0677	-0.1020	0.0102	-1.1766	16.3353	511.76***
FTSE JSE	0.0002	0.0005	0.0906	-0.1045	0.0122	-0.4422	11.6077	275.67***
Nikkei 225	0.0003	0.0007	0.0773	-0.0825	0.0129	-0.1374	8.2143	168.31***
Sensex	0.0005	0.0008	0.0859	-0.1410	0.0111	-1.5340	26.2457	665.59***
Shanghai	0.0002	0.0007	0.0560	-0.0887	0.0142	-1.1402	10.2152	399.42***
Assets:								
Gold	0.0002	0.0003	0.0469	-0.0589	0.0087	-0.2510	6.6315	145.76***
Oil	0.0002	0.0013	0.3196	-0.2822	0.0311	0.1720	26.5342	387.2***
Agriculture Index	0.0002	-0.0001	0.0496	-0.0525	0.0104	0.0381	4.7860	311.09***
BTC	0.0019	0.0016	0.1885	-0.2380	0.0321	-0.4342	8.4157	803.07***
ETH	0.0035	0.0018	0.8433	-0.8991	0.0685	-0.8805	35.7708	1107.02***
XRP	0.0020	-0.0015	0.9317	-0.5682	0.0678	1.7996	29.7718	501.99***
LTC	0.0014	0.0003	0.4598	-0.3902	0.0470	0.5725	14.7800	429.01***
Tether	0.0000	0.0000	0.0566	-0.0526	0.0050	0.6373	38.7853	546.14***
CRIX	0.0020	0.0030	0.1985	-0.4466	0.0497	-0.9765	9.4240	63.7***

Table 2 display the Pearson correlation coefficient between each index and all the assets under study, i.e., this only exhibit the constant correlation through the whole sample period and therefor it does not account for the time-varying correlation between the index and the assets. That is, this table will give a brief indication of the hedging capabilities of each asset. Overall, oil and the agriculture index report the highest positive correlation coefficients, additionally the coefficients are highly significant. From the definition of a hedge (See chapter 1)[8], table 2 subsidize earlier studies showing that oil and the agriculture index only will serve as a diversifier (Nandelenga et al., 2021). Regarding the cryptocurrencies, overall, the correlation coefficients are lower than the ones for oil and the agriculture index. This indicates that the cryptocurrencies under study does not follow the market as closely as oil and the agriculture index. Contrastingly, the coefficients for Bitcoin, XRP and Litecoin are mainly positive and significant, implying that they cannot be utilized by an investor for other than diversification purposes. For Ethereum and especially the CRIX index the results are more divided. Here are the coefficients often insignificant, i.e., they are not shown to be different from zero. This indicate that they can serve as a weak hedge (see chapter 1). Finally, the table clearly indicate that gold and especially Tether can be a strong hedge, as they report negative and significant correlation coefficients. To sum up, table 2 only provide brief indications that the cryptocurrencies and gold are more separated from the market than oil and the agriculture index, and it cannot be used to draw any conclusions about the hedging capabilities of the assets.

[8] A more detailed description of the definitions are provided in section 4.1 and table 3 parameterizes the definitions.

Table 2: Correlation matrix

Correlation matrix providing the Pearson correlation coefficient between the 19 stock indices and the 9 assets. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. . Significant at the 10% level.

	Gold	Oil	Agriculture index	BTC	ETH	XRP	LTC	Tether	CRIX index
MSCI World	0.0183	0.3415***	0.1643***	0.0875***	0.0386	0.1091***	0.0794***	-0.1502***	-0.0149
FTSE 100	-0.0514*	0.2928***	0.1408***	0.1048***	0.0475*	0.0819***	0.1002***	-0.1218***	0.0296
DAX 30	-0.0941***	0.2382***	0.1336***	0.1056***	0.0558*	0.0901***	0.0958***	-0.1154***	0.0359
CAC 40	-0.1098***	0.2693***	0.1294***	0.0955***	0.0448.	0.0611*	0.0833***	-0.1195***	0.0256
FTSE MIB	-0.1071***	0.2766***	0.1289***	0.0738**	0.0360	0.0692**	0.0749**	-0.1791***	-0.0071
SMI	-0.1240***	0.2000***	0.1102***	0.0565*	0.0208	0.0706**	0.0639**	-0.1115***	-0.0072
MOEX	0.0422.	0.3268***	0.1465***	0.1159***	0.0703**	0.0840***	0.1246***	-0.0454	0.0734**
OSEBX	-0.0542*	0.3452***	0.1664***	0.0954***	0.0195	0.0728**	0.0881***	-0.0798*	0.0040
OMXSPI	-0.1028***	0.2501***	0.1389***	0.1073***	0.0589*	0.0853***	0.0950***	-0.1211***	0.0217
OMXC20	-0.0468.	0.0990***	0.0577*	0.0493*	0.0047	0.0228	0.0585*	-0.0925**	0.0049
NASDAQ	-0.0057	0.2736***	0.1186***	0.0566*	0.0309	0.1053***	0.0490*	-0.1216***	-0.0446.
S&P 500	-0.0200	0.3187***	0.1357***	0.0586*	0.0270	0.1003***	0.0553*	-0.1464***	-0.0432.
Toronto	0.0830***	0.3913***	0.1520***	0.0882***	0.0262	0.1146***	0.0750**	-0.1722***	-0.0297
Ibovespa	0.0822***	0.2726***	0.2310***	0.0449.	-0.0077	0.0963***	0.0424.	-0.1169***	-0.0227
ASX 200	0.0023	0.1613***	0.0442.	0.0771**	0.0489*	0.0616*	0.1022***	-0.1542***	0.0132
Nikkei 225	-0.0953***	0.1150***	0.0987***	0.0949***	0.0327	0.0588*	0.0750**	0.0049	0.0935***
FTSE JSE	0.0472.	0.2282***	0.1377***	0.1415***	0.0707**	0.1037***	0.1269***	-0.0854**	0.0659**
Sensex	-0.0187	0.1168***	0.1076***	0.0992***	0.0443.	0.0520*	0.0937***	-0.1052***	0.0449.
Shanghai	0.0066	0.0979***	0.1007***	0.0419.	0.0077	0.0395	0.037	0.0140	0.0288

4. Methodology

This section will provide some useful definitions and present the econometric framework used to test which of the hedging, save haven or diversification capabilities the different assets have towards the different indices.

4.1 Definitions

Baur and Lucey (2010) were the first to formulate definitions that made it possible to empirically test if an asset acts like a safe haven, hedge or diversifier. Following this, Baur and McDermott (2010) defined an even clearer definition of these three properties, by distinguishing between a strong/weak hedge and safe haven. These definitions have later on been used on several different assets, such as precious metals and especially gold (Peng, 2020; Hood & Malik, 2013; Reboredo, 2013; Akhtaruzzaman et al., 2021), currencies (Tachibana, M, 2018), CDS (Ratner & Chiu, 2013), oil (Mensi et al. 2021) and Bitcoin (Bouri et al, 2017). Following Baur and Lucey (2010) and Baur and McDermott (2010) we define the three properties in this way:

4.1.1 Diversifier

A diversifier is defined as an asset that is positively (but not perfectly correlated) with another asset or portfolio on average.

4.1.2 Hedge

A strong (weak) hedge is defined as an asset that is negatively correlated (uncorrelated) with another asset or portfolio on average.

4.1.3 Safe haven

A strong (weak) safe haven is defined as an asset that is negatively correlated (uncorrelated) with another asset or portfolio in certain periods only, e.g., in times of falling stock markets.

