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Master's Thesis

The Rise of Cryptocurrencies as an Investment Hedge

The Shift from Traditional Investment Hedges: Can Cryptocurrencies Replace Bonds as an Investment Hedge?

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Abstract

This thesis uses a dynamic conditional correlation (DCC) model to investigate the correlation between major cryptocurrencies, US government bonds and the S&P 500 and MSCI World indices in order to establish the hedge, safe haven and diversifier properties of cryptocurrencies. While US Treasuries have exhibited negative correlation and hedging properties against equity risk for decades, recent extreme market conditions have caused investors to look for alternative asset classes for hedging. Having experienced rapid market growth and increasing investor interest in the past few years, cryptocurrencies could provide a solution to hedging for when bonds are no longer able to protect against equity risk. Our empirical results, however, indicate that at present cryptocurrencies should only be considered as a complement rather than a substitute to bonds in an investment portfolio. While certain cryptocurrencies showed some hedging capabilities, most cryptocurrencies examined in this study only exhibited diversifier benefits. Although cryptocurrencies are therefore unlikely to fully replace bonds as a hedge at present, cryptocurrencies are a relatively new asset class with a demonstrated capability for growth and resilience, indicating immense potential for future development, especially in light of the creation of a new decentralized financial system and its impact on the economy in the years to follow.

Key words: Cryptocurrency, Hedging, DCC-GARCH, US Treasury Yields, S&P 500, MSCI World Index

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1. Introduction and Background

The traditional 60/40 stock-bond portfolio is designed to provide growth through stocks while decreasing volatility through bonds. In times of market turmoil, this strategy relies on the inverse relationship between stocks and bonds; if stocks are expected to crash, this will be counterbalanced by the fixed income allocation of the portfolio. However, if bond yields are low, this part of the portfolio will neither contribute to growth in the portfolio or act as a hedge to mitigate risk. Over the past few decades, US Treasury yields have been regarded as some of the world's safest financial assets and have been widely used as a hedge against equity risk. At present, US Treasury yields are falling despite signs of economic recovery and rising interest rates and inflation. As bonds are subject to interest rate risk and especially sensitive to changes in inflation, higher rates would be detrimental to the value of bonds that have already been issued, particularly in the short-term.

Investors have conventionally relied on fixed income for both yields and hedging but as bonds are no longer providing yields or adequately mitigating risk, investors are looking for alternative asset classes to use as an investment hedge. In light of their increasing popularity, cryptocurrencies have begun to attract the attention of investors as an alternative hedge, especially considering their similarities with gold, which has acted as another traditional hedge alongside bonds. The cryptocurrency market has seen enormous growth in terms of the number of currencies, transaction volume and consumer base since the invention of Bitcoin in 2008. By 2021, the total market value of cryptocurrencies has surpassed 2 trillion USD and out of thousands of cryptocurrencies, Bitcoin is the largest and accounts for nearly half of the total cryptocurrency market with a market capitalization of over 1 trillion USD (see Appendix 4). The entire cryptocurrency market is based on the idea that money can be sent and received by anyone, anywhere in the world, without a financial intermediary. The blockchain technology behind cryptocurrencies is what makes them able to have this decentralized characteristic and reliability. The rapid growth of cryptocurrencies and innovation of technology have captured attention from many investors and researchers. Cryptocurrencies' prospects of greater efficiency, less bureaucracy, and more transparency could explain their potential to outperform traditional financial assets offered by conventional financial institution products.

Following the recent rise of cryptocurrencies, research and literature have emerged on the prospects of cryptocurrencies as a mainstream investment option, extending to their utility as a hedge. In the 2016(b) paper, Dyhrberg examined the hedging capabilities of Bitcoin against the FTSE stock index and fluctuations in the USD, indicating that Bitcoin possesses the same hedging capabilities as gold, which has traditionally been used alongside bonds to hedge against stock market risk. Previous research is predominantly limited to examining the hedging capabilities of bitcoin; however, we will extend this to the six main cryptocurrencies, which are representative of the top-heavy cryptocurrency market as a whole. Despite not being affected by inflation and government control, cryptocurrencies have generally been regarded as ambiguous and speculative financial instruments. As such, we are interested in finding out if, despite their speculative reputation, cryptocurrencies can act as an effective hedge against stock market risk. And potentially even more so than US government bonds, which have traditionally been regarded as some of the safest financial assets in the world. This is corroborated by the possibility that cryptocurrencies are not only a hedge against inflation but also a hedge against all the negative consequences, such as political instability and social disruption, that accompany it (Acheson, 2020). The aim of this thesis is to address and answer these questions.

1.1 Purpose and Research Question

With expected returns below 1 per cent, US treasuries are not particularly attractive assets to investors in terms of yields. Consequently, reducing portfolio volatility can be seen as the main purpose of US treasuries, which move in the desired direction to reduce stock market volatility. However, the overall effect is close to negligible as they do not move enough to have the same impact on the portfolio and adjusted for the effect of inflation, returns can even be negative. Regardless of this, US treasuries are still widely used; although to a lesser extent, as a diversifier or a hedge due to their negative correlation with the stock markets. This study aims to examine if cryptocurrencies also exhibit a negative correlation with the stock market and could therefore replace fixed income as a portfolio hedge.

The purpose of this study is to investigate the hedging properties of cryptocurrencies in relation to stock market returns. In order to explore this, we will model the co-movements of major cryptocurrencies with the S&P 500 and MSCI World indices. We will relate our discussion to the current and expected levels of 5-year and 10-year US Treasury prices in addition to the impacts of current economic conditions, such as inflation and interest rate fluctuations. By investigating the correlation between cryptocurrencies and the stock market, using the dynamic conditional correlation (DCC) model, the main purpose of this study is to answer the following research question:

Can cryptocurrencies replace bonds as an investment hedge?

Consequently, this thesis will establish what kind of hedging capabilities cryptocurrencies have and if cryptocurrencies can be used in place of US government bonds to hedge against stock market return risk. This involves exploring different categories of hedging and determining whether cryptocurrencies should be considered as a hedge, a safe haven or a diversifier based on the level and magnitude of correlation they exhibit with the stock market indices examined in this study.

2. Description of Cryptocurrencies

This section defines and outlines the properties of cryptocurrencies as an entity in addition to the specific characteristics of the six cryptocurrencies investigated in this study in order to highlight any significant differences and similarities that may have an impact on the hedging properties of the individual cryptocurrencies. Cryptocurrencies are broadly defined as virtual or digital money, which takes the form of tokens or coins (Conway, 2021). As stated in Satoshi Nakamoto's white paper that introduced cryptocurrencies in 2008, Bitcoin was created as an electronic payment system that; instead of trust, is based on cryptographic proof, which allows any two willing parties to transact directly with each other without a third party (Nakamoto, 2008). By design, cryptocurrencies do not require a central authority and are unaffected by government control and manipulation. Although cryptocurrencies operate independently of governments and banks, they can be exchanged like any physical currency. Most cryptocurrencies use a blockchain technology, which is a public ledger that contains records that are structured in blocks and chained together with cryptography. Blockchain technology was first introduced by bitcoin and has since been adapted and used as a foundation by other cryptocurrencies, as it effectively resolved the double-spending problem associated with digital currencies without the need for a central authority or third party (Nakamoto, 2008). Cryptocurrencies are generally created through a mining process and processed and traded across decentralized platforms.

Cryptocurrencies other than bitcoin are referred to as alternative cryptocurrencies known as "altcoins." Altcoins also use blockchain technology but have underlying differences with Bitcoin. Altcoins were generally designed to improve on Bitcoin's flaws; including mining and transaction speed, and also differ in terms of other intrinsic properties such as supply (Frankenfield, 2021). Altcoins account for approximately 40 per cent of the total cryptocurrency market and include mining-based cryptocurrencies, stablecoins, security tokens and utility tokens (Frankenfield, 2021). Due to the absence of regulation and defined criteria for investment, the altcoin market involves less investors and liquidity, leading to more volatile prices compared to Bitcoin (Conway, 2021).

2.1 Bitcoin

Released in 2009, Bitcoin (BTC) is the largest cryptocurrency by market capitalization, user base and popularity. Bitcoin uses a proof-of-work (PoW) system in order to release new tokens (Nakamoto, 2008). This involves solving a complex mathematical problem on the Bitcoin network, which both produces new bitcoins and makes the payment network secure (Frankenfield, 2020). Bitcoin is not regulated by a central authority and is instead backed by millions of computers across the world (Frankenfield, 2020). Bitcoin is deflationary by design as it has a limited supply, which is capped at 21 million. Bitcoin has a market capitalization of approximately 1 trillion USD, meaning that it accounts for nearly half of the global market capitalization for cryptocurrencies, which at the end of March 2021 was at around 2 trillion USD (Kharif, 2021).

One of the criticisms of Bitcoin is its mining speed; with a block time of approximately 10 minutes, it is considerably more time-consuming than that of other cryptocurrencies (IG, 2021).

2.2 Ethereum

Ethereum, launched in 2015, is a decentralized platform on which the second-largest cryptocurrency by market capitalization, Ether (ETH), is traded (Conway, 2021). In late March 2021, Ether had a market capitalization of nearly 200 billion USD (see Appendix 4). Ethereum is a programmable blockchain that enables its users to code and release their own decentralized applications (Ethereum, 2021). Ethereum builds on Bitcoin's innovation as it acts as a decentralized platform for developers and can be used for more than just payments, such as trading digital assets like other cryptocurrencies (Ethereum, 2021). Similar to Bitcoin, Ether is mined through a proof-of-work system, which rewards its miners with Ether. Unlike Bitcoin, Ether has an uncapped supply meaning that it could potentially be affected by inflation (IG, 2021).

2.3 Litecoin

Created in 2011, Litecoin (LTC) is an open source, fully decentralized payment network that is broadly defined as the 'silver to bitcoin's gold' (Conway, 2021). At the time of its release, Litecoin was seen as being created in reaction to Bitcoin as it has adapted many of the features of Bitcoin that worked well and improved upon the ones that required development (Fernando, 2021). Litecoin is a mining-based altcoin that is fundamentally the same as Bitcoin but has a faster block generation time and a maximum supply that is four times greater than that of Bitcoin at 84 million coins (Conway, 2021). Similar to Bitcoin, Litecoin also uses a proof-of-work system for mining. In late March 2021, Litecoin had a market capitalization of around 12 billion USD (see Appendix 4).

2.4 Stellar

Released in 2014, Stellar is an open blockchain network that can be used by anyone, allowing for cross-border transactions between any currencies although it does require users to hold its own currency, Lumens (XLM), in order to transact on the network (Conway, 2021). Stellar was created in order to support the digital representations of currencies and its native currency, Lumens, was designed solely to denominate network requirements so that not one single national currency is preferred or fixed while the rest are considered floating (Stellar, 2021). One of the benefits of having a network token is that it eases the movement of money between users, and as everyone holds and requires Lumens in order to transact on the network, Lumens will always be a medium of exchange between otherwise illiquid assets (Stellar, 2021). Similar to Ether, Lumens also has an uncapped supply (IG, 2021). Stellar does not use a proof-of-work system like Ethereum and Bitcoin but instead has a built-in inflation mechanism, which releases new Lumens into the network at the rate of 1 per cent per annum (Stellar, 2021). At the end of March 2021, Stellar had a market capitalization of 9 billion USD (see Appendix 4).

2.5 Tether

Launched in 2014, Tether (USDT) is the first and most widely integrated stablecoin, which is a group of cryptocurrencies that have tied their market value to a fiat currency or other external reference point to reduce volatility and smooth out price fluctuations (Conway, 2021). Tether is a fiat-collateralized stablecoin and its market value is pegged to the US dollar. The Tether platform is built on top of open blockchain technologies but Tether differs from other cryptocurrencies as it cannot be mined. The market capitalization of Tether at the end of March 2021 was 40 billion USD with a mostly stable price of 1 USD (see Appendix 4). While the value of Tether has previously dropped below 1 USD, it generally keeps its value stable as it is pegged to a fiat currency.

