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The potential role of cryptocurrencies as safe-haven assets: a worldwide empirical analysis

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Master in Monetary and Financial Economics

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CIÊNCIAS SOCIAIS
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Department of Political Economy

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Resumo

O papel das criptomoedas no panorama financeiro contemporâneo continua a ser um tema ambíguo e amplamente debatido na literatura. Enquanto alguns autores consideram criptomoedas, como a Bitcoin, uma forma de “ouro digital”, outros defendem que a sua natureza descentralizada as caracteriza como meros ativos especulativos sem valor intrínseco. Este estudo visa contribuir para esta discussão ao investigar o papel das criptomoedas, especificamente a Bitcoin e a Tether, como ativos de refúgio para várias regiões e classes de ativos, incluindo índices acionistas e *commodities*. Para tal, foi utilizado um modelo GARCH de Correlação Condicional Dinâmica de modo a estimar as correlações condicionais variáveis ao longo do tempo, especificamente nos níveis mais extremos de retornos negativos, entre as criptomoedas selecionadas e cinco índices regionais: S&P 500, STOXX 600, MSCI Asia Ex Japan, MSCI Pacific e MSCI World, além de duas *commodities*: Ouro e Petróleo.

Os valores de correlação obtidos levaram à conclusão de que tanto a Bitcoin quanto a Tether podem funcionar como ativos de refúgio em certas condições de mercado. A Bitcoin revelou-se particularmente eficaz como ativo de proteção durante os momentos mais extremos de retornos negativos, enquanto a Tether desempenhou um papel mais pronunciado de refúgio durante quedas moderadas do mercado. Em relação às *commodities*, a Tether exibiu capacidades tanto de proteção como de refúgio, enquanto o Bitcoin teve um papel de proteção mais limitado. Embora ambas as criptomoedas tenham mostrado comportamentos de refúgio, a sua eficácia revelou-se específica a cada ativo e dependente das condições de mercado.

Palavras-chave: Criptomoedas; Ativos de Refúgio; Bitcoin; Tether; DCC-GARCH.

Abstract

The role of cryptocurrencies in the contemporary financial landscape remains ambiguous and vastly debated in the literature. While some authors consider cryptocurrencies, such as Bitcoin, to be a form of “digital gold”, others contend that their decentralized nature categorizes them as speculative assets with no intrinsic value. This study intends to contribute to this discussion by investigating the role of cryptocurrencies, specifically Bitcoin and Tether, in functioning as safe-haven assets across various regions and asset classes, including stock indices and commodities. To accomplish this, a Dynamic Conditional Correlation GARCH model was utilized to estimate the time-varying conditional correlations, focusing on the most extreme levels of negative returns, between the selected cryptocurrencies and five regional indices: the S&P 500, STOXX 600, MSCI Asia Ex Japan, MSCI Pacific, and MSCI World, in addition to two commodities: gold and oil.

The correlation values obtained led to the conclusion that both Bitcoin and Tether can function as safe-haven assets under certain market conditions. Bitcoin proved particularly effective as a protective asset during the most extreme instances of negative market returns, while Tether demonstrated a more pronounced safe-haven role during moderate market downturns. Regarding commodities, Tether exhibited both hedging and safe-haven capabilities, whereas Bitcoin played a more limited protective role. Although both cryptocurrencies displayed varying degrees of safe-haven behavior across different asset classes, their effectiveness was found to be asset-specific and dependent on market conditions.

Keywords: Cryptocurrencies; Safe-haven Assets; Bitcoin; Tether; DCC-GARCH.

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Glossary

ADCC-GARCH - Asymmetric Dynamic Conditional Correlation – Generalised Autoregressive Conditional Heteroskedasticity

ADF - Augmented Dickey-Fuller

AIC - Akaike Information Criterion

ARMA-GARCH - Autoregressive Moving Average – Generalised Autoregressive Conditional Heteroskedasticity

AUD - Australian dollar

BEKK - Baba-Engle-Kraft-Kroner

BIC - Bayesian Information Criterion

BRIC - Brazil, Russia, India and China

CAD - Canadian dollar

CCC-GARCH - Constant Conditional Correlation - Generalized Autoregressive Conditional Heteroskedasticity

CHF - Swiss franc

CCC - Constant Conditional Correlation

CCC-GARCH – Constant Conditional Correlation - Generalised Autoregressive Conditional Heteroskedasticity

DCC - Dynamic Conditional Correlation

DCC-GARCH - Dynamic Conditional Correlation - Generalised Autoregressive Conditional Heteroskedasticity

EGARCH - Exponential GARCH

EPU - Economic Policy Uncertainty Index

ETF - Exchange Traded Fund

EUR - Euro

GARCH - Generalised Autoregressive Conditional Heteroskedasticity

GED - Generalised Error Distribution

GJR-GARCH - Golsten, Jagannathan and Runkle – Generalised Autoregressive Conditional Heteroskedasticity

JPY - Japanese Yen

KPSS - Kwiatkowski–Phillips–Schmidt–Shin

MSCI - Morgan Stanley Capital International

PCI - Partisan Conflict Index

PP - Phillips-Perron

TGARCH-DCC - Threshold Generalized Autoregressive Conditional Heteroskedasticity-A-Dynamic Conditional Correlation model

US - United States

USD - United States Dollar

VECH-GARCH - Vectorized Conditional Heteroskedasticity - Generalized Autoregressive Conditional Heteroskedasticity

WTI - West Texas Intermediate

1. Introduction and General Context

Due to their unique characteristics within the financial universe, cryptocurrencies have garnered considerable interest from investors, regulatory entities, the media and speculators since the creation of the first cryptocurrency back in 2009. This interest is primarily due to the fact they represent a revolutionary asset in the financial landscape, creating numerous opportunities for market participants.

The current leading cryptocurrency is Bitcoin, which was launched in January 2009. This digital currency quickly became a significant asset in the financial markets, even reaching a market capitalization of over 1 trillion dollars in 2021, according to information from CoinMarketCap.

However, since its creation, Bitcoin's journey has been quite turbulent. Created by Satoshi Nakamoto, Bitcoin emerged essentially as a means of payment, where transactions would be conducted through a peer-to-peer system, with the primary goal of establishing a secure electronic transaction system without any reliance on a financial intermediary, eliminating the need for a trust relationship between the parties involved (Nakamoto, 2008). In 2010, the first known transaction involving Bitcoin took place, where programmer Laszlo Hanyecz purchased two pizzas for approximately 10,000 Bitcoins (Cermak, 2017) - equivalent to more than 1000 million dollars at the peak of the digital asset's value in December 2024 (Figure 1).

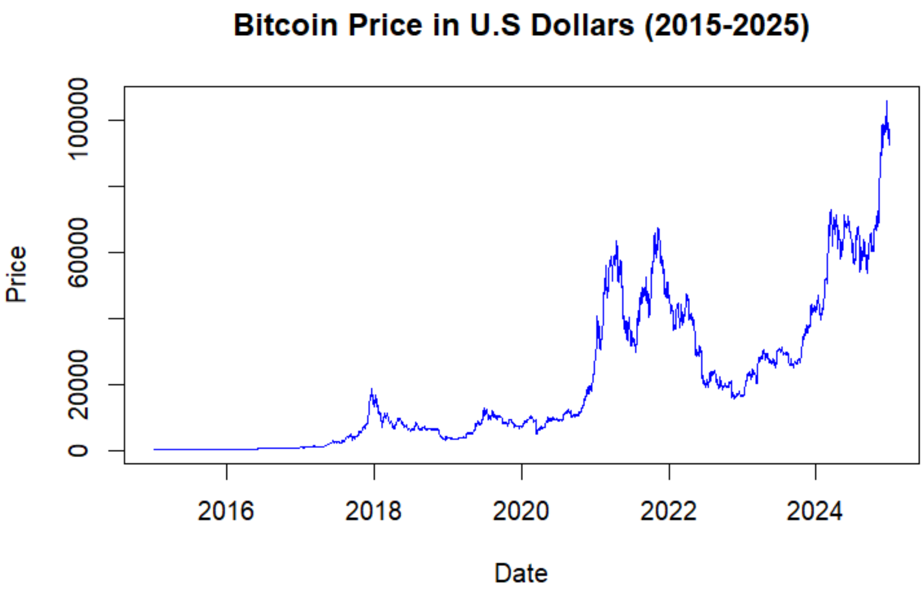

Figure 1: Bitcoin's Price Evolution Between 2015 and 2025.
Source: RStudio Output / Data from Reuters

Volatility continued to be one of Bitcoin's defining characteristics, stemming from its decentralized nature and the difficulty in assigning a fundamental value to it. The result has been speculative bubbles of significant magnitude followed by considerable losses, as seen in 2011 when Bitcoin surpassed 30 dollars in June - a 30-fold increase in a span of 5 months - only to end the year six times below that value, just above 4 dollars. A similar situation occurred in November 2013 when the digital currency tripled in value in that month alone, surpassing the 1,200-dollar mark, before dropping to 111.60 dollars by February 2014 – a decline of over 90% in just 3 months – due to a cyberattack on the Mt. Gox trading platform, which resulted in the loss of around 750,000 Bitcoins belonging to users (Christian, 2024).

In the following years, despite its characteristic volatility, Bitcoin's popularity continued to grow, and this trend was reflected in its price. It first reached 10,000 dollars in 2017, 50,000 dollars in 2021, and its all-time high of over 100,000 dollars in December 2024, the year in which the United States Securities and Exchange Commission approved the first Bitcoin Exchange Traded Fund (ETF) for trading, granting greater credibility and stability to the digital currency.

With Bitcoin's growing popularity and increasing mainstream attention, questions about its role in the financial system have become more prominent, mainly due to Bitcoin's detachment from regulatory and governmental oversight, which complicates the assessment of its intrinsic value, amplifying speculation and other factors, such as volatility. These characteristics fuel the ongoing debate in academic literature regarding Bitcoin's classification - whether it can serve as a currency, a speculative asset, or as explored in this dissertation, a safe-haven asset (Smales, 2018).