These definitions make a clear distinction between the three properties. A hedge is not supposed to reduce loss in times of a market shock, but only during the period as a whole. I.e., a hedge can be positively correlated with the stock market in certain periods, as long as it is negatively correlated on average. Similarly, a diversifier is only supposed to hold on average, and therefore it does not possess the property of reducing loss in times of market turmoil. Contrary, a safe haven asset is supposed to reduce loss in times of extreme market shocks. Hence, it can be either negatively or positively correlated with the market on average, as long as it is negatively correlated during the worst periods. Another important note is that a negative correlation between two assets will give an investor positive return on one asset every time the other asset exhibits large negative returns, while uncorrelated assets will reduce the overall loss. We can see that the distinction between a strong/weak hedge and safe haven which Baur and McDermott (2010) introduces in their paper is important for investors.

4.2 Econometric Model

The econometric model used to test the properties of the different assets in this article is based on the dynamic conditional correlation (DCC) - generalized autoregressive conditional heteroskedasticity (GARCH) model proposed by Engle (2002) and the dummy variable method of Ratner and Chiu (2013). The DCC-GARCH model of Engle is shown to capture and quantify the time-varying correlation between assets quite well compared to other methods. Even though it is a non-linear model that yields good results, the DCC-GARCH can be estimated pretty simple by the log-likelihood function. The DCC is shown to have great computational advantages over a multivariate GARCH model, because the numbers of parameters to be estimated are far less. This gives the DCC an advantage over a multivariate GARCH, because it can take on far larger correlation matrices (Engle, 2002). Cho & Parhizgari (2009) states that the DCC-GARCH is the superior measure of correlation since it continuously adjusts the correlation for the time-varying volatility. Since financial returns often display varying volatility over time, the DCC-GARCH would be the appropriate measure of correlation, hence a constant correlation model would not be able to capture characteristics like leverage effect, long memory in financial series, volatility clustering and leptokurtosis. This states that the DCC-GARCH would be the best model to disclose the true correlation of our data, as chapter 3.1 revealed that all our return series are leptokurtic. In the nature of being a GARCH model, the DCC-GARCH accounts for heteroskedasticity, by estimating the correlation coefficients of the standardized residuals (Chiang et al., 2007).

In the light of previous hedge and safe haven literature and all the abovementioned advantages, we adapt the DCC-GARCH model. To avoid the chance of getting biased estimates in higher dimensions, we follow Bouri et al. (2017) and estimate the DCC separately for pairs of returns. This is also in line with our research question, where we intend to test each asset against each stock index. In accordance with previous literature, we present the bivariate DCC-GARCH (1,1) model, which is estimated in two steps, as follows:

First a univariate GARCH (1,1) is estimated, and the standardized residuals are computed, to develop a measurement that captures the changing volatility in the time series (Aliyev et al., 2020). The GARCH model was first presented by Bollerslev (1986) and the mean and variance equations of the GARCH (1,1) is given as:

The mean equation:

$$r_t = \mu_t + \omega r_{t-1} + \varepsilon_t \tag{1}$$

where r_t is the return on the asset at time t, μ_t is the conditional mean of the returns at time t, ω is the autoregressive coefficient and ε_t is the residuals of the returns at time t. Here the mean equation shows an AR(1) model.

The variance equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{2}$$

where σ_t^2 is the conditional variance at time t since it is based on the information obtained at time t-1. α_0 is the constant, ε_{t-1}^2 is the ARCH term and it is captured by the α_1 parameter, which account for the volatility news obtained in the previous period. At last, the β_1 parameter captures the variance obtained at the previous period, the σ_{t-1}^2 or GARCH effect.

Secondly, the estimates for the standardized residuals obtained from the GARCH (1,1) model is used to estimate the time varying conditional correlations between the assets and the stock indices. The DCC (1,1) equation is given by $Q_t = q_{\cdot\cdot,t}$, a symmetric positive-definite matrix, that represents the time-varying covariance:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 \varepsilon_{t-1} {\varepsilon'}_{t-1} + \theta_2 Q_{t-1} \tag{3}$$

where $\bar{Q}$ is the unconditional correlation of the standardized residuals, ε_{t-1} and ${\varepsilon'}_{t-1}$, estimated from step one, the univariate GARCH process. The speed of the process is controlled by the non-negative scalar parameters θ_1 and θ_2. θ_1 and θ_2 satisfies $\theta_1 + \theta_2 < 1$, in order for the DCC model to be mean reverting, i.e., the long-run volatility to revert to the average level.

Equation 1-3 is estimated by maximizing the log-likelihood. We do not intend to elaborate any further on the DCC-GARCH model[9], as the parameters in equation 1-3 are not interpreted or used to assess the hedging or safe haven capabilities of the assets, but only to extract the dynamic conditional correlation between each pair of assets. The pairwise DCC is given by:

$$\rho_{ij,t} = DCC_{ij,t} = \frac{q_{ij,t}}{(\sqrt{q_{ii,t}}\sqrt{q_{jj,t}})} \tag{4}$$

[9] See Engle (2002) for a more detailed elaboration of the DCC-GARCH methodology.

where $q_{\cdot\cdot,t} = Q_t$ from eq. (3), i.e., the time-varying covariance between the asset and stock index of interest. Equation (4) represent the pairwise DCC between asset i and stock index j, and it is the equation of interest in order to assess the hedging and safe haven capabilities of the chosen assets in this paper (see chapter 3).

Subsequent to the DCC-GARCH estimation, we adapt the regression framework used by Ratner and Chiu (2013). Here is the DCC_t between each asset and each stock index drawn out from equation (4) and put into separate time series. Next, the DCC_t are regressed on dummy variables (D) representing great market shocks:

$$DCC_t = \gamma_0 + \gamma_1 D(r_{stock} q_{10}) + \gamma_2 D(r_{stock} q_5) + \gamma_3 D(r_{stock} q_1) \quad (5)$$

where D represent the abovementioned market shocks, respectively the lower 10%, 5% and 1% quantiles of the stock market return distribution. $D = 1$ if the stock return take place within these bins, and $D = 0$ otherwise.

Following the definitions presented in chapter 4.1, the asset under consideration will be a hedge or safe haven against the stock market under consideration when:

Table 3: Definitions

Conditions and conclusions of the hedging and safe haven capabilities. $\gamma_0, \gamma_1, \gamma_2$ *and* γ_3 from eq. (5).

Condition	Or	Conclusion
γ_1, γ_2 *and* $\gamma_3 = 0$	Insignificant	The asset is a weak safe haven
γ_1, γ_2 *and* $\gamma_3 < 0$		The asset is a strong safe haven
$\gamma_0 = 0$	Insignificant	The asset is a weak hedge
$\gamma_0 < 0$		The asset is a strong hedge

Note: For a strong hedge and safe haven, the coefficients need to be significant.

The student-t distribution is pervasively applied through the whole method, as our data is shown in table 1 to be leptokurtic and skewed. This is consistent with earlier literature which states that the distribution of stock returns are usually fat-tailed, i.e., either leptokurtic or skewed (Eom et al., 2019). Based on tests, where we used AIC and BIC as information criteria, we found the student-t and normal distribution to be the superior choice, over other distributions such as generalized normal distribution, skewed student-t and skewed normal distribution. Further we saw that the student-t and normal distribution were rotating on being the superior one based on which asset and stock market being used in the calculations, but with marginally differences. Given the relatively small differences in AIC and BIC between the two distributions and that the sktest in table 1 revealed that our data is either leptokurtic or skewed, we settled on the student-t distribution. This is in line with Peirò, A. (1994), which states that the student-t distribution is the superior distribution with regard to daily stock returns.

5. Empirical Results

In this section, we exhibit the empirical results from the econometric model presented in chapter 4.2. Additionally, the results from a portfolio analysis will be reported.

Based on AIC and BIC criteria we found that an AR(1) model was sufficient to capture the autocorrelation in the time series, and a more complex model was not needed. Furthermore, the same criteria found that the GARCH (1,1) gave the best estimations for the variance process, which is in line with Brooks & Burke (2003) who corroborate that GARCH (1,1) gives the appropriate number of lags in order to capture the volatility clustering in financial data. At last, the maximum likelihood values showed that the DCC (1,1)-GARCH (1,1) was the model that gave the best fit to our data.