2.6 Ripple

Ripple (XRP) is a digital asset built for payments on RippleNet, which is a payment network that operates based on an open-source, decentralized blockchain technology (Ripple, 2021). Created in 2012, Ripple is mainly targeted towards banks and financial institutions and was designed to improve the speed and transparency of international payments. XRP transactions are confirmed within seconds and at a significantly lower cost, which sets it aside from Bitcoin (Conway, 2021). XRP mining differs from the Bitcoin mining process as all XRP tokens are pre-mined and XRP coins are considered deflationary as they increase and decrease in circulation. At the end of March 2021, Ripple had a market capitalization of approximately 25 billion USD (see Appendix 4).

3. Literature Review

This literature review explores the rising trend of cryptocurrencies, leading to a discussion on the classification of cryptocurrencies as an asset class. In addition, this section will address the decline in fixed income hedging and the shift from traditional hedges. Finally, the theoretical framework of the hedge, safe haven and diversifier capabilities of cryptocurrencies will be addressed based on previous studies and literature. Existing research on cryptocurrencies is generally divided into investigating cryptocurrencies as an asset, predominantly through an investigation of empirical properties such as volatility dynamics, or alternatively from an investor perspective, through hedging abilities which are established by examining correlation. To a large extent, journals and articles on this topic are limited to studies and discussion of the market leading cryptocurrency, Bitcoin, and as such, the primary focus of this literature review will also intrinsically be on Bitcoin.

3.1 The Increasing Role of Cryptocurrencies and the Emergence of a New Asset Class

Cryptocurrencies have attracted overwhelming interest since the release of the technical white paper by pseudonymous Satoshi Nakamoto that introduced the first decentralized cryptocurrency, Bitcoin, with the underlying blockchain technology. Since then, thousands of cryptocurrencies have come into existence and vanished (Brown and Whittle, 2020). During the past few years, the rising popularity of cryptocurrencies has driven rapid market growth. While the general opinion on cryptocurrencies remains divided; primarily due to volatility and regulatory concerns, cryptocurrencies have unarguably made a significant impact on the financial system and altogether these digital assets are causing potential disruption to the traditional financial industry, which should not be overlooked. One of the criticisms underlying cryptocurrencies is the continuity of their upward trend and bull market. While there has been significant growth in the cryptocurrency market over the past few years, there are concerns about what the future will hold for cryptocurrencies and if they will be able to continue to grow and maintain their position in the market. Supporters see unlimited potential in cryptocurrencies, while critics focus on the risk associated with cryptocurrencies. There are also concerns about the energy consumption associated with mining, especially in light of the growing ESG trend, leading to uncertainty about cryptocurrencies' sustainability and future. Although it may be impossible to forecast what the future will hold, with a market capitalization of around 2 trillion USD, cryptocurrencies are unlikely to disappear overnight.

The emergence and growth of cryptocurrencies has prompted discussion on how cryptocurrencies should be classified in an economic context. Corbet et al. (2018) investigated the relationship between a variety of financial assets and the three main cryptocurrencies, ultimately demonstrating that cryptocurrencies can be considered as a new investment asset class as they are interconnected with each other and have similar patterns of connectedness with other asset classes. According to Bouri et al. (2018) Bitcoin can be seen as an alternative to mainstream currencies and even be considered as a part of an alternative economy. Bitcoin has also traditionally been compared to gold due to several shared characteristics; their primary value is derived from the scarcity of supply, which is finite and cannot be controlled by a government. Dyhrberg (2016b) showed that Bitcoin has a place on the financial markets and in portfolio management because it can be classified as something in between gold and the US dollar on a scale where one extreme would be pure store of value benefits and the other pure medium of exchange benefits. Dyhrberg analyzed if Bitcoin reacts to the same variables as the US dollar and the gold price using the GARCH framework, with price volatility as an indication of whether Bitcoin behaves like a well-known asset or something in between a commodity and currency. The results suggest that Bitcoin is somewhere in between a currency and a commodity due to its decentralized nature and limited market size (Dyhrberg, 2016b). Based on the consensus from previous literature and research, cryptocurrencies should therefore be placed in their own category and classified as a new asset class.

3.2 The Decline of Fixed Income Assets as an Investment Hedge

All major developed economies and countries around the world have started to cut interest rates since 2009 following the financial crisis, leading to a low interest rate environment, which makes other assets more attractive than the traditional fixed income instruments, such as bonds, as they do not provide positive yields (Fleischmann, Fritz and Sebastian, 2019). Bond investments under a low interest rate environment are typically associated with exposure to inflation risk. The cash flow and repayment of bond capital is fixed ex ante. Thus, any inflationary losses are fully captured by purchasing power. Junttila, Pesonen and Raatikainen (2018) found that the asset correlation of crude oil futures stayed exceptionally high after the global financial crisis, which might be explained by the zero-interest rate environment and low convenience yields due to the zero bound interest regime. Therefore, the old idea of "slow and steady wins the race" by using bonds seems to be outdated.

The correlation between stock and bond prices provides an indication of how well bonds will be able to protect a portfolio against equity risk. During the last few years, the protection from bonds against equity risk has weakened or even disappeared entirely (Nenin, 2021). Prior to 2018, bonds were negatively correlated with stock returns and provided protection during equity declines, however after 2018 bonds have exhibited positive correlation with stocks, indicating that they are no longer able to protect investors against equity risk (Nenin, 2021). Consequently, portfolio managers who had already questioned the role of bonds in the traditional 60/40 balanced portfolio are now "desperate enough to try something new'' as bonds are currently considered to be more risk than risk mitigation (Chen et al., 2021). Although bonds have a long history of being able to protect against equity risk, forward-looking investors have started to prepare for the day when bonds are no longer protective enough (Chen et al., 2021). As Bitcoin and other cryptocurrencies represent a new asset class, one solution to this problem could be using cryptocurrencies as a hedge in place of bonds (Riquier, 2021).

3.3 Cryptocurrencies as a Hedge, a Safe Haven and a Diversifier

Hedging has a crucial role in building investment portfolios as the purpose of hedging is to protect investors from losses using different hedging strategies. Baur and Lucey (2010) define a hedge as an asset that is uncorrelated or negatively correlated with another asset. A safe haven is an asset that provides hedging benefits during market turmoil, or in other words, is uncorrelated or negatively correlated with another asset in times of market turmoil (Baur and Lucey, 2010). A diversifier is defined as an asset that is positively but not perfectly correlated with another asset or portfolio on average (Baur and Lucey, 2010). In their 2010 paper, Baur and Lucey established that gold, which has traditionally been used alongside bonds to hedge against equity risk, acts as a hedge for stocks and as a safe haven in extreme stock market conditions. Gold can be seen as a hedge against inflation since it is a tangible commodity that has a limited supply and therefore tends to hold its value even when inflation is high. In their research, Baur and Lucey (2010) also showed that gold does not have hedging or safe haven capabilities in periods of rising stock markets or in the long-term. As gold shares several characteristics as the most popular cryptocurrency, Bitcoin, several researchers have expanded on Baur and Lucey's research by investigating the hedging, diversifier and safe haven properties of Bitcoin.

Similar to gold, Bitcoin is not affected by inflation as it has a limited supply that can only be increased through mining, which tends to occur at a stable pace. The shared characteristics between gold and Bitcoin have led to an emergence in research that explores the hedging capabilities of Bitcoin, widely regarded as 'virtual gold,' using the same methodologies as in the investigation of gold. In undoubtedly one of the most popular papers on this topic, Dyhrberg (2016a) found that Bitcoin has clear hedging capabilities against the FTSE Index and can therefore be used alongside gold to minimize or even eliminate specific market risks. Bitcoin also showed hedging capabilities against the US dollar, but only in the short-term. Dyhrberg's analysis showed that Bitcoin combines some of the advantages of commodities and currencies in the financial markets and therefore is a useful tool for portfolio management and can be used in anticipation of bad news by risk averse investors. Furthermore, Shahzad et al. (2020) compared gold and Bitcoin as a hedge across G7 stock markets and found that while gold acts as a hedge and a safe haven across several stock markets, Bitcoin only has such properties in certain markets, such as Canada. Although gold and Bitcoin share some similarities, Shahzad et al. (2020) also highlighted some main differences between gold and Bitcoin, which are related to tangibility, history, intrinsic value, volatility, use in the production process and acceptance as a global monetary reserve. Shahzad et al. (2020) also recognized the unprecedented profit opportunities provided by Bitcoin and concluded that the lack of correlation between Bitcoin and the stock markets is unsurprising due to the differences in their respective price drivers.

Urquhart and Zhang (2019) investigated the hedging and safe haven properties of Bitcoin and found that Bitcoin acts as an intraday hedge, diversifier and safe haven for certain world currencies. Based on their research, Urquhart and Zhang concluded that Bitcoin can be used as a hedge and diversifier at the intraday level by currency investors. In addition, Bitcoin offers safe haven benefits during market turmoil in the Canadian dollar, Swiss Franc and British Pound but not for the other currencies examined in this research (Urquhart and Zhang, 2019). Bouri et al. (2017) demonstrated that Bitcoin behaves as a strong hedge against commodity indices, especially energy commodities. Elie (2019) uncovered the hedging and safe haven properties of several cryptocurrencies against down movements in the S&P 500 index. Brière et al. (2015) showed in their research paper that the inclusion of even a small proportion of Bitcoin may dramatically improve the risk-return trade-off of well-diversified portfolios. Similarly, Kang et al. (2020) found that Bitcoin may strengthen the diversification benefits against other asset classes and act as an effective safe haven towards reducing downside risk. Furthermore, Kurka (2019) investigated if cryptocurrencies and traditional assets influence each other and found that the low amount of shocks received from other markets confirms the potential of Bitcoin as a hedge or a diversifier to traditional assets such as commodities, the foreign exchange and stocks. Kostika and Laopodis (2019) found that cryptocurrencies are suitable for inclusion in global investment portfolios due to their independence of the global stock markets and exchange rates. Due to the differential relationship between each cryptocurrency with the equity markets, cryptocurrencies represent a short-run investment vehicle within a well-diversified, global asset portfolio (Kostika and Laopodis, 2019). Although previous research on the hedge and diversifier capabilities of cryptocurrencies is inconclusive and lacks a clear consensus, it would seem like Bitcoin has some hedging capabilities against equity risk and cryptocurrencies in general are able to provide at least diversification benefits, especially in a global context.

3.4 Cryptocurrencies and Global Uncertainty

Bitcoin was introduced amid the 2008 financial crisis, during which the global financial system was considered to have failed fundamentally, leading to a loss of confidence in the global banking system and a financial reform in the years that followed the crash. Although the first cryptocurrency was not created in response to the financial crisis, the timing gave rise to its popularity and gave investors a choice rather than a solution to global uncertainty (Acheson, 2021). Bouri et al. (2017) examined whether Bitcoin can act as a hedge against global uncertainty and found that Bitcoin has hedging properties against uncertainty at the extreme ends of the Bitcoin market and global uncertainty, however only at shorter investment horizons.

Considering the rapid acceleration in the price of cryptocurrencies during the past few years from 2018 to 2021; covering the global COVID-19 pandemic period, there could be a connection between the price of cryptocurrencies and the state of economies' stability. Economic instability is another key factor to changes in cryptocurrencies' prices. Countries like Venezuela, which have experienced hyperinflation of their currency, have seen huge increases in the use of Bitcoin as a means of transaction as well as storing wealth. There are also some experts who raise concern of cryptocurrencies' upward trend as the crypto craze phenomenon similar to the dotcom hype cycle in late 1990s. While research and literature have not reached a consensus on the hedging capabilities of cryptocurrencies, Bitcoin has generally been considered as an inflation hedge due to its similar properties with gold, as first demonstrated by Dyhrberg (2016a). However, Bitcoin can be extended by represent more than just a hedge against inflation as it equally represents a hedge against the unexpected (Acheson, 2020). As such, Bitcoin could also act as a hedge for unstable governments and corruption among other political and social issues faced especially by developing countries (Acheson, 2020).