In light of these uncertainties and evolving discussions, this dissertation is motivated by the need to better understand the broader implications of cryptocurrencies - particularly Bitcoin - within the global financial ecosystem. By examining its potential as a safe-haven asset, this research aims to offer insights that are valuable to a diverse range of stakeholders, including investors, central banks, regulatory authorities, financial institutions, and the wider financial community.

For investors, both institutional and retail, this study seeks to provide valuable insights into the potential role of cryptocurrencies in portfolio construction. Specifically, it examines whether Bitcoin can contribute to diversification strategies that aim to reduce exposure to adverse macroeconomic conditions, such as financial market downturns or fiat currency devaluations.

For central banks and regulatory authorities, the exploration of Bitcoin's behavior during periods of market stress may inform future approaches to monetary policy and financial stability. If Bitcoin or similar decentralized assets exhibit safe-haven characteristics or countercyclical properties, their relevance to systemic risk management and policy formulation could increase substantially.

Financial institutions may also find this research pertinent as they evaluate the integration of cryptocurrencies into existing financial frameworks. The study's findings could influence investment strategies, risk management protocols, and the development of novel financial products tailored to evolving client needs and market dynamics.

Finally, for the broader financial community, this dissertation aims to enrich the understanding of Bitcoin not only as an asset class but as a component of the growing decentralized finance (DeFi) sector. By examining the interaction between digital assets and traditional financial markets, the study contributes to the ongoing effort to delineate the role of cryptocurrencies within the global economic landscape.

In relation to the existing literature regarding the potential safe-haven role of Bitcoin and cryptocurrencies in general, the research has primarily examined two periods of heightened market volatility: the COVID-19 pandemic and the Russia-Ukraine war. Conclusions regarding the safe-haven role of cryptocurrencies during these periods remain mixed. While some authors like Mariana et al. (2021) and Havidz et al. (2023) confirm the safe-haven properties of cryptocurrencies across different markets during troubled instances, others such as Choi and Shin (2022) and Dutta et al. (2020) provide opposing evidence. An alternative methodological approach used by Shahzad et al. (2019), Stensås et al. (2019) and others involves a percentile-based analysis, which identifies specific periods of extreme negative market returns to examine the correlations between equity markets and various asset classes, including cryptocurrencies, commodities, and bonds, during these critical periods. This dissertation aims to contribute to the ongoing discourse on the role of cryptocurrencies as safe-haven assets during periods of market distress by employing a comparable methodological approach over a ten-year period, from early 2015 to the end of 2024, providing a more up-to-date analysis of Bitcoin's performance as a safe-haven asset within quantile-based research. Additionally, this study expands the scope of analysis by incorporating a diverse range of regional equity markets, commodities and cryptocurrencies.

For this analysis, two cryptocurrencies with distinctly different properties were selected: Bitcoin and Tether. Bitcoin was chosen due to its status as the leading cryptocurrency in the market, as previously mentioned. Tether, on the other hand, was selected because it is a stablecoin, designed to maintain a relatively stable price by being pegged, in this case, to the US dollar, meaning, unlike most other cryptocurrencies, its value is not primarily driven by supply and demand dynamics. The existing literature has examined Tether's role as a safe-haven in specific contexts, such as the COVID-19 pandemic and the Ukrainian conflict. However, no studies have employed percentile-based regressions over multiple years to analyze this phenomenon. This dissertation seeks to contribute to the literature by incorporating this methodological approach into Tether's safe-haven research.

To evaluate the potential role of cryptocurrencies as a safe-haven, this study utilizes five regional indices as proxies for global equity markets: the S&P 500 for the United States, STOXX 600 for Europe, MSCI Asia ex Japan for Asia, MSCI Pacific for the Pacific region, and MSCI World for the global market. While most of the existing literature focuses primarily on the United States due to its global economic significance, as exhibited by authors such as Mariana et al. (2021) and Umar et al. (2021), this research seeks to explore potential differences in the behavior of digital assets across various regions. This investigation is particularly relevant given that cryptocurrencies face regulatory restrictions or outright bans in certain countries, such as China and Saudi Arabia.

Finally, this study will also analyze the daily returns of a selection of commodities, specifically gold and oil. Gold has been included due to its frequent identification in the literature as a safe-haven asset for stock market indices, as highlighted by Baur and Lucey (2010), Baur and McDermott (2016), Gomis-Porqueras et al. (2022) and others. Oil was selected for its common association with such analyses, as demonstrated by the works of Dutta et al. (2020), Kassamany et al. (2023), and others, as well as for its distinct characteristics compared to the other assets examined in this study.

To achieve this objective, a Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model will be utilized to establish the correlations between the two aforementioned cryptocurrencies and the other assets included in the analysis. The focus will be on the specific time periods where the markets experienced their worst performance, as determined by the 1%, 2.5%, 5%, and 10% lowest observed returns.

The results, based on the obtained correlation values, indicate that both Bitcoin and Tether can serve as safe-haven assets for North American, European, Asian, Pacific, and global market proxies under certain market conditions. Bitcoin, in particular, proves to be an effective protective asset during extreme instances of negative market returns, whereas Tether plays a more pronounced role as a safe-haven during moderate downturns. Regarding commodities, Tether demonstrates both hedging and safe-haven capabilities, while Bitcoin exhibits a more limited protective role, acting only as a weak safe-haven for oil in one of the analyzed quantiles. These findings partially align with conclusions drawn by other researchers while also offering new insights that contribute to the ongoing debate on the role of cryptocurrencies in modern finance and economics.

The organization of this thesis is as follows: Section II presents a review of the key literature on safe-haven analysis and the role of cryptocurrencies in this context. Section III provides a detailed description of the dataset used in the study, while Section IV outlines the methodology applied in conjunction with the dataset. Lastly, Sections V and VI discuss the application process and present the final results for both Bitcoin and Tether, respectively.

2. Literature Review

2.1. Cryptocurrencies and Blockchain

Given the innovative nature of cryptocurrencies and the technology behind their creation, it is important to define the associated concepts based on the available literature.

Cryptocurrencies are a set of digital assets that allow secure transactions through the use of blockchain technology, eliminating the need for a financial intermediary, such as a bank (Hardle et al., 2020). In this context, the leading cryptocurrency is Bitcoin: a decentralized digital currency that emerges as an alternative to fiat currency due to its independence from government entities, banks, and other institutions, which is again enabled through the blockchain (Umar et al., 2021).

In this regard, Rodeck and Curry (2022) define blockchain as a “distributed digital ledger” (DLT) designed to store information in interconnected blocks, where encryption and mathematical formulas ensure that the stored information cannot be altered. Since its creation in 2008, blockchain has been considered a revolutionary technology in several fields, particularly into the realm of finance (Krichen et al., 2022) and forms the foundation for all cryptocurrencies. Furthermore, one of the key characteristics of blockchain technology is its decentralization: instead of being controlled by a central authority, control is distributed across a network, providing a higher level of confidentiality and privacy (Rodeck and Curry, 2022).

2.2. Safe-havens, Hedges and Diversifiers

Considering the central theme of this dissertation, it is crucial to clarify what constitutes a safe-haven asset and to distinguish it from other asset categories, such as hedges and diversifiers. Baur and Lucey (2010) established foundational definitions on the matter, describing a safe-haven as an asset that is negatively correlated with other assets or portfolios specifically during periods of market crisis, whereas a hedge is defined as an asset that is negatively correlated (or uncorrelated) with another asset or portfolio on average, regardless of market conditions. According to these authors, assets considered safe-havens may at times move in the same direction as other assets; however, their defining feature is that they exhibit negative correlation or complete uncorrelation during periods of financial instability. As for a diversifier, an asset is considered a diversifier if it is positively (but not perfectly) correlated with another asset or portfolio on average.

Baur and McDermott (2010) further distinguish between weak and strong forms of these categories. A strong hedge is an asset that is negatively correlated with another asset or portfolio on average, while a weak hedge is completely uncorrelated. Similarly, a strong safe-haven is negatively correlated with another asset during market downturns, while a weak safe-haven is uncorrelated during such periods.

The most commonly accepted asset in the literature as a safe-haven is gold. According to Baur and Lucey (2010), gold can function as a hedge on average and as a short-term safe-haven (for about 15 trading days) during extreme market conditions in Germany, the United States, and the United Kingdom, based on the econometric model developed by the authors. Following this study, Beckmann et al. (2014) augment the model followed by Baur and Lucey (2010) to a smooth transition regression in order to allow for periods of heighten volatility in the stock markets to be accounted for, while also extending this analysis to include a broader range of stock markets, concluding that gold has performed as a weak or a strong safe-haven for the majority of the markets analyzed.

Baur and McDermott (2016) confirm the safe-haven property of gold, concluding through a similar model to Baur and Lucey (2010) that the precious metal served as a safe-haven for the US market on various occasions, particularly following the events of September 11 in 2001, and the collapse of Lehman Brothers in 2008. The authors attribute this property to behavioral tendencies and to gold’s historical role as a currency, although other assets, such as the US dollar during the 2008 financial crisis, have also exhibited this characteristic in certain instances. In similar fashion, Gomis-Porqueras et al. (2022) add to the aforementioned research, stating that gold also presents safe-haven properties for the European sovereign debt crisis, oil inflationary pressures and stock market crashes. Regarding the stock market, Ming et al. (2023) provide details concerning the safe-haven role of gold for stocks through a bivariate two-state regime-switching model, where the goal was to study the relationship between gold and different markets around the globe. On the matter, the authors conclude that out of the 24 countries examined, gold served as a safe-haven for 9 of them, those being Brazil, France, India, Indonesia, Italy, Mexico, Russia, South Korea, and Turkey.