Table 4 shows the coefficient estimates from equation (5). Employing the hedge and safe haven definitions summarized in table 3, we will now report our findings.

5.1 Hedge Results

The estimated results from table 4 provide clear evidence that neither crude oil, the agriculture index, the CRIX index or the four cryptocurrencies Bitcoin, Ethereum, XRP and Litecoin possess hedging capabilities. As the estimates of γ_0 are comprehensively positive and highly significant for all the 19 indices under study. However, the agriculture index and Ethereum reports insignificant coefficients for respectively Norway (OSEBX) and Brazil (Ibovespa). This indicates that the agriculture index and Ethereum can serve as a weak hedge against the Norwegian and Brazilian equity markets. Despite these two events, the abovementioned assets can only serve as an effective diversifier. We find statistically proof of gold being a strong hedge for 13 of the equity markets (FTSE 100, DAX 30, CAC 40, SMI, OSEBX, OMXSPI, OMXC20, S&P 500, NASDAQ, ASX 200, Sensex, Nikkei 225, FTSE MIB), as the coefficients γ_0 are significantly negative. Additionally, gold can serve as a weak hedge against the two stock indices MSCI World and FTSE JSE and only a diversifier against the four remaining equity markets. Interestingly, Tether exhibits the same hedging capabilities as gold, and our results shows that Tether can act as a strong hedge against as many as 17 of the 19 indices in our sample. The only two equity markets Tether does not serve as a hedge against, is respectively the Norwegian (OSEBX) and Chinese (Shanghai) equity markets, where it can only serve as an effective diversifier. This indicates that Tether holds as a strong hedge against more equity markets than gold. Furthermore, table 4 provide some other interesting information. For every index, where both gold and Tether function as a strong hedge, the absolute value for all the coefficients are greater for gold than for Tether, except for the stock index Sensex. This implies that the contrary price movement with the individual stock indices are larger for gold than for Tether.

These results suggests that both gold and Tether have strong abilities to reduce the exposure to risk affiliated with contrary price movements when included in an equity portfolio. While the remaining assets in this article only have the abilities to smooth out the unsystematic risk by exposing the portfolio to multiple different assets which on average will yield excessive long-term returns and reduce the risk associated with holding a single stock in the portfolio.

5.2 Safe Haven Results

Regarding the safe haven capabilities, insignificant coefficients from table 4 indicate that all the assets can serve as a weak safe haven (in the 5% and 10% quantile) for most of the indices. On the other hand, under the most extreme market conditions (1% quantile), oil and the agriculture index can only serve as a weak safe haven for respectively one (Shanghai) and three (OSEBX, FTSE MIB, Shanghai) of the indices. While gold, CRIX and the four volatile cryptocurrencies Bitcoin, Ethereum, XRP and Litecoin exhibit slightly better results by serving as a weak safe haven against 7 to 14 of the indices. Among these assets we find clear statistical evidence that only Ethereum, Litecoin and gold have the capabilities to act as a strong safe haven, but only on a few occasions. Ethereum serves as a strong safe haven against FTSE MIB (in the 5% quantile) and ASX 200 (in the 10% quantile), Litecoin against OMXC20 (in the 5% quantile) and FTSE 100 (in the 10% quantile), and gold against Ibovespa (in the 1% quantile) and Shanghai (in the 5% quantile), given that their coefficients are significantly negative. As for the hedging capabilities, Tether exhibits the most interesting safe haven results. Overall, Tether is not a safe haven, strong or weak, on only three occasions, MSCI World (in the 5% quantile), FTSE 100 (in the 10% quantile) and SMI (in the 1% quantile). Furthermore, Tether exhibit strong safe haven capabilities at multiple occasions in the 5% quantile (4 times) and in the 1% quantile (10 times), indicating that Tether might be the superior safe haven tool among the chosen assets.

The findings from table 4 suggests that only Tether have the abilities to protect the investors wealth during extreme market turmoil and that it can be beneficial for market participants to move their funds to Tether during a crisis. Moreover, the reported results reveal that the other assets fail to protect investors wealth during great market shocks, with a few exceptions. However, it is important to notice that the safe haven role of Tether mainly holds for the most extreme market conditions (in the 1% quantile), and the safe haven capabilities holds for less stock markets than its hedging capabilities.

Table 4: DCC-GARCH estimates

The table presents the hedging, safe haven and diversification capabilities for the 9 assets against the 19 indices. More specifically, the estimates of the coefficients from eq. (5), for each pair of asset and index. An asset is a strong (weak) hedge if the "Hedge" row is significantly negative (0 or insignificant), an asset is a strong (weak) safe haven if the percentile rows (1%, 5% and 10%) are significantly negative (0 or insignificant), and lastly a diversifier if the "Hedge" row is significantly positive. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. . Significant at the 10% level.

Panel A: World index and the European countries

	MSCI World	FTSE 100	DAX 30	CAC 40	FTSE MIB	SMI	MOEX	OSEBX	OMXSPI	OMXC20
Gold										
Hedge	-0.0054	-0.0917***	-0.1573***	-0.1612***	-0.1365***	-0.1466***	0.0142***	-0.0680***	-0.1473***	-0.0660***
1% percentile	-0.0687	0.0408*	0.0435	0.0741*	0.0122	-0.0258	0.0539***	-0.0173	-0.0052	-0.0423.
5% percentile	-0.0301	-0.0061	-0.0045	0.0056	-0.0001	0.0125	0.0103	-0.0044	0.0268.	0.0049
10% percentile	0.0185	0.0008	0.0203	-0.0035	0.0024	-0.0004	0.0007	0.0011	0.0055	-0.0095
Oil										
Hedge	0.3411***	0.3125***	0.2140***	0.2679***	0.2855***	0.1916***	0.3104***	0.3910***	0.2340	0.0982***
1% percentile	0.0505***	0.0591**	0.0898***	0.0578***	0.0278*	0.1148***	0.0924***	0.0852***	0.0726***	0.0808**
5% percentile	0.0167.	-0.0046	0.0193	-0.0065	0.0098	0.0455**	0.0058	0.0003	-0.0084	0.0278.
10% percentile	0.0044	0.0165*	-0.0038	0.0153*	0.0024	-0.0098	-0.0055	0.0023	0.0172*	0.0118
Bitcoin										
Hedge	0.0601***	0.0693***	0.0768***	0.0617***	0.0549***	0.0353***	0.1018***	0.0812***	0.0823***	0.0372***
1% percentile	0.0172	0.0930***	0.0412**	0.0718***	0.0315*	0.0017	0.0611***	0.0311**	0.0558**	0.0013
5% percentile	0.0106	0.0014	0.0075	-0.0009	-0.0084	0.0064	0.0093	0.0052	0.0122	-0.0006
10% percentile	0.0030	-0.0067	-0.0015	-0.0047	0.0003	-0.0003	0.0040	-0.0045	-0.0029	0.0008*
Ethereum										
Hedge	0.0532***	0.0523***	0.0678***	0.0613***	0.0534***	0.0463***	0.0615***	0.0464***	0.0709***	0.0452***
1% percentile	0.0380*	0.0976***	0.0499**	0.0592***	0.0332	-0.0062	0.0203	0.0544**	0.0332.	-0.0067
5% percentile	0.0045	-0.0143	-0.0104	-0.0083	-0.0303*	-0.0146	0.0259	-0.0083	0.0166	-0.0154.
10% percentile	-0.0021	-0.0103	-0.0037	-0.0071	-0.0077	0.0031	-0.0004	-0.0052	-0.0136.	0.0067
XRP										
Hedge	0.0903***	0.0683***	0.0827***	0.0557***	0.0504***	0.0528***	0.0746***	0.0662***	0.0762***	0.0221***
1% percentile	0.0632**	0.0563***	0.0282***	0.0276***	0.0151	-0.0166	0.0252	0.0095.	0.0284*	0.0024
5% percentile	0.0142	-0.0030	0.0011	0.0006	-0.0040	0.0180*	0.0118	0.0024	0.0051	-0.0025.
10% percentile	0.0131	-0.0027	0.0016	-0.0015	0.0044	-0.0072	0.0021	-0.0037.	0.0007	0.0016.
Litecoin										
Hedge	0.0498***	0.0692***	0.0796***	0.0712***	0.0638***	0.0468***	0.1073***	0.0543***	0.0807***	0.0485***
1% percentile	0.0378*	0.0555***	0.0373.	0.0730***	0.0197	-0.0117	0.0358.	0.0088	0.0499*	0.0102
5% percentile	0.0200.	0.0044	0.0008	-0.0190	-0.0186	0.0038	-0.0079	0.0015	-0.0007	-0.0125*
10% percentile	0.0023	-0.0124*	-0.0024	0.0011	0.0045	0.0002	-0.0011	-0.0034	0.0025	0.0106**