4. Data

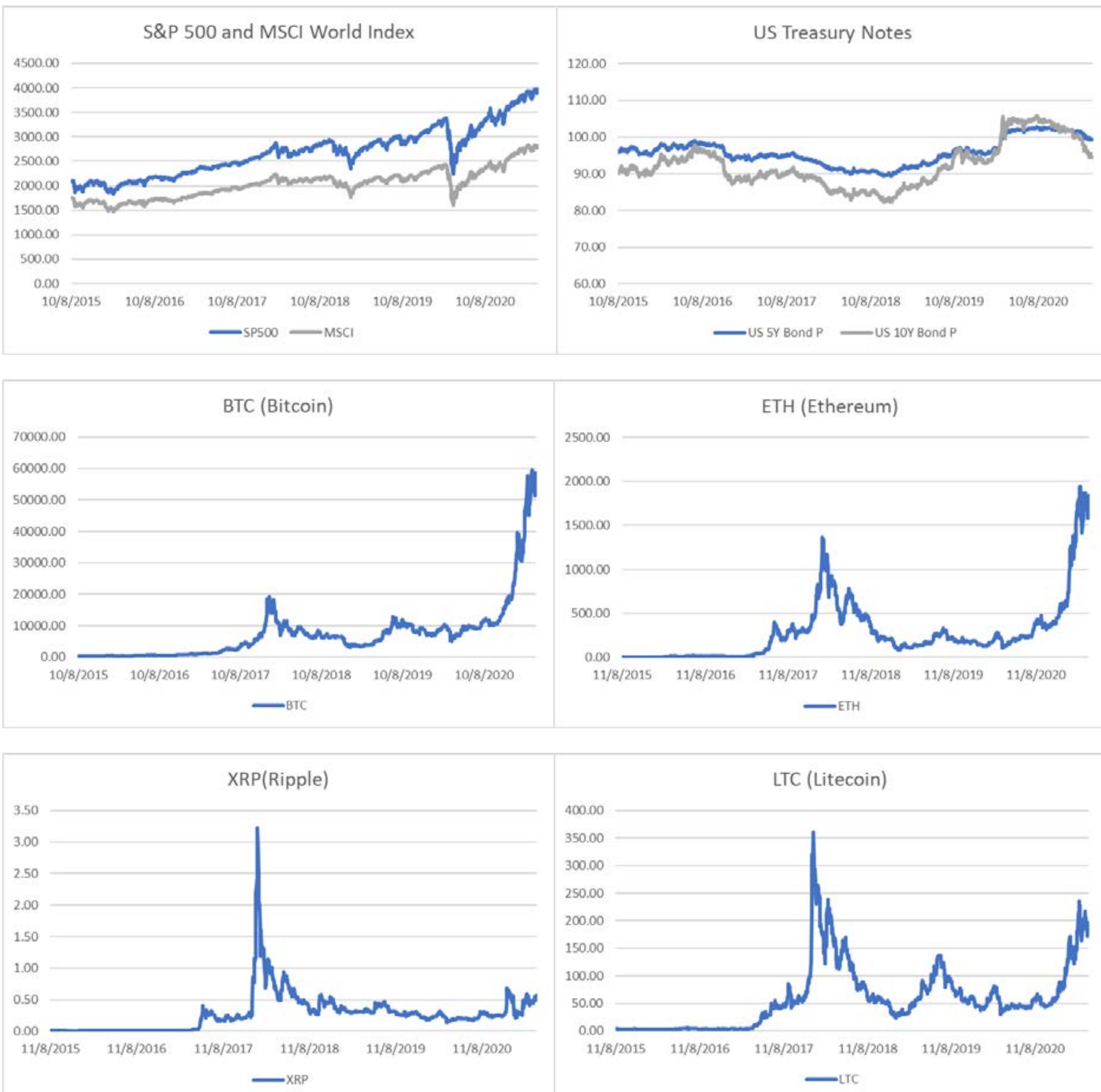
As the cryptocurrency market is top-heavy in terms of market capitalization, we consider the main cryptocurrencies to be representative of the market as a whole. We have therefore chosen to focus our research on Bitcoin, Ethereum, Ripple, Stellar, Tether and Litecoin. These cryptocurrencies include all main types of coins from standard blockchain coins to tokens and stablecoins. As the US has the highest trading volume in cryptocurrencies, our research is predominantly based on the US stock and bond markets.

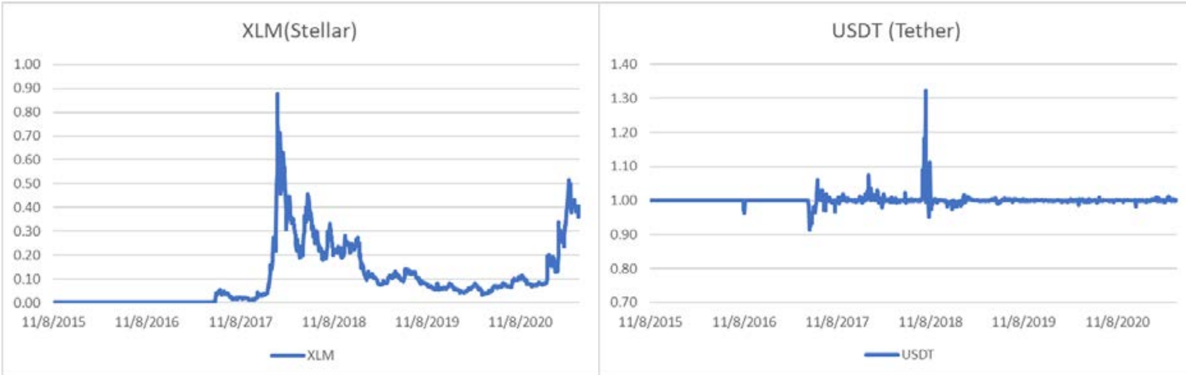
To represent the equity market prices, we have chosen the S&P 500 and the MSCI World indices. The S&P 500 represents the US stock markets while the MSCI World index is the benchmark for global stock markets across developed countries. As our primary focus is the US, we have selected the US 5-year and 10-year Treasury yields to represent the bond market. US Treasuries are generally regarded as some of the safest financial assets available to investors, making them widely popular in hedging and thus appropriate to represent bond markets in this study. The US government bond yields have also been converted into prices in order to ensure that the data is consistent with the stock market indices, which are expressed in daily prices.

Data for this research has been collected from CoinGecko and Datastream. We examine observations from 10 August 2015 to 31 March 2021, thereby incorporating over five years of data. The selected timeframe of the sample is primarily based on the availability of data for the six cryptocurrencies and consists of 1472 observations. The cryptocurrency price data has been downloaded from CoinGecko. The dataset is denominated in USD and consists of daily prices. As cryptocurrencies trade 24 hours 7 days a week, we have taken out cryptocurrency prices during the weekends when the stock and bond markets are closed to ensure that the dataset is consistent. Furthermore, we used the last observation for any missing daily prices. The daily prices for the equity indices and US Treasury yields were obtained from Datastream. Similar to the cryptocurrency dataset, the stock and bond data also covers daily observations from 10 August 2015 to 31 March 2021 and is denominated in USD.

Figure 1 displays the time series for daily cryptocurrency prices, the MSCI World Index, the S&P 500, the US Treasury 5-year note and the US Treasury 10-year note. These have been plotted in order to establish any preliminary co-movement. Based on our preliminary analysis on co-movements in Figure 1, the S&P 500 and the MSCI World Index exhibit a similar shape of price movement over time. The two maturities of US Treasury notes also exhibit similar trends as each other, however, the 10-year Treasury started to cross over the 5-year Treasury in 2019. The stock indices and bonds seem to move in opposite directions during the beginning of 2016 until around the end of 2018, which implies hedging properties in this preliminary analysis stage. Similarly for cryptocurrencies, based on the preliminary co-movements displayed in Figure 1, we can observe that most cryptocurrencies display similar trends over the investigated time period. The only stablecoin examined in this study, Tether, shows a relatively stable trend and is unlikely to be correlated with other assets. During the period between the end of 2017 and 2019, unstable cryptocurrencies illustrate some opposite movement to the stock indices trend. There is therefore a possibility that these cryptocurrencies can act as a hedge. The sharp spike displayed in the graph on cryptocurrencies' price was from the cryptocurrency boom; starting with the initial coin offering bubble at the end of 2017, followed by a crash in 2018.

Figure 1 - The Price Levels of All Cryptocurrencies, the Stock Indices and US Treasury Notes





5. Methodology and Calculations

Following the definition of a hedge, a safe haven and a diversifier in the reviewed literature, we are interested in examining the hedging properties of cryptocurrencies through an investigation of the correlations of cryptocurrencies paired with equity indices and how this compares to US Treasuries. Cryptocurrencies are, in general, highly volatile over the time period of this study and therefore they exhibit time-varying characteristics similar to other financial assets. As such, we are interested in modelling the correlations that could possibly incorporate an impact from past information to today's correlations. Engle's (2002) econometric model of dynamic conditional correlation (DCC) with multivariate GARCH is deemed appropriate to apply in this study in order to capture the time-varying conditional correlations of asset returns. In this study, bivariate correlations will be observed and therefore we have adopted the bivariate DCC-GARCH model.

5.1 Log Returns

In the first step, we transformed the price data into returns series in order to normalize all variables and to ensure comparability across the metric. With the price data of the financial assets being non-stationary, we transformed all of our variables into the form of daily logarithmic returns. In order to do this, we followed the below definition of logarithmic returns:

$$r_t = ln(\frac{S_t}{S_{t-1}})$$

Logarithmic transformations, in general, are useful to overcome any heteroscedasticity problems, or in other words, when the standard errors of a variable are not constant. It generally helps to rescale data so that the variance is more constant. Logarithmic transformations could also ensure that the distribution of the residuals that are positively skewed is closer to a normal distribution. Additionally, logarithmic returns can be interpreted as continuously compounded returns so that the frequency of compounding of the return does not matter and thus returns across assets can be more easily compared. Continuously compounded returns are also time-additive.

In general, the more frequently an asset is traded, the more clustered its volatility. As cryptocurrencies are traded 24/7, they exhibit a high trading frequency. In our research, we have chosen to examine daily returns as these are consistent with the stock indices, which are traded on weekdays and have daily return data.

Table 1 - Descriptive Statistics for Log Returns Series of All Cryptocurrencies, the Stock Indices and US Treasury Notes

	BTC	*ETH*	*XRP*	*LTC*	*XLM*	*USDT*	*S&P 500*	*MSCI World i*	*US 5Y Bond*	*US 10Y Bond*
Mean	0.003672	0.005362	0.002834	0.002654	0.003462	0.000000	0.000432	0.000316	0.000023	0.000032
Standard Error	0.001194	0.001907	0.001994	0.001696	0.002338	0.000328	0.000310	0.000262	0.000051	0.000104
Median	0.003052	0.001172	-0.002408	-0.000250	-0.001851	0.000000	0.000417	0.000582	0.000000	0.000000
Standard Deviation	0.045829	0.073177	0.076490	0.065063	0.089716	0.012568	0.011891	0.010041	0.001958	0.003984
Sample Variance	0.002100	0.005355	0.005851	0.004233	0.008049	0.000158	0.000141	0.000101	0.000004	0.000016
Kurtosis	9.327323	8.141350	19.477613	11.753299	41.016906	206.585191	20.965859	23.337276	2.745782	3.871960
Skewness	-0.487462	0.276472	2.001639	0.881963	3.336621	-6.253690	-1.067110	-1.526161	0.209264	-0.047757
Range	0.720814	1.085726	1.323859	1.018884	1.781349	0.409875	0.217335	0.188475	0.020022	0.047193
Minimum	-0.433714	-0.563080	-0.549548	-0.471381	-0.439361	-0.283338	-0.127652	-0.104412	-0.009293	-0.027366
Maximum	0.287099	0.522647	0.774311	0.547503	1.341988	0.126537	0.089683	0.084063	0.010729	0.019827
Sum	5.405310	7.892250	4.171244	3.906829	5.095515	-0.000094	0.635568	0.464723	0.034043	0.046509
Count	1472	1472	1472	1472	1472	1472	1472	1472	1472	1472
Confidence Level(95.0%)	0.002343	0.003741	0.003911	0.003327	0.004587	0.000643	0.000608	0.000513	0.000100	0.000204

Descriptive Statistic for Log-returns series

The logarithmic returns series are observed with descriptive statistics; illustrated in Table 1. All data variables will be used in the form of logarithmic returns for the modelling of correlation in the following part. Similar to most financial assets' time series, the coefficient of kurtosis is significantly in excess of normal distribution's reference value of three, which means that the returns series exhibit leptokurtosis. The returns series also shows slight skewness; both negative and positive, signifying that the data is slightly non-symmetrical.