Other studies regarding gold’s role as a safe-haven have emerged through the use of several regression models. Relating to this point, Salisu et al. (2021) sought to test gold’s safe-haven property during another period of heightened economic and social instability, this time during the COVID-19 pandemic. They concluded that gold did in fact offer a higher level of protection compared to other similar assets, such as silver and platinum, although it had done so more effectively in the past. A similar conclusion was obtained by Choudhury et al. (2022) and Gomis-Porqueras et al. (2022), with the authors defending that gold also performed as a weak safe-haven for stocks on the breakout of COVID-19. Regarding other markets, Wang and Lee (2021) investigated whether gold could serve as a safe-haven for exchange rates, confirming this hypothesis through a time-varying parameter vector autoregression in the short term for the US dollar, euro, and British pound.

2.3. Cryptocurrencies as safe-havens

In recent literature, numerous comparisons between gold and Bitcoin, the leading cryptocurrency, have emerged. Popper (2015) argues that Bitcoin shares many similarities with gold for investment purposes, not only due to its role as a portfolio diversifier but also as a hedge, considering the cryptocurrency as "digital gold". Baur et al. (2018) also discuss the similarities between these two assets, stating that Bitcoin shares many characteristics with gold: both are decentralized, not reliant on government action, globally available for exchange at any time, and require "mining". However, Baur et al. (2017) also state that Bitcoin exhibits distinct return, volatility and correlation characteristics in comparison to gold.

With the aforementioned points in mind and considering that gold is regarded as the primary safe-haven asset in literature, numerous studies have been conducted to investigate the potential for cryptocurrencies, similar to the precious metal, to function as safe-haven assets during historical periods of social and economic turmoil, such as the COVID-19 pandemic and the Russia-Ukraine conflict – the two main periods of profound social and economic instability since cryptocurrencies became relevant in the financial landscape.

Regarding the COVID-19 crisis, some authors advocate for the role of cryptocurrencies as a reliable safe-haven asset. On the matter, Mariana et al. (2021) sought to explore through a DCC (Dynamic Conditional Correlation) model the possible role of the two largest cryptocurrencies by market capitalization (Bitcoin and Ethereum) as safe-haven assets in response to the negative shock observed in the US stock market at the onset of the COVID-19 pandemic crisis. They concluded that from the start of the pandemic shock (March 11, 2020) until the end of the period under analysis (April 6, 2020), both cryptocurrencies, despite notable volatility, exhibited safe-haven properties. Interestingly, Ethereum demonstrated greater capacity in this regard than Bitcoin, due to its higher correlation with gold. A similar conclusion was achieved by Melki and Nefzi (2022), who through a logistic smooth transition model, stated that both Bitcoin and Ethereum could act as safe-havens for commodities during the beginning of the pandemic crisis, with the latter providing a stronger capability to act as a safe-haven asset, just like Mariana et al. (2021) concluded.

An analysis solely regarding emerging markets was conducted by Ustaoglu (2022), with the author using an asymmetric dynamic conditional correlation-generalized autoregressive conditional heteroskedasticity model to conclude that both Bitcoin and Ethereum also performed as weak safe-havens for the majority of the so-called emerging stock market (ESM) during the COVID-19 outbreak, with Bitcoin showing weak safe-haven characteristics for countries such as Argentina, China, Egypt, India, Indonesia, Kuwait, and Pakistan, while Ethereum demonstrated similar characteristics for markets in China, Colombia, Egypt, India, Indonesia, Kuwait, and Malaysia.

A non-financial market-based approach was utilized by Rubbaniy et al. (2020), where the application of a wavelet coherence approach allowed the authors to compare the global COVID-19 fear index (GFI) to cryptocurrency returns, namely Bitcoin, Ethereum and Ripple returns. Their findings suggest that the GFI had a positive impact on the returns of all the cryptocurrencies analyzed, due to the co-movement demonstrated by the variables during the pandemic outbreak, suggesting that Bitcoin, Ethereum and Ripple could have been used as safe-havens during the pandemic. A similar conclusion was obtained by Goodell and Goutte (2021), who using the same model as Rubbaniy et al. (2020) established that the levels of COVID-19 caused a rise in Bitcoin prices, highlighting the potential for Bitcoin to act as a safe-haven investment during the global pandemic.

Corbet et al. (2020) provided a different approach to this matter by exploring the relationship between market sentiment during the breakout of the COVID-19 pandemic and the volume and returns of crypto assets through sentiment data obtained from social media, concluding that the volume and price of cryptocurrencies increased during periods of high instability, contributing to the conclusion that digital assets can in fact act as a safe-haven asset. Still on the topic of market sentiment, Marobhe (2021) employed a bayesian estimation of structural vector autoregressive model with the objective of studying how COVID-19 induced panic affected the price of three cryptocurrencies (Bitcoin, Ethereum Litecoin) and three stock indexes (S&P500, FTSE100, and SSE Composite). The author concluded that although the returns of all cryptocurrencies suffered massively amidst the early days of the outbreak, all of them recovered by April 2020 and remained resistant to further COVID induced shocks. These results are dissimilar to those for the stock indexes, which were vulnerable to shocks all the way throughout 2020 and until June 2021. These differences in behavior between the two asset classes contribute to the conclusion that cryptocurrencies can in fact act as safe-havens for stocks.

Although the previous studies argue in favor of the role of cryptocurrencies as a safe-haven for a multitude of markets during the COVID-19 crisis, others conclude the exact opposite. In this regard, Dutta et al. (2020) focused on examining the safe-haven properties of digital assets and gold for the oil market during the beginning of the pandemic using a DCC-GARCH model. Their findings revealed that, while gold functioned as a safe-haven for oil during the crisis, Bitcoin served solely as a diversifier. Cocco et al. (2022) applied a similar methodology to assess whether Bitcoin and Ethereum could serve as safe-haven assets during the COVID-19 period for major stock market indices, oil, gold, commodities, and the US dollar index. The authors conclude that, while there are instances of negative correlations between the two cryptocurrencies and some of the markets analyzed, Bitcoin and Ethereum lack key characteristics traditionally associated with safe-haven assets. Specifically, their limited convertibility to cash, complexity of use, potential for degradation over time, and lack of association with entities of unquestionable credibility render them unsuitable for fulfilling the role of a reliable safe-haven. Kumar (2020) also utilized the Dynamic Conditional Correlation Model to examine the safe-haven properties of gold and Bitcoin in relation to equity markets, focusing on the Indian, North American, Chinese, and French markets, represented by the NSE50, DJIA, SSE, and CAC40 indices, respectively. In the context of the COVID-19 pandemic, the author found that although both assets had previously shown potential as safe-havens due to their low correlation with equity returns, this characteristic diminished during the peak of the COVID-19 market crisis. In particular, the study observed a positive correlation between these assets and equity returns during the pandemic's initial stages.

In a related study, using a Vector Autoregressive model, Choi and Shin (2022) examined the effects of inflation and uncertainty on Bitcoin and gold. They concluded that while Bitcoin responded positively to inflation and policy uncertainty - highlighting its independence from government entities - financial uncertainty shocks had a negative impact on Bitcoin's returns. This adverse effect was not observed for gold, leading the authors, in alignment with Dutta et al. (2020), to conclude that Bitcoin, unlike gold, did not function as a safe-haven asset during the breakout of the pandemic. Similarly to the previous authors, Chemkha et al. (2021) employed a multivariate asymmetric dynamic conditional correlation model to compare Bitcoin and gold alongside major stock market indices and currencies, including the S&P 500, Eurostoxx 50, Nikkei 225, FTSE 100, as well as the Euro (EUR), British Pound (GBP), and Japanese Yen (JPY). Their findings indicate that, while Bitcoin serves as an effective hedging asset, it did not offer investors the same level of protection from the market shock induced by COVID-19 as gold did. Kayral et al. (2023) extended this analysis for a larger range of stock market indices, where the authors based on a Diagonal VECH-GARCH modelling procedure were able to estimate the dynamic conditional correlations between G7 stock markets, Bitcoin and gold during the COVID-19 pandemic, with their conclusions not differing substantially from the aforementioned studies: while gold showed a strong capability to act as a hedge for the stock markets in question, Bitcoin could not be considered a safe-haven for any of the markets analyzed.

On a broader scale regarding the crypto market and drifting from the sole gold-bitcoin comparisons, Vukovic et al. (2021) aimed to assess the potential of the cryptocurrency market as a whole to function as a safe-haven during the COVID-19 pandemic. Using Ordinary Least Squares (OLS), quantile, and robust regressions, they concluded that among the cryptocurrencies analyzed - Bitcoin, Ethereum, XRP, Bitcoin Cash, and Tether - only Tether demonstrated safe-haven potential, since it was the only digital asset that remained unaffected by broader market movements, represented in this study by the S&P 500. A similar conclusion was obtained by Conlon et al. (2020), who through a Conditional Value at Risk approach (CVAR), studied the role of Bitcoin, Ethereum and Tether in the construction of investment portfolios, concluding that although Bitcoin and Ethereum are not found to act as safe-havens for international equity markets, Tether, due to its association with the US Dollar, acted as a safe-haven for all markets analyzed during the COVID-19 turmoil. Ji et al. (2020) in similar terms intended to study the safe-haven properties of several assets (namely Bitcoin) through the investigation of whether the instability of a stock index could be offset by any of the assets under analysis, stating that solely gold and soybean commodity futures acted as safe-havens during the pandemic, with Bitcoin not showing the same property.

Finally, AlAlii (2020) sought to study if some potential safe-haven assets, such as the Swiss franc, gold and Bitcoin exhibited that property during the pandemic breakout through an Ordinary Least Squares regression. While the Swiss franc and gold had positive and non-market dependent returns during the breakout, Bitcoin showed negative returns and a statistically significant positive relation with the S&P500 returns, indicating the lack of capability for the cryptocurrency to act as a safe-haven asset during this time period.