CRIX										
Hedge	0.0209***	0.0254***	0.0381***	0.0246***	0.0100***	0.0117***	0.0751***	0.0151***	0.0263***	0.0097***
1% percentile	-0.0091.	0.0173**	0.0000.	0.0000*	0.0000*	0.0000	0.0051	0.0007	0.0000	0.0000*
5% percentile	0.0006	0.0013	0.0000	-0.0000	-0.0000	-0.0000	0.0037	0.0004.	0.0000	-0.0000
10% percentile	0.0029	-0.0019	-0.0000	-0.0000	0.0000	0.0000	-0.0013	-0.0003	0.0000	0.0000
Agriculture Index										
Hedge	0.1755***	0.1319***	0.1046***	0.0936***	0.1038***	0.0925***	0.1412***	0.1705	0.1262***	0.0569***
1% percentile	0.0710***	0.0994***	0.0719***	0.1216***	0.0323	0.0731***	0.0630***	0.0472	0.1012***	0.0481***
5% percentile	0.0212*	0.0054	0.0350***	0.0107	0.0278*	0.0258*	0.0041	0.0058	0.0003	0.0046
10% percentile	0.0002	-0.0013	-0.0007	0.0118	0.0099	-0.0001	-0.0046	-0.0024	0.0031	0.0051
Tether										
Hedge	-0.0121***	-0.0254***	-0.0312***	-0.0124***	-0.0444***	-0.0164***	-0.0107***	0.0124***	-0.0309***	-0.0395***
1% percentile	-0.0034	-0.0683***	-0.0034.	-0.0266***	-0.0270**	0.0168**	-0.0000	0.0103	-0.0402***	-0.0010
5% percentile	0.0073*	0.0071	-0.0038***	-0.0031	-0.0015	-0.0150***	-0.0000*	-0.0009	-0.0051	-0.0017
10% percentile	-0.0019	0.0124*	0.0008	-0.0004	0.0034	0.0011	-0.0000	-0.0057.	0.0021	0.0022

Panel B: North America, South America, Oceania, Asia and South Africa

	S&P 500	NASDAQ	Toronto	Ibovespa	S&PASX 200	FTSE JSE	Sensex	Nikkei 225	Shanghai
Gold									
Hedge	-0.0627***	-0.0569***	0.0725***	0.0870***	-0.0444***	0.0028	-0.0370***	-0.1177***	0.0147***
1% percentile	-0.0406	-0.0587	-0.0263	-0.0688***	0.0268***	-0.0103	0.0221	0.0179*	-0.0161
5% percentile	-0.0347	-0.0071	-0.0140	0.0013	0.0020	0.0080	0.0154	0.0026	-0.0207**
10% percentile	0.0355	0.0245	0.0067	-0.0004	-0.0008	0.0025	0.0046	0.0014	0.0069
Oil									
Hedge	0.3062***	0.2276***	0.4215***	0.2921***	0.1493***	0.2531***	0.1441***	0.1390***	0.1343***
1% percentile	0.0370***	0.0585***	0.0697***	0.0690***	0.0486***	0.0547***	0.0447***	0.0335**	-0.0044
5% percentile	0.0022	0.0008	0.0206*	-0.0051	0.0082*	-0.0077	0.0102.	0.0173**	-0.0039
10% percentile	0.0076.	0.0047	0.0026	0.0008	-0.0006	-0.0031	0.0014	0.0021	0.0019
Bitcoin									
Hedge	0.0416***	0.0473***	0.0684***	0.0445***	0.0859***	0.1105***	0.0567***	0.0749***	0.0359***
1% percentile	0.0238.	0.0232.	0.0956***	0.0000***	0.0341***	-0.0004	0.0419*	0.0387*	-0.0069
5% percentile	0.0022	0.0050	-0.0012	0.0000*	0.0016	0.0133	0.0275*	0.0136	-0.0052
10% percentile	0.0159**	0.0117*	0.0042	0.0000	-0.0033.	0.0025	-0.0029	0.0111	0.0035
Ethereum									
Hedge	0.0460***	0.0555***	0.0442***	-0.0004	0.0825***	0.0771***	0.0282***	0.0563***	0.0298***
1% percentile	0.0126	0.0198	0.1286***	0.0308	0.0373*	-0.0045	0.0827***	0.0125	-0.0130
5% percentile	0.0144	0.0044	-0.0096	-0.0044	0.0135	0.0086	0.0118	0.0063	0.0051
10% percentile	-0.0008	0.0102.	0.0023	0.0107	-0.0165*	0.0052	0.0044	-0.0061	0.0020

XRP									
Hedge	0.0872***	0.0934***	0.0987***	0.0789***	0.0752***	0.0893***	0.0292***	0.0756***	0.0763***
1% percentile	0.0770***	0.0537**	0.1504***	0.0071	0.0000***	-0.0074	0.0047	0.0000**	-0.0112
5% percentile	0.0050	0.0029	0.0032	0.0076	0.0000	0.0101	0.0024	0.0000	0.0002
10% percentile	0.0156.	0.0161.	-0.0058	0.0124.	0.0000	0.0019	0.0008	0.0000	0.0013
Litecoin									
Hedge	0.0298***	0.0313***	0.0344***	0.0232***	0.0973***	0.1097***	0.0602***	0.0640***	0.0334***
1% percentile	0.0288	0.0370*	0.1208***	0.0092	0.0128	0.0073	0.0072	0.0012	-0.0396.
5% percentile	0.0069	0.0033	-0.0075	0.0040	0.0094.	0.0140	0.0121	0.0099	-0.0049
10% percentile	0.0153*	0.0166*	0.0080	0.0062.	-0.0050	-0.0044	-0.0046	-0.0017	0.0109
CRIX									
Hedge	0.0129***	0.0145***	0.0222***	0.0107***	0.0583***	0.0648***	0.0302***	0.0815***	0.0239***
1% percentile	-0.0079	0.0011	0.0000***	0.0000.	0.0017	0.0000	-0.0000	0.0071	-0.0090
5% percentile	0.0028	-0.0019	-0.0000	0.0000	-0.0002	0.0000	0.0000	-0.0014	-0.0076
10% percentile	0.0029	0.0025*	0.0000	-0.0000	-0.0009	-0.0000	0.0000	0.0002	0.0056
Agriculture Index									
Hedge	0.1422***	0.1150***	0.1612***	0.2466***	0.0428***	0.1364***	0.1034***	0.1032***	0.0990***
1% percentile	0.0747***	0.0632***	0.0614***	0.0468***	0.0496***	0.0388***	0.0491***	0.0176**	0.0243.
5% percentile	0.0121	0.0025	-0.0003	-0.0062	0.0041	-0.0041	0.0053	0.0054	-0.0091
10% percentile	0.0035	0.0031	-0.0009	0.0059.	-0.0025	0.0028	-0.0001	0.0007	0.0030
Tether									
Hedge	-0.0054***	-0.0018***	-0.0152***	-0.0682***	-0.0307***	-0.0245***	-0.0705***	-0.0332***	0.0110***
1% percentile	-0.0034***	-0.0085***	-0.0000***	-0.0000***	-0.0175	-0.0242*	-0.0000***	-0.0069	0.0000
5% percentile	0.0000	-0.0007	-0.0000	-0.0000	-0.0117.	0.0015	-0.0000*	-0.0032	-0.0000
10% percentile	-0.0000	0.0010	-0.0000	-0.0000	0.0011	-0.0071	-0.0000	-0.0017	0.0000

Note: "Hedge" represents γ_0 , "1% percentile" represents γ_1, "5% percentile" represents γ_2, "10% percentile" represents γ_3 from equation (5). Panel A provides the estimation results for the World index and the European countries, while Panel B provides the estimation results for the countries in North America, South America, Oceania, Asia and South Africa.