5.2 Jarque-Bera Test for Non-normality

The Jarque-Bera test is one of the most common tests used to confirm the non-normality of the data distribution (Brooks, 2019). The Jarque-Bera test uses the property of a normally distributed random variable, where the entire distribution is characterized by the first two moments: the mean and the variance. Normally distributed data does not contain skewness and kurtosis or the third and fourth moment, respectively. Therefore, the Jarque-Bera test is used to test the joint hypothesis that the coefficient of skewness is zero and the excess kurtosis is zero.

The Jarque-Bera test statistic is given by:

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \sim (\chi^2)$$

where S is the coefficient of skewness and K is the coefficient of kurtosis. The test statistic asymptotically follows a Chi-square distribution. The null hypothesis is that the data is normally distributed and vice versa for the alternative hypothesis. The null hypothesis will be rejected if the residuals from the model are not normally distributed, for example; if they are either significantly skewed or leptokurtic.

The univariate returns series are tested in order to confirm that the returns series are non-normal. As shown in Table 2 below, the large value of the test statistic concludes that the null hypothesis is rejected on a one percent significance level. Thus, the Jarque-Bera test gives support to the fact that the univariate samples of the logarithmic returns are not normally distributed, which is expected due to the characteristics of financial time series. The test result is in accordance with the high kurtosis level as shown in Table 1. The descriptive statistics of the log-returns series show that the data is not normally distributed. This implies that the data accommodates fat tails and that Student's t-distribution would be more appropriate when fitting the data to the first stage GARCH model.

Table 2 - Jarque-Bera Test Results

	BTC	*ETH*	*XRP*	*LTC*	*XLM*	*USDT*	*S&P 500*	*MSCI World ir*	*US 5Y Bond*	*US 10Y Bond*
JB-Test	5353.3***	4052.4***	24082***	8599.8***	105190***	2609300***	27046***	33736***	468.6338***	911.9151***
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

***0.01 confidence level

**0.05 confidence level

*0.10 confidence level

5.3 Unit Root Test

Stationarity is one of the most important preliminary properties of time series data. Confirming stationarity is crucial when examining time series data because if a series is not stationary, this can strongly influence its behavior and properties. A series is strictly stationary if the distribution of its values remains the same as time progress. A series is considered to be weakly stationary if it has a constant mean, a constant variance and a constant autocovariance structure (Brooks, 2019).

Therefore, prior to the Dynamic Conditional Correlation-GARCH analysis, the Unit Root Test of Stationarity is performed in order to investigate the stationarity of the time series data. As such, the Dickey-Fuller (DF) test of unit root at lag 1 was conducted without trend-stationarity and a drift model.

The DF test regression and null hypothesis is defined as:

$$\Delta y_t = \omega y_{t-1} + u_t$$

$$H_0: \omega = 0 \, , H_1: \omega < 0$$

Table 3 - Dickey-Fuller Test Results

	BTC	ETH	XRP	LTC	XLM	USDT	S&P 500	MSCI World ir	US 5Y Bond	US 10Y Bond
DF	-26.1793***	-25.6868***	-23.6916***	-26.1271***	-26.4631***	-36.5126***	-26.9111***	-23.9025***	-27.762***	-27.634***
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

***0.01 confidence level

**0.05 confidence level

*0.10 confidence level

Table 3 illustrates the results of the Dickey-Fuller test. All variables in our series of logarithmic returns reject the null hypothesis of having a unit root present against the autoregressive alternative at the 0.01 confidence level. The negative test statistic shows strong rejection of the null hypothesis. We can see the stationarity of the time series in the plots of the logarithmic return series of all variables, which is included in Appendix 1.

5.4 Lagrange Multiplier Test for ARCH Effects

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are in widespread use in finance as non-linear models. GARCH models take into account both previous volatility and conditional heteroscedasticity. For general OLS estimators, the variance of the disturbance term is assumed to be consistent, or in other words, has a homoscedasticity property. However, if the variance of the disturbance term is not constant over time or follows heteroscedasticity, it is more appropriate to consider a model that does not assume constant variance of the disturbances but instead describes the variance characteristics of the disturbances. In the presence of heteroscedasticity, the data has ARCH effects and therefore the ARCH or GARCH model is one of the more appropriate models to use.

In testing for ARCH effects, we have used the Lagrange multiplier test proposed by Engle (1982). The below equation (1) is first regressed for residuals, $\hat{u}_t$. Then the residuals are squared and equation (2) is regressed on q lags to test for ARCH order q to obtain R^2 for test statistic (3):

$$(1)\ y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \beta_4 x_{4t} + u_t$$

$$(2)\ \hat{u}_t^2 = \gamma_0 + \gamma_1 \hat{u}_{t-1}^2 + \ldots + \gamma_t \hat{u}_{t-q}^2 + v_t$$

$$(3)\ \ TR^2 \sim \chi^2(q)$$

$$\text{H0: } \gamma_0 = 0, \gamma_1 = 0, \ldots \gamma_q = 0$$

$$\text{H1: } \ \gamma_0 \neq 0, \gamma_1 \neq 0, \ldots \gamma_q \neq 0$$

The test of joint null hypothesis is that all q lags of the squared residuals have coefficient values that are close to zero and therefore there are no ARCH effects as the errors are not autocorrelated.

To test the ARCH effects or serial correlations problem, Engle's ARCH test was performed on each of the return series. The test results are presented in the table below (Table 4).

Table 4 - ARCH Effect Results

	BTC	ETH	XRP	LTC	XLM	USDT	S&P 500	MSCI World ir	US 5Y Bond	US 10Y Bond
ARCH	6.0212**	16.949***	60.297***	53.5996***	47.6921***	21.7507***	373.4614***	173.8682***	76.3176***	242.7748***
P-value	0.0141	3.84E-05	8.10E-15	2.46E-13	4.99E-12	3.10E-06	0	0	0	0

***0.01 confidence level

**0.05 confidence level

*0.10 confidence level

It can be concluded that the squared residuals from previous lags are correlated with the squared residuals at time t and hence we found ARCH effects in all of the return series. The test rejected the null hypothesis of no ARCH effects at the 0.05 and 0.01 confidence levels. The presence of ARCH effects in the dataset motivates the use of the ARCH-GARCH family model in our study.

5.5 The GARCH Model

Initially, the Autoregressive Conditional Heteroskedasticity (ARCH) model was developed based on two main motivations. First, to accommodate for when the variance of the errors is not constant and leads to an incorrect estimation and second, to capture the volatility clustering effect, which is a common feature of financial asset returns.

Bollerslev (1986), has extended the ARCH model to GARCH by allowing the conditional variance to depend on past values of the squared errors and also upon its previous lags of its conditional variances. The conditional variance equation in the simplest case can be written as $\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2$, where the last term is added from the ARCH model of $\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2$.

Due to the presence of ARCH effects and some observable volatility clustering in our return series, we applied the GARCH model in order to capture such effects in our study. In addition, we selected the GARCH (1,1) model as it is generally found sufficient for capturing volatility dynamics.

5.6 Dynamic Conditional Correlation (DCC-GARCH)

Appendix 2 shows a table of simple, static correlations between cryptocurrencies, US treasuries and the stock indices. The table depicts negative correlations between US treasuries and the stock indices. This implies the possibility that US treasuries can be used as a hedge. Weaker negative correlations can be observed between several cryptocurrencies and the stock indices. However, these correlations are unconditional and do not reveal the dynamic linkages between each series. Therefore, we are interested in modelling a class of conditional time-varying correlations and the dynamic conditional correlation (DCC) model can be used to estimate the dynamic correlations directly instead of modelling the conditional covariance matrix. The dynamic conditional correlation (DCC) model was first introduced by Engle in 2002 to capture the dynamic correlations of asset returns. The model has its formation from the constant conditional correlation model (CCC), however; in DCC the correlations are allowed to vary over time to capture the dynamic relationship in time series data. The GARCH model is popular when modelling volatilities in financial markets as it can capture the time-varying volatilities of assets. Engle (2002) proposed the DCC model as a simple class of a multivariate GARCH model. The DCC model reduces the number of parameters in the multivariate GARCH framework by requiring the correlations between disturbances to be fixed through time as an alternative approach in modelling dynamic conditional correlations. All in all, the DCC-GARCH model is applied to capture the degree of volatility correlation changes or spillovers between two returns series.

Bouri et al. (2016) used the bivariate DCC model to investigate the correlations between returns series for Bitcoin, gold and the dollar. (Junttila, Pesonen and Raatikainen, 2018) also used the DCC-GARCH model to examine the risk correlations between crude oil, gold and the stock market. Burdekin et al. (2021) also used this model to analyze gold as a hedge during the recent COVID-19 pandemic.

The dynamic conditional variance-covariance matrix of the DCC model is defined as:

$$H_t = D_t R_t D_t$$

And the general multivariate GARCH model is defined as:

$$r_t = \mu + u_t$$

$$u_t | \Omega_{t-1} \sim N(0, H_t)$$

where $R_t$is a time-varying or conditional correlation matrix, D_t is a diagonal conditional standard deviations matrix $diag[\sqrt{h_{i,t}}]$ and r_t is a vector of returns of assets at time *t*.

The estimation of the DCC model can be done in two steps. First, a series of univariate GARCH is estimated; followed by an estimation of correlation (Engle, 2002). The estimation of univariate GARCH is conducted in order to extract the standardized residual, u_t, for modelling the dynamic conditional correlation in a DCC-based covariance matrix.

To elaborate more on the component of the H_t matrix, we first look into the diagonal conditional standard deviations' matrix D_t below:

$$D_t = diag[\sqrt{h_{i,t}}] \text{ or}$$

$$D_t = \begin{bmatrix} \sqrt{h_{1,t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2,t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{h_{i,t}} \end{bmatrix}$$

where h_{it} are the conditional variances generated from the variance equation of the univariate GARCH process for each of the return series. The variance equation of a univariate GARCH process can be written as:

$$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}$$

Another element of the H_t matrix is R_t, the conditional correlation matrix of standardized residuals $u_{t,}$ which can be described in matrix form as:

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1i,t} \\ \rho_{12,t} & 1 & \rho_{23,t} & \vdots \\ \vdots & \rho_{23,t} & \ddots & \rho_{i-1i,t} \\ \rho_{1i,t} & \cdots & \rho_{i-1i,t} & 1 \end{bmatrix}$$

The parameterization of R_t can be done by several methods. With the time-varying characteristic, the R_t shall be inverted for each time t. Under the general requirement that H_t has to be a positive-definite matrix, R_t should also be positive-definite as all the diagonal elements in H_t are positive. In this study, the GARCH-resembling formulation proposed by Engle (2002) is followed in the modelling of a correlation structure and $R_t$can then be constructed as:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

$$R_t = diag\{Q_t^*\}^{-1} Q_t diag\{Q_t^*\}^{-1}$$

Q_t, the covariance matrix version of a correlation structure can be written as:

$$Q_t = (1 - \alpha - \beta)\overline{\mathrm{Q}} + \alpha \epsilon_{t-1} \epsilon'_{t-1} + \beta Q_{t-1}$$

$\overline{\mathrm{Q}}$ is $cov[\epsilon_{t-1}\epsilon'_{t-1}]$, the unconditional covariance matrix of the standardized residuals ϵ_t from the first stage estimation, $\epsilon_t = D_t^{-1} u_t$.

Q_t^* is a diagonal matrix with the square root of the diagonal elements of Q_t as demonstrated below;

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11t}} & 0 & \ldots & 0 \\ 0 & \sqrt{q_{22t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \ldots & 0 & \sqrt{q_{nnt}} \end{bmatrix}$$

The parameters α and β are non-negative scalar and shall be summed up to less than one, $\alpha + \beta$ < 1. This is for the mean reverting model and to ensure positive unconditional variances in the first stage of the univariate GARCH estimation.