While much of the literature on the potential role of cryptocurrencies as a safe-haven focuses on the period linked to the COVID-19 pandemic, due to the resulting social and economic impacts associated with this phenomenon, other periods of significant instability have also been used for this kind of analysis, such as the Russia-Ukraine war. On this matter, Fakhfekh et al. (2023) aimed to explore if cryptocurrencies – namely Bitcoin and Tether - could display safe-haven characteristics during the conflict for G7 investors, concluding through a Threshold Generalized Autoregressive Conditional Heteroskedasticity-A-Dynamic Conditional Correlation model (TGARCH-ADCC) that the cryptocurrencies under analysis could not be considered as safe-haven assets during the period of the conflict, with Bitcoin and Tether serving solely as diversifiers. Similarly, Hampl et al. (2024) utilized a cross-quantilogram approach to assess whether cryptocurrencies, including Bitcoin, Ethereum, Tether, and Solana, could function as safe-havens for one another, as well as for gold, stock and commodity markets, and selected exchange currencies during wartime. Their findings suggest that, overall, these cryptocurrencies exhibit weak safe-haven properties in relation to the commodity market, while demonstrating strong safe-haven characteristics for foreign exchange currencies. Specifically, Tether and Solana are found to provide safe-haven properties for gold, with Tether also displaying weak safe-haven characteristics for the stock market, due to its association with the US Dollar.

Havidz et al. (2023) provided a contrasting perspective by employing a quantile regression on panel data, demonstrating that Bitcoin has functioned as a strong safe-haven for traditional assets during the conflict, particularly stock markets and government bonds in the five largest European and Asian economies: Germany, France, the United Kingdom, Japan, and China. Furthermore, the study revealed that gold also acted as an effective safe-haven for both stocks and wheat. This is particularly relevant given the context of the ongoing conflict, as Russia and Ukraine collectively account for approximately 25% of the world's wheat supply. Liu (2023) arrived at a similar conclusion for Bitcoin in the short-term through the use of a Vector Autoregression Model (VAR) and an Autoregressive Moving Average - Generalized Autoregressive Conditional Heteroskedasticity (ARMA-GARCH) model, stating that the impact of the geopolitics associated with the conflict impacted Bitcoin's yield positively during a brief time span, allowing the cryptocurrency to be perceived as a short-term safe-haven.

Regarding other periods of instability, Umar et al. (2021) sought to investigate whether Bitcoin could function as a safe-haven during periods of political and economic uncertainty in the United States between 2010 and 2020, a period marked by three presidential elections and the onset of the pandemic crisis. Their findings were mixed: in certain periods, Bitcoin did indeed serve as a safe-haven amid political and economic instability, driven by the positive impact of the uncertainty proxies used - namely, the Partisan Conflict Index (PCI) and the Economic Policy Uncertainty Index (EPU) - on the price of the digital asset. However, the reverse was also observed, with instances where the PCI and EPU negatively affected Bitcoin's returns.

Another recurring approach in the literature is the examination of the potential safe-haven role of cryptocurrencies during the exact time frames where the market recorded its worst percentage returns. This is typically conducted by analyzing the correlations between cryptocurrency returns and market returns within the percentiles that represent these lowest market returns, commonly using the first, fifth, and tenth percentiles.

In this matter, Shahzad et al. (2019), through a bivariate approach by percentiles in a panel data framework, aimed to determine whether Bitcoin, gold, and commodities could exhibit safe-haven properties against various indices, including the American (represented by the S&P 500), global, “developed”, “emerging”, and Chinese indices. They concluded that Bitcoin possesses some weak safe-haven properties for the global and Chinese indices under certain extreme market conditions. In addition to the work done by Shahzad et al. (2019), Fabris and Ješić (2023) focused their analysis on the European market landscape, exploring the potential of gold and Bitcoin as safe-haven assets for European stock indices by using quantile regression models to distinguish between “normal times” and periods of market stress. Their percentile-based analysis indicates that gold, due to its negative albeit insignificant correlation with the DAX 40 (the German index) and the EURONEXT 100 index, could indeed serve as a safe-haven asset, though the same conclusion does not hold for Bitcoin, due to its significant positive correlation with the two stock indices.

Stensås et al. (2019) achieved a similar conclusion when investigating the potential of Bitcoin and certain commodities to serve as a diversifier, hedge, or safe-haven asset for investors in both developed and developing markets. Using a Dynamic Conditional Correlation GARCH model to examine the 1%, 5%, and 10% worst daily returns for these indices, the authors found that Bitcoin acted as a hedge for developing markets such as Brazil, Russia, India, and South Korea. In other cases, it primarily served as a diversifier. They also found that Bitcoin could function as a safe-haven asset for the US market, particularly in the first percentile of worst returns of the S&P 500, as well as for the MSCI World, BRIC, and Pacific indices at the 1% level, Zimbabwe at 1%, and India at 5%. Bitcoin also showed safe-haven potential during high-uncertainty events, such as the US elections, the Brexit referendum, and the 2015 Chinese stock market crash. Kassamany et al. (2023) expanded this analysis to encompass additional markets, examining the interactions between Ethereum, the second most popular cryptocurrency, and a range of assets including fiat currencies, US and European stock markets, bonds, crude oil, and gold. Utilizing a percentile regression approach, the authors concluded that Ethereum does not function as a hedge or safe-haven for any of the markets analyzed, with the exception of crude oil and European bonds during periods of market distress. This conclusion is based on the observed negative and statistically significant correlation between Ethereum and these specific assets under conditions of market turmoil. Urquhart and Zhang (2018) approached the topic from a different perspective, focusing on Bitcoin’s role as a potential safe-haven specifically for fiat currencies. Their study analyzed six major developed currencies - the Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Euro (EUR), British pound (GBP), and Japanese yen (JPY) - with the US dollar (USD) as a reference for comparison purposes. By applying an asymmetric dynamic conditional correlation model, they arrived at a conclusion that contrasts with that of Kassamany et al. (2023) for Ethereum, finding that in this case Bitcoin demonstrates safe-haven properties during periods of substantial market stress (i.e., when returns are at their lowest) for the CAD, CHF, and GBP.

On a different note, Kliber et al. (2019) explored if Bitcoin could display itself as a hedge, diversifier, or safe-haven across stock markets in different countries, including Sweden, China, Estonia, Japan, and Venezuela, chosen for their unique economic characteristics and currencies. To analyze this, the researchers employed a Stochastic Volatility Model combined with a Dynamic Conditional Correlation Model to estimate the volatility relationships between these stock indices and Bitcoin's price. They found that Bitcoin acted as a safe-haven specifically for Venezuela and investments in bolivars, while showing hedging and diversifying properties for the remaining markets.

Based on the reviewed literature, it is possible to conclude that while cryptocurrencies share certain similarities with gold - the most widely recognized safe-haven - their role as such remains ambiguous. This uncertainty primarily stems from two key factors: first, the unique characteristics and behavior of cryptocurrencies as financial assets; and second, their fluctuating correlations with various financial markets during periods of heightened volatility.

In addition, the literature primarily examines the volatility of cryptocurrencies during two significant events: the COVID-19 pandemic and the Russia-Ukraine conflict. These events, given their profound social and economic impacts, provided an opportunity to analyze cryptocurrencies' potential as safe-haven assets in greater detail. However, the results remained mixed, with some studies arguing in favor of crypto's role as a safe-haven for equity, bond, oil and currency markets, while others point in the opposite direction.

To address this uncertainty, this study seeks to clarify cryptocurrencies' role in the economy by utilizing percentile-based regressions, one of literature's alternative approaches. By identifying specific periods when the market experienced its lowest returns, the research aims to provide insights into whether cryptocurrencies, namely Bitcoin and Tether, can consistently act as safe-haven assets for global markets and commodities.

3. Dataset

A dataset comprising the daily returns of all the financial assets under analysis was constructed for this study. The dataset covers the period from March 9, 2015, to December 31, 2024. This timeframe was chosen because Tether was first introduced in late 2014, with data being only available since March 2015, making it infeasible to include information from earlier months. Additionally, it is important to note that while cryptocurrency markets operate continuously, including weekends and holidays, traditional financial markets do not. Consequently, the daily observations of cryptocurrency returns over the past decade do not correspond in number to those of stock indexes. Given that the primary goal of this study is to establish correlations between the different assets under consideration, and to ensure robustness in the analysis, the dataset will be restricted to daily cryptocurrency observations that coincide with the days where traditional financial markets were operating. Specifically, this will exclude weekends and holidays, ensuring that the analysis focuses only on the days when both cryptocurrency markets and traditional financial markets are open.

In terms of the variables employed in this study, it is essential to emphasize that the primary objective is to conduct a comprehensive global analysis of the safe-haven properties of cryptocurrencies by examining the relationships between crypto assets and major regional and global stock indexes during periods of market turmoil. To this end, the indices selected for the analysis intend to serve as proxies for the most significant economic regions globally. These include the S&P 500, representing the North American economy; the STOXX 600 for Europe; the MSCI Asia ex Japan for Asia; the MSCI Pacific Index for the Pacific region; and the MSCI World Index for the global economy. The MSCI Asia excluding Japan index was utilized to avoid duplicating the Japanese stock index in the analysis, as Japan is a significant driver of both the MSCI Asia and MSCI Pacific indices.

Regarding cryptocurrencies, two digital assets with distinct characteristics were chosen: Bitcoin and Tether. Bitcoin was selected due to its dominant position as the leading cryptocurrency by market capitalization while in contrast, Tether was chosen as a representative stablecoin, designed to maintain a relatively stable price by being pegged to the US dollar. Unlike most other cryptocurrencies, Tether's value is not primarily influenced by supply and demand dynamics, but rather by its peg mechanism, which makes it a noteworthy inclusion in safe-haven analysis (Shao & Rajapaksa, 2024).