5.3 Portfolio Analysis

An asset possessing strong hedging capabilities would not necessarily be an effective hedge, but only imply that the asset has strong abilities to reduce the portfolio risk affiliated with contrary price movements. On the other hand, an effective hedge should reduce the risk of the portfolio remarkable without having a great impact on the expected return. As we found strong evidence for both gold and Tether being a hedge, we will in this section conduct a portfolio analysis in order to answer research question 2 in our paper.

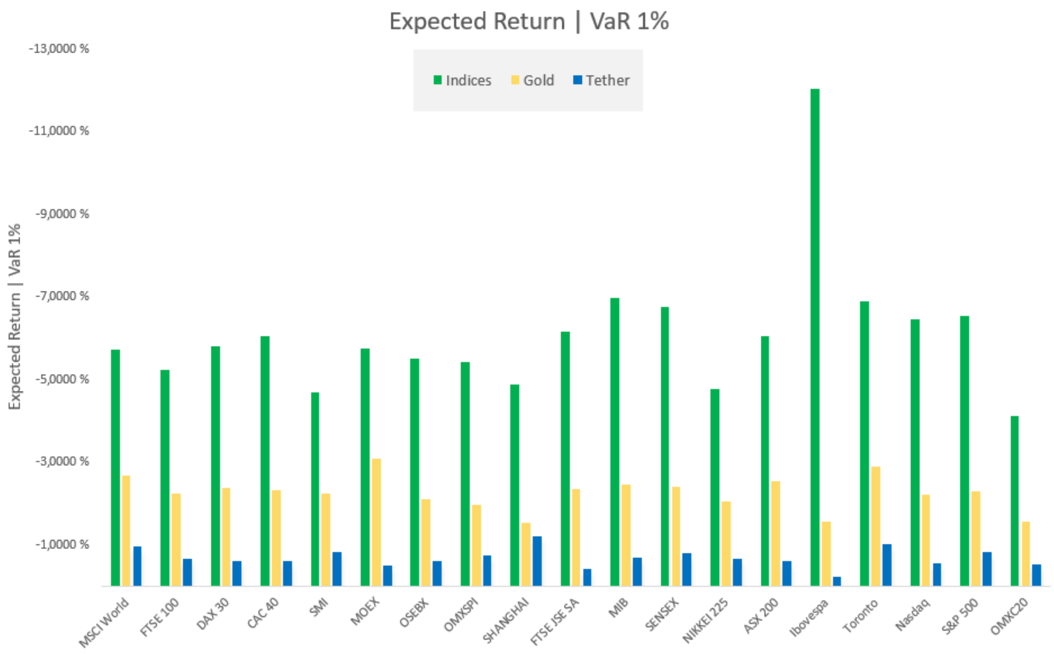
The portfolio analysis will provide the three key descriptive measures, expected return, standard deviation and value at risk (VaR), in order to get a greater understanding of the risk-return relationship of portfolios consisting of index and, gold or Tether. The figures in this section is derived from the results showed in appendix A. We have chosen to analyze portfolios with respectively 100% invested in the index, as well as the minimum variance portfolios for the combinations of index and gold, and index and Tether. The portfolio analysis is conducted on a sample constrained by Tether, as a result, the sample spans from 9th of November 2017 to 8th of December 2021.

Figure 1 exhibit information of the average return of the different portfolios when the given index is beneath the VaR (1%, 5% and 10% threshold) for the applicable index. As the VaR quantifies the possible loss of a portfolio within a given level of probability, will the expected return given the VaR reveal how well the portfolio performs during market distress, i.e., the hedging capabilities against downside risk. It is worth mentioning that this portfolio analysis will only test the hedging capabilities and not the safe haven capabilities, since there is no rebalancing of the portfolios throughout the period. Figure 1 shows that both Tether and gold reduces the downside risk of the portfolios significantly. On every occasion combining the index with either gold or Tether reduces the total loss for an investor, compared to a portfolio consisting solely of the index. This shows that a risk adverse investor would benefit from including either Tether or gold in the portfolio, in order to be well protected against extreme market downdraws. Additionally, the figure display that Tether is advantageous compared to gold regarding the loss protection capabilities, as the expected loss in times of market turmoil on the portfolios containing Tether is less than for portfolios containing gold. The findings hold for all the three VaR thresholds and for every stock index.

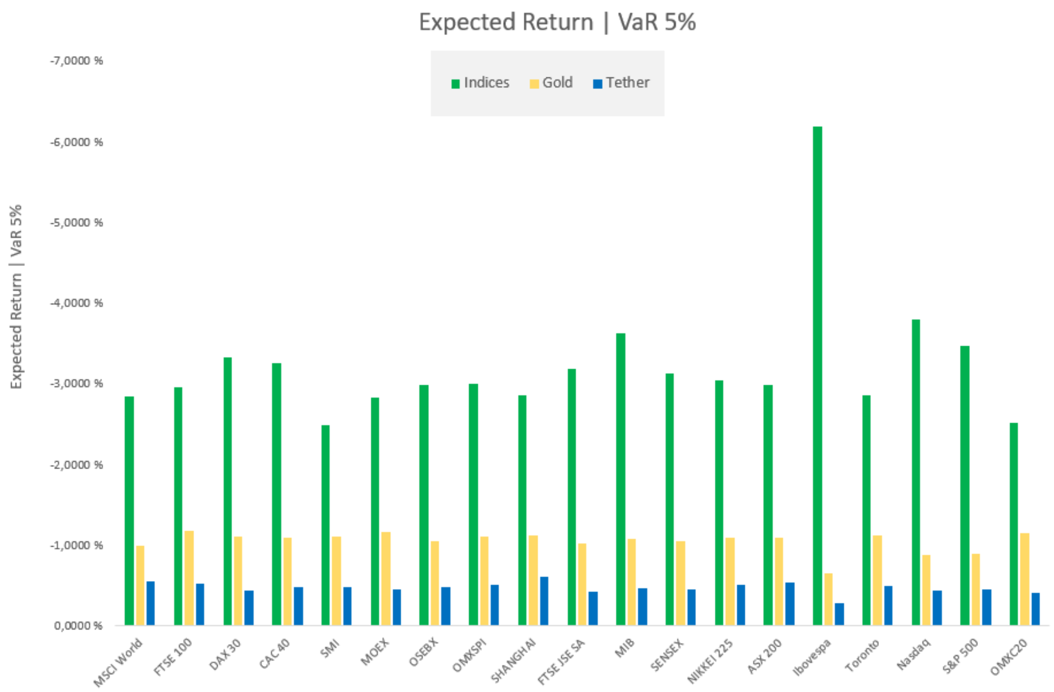
Figure 1: Downside risk measure

Average return on portfolios when the given index is beneath the value at risk threshold of (i) 1%, (ii) 5%, and (iii) 10% for the applicable index, between 9th November 2017 and 8th December 2021. Green represents 100% invested in the index, yellow represents the minimum variance portfolio of gold and the index, while blue represents the minimum variance portfolio of Tether and the index.