Then, the typical element of conditional correlations R_t is given by:

$$\rho_{ij,t} = \frac{q_{ij}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}$$

In the estimation of the two-stage DCC model, the likelihood used in the first stage replaces R_t with the identity matrix I_n which leads to the sum of the quasi-likelihood of the individual GARCH equations for the assets:

$$L(\theta_1) = -\frac{1}{2}\sum_{t=1}^{T}(n\,ln(2\pi) + \sum_{i=1}^{n}\left[\ln(h_{it}) + \frac{r_{it}^2}{h_{it}}\right])$$

In the second stage, the conditional likelihood is maximized with respect to any unknown parameters in the correlation matrix. The log-likelihood function for the second estimation is given as:

$$L(\theta_2|\theta_1) = \sum_{t=1}^{T} ln\,|R_t| \;+ \epsilon_t' R_t^{-1} \epsilon_t$$

where θ_1 denotes all unknown parameters that were estimated in the first stage and θ_2 denotes all those estimates under the second stage.

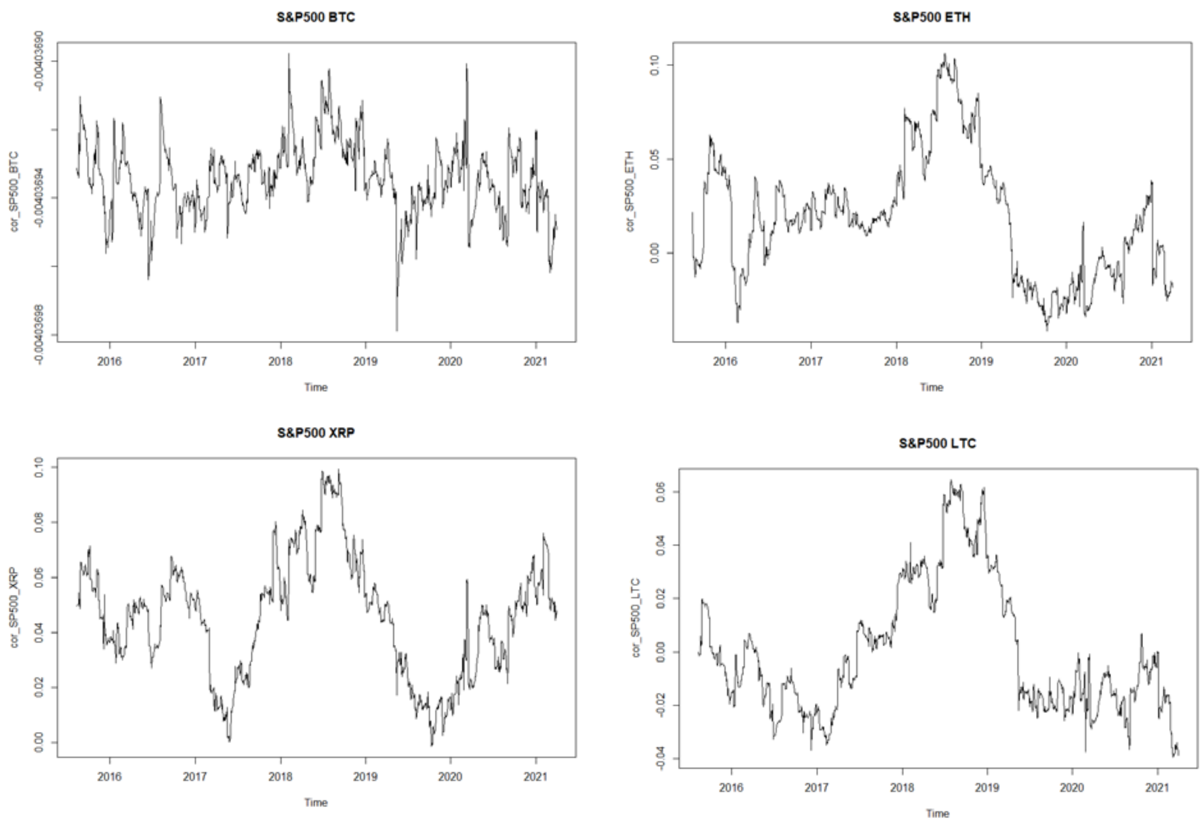
6. Empirical Results

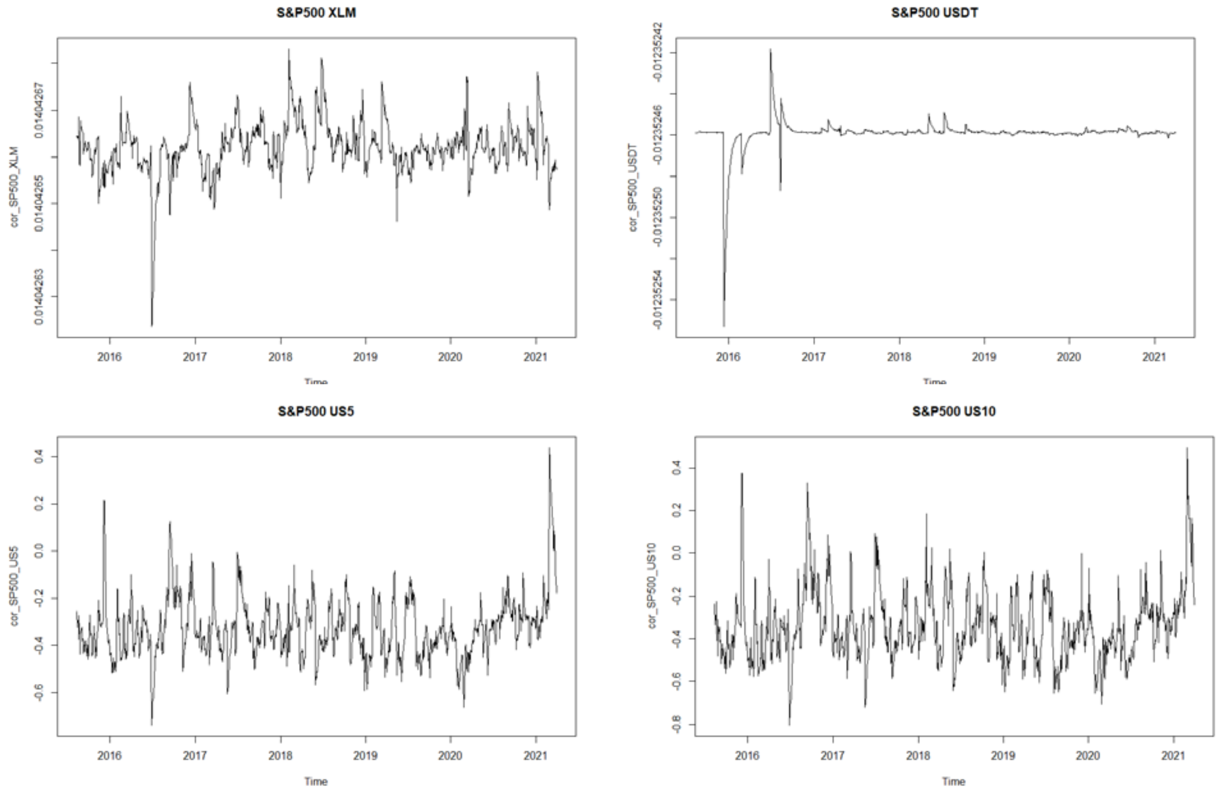
This section includes discussion and analysis on the results of the DCC-model. This involves interpretation of the individual plotted correlations as well as the estimation results. As the S&P 500 and the MSCI World indices represent different markets and therefore display different correlations with the investigated asset classes, our analysis is divided into first discussing the results from the S&P 500 correlations, followed by the results from the MSCI World index correlations and finally a summary of both results. Following the definitions of a hedge, a diversifier and a safe haven in the reviewed literature, we will discuss the implications of the results on the hedging capabilities of bonds compared to cryptocurrencies.

6.1 Dynamic Conditional Correlations for the S&P 500, US Treasuries and Cryptocurrencies

Figure 2 illustrates the dynamic correlations between the S&P 500 and US 5-year and 10-year Treasuries as well as the six cryptocurrencies investigated in this study. Based on the correlations in this figure, we can observe that bonds have provided protection against equity risk up until the aftermath of the COVID-19 pandemic, during which correlation between stocks and bonds has started to trend positive. This is in line with the previously discussed narrative, derived predominantly from the financial press, which demonstrated that bonds; which have a long history of providing protection against equity risk, are no longer performing as well as they have historically to hedge against stock market risk. By contrast, the correlation between stocks and major cryptocurrencies examined in this study has generally followed a more negative trend amid recent inflation concerns and market uncertainty associated with the COVID-19 pandemic. Generally, however, cryptocurrencies tend to exhibit weak positive correlation with the stock market, indicating that they are more suitable to be used as a diversifier rather than a hedge in an investment portfolio, especially during a bull market. Conversely, during times of economic uncertainty and market turmoil, major cryptocurrencies such as Bitcoin and Ethereum, seem to have improved hedging capabilities. The periods of economic uncertainty, market turmoil and financial crises specified during this study are selected by the major downward movement of the S&P 500 index during the investigated periods and the main events are as follows; first, Brexit in June 2016, then the US trade ban on China in 2018 and finally, the COVID-19 pandemic that started in early 2020.

Figure 2 - Dynamic Conditional Correlations (S&P 500 with Cryptocurrencies and US Govt Bonds)





6.1.1 Correlation Between US Treasuries and the S&P 500

Both the US 5-year and 10-year Treasuries follow a similar correlation pattern and are generally negatively correlated with the S&P 500, and are therefore classified as a hedge against stock market risk. From late February 2021 onwards, it can be observed that the correlation between the stock market and both Treasuries increased significantly to an all-time high during the measured period, indicating that bonds have not recently performed as well as they have historically to protect against stock market risk. During this time, both US Treasury prices and the S&P 500 declined, presumably in anticipation of the results from Johnson & Johnson's single-dose vaccine trial on 26 February 2021 and the 1.9 trillion USD COVID-19 relief bill vote by the United States senate on 27 February 2021. The Johnson & Johnson vaccine was one of the world's most closely watched trials due to requiring only one dose and being backed up by the largest pharmaceutical firms in the world, and as such the outcome had a significant impact on the uncertain financial markets in the COVID-19 era. Looking at the catalyst for the positive correlation trend in more detail, this first started on 26 February 2021 when stock prices went down in tandem with bond prices. Yields move inversely to prices, therefore when bond prices decrease, bond yields increase. The rise in bond yields reflects both expectations of inflation and economic recovery from the COVID-19 pandemic, as investors feel less of a need to hold Treasuries, which are considered to be some of the world's safest assets, when the market is healthy. A stronger economy is often accompanied by inflation, raising investor concerns for inflation and pushing bond prices down and yields up.

6.1.2 Correlation Between Bitcoin and the S&P 500

Looking at the individual correlations of cryptocurrencies and the S&P 500 in more detail, we can see that the correlation between the S&P 500 and Bitcoin is marginally negative, meaning that Bitcoin has some hedging capabilities against stock market risk. During market turmoil, correlation decreased even further, indicating that Bitcoin's hedging capabilities improve during adverse economic conditions and a bear market. This finding is aligned with previous studies by, for instance, Kang et al. (2020), in which Bitcoin was found to be a strong hedge against the S&P 500 during the earlier period of 2011 to 2016. In addition, our results are similar to those found by Dyhrberg (2016a). Dyhrberg (2016a) concluded that Bitcoin has clear hedging capabilities against the FTSE Index and can therefore be used alongside gold to minimize or even eliminate specific market risks. However, it is worth noting that in our study the overall correlation between Bitcoin and the S&P 500 is nevertheless very marginally negative throughout the investigated time period, indicating that Bitcoin does not act as a strong hedge against equity risk but more as a diversifier, especially during a bull market. In times of market turmoil, however, Bitcoin does provide improved hedging capabilities against equity risk as correlation starts to trend more negative. Examples of periods of lower correlation between Bitcoin and the S&P 500 include Brexit in June 2016, the US trade ban on China and the aftermath and financial uncertainty brought upon by the COVID-19 pandemic. The most notable spikes in correlation include the period of the 2018 cryptocurrency bubble and the beginning of the COVID-19 pandemic, however even during these events, correlation remained negative. In 2018 the S&P 500 also experienced a 6 per cent fall, which was the lowest for the index in a decade. During the 2020 stock market crash and the beginning of the COVID-19 pandemic, the S&P 500 lost 34 per cent of its value. Based on the estimation results from the DCC model, we can also observe that the small alpha shows persistence in correlation, meaning that the correlation is affected less by information each day and mostly reflects accumulated information over a long-term horizon.