Additionally, the study incorporated two commodities - gold and oil - due to their widely recognized roles as protective assets during periods of stock market volatility, a relationship that has been frequently documented in the literature by authors such as Baur and McDermott

(2016), Baur and Lucey (2010) and Stensås et al. (2019). For this analysis, oil refers specifically to West Texas Intermediate (WTI) crude oil, priced per barrel.

The final dataset consists of 2569 observations, representing the daily returns in US dollars of each variable over the study period. To ensure consistency and reliability, all data, including the closing prices of Bitcoin, gold, and oil, were sourced from Reuters, while Tether data was obtained from CoinMarketCap. Due to Tether's different data source, inconsistencies regarding the time frames captured were identified. In order to handle this situation, for the days where there were missing values for the closing price of the stablecoin, the closing price of the previous period available was used instead.

Table 1 provides the descriptive statistics for each variable under consideration, with the corresponding graphics available in the appendix. Bitcoin, with an average daily return of 0,319%, generated the highest mean daily return among the assets analyzed over the past decade, significantly outperforming traditional assets such as the S&P 500 and the STOXX 600. However, Bitcoin also exhibits considerable volatility, with a standard deviation notably higher than most other assets, indicating that while it offers substantial return potential, it is also subject to significant price fluctuations. In contrast, Tether demonstrates a very low average return, consistent with its function as a stablecoin pegged to the US dollar. While Tether provides minimal returns, its low standard deviation positions it as one of the least volatile assets in the dataset, slightly more volatile than the traditionally recognized safe-haven asset, gold. However, Tether's kurtosis suggests that, although it remains stable most of the time, it has experienced occasional extreme price movements over the past decade.

With regard to the stock market indices, the S&P 500 emerges as the best performer, offering the highest returns while maintaining a level of volatility similar to that of the other indices. The STOXX 600, representing European markets, records lower average returns than the S&P 500 but exhibits a similar level of volatility, suggesting comparable price fluctuations despite the difference in performance. The MSCI Pacific displays the highest level of volatility among the indices, reflecting greater variability in daily returns, while achieving average returns higher than those of the STOXX 600 but lower than the S&P 500. The MSCI Asia Ex Japan has the lowest average returns of all the indices, coupled with moderate volatility, placing it at the lower end of both performance and risk within the dataset. The MSCI World index, which represents a globally diversified portfolio, reports lower volatility compared to the S&P 500, STOXX 600, and MSCI Pacific. However, its average returns, while higher than the MSCI Asia Ex Japan, remain below those of the S&P 500 and MSCI Pacific.

Finally, it is noteworthy that oil is the only asset in the dataset that presents negative mean daily returns, setting it apart from the stock market indices in terms of performance. Despite this, oil exhibits significantly higher levels of volatility, far exceeding that of any stock index, indicating substantial fluctuations in its daily returns over the observed period.

Table 1: Descriptive Statistics

Variable	Mean	Min	Max	SD	Skewness	Kurtosis
S&P500	0,00047	-0,11984	0,09383	0,01106	-0,53769	18,27052
STOXX600	0,00016	-0,11478	0,08405	0,01016	-0,91102	15,07335
MSCI Pacific	0,00037	-0,12396	0,10226	0,01261	-0,23381	12,38790
MSCI Asia Ex Japan	0,00012	-0,05663	0,06294	0,01026	-0,17320	6,47126
MSCI World	0,00034	-0,09915	0,08770	0,00946	-0,83225	19,04774
Oil	-0,00075	-3,01966	0,53086	0,07176	-30,73452	1257,39675
Gold	0,00035	-0,04941	0,05090	0,00863	-0,11948	6,33123
Bitcoin	0,00319	-0,38980	0,26921	0,04249	-0,02681	9,80413
Tether	0,00004	-0,24673	0,13489	0,00930	-4,17438	266,59685

Since the primary objective of this dissertation is to examine the dynamic correlations between asset classes, it is essential to understand how the variables have interacted with each other over the 10-year period under analysis. In this context, Table 2 provides a correlation matrix that illustrates the relationships between the variables being investigated.

In this context, equity markets, such as the S&P 500 and STOXX600, demonstrate strong correlations with one another, reflecting the close integration of developed markets, particularly between the US and Europe. In contrast, indices like MSCI Asia Ex Japan and MSCI Pacific show more moderate correlations with other equity markets. The MSCI Asia Ex Japan, in particular, has a stronger connection with European equities, while the MSCI Pacific index tends to behave more independently. Notably, the MSCI World Index exhibits a particularly strong correlation with the US market, highlighting the significant influence of the US economy on global equities. Due to the high correlation value between the MSCI World Index and the US market, including both variables as independent predictors in the final model could introduce multicollinearity (Studenmund, 2016), making it difficult to isolate their individual effects on the dependent variable. However, since this study analyzes them separately, multicollinearity will not be a concern in the final model.

Regarding commodities, gold stands out with its minimal correlation to equities, which is characteristic of safe-haven assets that tend to preserve value during periods of financial uncertainty. This reinforces its role as a hedge during market turbulence. In contrast, oil exhibits slightly stronger correlations with equity markets, especially within the Asia-Pacific region, suggesting that oil prices are more influenced by regional economic dynamics, particularly in countries with high energy consumption.

In the cryptocurrency market, Bitcoin shows a very weak correlation with traditional financial assets, including global equities. This indicates that Bitcoin does not generally follow the trends of traditional markets, which, coupled with its modest correlation with gold, hints at its potential role as a hedge or a safe-haven asset, though its volatility limits its reliability. Similarly, Tether displays extremely low and statistically insignificant correlations with other markets, which is consistent with its design as a stablecoin, primarily intended for providing liquidity and stability rather than acting as a growth or risk-mitigating asset.

Table 2: Correlation Matrix

Correlations	S&P500	STOXX600	MSCI Pacific	MSCI Asia Ex Japan	MSCI World	Oil	Gold	Bitcoin	Tether
S&P500	1,00000	0,58204***	0,20724***	0,32386***	0,95819 ***	0,02200	0,00755	-0,02982	-0,00783
STOXX600	-	1,00000	0,34343***	0,48375***	0,73010***	0,06469**	0,01602	0,02772	-0,00028
MSCI Pacific	-	-	1,00000	0,51517***	0,34423***	0,06860***	-0,00256	0,11531***	0,00356
MSCI Asia Ex Japan	-	-	-	1,00000	0,45931***	0,08653***	0,10193***	0,09558***	0,00022
MSCI World	-	-	-	-	1,00000	0,04828**	0,01363	-0,00299	-0,00400
Oil	-	-	-	-	-	1,00000	0,04359**	0,03518 .	-0,01471
Gold	-	-	-	-	-	-	1,00000	0,08734***	-0,02048
Bitcoin	-	-	-	-	-	-	-	1,00000	-0,00033
Tether	-	-	-	-	-	-	-	-	1,00000

(Note: ***, **, *, indicate statistical evidence at the 1% level, 5% and 10%, respectively.)

Before proceeding with the presentation of the methodology, GARCH model and, consequently, with the DCC estimation, it's necessary to first verify if the variables under use are stationary, since the model relies on estimating conditional variances (volatility) and conditional correlations between the variables, both of which require that the series do not exhibit unit roots. Non-stationary data would make these estimates unreliable, as non-stationary series can have changing variance and mean over time, leading to potentially misleading results for both the volatility and correlations between assets (Baumöhl and Lyocsa, 2009).

With this objective in mind, the Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test were applied to each variable to check for stationarity. These tests were performed using a constant[1] in their specifications, allowing for the assessment of whether the variables exhibit stationarity around a fixed mean. The results showed that all variables are stationary: the ADF and PP tests yielded p-values under 0,01 for every variable, allowing for the rejection the null hypothesis of non-stationarity. Meanwhile, The KPSS test returned p-values greater than 0,1, meaning a failure to reject the null hypothesis of stationarity. These findings confirm that all series are stationary. All the results can be seen in the table below, with the RStudio outputs being present in the appendix.

[1] The stationarity tests were also performed using different deterministic components, including none / trend and intercept, leading to no changes in the results.

Table 3: Stationarity Tests

S&P500			STOXX600			MSCI Pacific		
ADF	**PP**	**KPSS**	**ADF**	**PP**	**KPSS**	**ADF**	**PP**	**KPSS**
<0,01	<0,01	>0,1	<0,01	<0,01	>0,1	<0,01	<0,01	>0,1

MSCI Asia Ex Japan			MSCI World			Oil		
ADF	**PP**	**KPSS**	**ADF**	**PP**	**KPSS**	**ADF**	**PP**	**KPSS**
<0,01	<0,01	>0,1	<0,01	<0,01	>0,1	<0,01	<0,01	>0,1

Gold			Bitcoin			Tether		
ADF	**PP**	**KPSS**	**ADF**	**PP**	**KPSS**	**ADF**	**PP**	**KPSS**
<0,01	<0,01	>0,1	<0,01	<0,01	>0,1	<0,01	<0,01	>0,1

4. Methodology

Regarding the methodology employed, the method chosen was a Dynamic Conditional Correlation – Generalized Autoregressive Conditional Heteroskedasticity model (DCC-GARCH). First introduced by Engle (2002), this model aims to capture time-varying correlations between multiple financial time series. It is widely used in portfolio optimization, risk management, and asset pricing due to its ability to capture both individual volatility dynamics and dynamic correlations (Stensas et al., 2019).

Alternative methodological approaches include rolling regressions and exponential smoothing techniques, which could be employed to address dynamic correlations. However, as noted by Engle (2002), the rolling regression approach relies on an ad hoc method to determine the window width, which does not account for sudden changes in volatility. While this method can capture time variations in correlations, it raises significant concerns regarding the selection of an appropriate rolling window length. Similarly, exponential smoothing techniques lack a robust statistical framework for assessing and diagnosing the quality of competing models. Specifically, the smoothing parameters are typically determined based on goodness-of-fit measures rather than established statistical criteria, such as hypothesis testing for parameters or residual diagnostics to ensure white noise. Consequently, exponential smoothing models are often considered ad hoc from a statistical perspective (Fomby, 2008). Furthermore, in the context of volatility and correlations, exponential smoothing methods, including Exponentially Weighted Moving Average (EWMA) models, have been criticized for producing suboptimal volatility estimates due to their reliance on fixed parameter weights (Martin, 1998).