Panel A: Value at Risk threshold 1%



Panel B: Value at Risk threshold 5%



Panel C: Value at Risk threshold 10%

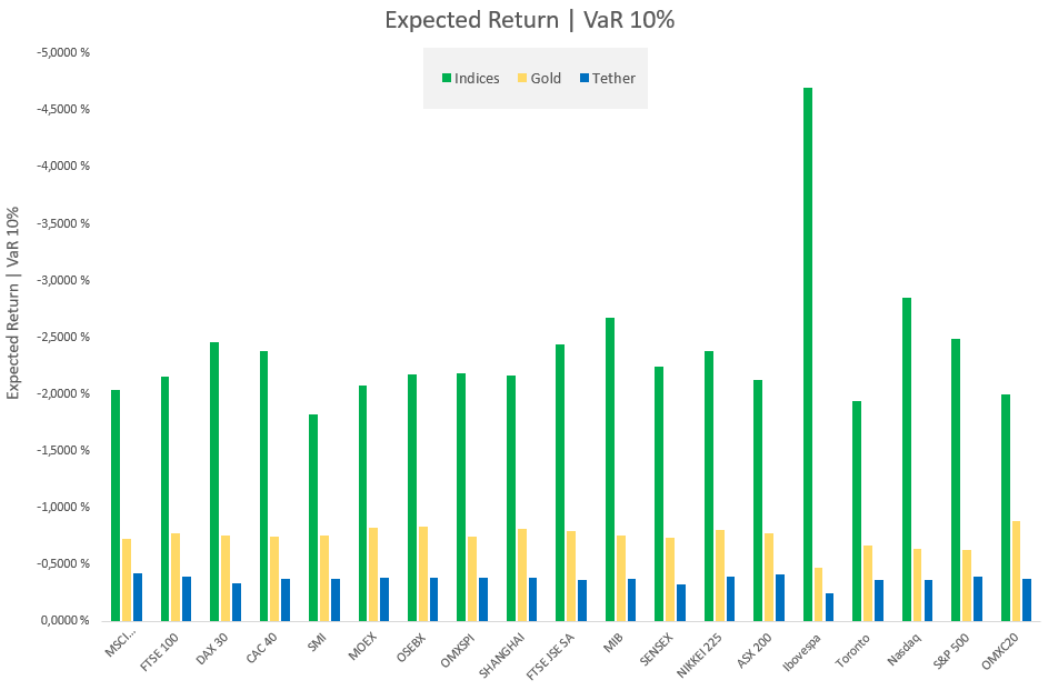


Figure 2 provide the descriptive measures expected return and standard deviation of the abovementioned portfolios[10]. This gives the overall picture of the hedging capabilities, as it covers the entire time horizon and not only the days with the most extreme market downdraws. Figure 1 revealed that Tether is superior regarding loss protection, but figure 2 disclose that the significant reduction in standard deviation for the portfolios including Tether also results in a large reduction in the portfolios expected return, when looking at the entire period. Contrastingly, figure 2 shows that gold got the capabilities of reducing the risk significantly without having a great impact on the expected return**.** The figure shows that the standard deviation for all portfolios including gold is lower than the portfolios consisting solely of the indices. Gold also manages to increase the expected return of the portfolio for 11 of the indices (see appendix A). For the remaining indices except for NASDAQ, a portfolio including gold will only lower the expected return slightly compared to the reduction in standard deviation, giving a positive volatility vs. expected return tradeoff[11]. To sum up, even though both gold and Tether possesses hedging capabilities (see chapter 5.1), does the descriptive portfolio analysis reveal that only a portfolio including gold will increase the performance when looking at the expected return-standard deviation relationship.

[10] 100% invested in index, minimum variance portfolio of index and gold, and minimum variance portfolio of Tether and index

[11] For NASDAQ, there is a reduction in the standard deviation of 90.7% and reduction in the expected return of 89,9%.

Figure 2: Expected return – Volatility relationship

Average return and standard deviation of portfolios between 9th November 2017 and 8th December 2021. Green represents 100% invested in the index, yellow represents the minimum variance portfolio of gold and the index, while blue represents the minimum variance portfolio of Tether and the index.

Note: The portfolio consisting solely of the index Ibovespa (green) is neglected from the figure due to visibility. As the standard deviation of Ibovespa is far higher than the remaining indices.

6. Discussion

The reported results in section 5.1 revealed that both gold and Tether possessed hedging capabilities against the majority of the indices, while the rest of the assets under study lacked these capabilities. Our findings are in line with previous literature of gold being a hedging tool, which is the asset in our study where there are great mutually agreement of its role as a hedging tool (Baur & Lucey, 2010; Baur & McDermott, 2010). The case is different for the cryptocurrencies, with Tether as an exception, where we found no evidence for the four volatile cryptocurrencies being a hedge[12]. This complements previous literature where the findings on the hedging capabilities among the cryptocurrencies have been contrary. An explanation for the lack of hedging capabilities among the four abovementioned cryptocurrencies, could be that these cryptocurrencies are highly volatile as table 1 revealed. This shows that cryptocurrencies are still emergent and not yet fully accepted by firms and investors, and instead used as speculative investment alternatives. This implies that investors still do not consider these cryptocurrencies to be a store of value. Since cryptocurrencies do not have any intrinsic value as stocks, their price is driven by investors demand, and without the confidence from the majority of the investors that they can serve as a store of value, cryptocurrencies cannot serve as a hedging tool. The lack of trust investors have against the four volatile cryptocurrencies hedging capabilities have been strengthened by the covid-19 pandemic, where the cryptocurrencies had the opportunity to prove they were a beneficial store of value, but instead they were still exposed to large price fluctuations.

On the last cryptocurrency, Tether, we found strong evidence that it can serve as a hedge, which is in line with previous literature (Conlon et al., 2020). An explanation for this could be that investors in the cryptocurrency market acknowledges Tether as a liquid[13] and steady coin in contrast to the other highly volatile cryptocurrencies. This makes Tether a suitable place to move funds to when investors expect a drop in their other cryptocurrency holdings, i.e., Tether would be an easy and secure place to channel the funds to, and at the same time keep the holdings in the cryptocurrency market. This will create adverse price movements between Tether and the more volatile cryptocurrencies. These adverse price movements can be further reinforced, as the US dollar have been proved to function as a safe haven its price would increase during market turmoil (Wen & Cheng, 2018), resulting in an appreciation of Tether since it is pegged to the US dollar. As the price of Tether remains quite constant throughout

[12] Bitcoin, Ethereum, Litecoin, XRP
[13] See appendix B

the whole time period, and with some elements of the abovementioned small spikes (drops) of adverse price movements related to the higher (lower) demand and its peg to the US dollar, the average correlation would become slightly negative[14]. I.e., Tether will be a hedge against the other cryptocurrencies, but with coefficients close to zero, which is confirmed by Wang et al., (2020). And because our results show a positive correlation between the volatile cryptocurrencies and the indices in our study, this could explain why Tether proves to be a hedge against the stock indices, but with absolute values close to zero. The constant price of Tether and small spikes (drops) of adverse price movements with the stock indices are verified by table 1 and table 4, where we can see a mean return close to zero, and strong safe haven results during the worst market shocks (1% percentile).