6.1.3 Correlation Between Altcoins and the S&P 500

Other cryptocurrencies generally tend to exhibit weak positive correlation with the stock market, indicating that they are more suitable to be used as a diversifier rather than as a hedge in an investment portfolio. Out of all the altcoins, Ether has the weakest correlation with the S&P 500, indicating that it is the superior altcoin hedge. There are some notable declines in correlation with the S&P 500 in early 2016, 2019 and following the COVID-19 crisis. During these periods, correlation was slightly negative and generally followed a similar pattern to Bitcoin. Outside of these periods, however, Ether mainly exhibited a weak positive correlation, indicating that it can only be used as a diversifier against equity risk. Ripple and Litecoin also seem to follow a similar pattern and mostly show weak positive correlation with the S&P 500. Although quite marginal in scale, the most notable spikes in correlation with the S&P 500 for Ripple and Litecoin were between 2018 and 2019. During this time period, Ether also experienced its all-time high in positive correlation. These events coincide with the cryptocurrency bubble of 2018. The correlation between the S&P 500 and the only stablecoin examined in this study, Tether, is mostly flat as expected. Although Tether does not indicate strong hedging capabilities through negative correlation with the S&P 500, its stablecoin characteristics nevertheless provide protection during extreme market declines. Based on the stable correlation Tether has with the S&P 500 throughout the entire time period, it is not subject to any sharp declines or increases that have had an effect on other cryptocurrencies and US Treasuries. Stellar does not seem to follow a similar correlation pattern with any cryptocurrency and its co-movements with the S&P 500 appear mostly random, with no significant economic events as a driver for extreme movements. While the correlation between the S&P 500 and Stellar does show some fluctuations over time, it remains marginally positive over time.

6.1.4 Discussion and Analysis

The results from the DCC model are slightly disappointing considering the recent decline in bonds' hedging capabilities and cryptocurrencies' overwhelming market growth. As bonds are no longer providing the protection against stock market risk that they traditionally have, in turn we would have expected an extremely non-traditional asset class like cryptocurrencies to then exhibit stronger hedging capabilities in the current financial environment. Our findings for Bitcoin are mostly in line with previous research. Bouri et al. (2016) found that Bitcoin works as a hedge but only in short investment horizons, which is in line with our findings as Bitcoin only exhibits strong hedging capabilities for short periods of time, especially during economic uncertainty. Shahzad et al. (2020) concluded that the lack of correlation between stock markets and Bitcoin is not surprising due to different price driving factors. We would have expected to find some negative correlations between altcoins and the S&P 500. Especially as, to our knowledge, there has not been previous research regarding the hedging capabilities of altcoins in relation to a notable stock market index. Based on the results of the DCC model, we would suspect that derivatives, which were also previously considered extremely risky, are used in investment portfolios to hedge against equity risk. Despite having been involved in triggering one of the biggest financial crises, derivatives are now seen as an effective risk management tool due to having been so heavily regulated in the aftermath of the 2008 financial crisis.

Table 5 - DCC-GARCH (1,1) Estimation Results S&P 500

(Variance Equation)	*S&P500*	*US 5Y Bond*	*US 10Y Bond*	*BTC*	*ETH*	*XRP*	*LTC*	*XLM*	*USDT*
Constant	*****0.000843**	**-0.000040**	**0.000005**	*****0.00312**	**0.001377**	*****-0.002873**	**0.000124**	*****-0.00365**	**0.000000**
(Std. Error)	0.000143	0.000042	0.000090	0.000643	0.001150	0.000787	0.000697	0.001162	0.000000
p-value	0.000000	0.342274	0.959224	0.000001	0.231030	0.000261	0.859300	0.001685	0.523350
ARCH-Alpha	*****0.195459**	*****0.073431**	*****0.069553**	*****0.131733**	*****0.26204**	*****0.243826**	*****0.106842**	****0.187948**	*****0.168902**
(Std. Error)	0.049548	0.018780	0.018995	0.020677	0.090362	0.053688	0.019996	0.075531	0.008543
p-value	0.000080	0.000092	0.000251	0.000000	0.003733	0.000006	0.000000	0.012833	0.000000
GARCH-Beta	*****0.803538**	*****0.920134**	*****0.865422**	*****0.867267**	*****0.736958**	*****0.755174**	*****0.892158**	*****0.811052**	*****0.766444**
(Std. Error)	0.040464	0.017188	0.012996	0.026439	0.089087	0.071628	0.028693	0.077535	0.010914
p-value	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

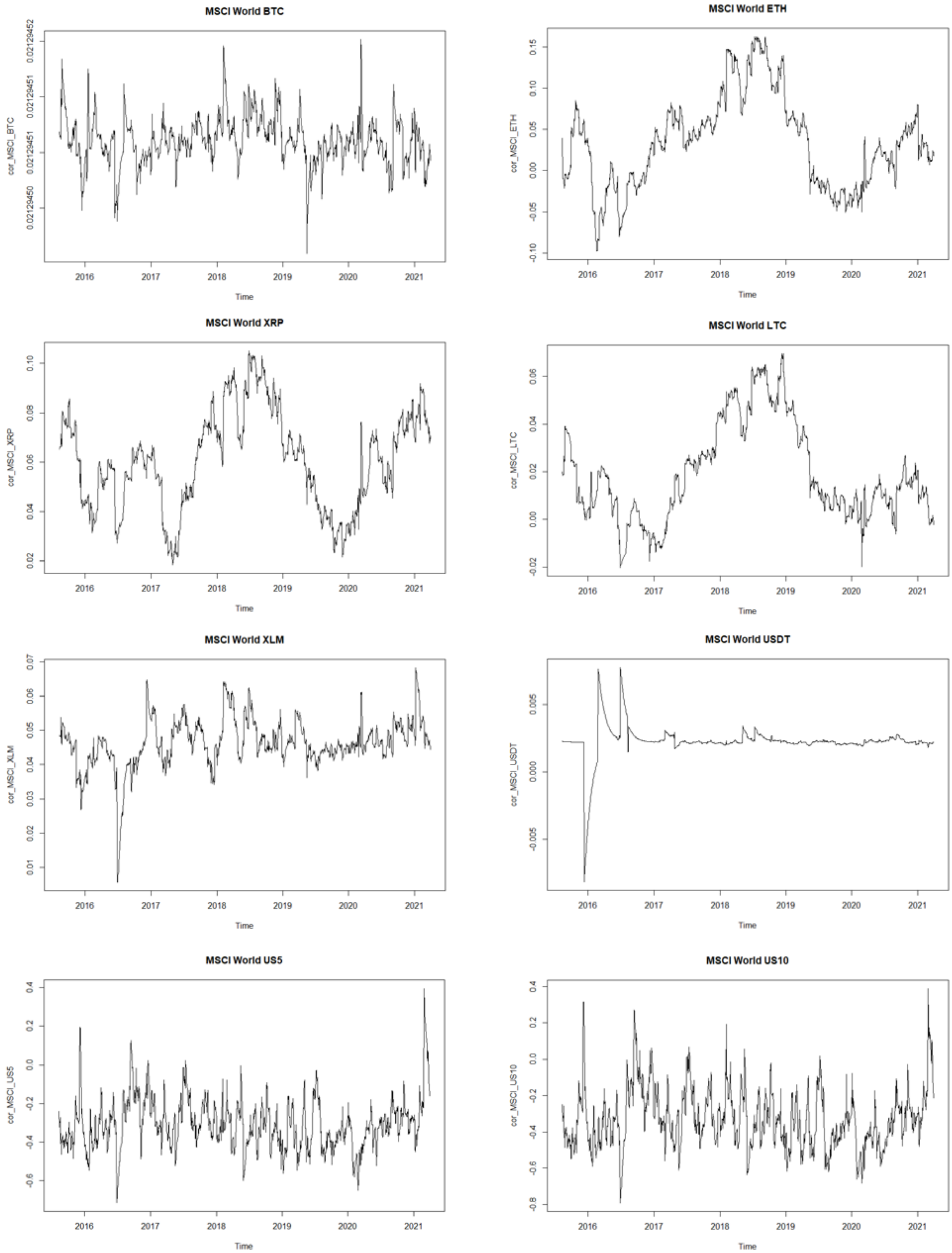
(DCC Equation)	*S&P500*	*S&P500*	*S&P500*	*S&P500*	*S&P500*	*S&P500*	*S&P500*	*S&P500*
	US 5Y Bond	*US 10Y Bond*	*BTC*	*ETH*	*XRP*	*LTC*	*XLM*	*USDT*
Dcc-Alpha	*****0.053735**	*****0.077763**	**0.000000**	**0.003917**	**0.003500**	**0.002850**	**0.000000**	**0.000000**
(Std. Error)	0.020872	0.022366	0.000029	0.004760	0.004214	0.003032	0.000605	0.000024
t-value	2.574469	3.476863	0.000119	0.823020	0.830460	0.940080	0.000004	0.000237
p-value	0.010039	0.000507	0.999905	0.410498	0.406279	0.347180	0.999997	0.999810
Dcc-Beta	*****0.857112**	*****0.830447**	*****0.948682**	*****0.989284**	*****0.986253**	*****0.99102**	**0.920700**	*****0.911885**
(Std. Error)	0.076107	0.060521	0.187316	0.007321	0.006386	0.003438	0.942558	0.157623
t-value	11.261916	13.721652	5.064616	135.130000	154.439870	288.244400	0.976810	5.785230
p-value	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.328663	0.000000
Log-Likelihood	12241.52	11228.23	7516.492	6818.111	6980.239	6952.368	6694.536	-531842.2
AIC	-16.6150	-15.238	-10.1950	-9.2461	-9.4664	-9.4285	-9.0782	722.63

Parameter estimates of a bivariate DCC-GARCH(1,1) model for S&P500 index with US Treasury Notes and the Cryptocurrencies, August 10, 2015 to March 31, 2021

6.2 Dynamic Conditional Correlations for the MSCI World Index, US Treasuries and Cryptocurrencies

The MSCI World index is the composite stock index we chose to represent the international characteristic comparable to cryptocurrencies' global digital asset nature. The MSCI World index captures large and mid-cap representation across 23 countries in the developed markets. As illustrated in Figure 1, the MSCI World index and the S&P 500 are very likely moving along the same trend and are highly correlated with each other. Therefore, the results of the correlations of the MSCI World index with US governments bonds and the cryptocurrencies studied in this paper replicate a similar pattern to ones in the S&P 500 index. Figure 3 exhibits the time-varying correlations of the MSCI World index with US Treasuries and the selected cryptocurrencies. In the following sections, discussion about correlations of each pair will be elaborated. Similar to section 6.1, the periods of financial uncertainty, market turmoil and financial crises under our focus in this section are Brexit in June 2016, the US trade ban on China in 2018 and the global COVID-19 pandemic starting in the beginning of 2020.

Figure 3 - Dynamic Conditional Correlations (MSCI world index with Cryptocurrencies and US Govt bonds)



6.2.1 Correlation Between US Treasuries and the MSCI World Index

From Figure 2, we first take a look at the traditional hedge assets of US government bonds; 5-year and 10-year. Both treasuries exhibit the same pattern of correlation with the MSCI World index. The correlations have been negative overall during the period, which implies that government bond prices and stocks move in opposite directions. If the bond prices go up, the stock prices go down. This relation indicates a capability of US government bonds as a hedge between 2015 and 2021; as same as in relation with the S&P 500. However, under the investigated period, the correlation occasionally reached a positive bound. This occasional touch could be seen as a signal of inefficiency for bonds as a hedge. Especially, from 2020 onwards, the negative correlations started moving upward toward the positive bound. There had been a lowering trend in Treasury yields around mid-2018 to 2020. Fear of inflation could be one of the key reasons for this negative relationship. However, starting from early 2021, when the US government announced the stimulus package, there was a sudden rise in correlations before they adjusted back to previous levels. The stimulus package reflected people's encouragement on future economic growth and hence resulted in lower bond prices as investors no longer needed to hold bonds as a hedge against an equity decline. Apart from that, a decline of negative correlation at the very end of this study's investigated period reflects the possibility of a declining trend of US treasuries as a hedge. If we look at the two spikes of negative correlation during the two market uncertainty events; Brexit in June 2016 and the global lockdown from COVID-19 in March 2020, we can see that the negative spike is much softer in the later event.