Various types of multivariate GARCH models, such as the Baba-Engle- Kraft-Kroner (BEKK) and Constant Conditional Correlation (CCC) models, have been widely utilized in the literature to evaluate the hedging and safe-haven properties of different assets (Bouri et al., 2017). However, as noted by Engle (2002) and Bouri et al. (2017), these models often encounter challenges such as convergence issues and unreasonable parameter estimates.

In this context, the DCC-GARCH model emerges as an extension of the CCC-GARCH model, offering notable advantages. Unlike other multivariate GARCH variants, the DCC-GARCH model retains the straightforward interpretation of univariate GARCH models while incorporating an easily computable correlation estimator (Engle & Sheppard, 2001). Additionally, its time-varying nature enables it to accommodate correlations that may fluctuate over time, taking on positive, negative, or zero values as necessary (Ratner & Chiu, 2013).

The estimation of the DCC-GARCH model can be accomplished in two steps: i) the estimation of the univariate GARCH (1,1) model for each time series, ii) the estimation of time-varying conditional correlations using the standardized residuals generated from step i) (Stensås et al., 2019).

Regarding the model, the conditional distribution equation can be enunciated as:

$$r_t \mid I_{\{t-1\}} \sim N(0, H_t) \tag{1}$$

$$H_t = D_t R_t D_t \tag{2}$$

Where r_t is the k x 1 demeaned vector of returns, with k being the number of assets being analyzed at time t, conditional to the information obtained in the previous period. H_t denotes the time-varying covariance matrix of r_t, with D_t being the diagonal matrix containing the time-varying conditional standard deviations (volatilities) for the returns of each asset at time t that are obtained from the GARCH model:

$$D_t = diag\left(\sqrt{h_{\{1,t\}}}, \sqrt{h_{\{2,t\}}}, \dots, \sqrt{h_{\{N,t\}}}\right) \tag{3}$$

Where $h_{i,t}$ represents the conditional variance for asset i at time t, as modeled by the GARCH process.

R_t on the other hand is the time-varying correlation matrix between asset returns at time t, which follows a dynamic process modeled by the DCC model:

$$R_t = (diag(Qt)^{-\frac{1}{2}})Qt(diag(Qt)^{-\frac{1}{2}}) \tag{4}$$

Where Q_t is the conditional time-varying covariance matrix that follows an evolution driven by past data and can be seen in the following equation:

$$Q_t = (1 - \alpha - \beta)\backslash Q_c + \alpha\, z_{\{t-1\}} z'_{\{t-1\}} + \beta\, Q_{\{t-1\}} \tag{5}$$

Q_c is the unconditional covariance matrix of the returns, α and β are parameters that control the persistence and the sensitivity of the model to past returns and volatility, respectively and $z_{\{t-1\}} z'_{\{t-1\}}$ is the outer product of the standardized residuals vector from the previous time step.

Following the DCC-GARCH estimation, the same principle used by Ratner and Chiu (2013) and Stensås et al. (2019) is used, where the time-varying correlations Rt are extracted from equation 4 into a separate time series, leading to:

$$DCC_t = c_0 + c_1 D(r_{asset} q_1) + c_2 D\left(r_{asset} q_{2,5}\right) + c_3 D(r_{asset} q_5) + c_4 D(r_{asset} q_{10}) \quad (6)$$

Where D represent extreme market movements, taking a value of one when the asset's return exceeds a specified threshold, defined by the lower 1st, 2,5th, 5th and 10th percentiles of the return distribution. The cryptocurrency under analysis is considered a diversifier if c_0 is significantly positive, a weak hedge if c_0 is zero, and a strong hedge if c_0 is negative. Additionally, it is classified as a weak safe-haven if the parameters c_1, c_2, c_3 or c_4 are negative or insignificantly different from zero, and as a strong safe-haven if they are significantly negative. For this analysis, an additional quantile was introduced into the original model, specifically between the 1st and 5th quantiles, to capture a broader range of correlations. This adjustment was considered beneficial for this study due to the significant gap that exists between the 1st and 5th quantiles, as noted by authors such as Baur and Lucey (2010).

5. Application

Since all variables in use are stationary, it is possible to proceed to the first step in implementing the DCC-GARCH methodology, which involves fitting univariate GARCH models to each individual time series. This step is essential for modeling each variable's volatility, which is crucial for analyzing dynamic correlations. The GARCH model plays a key role in this process, as it captures the influence of volatility on correlations over time and accounts for important phenomena such as volatility clustering, where periods of high or low volatility tend to persist.

To enhance the accuracy of volatility modeling, the standard GARCH model was evaluated alongside the EGARCH and GJR-GARCH specifications. These models account for potential asymmetric effects in volatility, recognizing that time series (namely financial) often exhibit differences in how positive and negative shocks impact the variables (Shamiri and Isa, 2009). By incorporating these asymmetries, the models aim to provide a more precise representation of volatility dynamics, which is particularly important for analyzing stock indices and asset returns. Each model was assessed under three distributional assumptions: Normal, Student's t, and Generalized Error Distribution (GED). Model selection was conducted by minimizing the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). In cases where the AIC and BIC produced conflicting results, the BIC was prioritized due to its stricter penalization of model complexity (Vieira et al., 2023).

The results of the GARCH model analysis can be seen in Table 4, with the optimal results being highlighted in green. The standard GARCH model provides the worst results in terms of AIC/BIC for almost every variable, regardless of the distribution. As such, this model will not be used for any variable. For the S&P500 and STOXX600, the EGARCH model with the GED distribution consistently emerges as the best fit. This pattern continues with the MSCI Pacific, where the same model and distribution are preferred. In the MSCI Asia Ex Japan, the GJRGARCH model with the GED distribution proves to be the most suitable. The MSCI World index is also best modeled by the EGARCH model with the GED distribution. In the case of oil, the GJRGARCH model with the Student's t-distribution is the most appropriate choice. For gold, the GJRGARCH model with the GED distribution stands out as the best fit. In the case of crypto, Bitcoin is best modeled by the EGARCH model with the Student's t-distribution, while Tether is most accurately represented by the GJRGARCH model with the GED distribution.

Table 4: Akaike Information Criteria and Bayesian Information Criteria for GARCH, EGARCH and GJR-GARCH Models

	S&P500					
	GARCH		EGARCH		GJRGARCH	
	AIC	BIC	AIC	BIC	AIC	BIC
Normal	-6,68045	-6,66679	-6,71037	-6,69442	-6,70162	-6,68567
Student's t	-6,75380	-6,73785	-6,78559	-6,76737	-6,77947	-6,76125
GED	-6,75746	-6,74152	-6,78586	-6,76764	-6,77917	-6,76095
	STOXX600					
	GARCH		**EGARCH**		**GJRGARCH**	
	AIC	BIC	AIC	BIC	AIC	BIC
Normal	-6,69250	-6,67884	-6,74359	-6,72765	-6,73317	-6,71722
Student's t	-6,75470	-6,73876	-6,80033	-6,78210	-6,79105	-6,77283
GED	-6,75536	-6,73942	-6,79289	-6,77467	-6,78458	-6,76636
	MSCI Pacific					
	GARCH		**EGARCH**		**GJRGARCH**	
	AIC	BIC	AIC	BIC	AIC	BIC
Normal	-6,12587	-6,11220	-6,16119	-6,14525	-6,16457	-6,14862
Student's t	-6,20458	-6,18863	-6,23307	-6,21485	-6,23038	-6,21216
GED	-6,23146	-6,21552	-6,25506	-6,23684	-6,25403	-6,23581
	MSCI Asia Ex Japan					
	GARCH		**EGARCH**		**GJRGARCH**	
	AIC	BIC	AIC	BIC	AIC	BIC
Normal	-6,48583	-6,47217	-6,50757	-6,49163	-6,50746	-6,49152
Student's t	-6,51241	-6,49647	-6,52892	-6,51070	-6,52890	-6,51068
GED	-6,51527	-6,49933	-6,53069	-6,51247	-6,53069	-6,51247
	MSCI World					
	GARCH		**EGARCH**		**GJRGARCH**	
	AIC	BIC	AIC	BIC	AIC	BIC
Normal	-6,96456	-6,95089	-6,98656	-6,97061	-6,99715	-6,98121
Student's t	-7,02381	-7,00787	-7,05266	-7,03444	-7,05952	-7,04130
GED	-7,02306	-7,00711	-7,04477	-7,02655	-7,05182	-7,03360
	Oil					
	GARCH		**EGARCH**		**GJRGARCH**	
	AIC	BIC	AIC	BIC	AIC	BIC
Normal	-4,49222	-4,47855	-4,65861	-4,64267	-4,49782	-4,48187
Student's t	-4,75023	-4,73428	-4,75006	-4,73184	-4,75245	-4,73423
GED	-4,71777	-4,70182	-4,71218	-4,69396	-4,71871	-4,70049
	Gold					
	GARCH		**EGARCH**		**GJRGARCH**	
	AIC	BIC	AIC	BIC	AIC	BIC
Normal	-6,72615	-6,71248	-6,73164	-6,71570	-6,73159	-6,71564
Student's t	-6,81045	-6,79450	-6,81248	-6,79425	-6,81292	-6,79469
GED	-6,81345	-6,79750	-6,81583	-6,79761	-6,81598	-6,79776
	Bitcoin					
	GARCH		**EGARCH**		**GJRGARCH**	
	AIC	BIC	AIC	BIC	AIC	BIC
Normal	-3,58386	-3,57020	-3,59001	-3,57407	-3,58532	-3,56937
Student's t	-3,83253	-3,81659	-3,84668	-3,82846	-3,83374	-3,81552
GED	-3,83733	-3,82139	-3,84379	-3,82557	-3,83703	-3,81881
	Tether					
	GARCH		**EGARCH**		**GJRGARCH**	
	AIC	BIC	AIC	BIC	AIC	BIC
Normal	-9,13196	-9,11830	-10,39204	-10,37609	-9,29521	-9,27927
Student's t	-12,49198	-12,47604	-10,80771	-10,78949	-12,51838	-12,50016
GED	-7,69391	-7,67797	-11,19350	-11,17528	-7,85107	-7,83284

To assess the suitability of the selected models, the presence of autocorrelation in the residuals of each EGARCH/GJR-GARCH model was evaluated using the Ljung-Box test. Autocorrelation in the residuals suggests that the model has not fully captured the underlying data patterns, potentially resulting in biased forecasts and misleading statistical inferences. In this test, a p-value below 0,05 indicates that the null hypothesis - asserting that the residuals are uncorrelated (i.e., white noise) - is rejected, suggesting possible model misspecification.