Regarding the safe haven capabilities from section 5.2, the results were vague, suggesting that only the stablecoin Tether successfully functioned as a strong safe haven towards more than two stock indices. A reason for this could be that Tether is a well-established and liquid stablecoin, continuing to maintain its value, as discussed above. This makes it an attractive asset for investors to flee to, and investors in the applicable stock markets seem to put money into Tether, creating adverse movement between Tether and the stock indices in times of market turmoil. Interestingly, gold fail to be a safe haven which is in contrast to previous literatures findings. An explanation for this could be that in our dataset, a large fraction of the worst market downdraws globally occurred during the covid-19 pandemic, and according to Cheema & Szulcsyk (2022) and Drake (2021) gold did not function as a safe haven during the Covid-19 pandemic. Concerning Bitcoin, earlier findings on the safe haven capabilities are disperse. Our results subsidize this ongoing debate, suggesting that Bitcoin is a poor safe haven towards different equity markets across the globe. Klein et al. (2018) argued that the poor safe haven results for Bitcoin also holds for the broad CRIX index, as Bitcoin is the largest component in the index. Furthermore, our results revealed that none of the other volatile cryptocurrencies could serve as a safe haven. An explanation for this could be that since there is a tight co-movement and spillover effect between the cryptocurrencies, the poor safe haven results for Bitcoin should hold for the rest of the volatile cryptocurrencies in our study (Bouri et al., 2019; Qiao et al., 2020; Ji et al., 2019).

As for the portfolio analysis, not surprisingly, Tether exhibit good capabilities to offset the downside risk when included in a portfolio with the index. However, the results also revealed

[14] Table 1 shows that that the price of Tether remains quite constant, as its mean is close to zero, but the maximum and minimum values reveal that Tether is subject to some distinct price fluctuations.

that the risk reducing capabilities come at the expense of the expected return, showing that an investor would not benefit from keeping Tether constantly in the portfolio. A reason for this could be that Tether is pegged to the US dollar and constantly offer a limited return which is also revealed by table 1. The portfolio analysis disclosed insufficient returns and the safe haven capabilities of Tether were mainly observed in the worst percentile. This indicates that investors only use Tether, rightly so, on the most extreme occasions and when they are especially stressed.

As argued, Tether exhibited low return on average making it an ineffective hedge. Contrastingly, table 1 disclosed that gold exhibited higher returns throughout the sample period, which makes it a more effective hedge as revealed from the portfolio analysis. As a result, gold offers a good protection against the downside risk as well as the expected return either increases or drops insignificantly when embedded into a portfolio with individual indices. These findings are broadly established in the literature.

6.1 Limitations

There are a few limitations considering the results in our study. Firstly, since the introduction of cryptocurrencies we have witnessed a highly bullish stock market, with few market downdraws. The fact that the time horizon in our paper do not include several market downdraws can lead to spurious findings, as the hedging and safe haven role among the assets need to be confirmed by several periods of market distress in order to reveal their true ability. Furthermore, due to its short lifetime, the cryptocurrency market is proved to be extremely volatile and during the pandemic it has risen to new peaks. Consequentially, many authors have classified the cryptocurrency market as a speculative bubble. This makes the future role of cryptocurrencies as a hedging and safe haven tool uncertain, and our findings might not be valid in the near future.

Secondly, our choice of method limits the interpretation of the safe haven results for the assets in this study. The main regression (see eq. 5) is based on dummy variables associated with single days of extreme market turmoil, given by the 1%, 5% and 10% threshold, and not with a higher frequency or by certain periods of market downdraws. This will disclose how investors react to market turmoil and the immediate repercussion of their actions, rather than their acceptance of the asset as an adequate safe haven asset. This choice also makes our safe haven results heavily shaped by the covid-19 pandemic, as most of the severe days in our sample occurs during this period, thereby our results will be densely influenced by how investors reacted during the pandemic.

Finally, there are a lot of skepticism concerning the liquidity in the cryptocurrency market, which is an important feature in order to be a useful hedge or safe haven. Several studies have pointed out that the liquidity among these currencies are low compared to traditional financial assets. Generally speaking, since cryptocurrencies are not as broadly adopted as an investment class compared to other financial assets, the limited liquidity might threaten our findings. However, the covid-19 pandemic has affected cryptocurrencies in several ways. Corbet et al. (2022) argue that the trading volume have increased during covid-19 pandemic, making the cryptocurrency market more liquid. Appendix B displays that Tether is a major source of liquidity within the cryptocurrency market, and that it is highly liquid compared to the broadly traded stock index S&P 500. This is a clear indication that the liquidity would not halt the findings on the hedging and safe haven capabilities of Tether in this paper.

7.Conclusion

The aim of this article has been to assess the hedging, safe haven and diversification capabilities among the growing asset class cryptocurrencies and compare this to more well-established assets, such as gold, oil and the agriculture index. Our paper provides useful insight to the ongoing debate on cryptocurrencies role as a hedging and safe haven tool, as previous research on this topic is disperse. We infiltrate this debate by including several different cryptocurrencies and multiple indices across the globe. Additionally, our paper extends previous literature by highlighting the practical significance of including the potential hedging assets into a portfolio.

Our answer to RQ 1 is based on the time-varying correlation, more specifically a DCC-GARCH model was utilized. We found strong statistical evidence of both gold and Tether having the abilities to offset the risk associated with contrary price movements. I.e., gold and Tether are both good candidates for an investor to use as a hedging tool, while the other assets only functioned as an effective diversifier. Secondly, Tether was the only asset in our study that showed proof of being a safe haven asset, by offsetting loss during the absolutely worst days (1% quantiles) and thereby serving as a strong safe haven against multiple stock indices during these days. The remaining assets lacked these abilities to protect investors wealth during stormy weather.

In answer to RQ 2 we conducted a portfolio analysis, namely, to compare the hedge effectiveness of gold and Tether. Here we clearly saw that including gold in the portfolio was more beneficial than including Tether. Despite both assets showing great capabilities of offsetting the downside risk of a portfolio, gold was the only one doing so without heavily reducing the expected return of the portfolio.

To conclude our main research question, even with the introduction of cryptocurrencies, gold is still the superior hedging tool. On the flip side, we conclude that Tether is the superior safe haven tool, but only on the most severe market days. This shows that during the covid-19 pandemic, golds capability as a safe haven tool has vanished.

The findings in our paper can be utilized by investors who are exposed to one of the 19 equity indices in our study. The results suggest that investors should hold gold in their portfolio, and in times of extreme market uncertainty it may be useful to channel some of the portfolio holdings to Tether in order to reduce the loss. In addition, our results may imply that investors also could benefit from moving their funds from other cryptocurrencies to Tether in times of market turmoil, in order to both reduce loss and keep the holdings in the cryptocurrency market. However, this has not been the aim of our paper and our results are only an indication, but it is something that can be examined in further research. It would also be interesting to conduct an expanding or rolling window portfolio analysis, in order to test whether an investor actually would benefit from moving the funds to Tether in times of extreme market shocks. This will highlight how much loss an investor may reduce, when reacting to a market shock. Another interesting research that can be carried out, is to examine how the cryptocurrencies that demonstrate hedging or safe haven capabilities, performs in a portfolio with multiple assets, rather than merely the index.

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Appendices

Appendix A:

A.1. Value at Risk measures

Table A1 shows the Value at Risk measures with thresholds of (i) 1%, (ii) 5%, (iii) 10% for the 19 indices. The time horizon is 9th of November 2017 to 8th of December 2021.

A.2. Hedging properties

Table A2 shows the expected return, standard deviation and expected return of portfolios when the applicable index is beneath the Value at Risk reported in Table A1 for that index. For each index we report three portfolios with respectively 100% invested in the index, the minimum variance portfolio of index and gold, and the minimum variance portfolio of index and Tether. The time horizon is 9th of November 2017 to 8th of December 2021.