6.2.2 Correlation Between Bitcoin and the MSCI World Index

Slightly different from Bitcoin's relationship with the S&P 500, the time-varying correlation between the MSCI World index and Bitcoin shows marginal positive correlation over the investigated period. This result strengthens the implication of Bitcoin as a diversifier rather than a hedge asset. Our findings on Bitcoin as a hedge toward equity are not as expected from previous studies discussed in the literature review section, where other researchers examined Bitcoin correlations and concluded hedging possibilities of Bitcoin towards several kinds of financial assets during the earlier timespan (Urquhart and Zhang, 2019; Bouri et al., 2017; Kurka, 2019). However, similarly with the trend relationship of the S&P 500, during the short time period of market uncertainty events, namely Brexit in 2016, the US trade ban on China in 2018 and the beginning of a global lockdown following the COVID-19 pandemic in the first quarter of 2020, the correlation between Bitcoin and the MSCI World tends to fluctuate downward, signaling better hedge capabilities.

6.2.3 Correlation Between Altcoins and the MSCI World Index

The correlation of altcoins with the MSCI World index is similar to the correlations with the S&P 500 index. Altcoins generally have positive correlations with the MSCI World Index overall, however; on a marginal scale of less than the 0.1 level. Ether, Litecoin and Ripple illustrate a similar pattern of correlations with MSCI World index. The correlations of the three coins increased significantly in 2018 during the cryptocurrency boom period and also dropped back significantly in 2019 prior to the rise again in 2020 during market uncertainty caused by the global COVID-19 pandemic. Stellar has relatively smaller fluctuation during the investigated period and the correlations exhibit a trend that is closer to the Bitcoin pair. This observation is quite unexpected as with the initial characteristic of altcoins, we would expect Stellar to have a similar correlation trend with the Ripple pair as these two altcoins offer similar characteristics as described in Section 2. The significant drop in Stellar correlations found in June 2016 could be a consequence of the Brexit announcement and the rise in 2018 from the cryptocurrency bubble. For Tether, as the coin is tied to the US dollar, it is unsurprising to see a flat relationship with the MSCI World index.

6.2.4 Discussion and Analysis

Interestingly, the parameter estimates of DCC (Table 6) found the significance of the DCC-beta value close to one for all cryptocurrencies with the MSCI World index, in which it implies high persistence in the correlations. The GARCH and ARCH effect results from the first stage are all significant at the 0.01 confidence level and the GARCH-beta coefficients are higher than the ARCH-alpha coefficients, indicating that the conditional variances are affected by the prior ones of the returns series. Significance of both coefficients also indicates that the GARCH model is suitable for estimation.

Overall, both US Treasuries exhibit their correlations as a hedge against the MSCI World index during the investigated period. The cryptocurrencies do not demonstrate a hedging capability, however, considering a marginal positive relationship with the MSCI World index, the cryptocurrencies have potential to be a good diversifier in a portfolio. These findings are in line with research by Kostika and Laopodis (2019) according to which cryptocurrencies are suitable to include in a global investment portfolio due to their independency of the global stock markets and exchange rates. However, slightly in contrast with our studies, research by Bouri et al. (2019) and Shahzad et al. (2020); which investigated cryptocurrencies' correlations with equity indices, found that some cryptocurrencies act as a stronger hedge toward equity indices in a different region. For example, Bouri et al. (2019) found that Bitcoin, Ethereum and Litecoin are hedges, especially in the Asia-Pacific and Japan. This could imply that each cryptocurrency is likely to reflect the stock market differently in each region or country. Nevertheless, with the world composite index, the correlations still reflect a diversification benefit.

Table 6 - DCC-GARCH (1,1) Estimation Results MSCI World Index

(Variance Equation)	*MSCI World*	*US 5Y Bond*	*US 10Y Bond*	*BTC*	*ETH*	*XRP*	*LTC*	*XLM*	*USDT*
Constant	*****0.000759**	**-0.000040**	**0.000005**	*****0.00312**	**0.001377**	*****-0.002873**	**0.000124**	*****-0.00365**	**0.000000**
(Std. Error)	0.000131	0.000042	0.000090	0.000643	0.001150	0.000787	0.000697	0.001163	0.000000
p-value	0.000000	0.342703	0.959234	0.000001	0.231013	0.000261	0.859303	0.001693	0.520041
ARCH-Alpha	****0.185826**	*****0.073431**	*****0.069553**	*****0.131733**	*****0.26204**	*****0.243826**	*****0.106842**	****0.187948**	*****0.168902**
(Std. Error)	0.082457	0.018727	0.019069	0.020679	0.090232	0.053673	0.020010	0.075558	0.008484
p-value	0.024221	0.000088	0.000265	0.000000	0.003683	0.000006	0.000000	0.012866	0.000000
GARCH-Beta	*****0.811761**	*****0.920134**	*****0.865422**	*****0.867267**	*****0.736958**	*****0.755174**	*****0.892158**	*****0.811052**	*****0.766444**
(Std. Error)	0.06319	0.017150	0.012996	0.173817	0.089119	0.071631	0.028720	0.077576	0.010826
p-value	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

(DCC Equation)	*MSCI World*	*MSCI World*	*MSCI World*	*MSCI World*	*MSCI World*	*MSCI World*	*MSCI World*	*MSCI World*
	US 5Y Bond	*US 10Y Bond*	*BTC*	*ETH*	*XRP*	*LTC*	*XLM*	*USDT*
Dcc-Alpha	*****0.051311**	*****0.063345**	**0.000000**	**0.006805**	**0.003298**	**0.002327**	**0.001897**	**0.000838**
(Std. Error)	0.017777	0.016144	0.000060	0.004264	0.004060	0.003190	0.007409	0.001211
t-value	2.886462	3.928630	0.000014	1.595900	0.812230	0.729590	0.256080	0.691920
p-value	0.003896	0.000087	0.999989	0.110510	0.416659	0.465643	0.797891	0.488987
Dcc-Beta	*****0.869919**	*****0.866506**	*****0.927688**	*****0.987387**	*****0.986261**	*****0.991351**	*****0.961257**	*****0.959226**
(Std. Error)	0.047651	0.032198	0.185217	0.005152	0.007254	0.002829	0.099473	0.021798
t-value	18.256152	26.911753	5.008647	191.636100	135.956450	350.399070	9.663500	44.005820
p-value	0.000000	0.000000	0.000001	0.000000	0.000000	0.000000	0.000000	0.000000
Log-Likelihood	12461.95	11449.3	7746.975	7049.96	7211.524	7182.534	6925.967	-531536.4
AIC	-16.9140	-15.538	-10.508	-9.5611	-9.7806	-9.7412	-9.3926	722.21

Parameter estimates of a bivariate DCC-GARCH(1,1) model for MSCI World index with US Treasury Notes and the Cryptocurrencies, August 10, 2015 to March 31, 2021

6.3 Summary of Results

The correlations of cryptocurrencies with the two stock indices; the S&P 500 and the MSCI World index, generally present a marginal positive relationship, implying that cryptocurrencies can be considered as a good diversifier rather than a hedge during the investigated period of August 2015 to March 2021. As discussed previously, this finding is slightly different from previous studies (Bouri et al., 2019; Shahzad et al., 2020), where they concluded stronger hedging capabilities for some coins, such as Bitcoin, against the global equity index under an earlier investigation period. The parameter estimates generate an alpha that is close to zero and a beta that is close to one, indicating more persistence in the correlations of cryptocurrencies compared to the correlations with the US Treasuries. US Treasuries, however, demonstrate negative correlations with stock indices over the investigated period. Despite a declining trend of negative correlation at the very end, US Treasuries remain qualified as a hedge against equity.

Additionally, the pattern of correlation pairs with the coins that have similar characteristics are interestingly not similar to each other as initially expected. The first pair of Ripple and Stellar, where both coins predominantly represent payment systems, do not show a similarity in the correlation trend. In the case of another pair; Bitcoin and Litecoin, where one is deemed as digital gold and the other one is silver, the two pairs' correlations as well do not represent a similar trend.

7. Conclusion

The purpose of this study was to establish if cryptocurrencies can be used as a hedge against stock market risk in place of bonds, which are not considered as an effective hedge amid a low-yield environment and inflation expectations. Bonds have traditionally provided adequate protection against equity declines but have lost some of their appeal following the improving economic conditions and enormous stimulus packages. This study aimed to investigate new possibilities for investors in portfolio and risk management brought upon by the emergence of cryptocurrencies as a new asset class that can be categorized as a hybrid between a currency and a commodity. As such, the hedging capabilities of cryptocurrencies against stocks in the S&P 500 and MSCI World indices in comparison to US Treasuries were examined using the DCC-GARCH model.

Based on the dynamic conditional correlations, cryptocurrencies can be integrated into hedging as a complement rather than a substitute. Predominantly exhibiting negative correlation with the stock market during the investigated time period, bonds have had superior hedging capabilities against equity risk up until recently. With expectations of economic recovery following the COVID-19 pandemic and the accompanying inflation concerns, bond prices have declined in tandem with stock prices while yields are on the rise. As bond and stock prices are both trending positive, bonds no longer hedge against stock market risk the same way they have in the past. To answer the research question; cryptocurrencies display diversifying capabilities but cannot replace bonds as a hedge. Out of all the cryptocurrencies investigated in this study, we found that only Bitcoin has hedging capabilities but this is limited to a short-term time horizon and extreme market conditions. The majority of altcoins examined in this study did not exhibit any hedging capabilities throughout the investigated time period but can be used for diversification purposes as they generally tend to have a weak positive correlation with the stock market. Out of all the altcoins included in this study, we found that Ether and Litecoin provided superior diversifier benefits that can be extended to limited hedging capabilities during short-term economic uncertainty.

The main limitations of our research include the focus on the S&P 500 and MSCI World indices as a proxy for stocks as well as US Treasuries as a proxy for bonds. Our research could have had different results with an alternative market approach and stock index selection. Our findings were limited to developed markets, and especially the United States. However, it is possible that cryptocurrencies could have better hedging capabilities in emerging markets. Additionally, it is possible that cryptocurrencies that were not included in this study could have exhibited better hedging capabilities. Future research could be extended to other cryptocurrencies in addition to the time period following the aftermath of the COVID-19 pandemic. Although cryptocurrencies did not exhibit strong hedging or safe haven properties in this study, it is possible that this will change over time as cryptocurrencies are adapted as a more mainstream investment and asset class.

Additionally, further studies may include modelling of correlations by different models or investigate the asymmetric possibilities of cryptocurrencies. As cryptocurrencies are still a relatively new concept, the cryptocurrency market is facing new developments and speculation each day, indicating limitless market growth possibilities and various prospects for future research on the topic. Although it is nearly impossible to predict what the future will hold for such a volatile asset class, cryptocurrencies represent the construction of a new decentralized financial system that has proven to work even under extreme market conditions and stress, suggesting that cryptocurrencies are here to stay and their peak is yet to come.