Table 5: Initial Ljung-Box Test based on AIC/BIC

Variable	Ljung-Box P.Values
S&P500	0,506
STOXX600	0,9688
MSCI Pacific	0,958
MSCI Asia Ex Japan	0,4914
MSCI World	0,1571
Oil	0,9264
Gold	0,4558
Bitcoin	0,0054
Tether	1

As observed from the table, with the exception of Bitcoin, all Ljung-Box p-values are greater than 0,05, indicating that there is no statistical evidence of autocorrelation in the residuals for the remaining assets. This suggests that the EGARCH/GJR-GARCH models used to estimate volatility are well-specified, and the residuals are consistent with white noise for each variable. In the case of Bitcoin, however, the presence of autocorrelation in the residuals warrants the adoption of an alternative model. After further testing, the chosen model was the GJR-GARCH with a normal distribution, as it crucially eliminated autocorrelation in the residuals (Figure 10, Appendix).

As such, the univariate GARCH models to model volatility will be the following:

- S&P500: EGARCH with GED distribution
- STOXX600: EGARCH with Student's t-distribution
- MSCI Pacific: EGARCH with GED Distribution
- MSCI Asia Ex Japan: GJR-GARCH with GED Distribution
- MSCI World: GJR-GARCH with Student's t-distribution
- Oil: GJR-GARCH with Student's t-distribution
- Gold: GJR-GARCH with GED distribution
- Bitcoin: GJR-GARCH with Normal distribution
- Tether: GJR-GARCH with Student's t-distribution

With the univariate EGARCH/GJR-GARCH models successfully estimated for each variable, the individual volatility dynamics of each asset have been accounted for. The next step is to fit the Dynamic Conditional Correlation (DCC) models, which will allow for the dynamic assessment of the correlations over time while incorporating the volatility fluctuations determined in the EGARCH/GJR-GARCH process. This approach aims to capture the evolving correlations between the two selected crypto assets - Bitcoin and Tether - and the remaining variables, with a particular focus on periods of market distress, which will be introduced in the final model estimation.

To achieve this objective, it was first necessary to determine the appropriate distribution for each DCC model. Since the Generalized Error Distribution (GED) was unavailable for these models, the choice was limited to the normal distribution and the Student's t-distribution. Given that the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were lower for the Student's t-distribution across all variables, this distribution has been selected for the analysis.

Table 6: Akaike Information Criteria and Bayesian Information Criteria for each DCC model

	SP500		**STOXX600**		**MSCI Pacific**		**MSCI Asia Ex Japan**	
Bitcoin	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
Normal	-10,28958	-10,25769	-10,32629	-10,29440	-9,76010	-9,72821	-10,08784	-10,05596
T-Student	-10,52449	-10,49032	-10,54790	-10,51374	-10,00166	-9,96749	-10,26700	-10,23283
	MSCI World		**Oil**		**Gold**		**Tether**	
Bitcoin	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
Normal	-10,55894	-10,52705	-7,86156	-7,82967	-10,32643	-10,29454	-12,04985	-12,01796
T-Student	-10,78360	-10,74943	-8,50520	-8,47103	-10,58558	-10,55142	-13,70455	-13,67038

6. Final Results

6.1. Results: Bitcoin

With the successful completion of the DCC-GARCH modeling process, the final step of the methodology could be carried out. This concluding phase involved the extraction of the pairwise conditional correlations, which were then structured into distinct time series. This approach facilitated a comprehensive assessment of the dynamic correlations between Bitcoin/Tether and the other variables under consideration. The results of this analysis for Bitcoin are presented in the table below.

Table 7: Final Results for Bitcoin

Bitcoin	Hedge (C_0)	1% Quantile (C_1)	2,5% Quantile (C_2)	5% Quantile (C_3)	10% Quantile (C_4)
S&P500	0,04084 ***	-0,01464 ***	-0,00761 *	0,00347	0,00031
STOXX600	0,05726 ***	-0,00385	0,00313	-0,00088	0,00286
MSCI Pacific	0,11096 ***	-0,02056	0,01224	-0,00668	0,01413 **
MSCI Asia Ex Japan	0,09512 ***	-0,01410	-0,01647	0,01111	0,01918 ***
MSCI World	0,05357 ***	-0,00312	-0,00399	0,00118	0,00210 *
Oil	0,03833 ***	0,04042 ***	0,01068	-0,00923 *	0,00818 ***
Gold	0,08115 ***	0,01612	0,00845	0,00068	0,00654
Tether	0,03016	0,00920	0,02078	0,01731	-0,03297 ***

(Note: ***, **, *, indicate statistical evidence at the 1% level, 5% and 10%, respectively.)

Based on the results presented in the table, it can be concluded that Bitcoin does not function as a hedge for any of the financial assets included in this analysis. Instead, Bitcoin primarily serves as a diversifier for all variables examined, with the sole exception of Tether. This conclusion is supported by the statistically significant positive value of c_0, which indicates that Bitcoin generally moves in the same direction as most other assets under consideration. Although the correlation value between Bitcoin and Tether is also positive, the absence of statistical significance undermines its role as a diversifier in this specific case. This finding is unsurprising given Tether's fundamental design as a stablecoin, which is intended to maintain a fixed value pegged to the US Dollar. As a result, significant co-movement between Bitcoin and Tether would not necessarily be expected, as Tether's primary function is to provide price stability rather than to exhibit strong directional movement in response to market fluctuations.

Bitcoin's lack of hedging capabilities can be further contextualized by considering the explanation provided by Baur and McDermott (2010). According to their research, the common currency denomination of financial indices, such as the US Dollar in this case, can lead to increased co-movement between assets when compared to situations where local currencies are used. This phenomenon may help explain the observed results, as Bitcoin's valuation is typically denominated in US Dollars, similar to the financial indices analyzed. The shared currency base could contribute to Bitcoin's tendency to move in tandem with other assets rather than acting as a hedge against their fluctuations.

With regards to Bitcoin's safe-haven role, it is possible to conclude that the world's leading cryptocurrency serves as a safe-haven asset for all the stock indices under analysis at the 1% percentile level. Specifically, Bitcoin functions as a weak safe-haven for the STOXX600, MSCI Pacific, MSCI Asia Ex Japan, and MSCI World indices, while it notably acts as a strong safe-haven for the S&P 500, due to the statistical relevance of the negative correlation between the two assets. These findings indicate that, while Bitcoin's safe-haven role is evident during periods of extreme negative returns across all stock indices, this characteristic is especially pronounced for the United States, the world's largest and most influential economy. As for the remaining assets in this analysis, Bitcoin does not behave as a safe-haven asset at this level. While it shows a statistically significant correlation with oil, all the values are in fact positive. It is noteworthy to mention that the positive correlation with gold, albeit statistically insignificant, alongside the negative correlations with stock indices, can reinforce the idea of authors such as Popper (2015) of Bitcoin as "digital gold".

When examining the 2,5% quantile, Bitcoin's safe-haven characteristic continues to hold, albeit to a lesser extent. While it remains a strong safe-haven asset for the United States, the statistical relevance of this relationship is only observed at the 10% significance level. Regarding the other stock indices, Bitcoin no longer qualifies as a safe-haven asset for the European and Pacific regions. However, it can still be considered a weak safe-haven for the Asian region and the World Index. Similar to the 1% percentile analysis, Bitcoin does not demonstrate safe-haven characteristics for the commodities analyzed, nor for Tether.

At the 5% quantile, Bitcoin no longer acts as a protective asset for the S&P 500, signaling a decrease in its safe-haven characteristics at this level of market stress. However, it continues to serve as a weak safe-haven for the STOXX 600 and MSCI Pacific indices, which is interesting given that these were the only two indices that did not display any safe-haven properties at the 2,5% level. This shift indicates that Bitcoin's safe-haven role can vary depending on the market conditions. Additionally, in terms of commodities, Bitcoin acts as a strong safe-haven for oil at the 10% significance level, a significant change from earlier analyses where it did not display any safe-haven characteristics for commodities.

Finally, at the 10% quantile, despite the presence of some statistically significant correlations across all the assets analyzed, all of these correlations are positive, indicating that Bitcoin does not exhibit safe-haven capabilities at this level. The only exception is the negative correlation observed with Tether at the 1% level, which, according to the definition of a safe-haven asset, could suggest that Bitcoin acts as a strong safe-haven for Tether during the 10% lowest returns of the stablecoin. However, given that Tether is a stablecoin, not designed to fluctuate in price, this negative correlation does not lead to a feasible conclusion regarding Bitcoin’s role as a safe-haven asset for Tether, despite the statistical evidence.