Table A1: Value at Risk measures

Value at Risk	MSCI World	FTSE 100	DAX 30	CAC 40	FTSE MIB	SMI	MOEX	OSEBX	OMXSPI	OMXC20
VaR (1%)	-0,0319	-0,0356	-0,0399	-0,0421	-0,0382	-0,0294	-0,0352	-0,0370	-0,0348	-0,0294
VaR (5%)	-0,0164	-0,0164	-0,0189	-0,0187	-0,0211	-0,0143	-0,0162	-0,0169	-0,0187	-0,0170
VaR (10%)	-0,0092	-0,0112	-0,0141	-0,0125	-0,0145	-0,0097	-0,0113	-0,0114	-0,0111	-0,0124

Value at Risk	NASDAQ	S&P 500	Toronto	Ibovespa	ASX 200	FTSE JSE	Nikkei 225	Sensex	Shanghai
VaR (1%)	-0,0452	-0,0438	-0,0305	-0,0711	-0,0349	-0,0338	-0,0401	-0,0375	-0,0378
VaR (5%)	-0,0231	-0,0198	-0,0133	-0,0383	-0,0164	-0,0198	-0,0205	-0,0171	-0,0184
VaR (10%)	-0,0154	-0,0111	-0,0081	-0,0271	-0,0094	-0,0145	-0,0138	-0,0113	-0,0126

Table A2: Hedging properties

Hedging properties	MSCI World			FTSE 100			DAX 30			CAC 40		
	MSCI World	Gold	Tether	FTSE 100	Gold	Tether	DAX 30	Gold	Tether	CAC 40	Gold	Tether
Expected Return	0,0004	0,0004	0,0001	0,0000	0,0002	0,0000	0,0002	0,0003	0,0000	0,0003	0,0003	0,0000
Standard Deviation	0,0111	0,0072	0,0046	0,0115	0,0071	0,0047	0,0132	0,0075	0,0048	0,0128	0,0073	0,0048
Expected Return | VaR (1%)	-0,0573	-0,0268	-0,0095	-0,0522	-0,0225	-0,0066	-0,0579	-0,0237	-0,0059	-0,0604	-0,0232	-0,0060
Expected Return | VaR (5%)	-0,0284	-0,0100	-0,0056	-0,0296	-0,0117	-0,0052	-0,0333	-0,0111	-0,0044	-0,0325	-0,0110	-0,0048
Expected Return | VaR (10%)	-0,0204	-0,0073	-0,0043	-0,0216	-0,0078	-0,0040	-0,0246	-0,0075	-0,0033	-0,0237	-0,0074	-0,0037

Hedging properties	FTSE MIB			SMI			MOEX		
	FTSE MIB	Gold	Tether	SMI	Gold	Tether	MOEX	Gold	Tether
Expected Return	0,0002	0,0003	0,0000	0,0003	0,0003	0,0001	0,0006	0,0004	0,0001
Standard Deviation	0,0145	0,0077	0,0047	0,0100	0,0067	0,0046	0,0117	0,0074	0,0048
Expected Return | VaR (1%)	-0,0696	-0,0246	-0,0069	-0,0469	-0,0222	-0,0083	-0,0574	-0,0308	-0,0051
Expected Return | VaR (5%)	-0,0362	-0,0108	-0,0047	-0,0249	-0,0110	-0,0049	-0,0282	-0,0117	-0,0046
Expected Return | VaR (10%)	-0,0267	-0,0076	-0,0037	-0,0182	-0,0075	-0,0037	-0,0207	-0,0082	-0,0038

Hedging properties	OSEBX			OMXSPI			OMXC20		
	OSEBX	Gold	Tether	OMXSPI	Gold	Tether	OMXC20	Gold	Tether
Expected Return	0,0004	0,0004	0,0001	0,0005	0,0004	0,0001	0,0006	0,0004	0,0001
Standard Deviation	0,0116	0,0071	0,0048	0,0117	0,0072	0,0047	0,0110	0,0073	0,0047
Expected Return | VaR (1%)	-0,0549	-0,0209	-0,0060	-0,0541	-0,0196	-0,0073	-0,0411	-0,0156	-0,0051
Expected Return | VaR (5%)	-0,0299	-0,0105	-0,0048	-0,0300	-0,0111	-0,0051	-0,0252	-0,0115	-0,0042
Expected Return | VaR (10%)	-0,0217	-0,0083	-0,0038	-0,0218	-0,0075	-0,0039	-0,0200	-0,0088	-0,0037

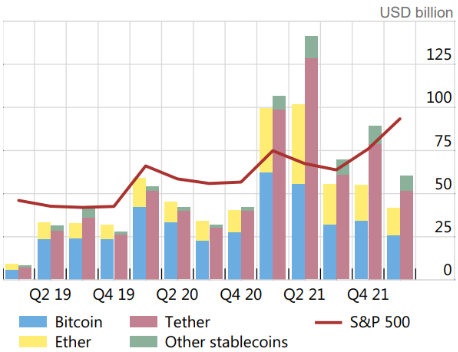
Hedging properties	NASDAQ			S&P 500			Toronto		
	NASDAQ	Gold	Tether	S&P 500	Gold	Tether	Toronto	Gold	Tether
Expected Return	0,0008	0,0004	0,0001	0,0006	0,0004	0,0001	0,0003	0,0003	0,0001
Standard Deviation	0,0149	0,0078	0,0049	0,0134	0,0075	0,0047	0,0117	0,0074	0,0046
Expected Return | VaR (1%)	-0,0646	-0,0220	-0,0054	-0,0655	-0,0228	-0,0083	-0,0688	-0,0288	-0,0101
Expected Return | VaR (5%)	-0,0380	-0,0088	-0,0044	-0,0347	-0,0089	-0,0046	-0,0286	-0,0112	-0,0050
Expected Return | VaR (10%)	-0,0285	-0,0064	-0,0036	-0,0248	-0,0063	-0,0039	-0,0194	-0,0067	-0,0037

Hedging properties	Ibovespa			ASX 200			FTSE JSE		
	Ibovespa	Gold	Tether	ASX 200	Gold	Tether	FTSE JSE	Gold	Tether
Expected Return	-0,0001	0,0003	0,0000	0,0002	0,0003	0,0000	0,0002	0,0003	0,0000
Standard Deviation	0,0254	0,0088	0,0052	0,0114	0,0072	0,0046	0,0135	0,0080	0,0049
Expected Return | VaR (1%)	-0,1203	-0,0155	-0,0021	-0,0606	-0,0255	-0,0061	-0,0616	-0,0236	-0,0042
Expected Return | VaR (5%)	-0,0619	-0,0066	-0,0028	-0,0299	-0,0110	-0,0054	-0,0319	-0,0103	-0,0043
Expected Return | VaR (10%)	-0,0470	-0,0047	-0,0025	-0,0212	-0,0077	-0,0041	-0,0244	-0,0080	-0,0037

Hedging properties	Nikkei 225			Shanghai			Sensex		
	Nikkei 225	Gold	Tether	Shanghai	Gold	Tether	Sensex	Gold	Tether
Expected Return	0,0002	0,0003	0,0000	0,0001	0,0002	0,0000	0,0006	0,0004	0,0001
Standard Deviation	0,0126	0,0075	0,0050	0,0118	0,0074	0,0050	0,0129	0,0075	0,0049
Expected Return | VaR (1%)	-0,0478	-0,0204	-0,0064	-0,0488	-0,0154	-0,0120	-0,0676	-0,0240	-0,0081
Expected Return | VaR (5%)	-0,0304	-0,0109	-0,0051	-0,0286	-0,0112	-0,0060	-0,0313	-0,0106	-0,0045
Expected Return | VaR (10%)	-0,0238	-0,0081	-0,0039	-0,0217	-0,0082	-0,0038	-0,0225	-0,0073	-0,0032

Appendix B

The figure shows the average daily trading volumes of Bitcoin, Tether, Ether, other stablecoins and S&P 500 in the period between 2019 to 2022.



Source: FSB (2022)

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