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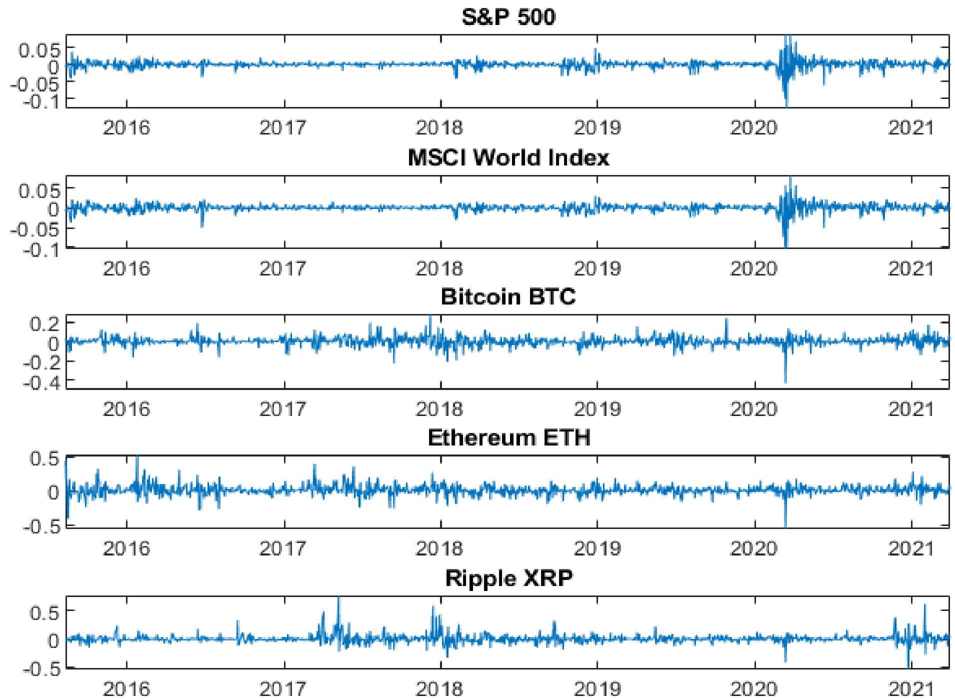
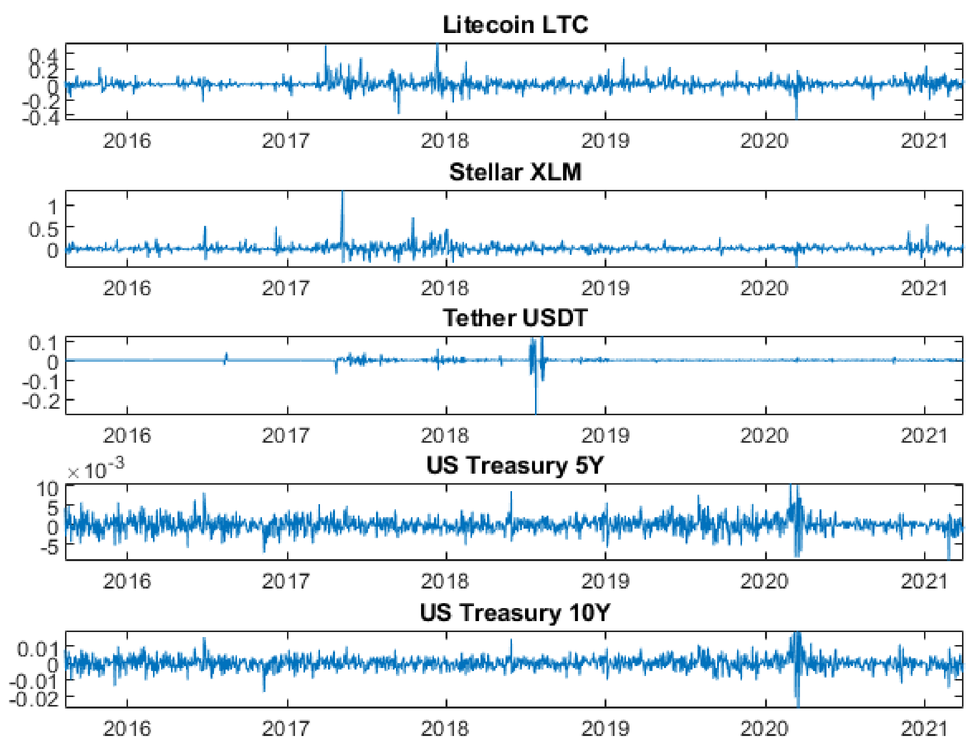
9. Appendices

Appendix 1: Plot of Log Returns Series

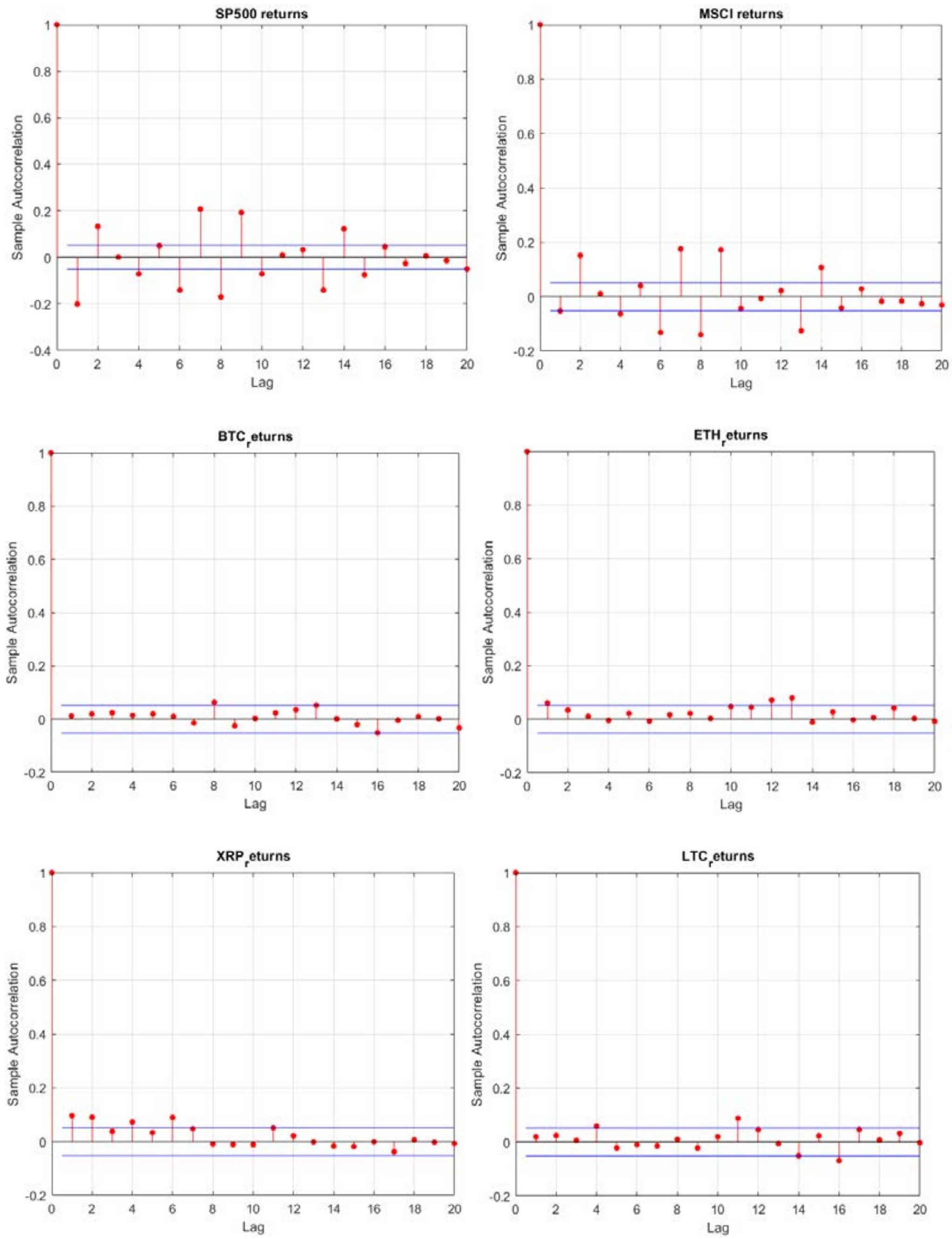


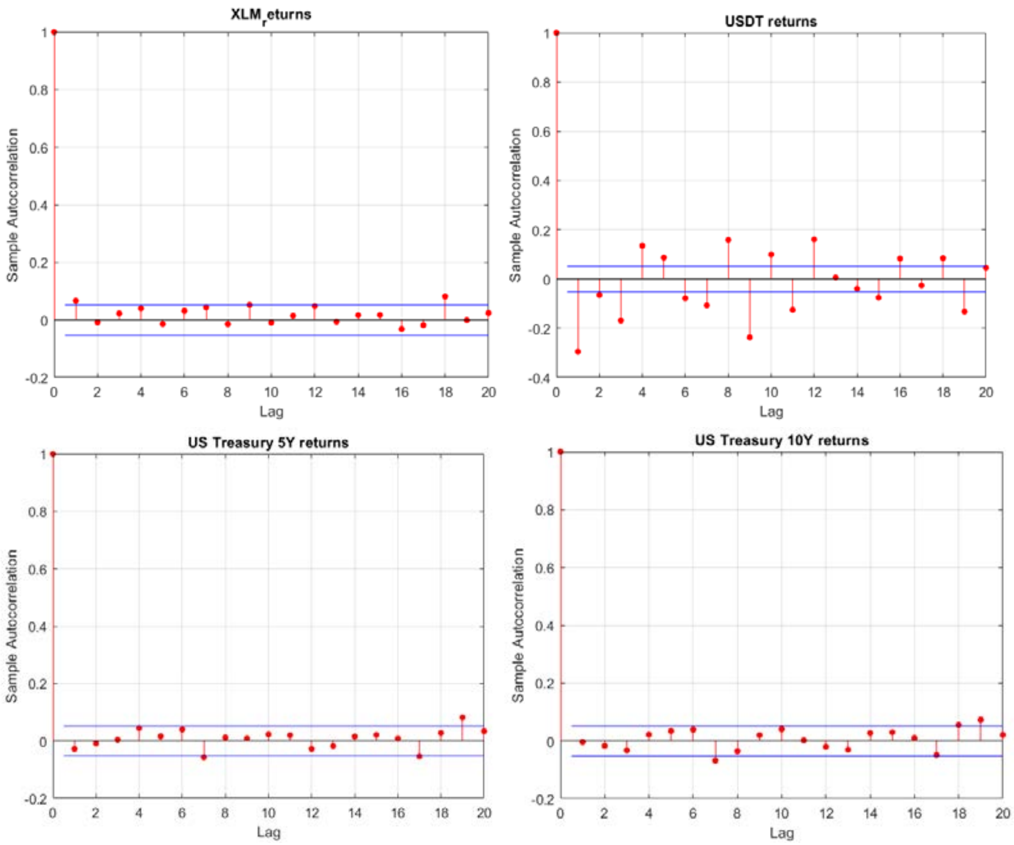


Appendix 2: Correlation Matrix of Stock Indices, US Treasuries and Cryptocurrencies

	S&P 500	*MSCI*	*US 5Y Bond*	*US 10Y Bond*	*BTC*	*ETH*	*XRP*	*LTC*	*XLM*	*USDT*
S&P 500	1									
MSCI	0.957679	1								
US 5Y Bond	-0.358899	-0.350737	1							
US 10Y Bond	-0.387516	-0.378486	0.929508	1						
BTC	-0.050622	-0.017372	-0.012247	-0.008675	1					
ETH	-0.042152	-0.020439	0.016714	0.019201	0.533072	1				
XRP	-0.004418	0.019403	0.023860	0.017889	0.374816	0.331042	1			
LTC	-0.040630	-0.004708	-0.003320	-0.001080	0.663551	0.516277	0.432808	1		
XLM	-0.015425	0.003516	-0.016118	-0.004360	0.406297	0.345906	0.591679	0.431968	1	
USDT	-0.010780	-0.004385	-0.036522	-0.040422	-0.027022	0.006328	-0.007987	-0.027336	-0.011001	1

Appendix 3: Autocorrelation Functions of Stock Indices, US Treasuries and Cryptocurrencies




XLM_returns
USDT returns
US Treasury 5Y returns
US Treasury 10Y returns
Sample Autocorrelation
Lag

Appendix 4: Market Capitalization of the Selected Cryptocurrencies

	Market Cap (US$)	Trading Volume(24h)	Circulating Supply	Maximum Supply	Release Year
Bitcoin (BTC)	1,044,446,559,059	47,686,580,918	18,667,250	21,000,000	2008
Ethereum (ETH)	194,913,443,083	16,599,472,938	115,240,935	N/A	2015
Tether (USDT)	40,500,517,197	69,313,550,904	40,475,941,170	N/A	2014
Ripple (XRP)	25,006,533,342	2,795,107,715	45,404,028,640	100,000,000,000	2012
Litecoin (LTC)	12,351,098,573	2,162,823,815	66,752,415	84,000,000	2011
Stellar (XLM)	9,060,062,003	1,322,103,231	22,687,533,551	50,001,806,812	2014

**Historical Information from coinmarketcap.com as of 28th March 2021.*

Source: coinmarketcap.com/historical snapshot [Accessed 21 May 2021]