Overall, this analysis allows for the conclusion that Bitcoin demonstrated a certain ability to serve as a safe-haven against market fluctuations for the assets examined, particularly during periods of heightened instability. More specifically, Bitcoin proved to be a safe-haven asset for the S&P 500 in the periods where the American stock index showcased its most extreme negative returns, although this characteristic faded as less severe market conditions were included. These findings are consistent with those of Mariana et al. (2020), Stensas et al. (2019), and Marobhe (2021), all of whom corroborate Bitcoin’s role as a safe-haven for the S&P 500. Notably, Stensas et al. (2019) found, similar to this analysis, that Bitcoin’s safe-haven properties for the S&P 500 were most pronounced in the left tail of the return distribution.

For the other stock indices assessed, Bitcoin acted as a weak safe-haven in at least one of the quantiles analyzed for every variable, providing some degree of protection for a multitude of stock indices. These results align with the findings of Stensas et al. (2019), Havidz et al. (2023), and Shahzad et al. (2019), who similarly identify Bitcoin’s safe-haven capabilities across multiple stock indices. Furthermore, in accordance to Melki and Nefzi (2022), Bitcoin also exhibited safe-haven characteristics against fluctuations in oil prices, further underscoring its potential to serve as a safe-haven for diverse asset classes in times of economic and market uncertainty.

Finally, a particularly noteworthy observation was the consistent positive correlation between Bitcoin and gold across all quantiles of gold’s most negative returns. This finding is significant because, as demonstrated in the literature review by authors such as Baur and Lucey (2010), Baur and McDermott (2016), Gomis-Porqueras et al. (2022) and Ming et al. (2023), gold has long been regarded as a traditional safe-haven asset. As previously mentioned, the sustained positive relationship between Bitcoin and gold, albeit statistically insignificant, may lend further support to the emerging narrative promoted by Popper (2015), which characterizes Bitcoin as “digital gold”.

6.2. Results: Tether

As for Tether, the same process of extracting the pairwise conditional correlations into separate time series was undertaken, leading to the results present in the table below.

Table 8: Final Results for Tether

Tether	Hedge (C_0)	1% Quantile (C_1)	2,5% Quantile (C_2)	5% Quantile (C_3)	10% Quantile (C_4)
S&P500	0,00844 ***	-0,00419	-0,00336	0,00693 *	-0,00505 **
STOXX600	0,01446 ***	0,00471	-0,00958	0,00276	0,00166
MSCI Pacific	0,01911 ***	0,00469 **	-0,00334 **	0,00226 **	-0,00105
MSCI Asia Ex Japan	0,00791 ***	0,00533	0,00519	-0,00377	-0,00222
MSCI World	0,01478 ***	0,00230	-0,00440	0,01222 **	-0,01212 ***
Oil	-0,00378 ***	-0,00368 **	-0,00242 **	0,00122	-0,00033
Gold	-0,02010 ***	0,00487	0,00336	0,00035	-0,00162
Bitcoin	0,05941 ***	-0,04092	-0,02154	0,00070	-0,00110

(Note: ***, **, *, indicate statistical evidence at the 1% level, 5% and 10%, respectively.)

The analysis regarding Tether's potential as a hedging instrument reveals that, while the stable coin does not exhibit strong hedging characteristics for any of the stock indices analyzed, it does show significant hedging properties for the commodities considered in the study. This conclusion is based on the negative and statistically significant correlation observed between Tether and both gold and oil. The presence of this negative correlation indicates that Tether could serve as a protective asset for investors seeking to hedge against fluctuations in commodity prices. These findings align with those of Hampl et al. (2024), who similarly support Tether's ability to act as a protective asset within the commodity market.

It is also important to highlight that although Tether exhibits positive and statistically significant correlations with the stock indices under consideration, the correlation values remain very close to zero. This near-zero correlation was also confirmed by Vukovic et al. (2021) and could be indicative of Tether's latent potential to act as a hedge against stock market fluctuations, even if it does not strictly meet the formal criteria for classification as a hedging instrument. These findings suggest that while Tether may not consistently provide a robust hedge against equity market volatility, its correlation structure implies that it might still offer some degree of protection for stock markets.

With respect to Tether's role as a safe-haven asset, the results suggest that the stablecoin exhibits varying degrees of safe-haven characteristics depending on the specific market conditions and statistical quantiles analyzed. At the extreme left tail of the distribution, within the 1% quantile, Tether qualifies as a weak safe-haven for both the S&P 500 and Bitcoin. However, it can be considered a strong safe-haven for oil, as evidenced by its statistically significant negative correlation at the 5% level. For the remaining financial assets analyzed, the correlation values remain positive but are nonetheless close to zero, suggesting limited safe-haven potential.

As the 2,5% quantile, Tether's safe-haven properties become more pronounced. At this level, the stablecoin emerges as a safe-haven asset for the majority of the variables examined, with the exception of the MSCI Asia Ex Japan index and gold. Specifically, Tether serves as a weak safe-haven for the S&P 500, STOXX 600, MSCI Pacific, MSCI World, and Bitcoin, offering some degree of protection against extreme market downturns. Furthermore, Tether's role as a strong safe-haven asset is more evident for both the MSCI Pacific index and oil, with statistical significance observed at the 5% level. This expanded safe-haven role at the 2,5% quantile suggests that Tether may provide increased stability during severe market distress, particularly for select stock indices and commodities.

Regarding the 5% quantile, Tether's safe-haven capabilities diminish significantly. At this level, the stablecoin ceases to be a safe-haven for most of the variables included in the analysis, with the exception of the MSCI Asia Ex Japan index, for which it qualifies as a weak safe-haven. Interestingly, this finding contrasts with previous quantiles, as the MSCI Asia Ex Japan index was one of the few variables that did not exhibit any level of protection through Tether at more extreme quantiles. This reversal suggests that Tether's safe-haven properties may be more context-dependent, varying based on the degree of market distress and the specific financial assets in question.

Finally, at the 10% quantile, Tether once again demonstrates broader safe-haven characteristics. In this scenario, it qualifies as a safe-haven asset for all variables analyzed, with the sole exception of the European index. Notably, Tether emerges as a strong safe-haven for the S&P 500 at the 5% level and for the MSCI World at the 1% level, highlighting its potential as a stabilizing force during moderate market downturns. For the remaining financial variables, Tether functions as a weak safe-haven, further reinforcing its role as a protective asset during periods of heightened uncertainty.

The findings of this analysis indicate that Tether exhibits safe-haven characteristics for each variable considered in at least one instance, although its effectiveness as a safe-haven asset varies across different quantiles. The stablecoin demonstrates its strongest safe-haven properties at the mildest levels of negative returns, suggesting that while it provides stability during periods of market distress, its protective capacity is more pronounced during moderate downturns rather than in the most extreme financial crises. These findings regarding Tether's protective role align with the ones obtained by Vukovic et al. (2021), Conlon et al. (2020) and Hampl et al. (2024), who also regarded Tether, due to its association with the US Dollar, as a safe-haven for stock markets during broader market movements. Despite this, there is no record in the literature regarding Tether's enhanced safe-haven ability at the mildest levels of negative returns.

A closer examination of the different quantiles highlights notable variations in Tether's safe-haven role. Specifically, a comparison between the 1% and 5% quantiles and the 2,5% quantile reveals key distinctions. While Tether's safe-haven properties appear more limited at the extreme 1% and 5% quantiles, they become significantly stronger at the 2,5% level. This shift underscores the necessity of including the 2,5% quantile in the original model, as it provides a more comprehensive understanding of the performance of cryptocurrencies as a safe-haven asset. These findings are consistent with the conclusions drawn by Baur and Lucey (2010), who emphasized that the gap between the 1st and 5th percentiles can be substantial and, if overlooked, may result in the loss of critical insights. In the context of Tether, this reinforces the idea that evaluating safe-haven properties solely at the most extreme quantiles could lead to an incomplete assessment of its actual performance as a protective asset. By incorporating the 2,5% quantile, this study provides a more nuanced perspective, highlighting Tether's ability to serve as a stabilizing force under various market conditions.

6.3. Results: Comparison

Based on the results obtained for both cryptocurrencies, a comparison of their respective performances can now be made. Building on the analysis of Bitcoin and Tether's hedging capabilities, it is apparent that both cryptocurrencies exhibit limited hedging characteristics for stock indices. However, Tether distinguishes itself by offering potential protection for commodities, particularly gold and oil. This finding reinforces the notion that, while neither cryptocurrency serves as a traditional hedge for equities, Tether may provide protection for specific asset classes, particularly during periods of market volatility. Additionally, in terms of hedging potential, it is important to note that Tether's correlation values for c_0 are consistently lower than Bitcoin's for the same variables. This suggests that, although neither cryptocurrency fulfills this role optimally, Tether may offer a superior hedge potential in comparison to Bitcoin.

When evaluating safe-haven characteristics, Bitcoin's role is most significant at the extreme lower quantiles (such as the 1% and 2,5% levels), where it acts as a safe-haven for most stock indices, particularly the S&P 500. However, as market conditions become less extreme (e.g., at the 5% and 10% quantiles), Bitcoin's effectiveness as a safe-haven diminishes substantially. In contrast, Tether exhibits the opposite behavior: while it provides some level of protection across all quantiles, it shows a more pronounced role as a safe-haven during moderate downturns (i.e., at the 10% quantile). This is because, within this interval, the stablecoin demonstrates a negative correlation with almost all other variables in the analysis. This pattern suggests that as more observations are considered, Tether's safe-haven qualities become increasingly evident. Its stability and low volatility provide more reliable protection for financial markets over time, aligning with its relatively superior ability to function as a hedge compared to Bitcoin.

Overall, while neither Bitcoin nor Tether consistently serves as a hedge for equity markets, Tether offers a greater potential for hedging commodities and may provide diversification benefits under specific market conditions. Regarding the safe-haven capabilities of the two cryptocurrencies, both have demonstrated the ability to function as safe-havens for certain markets under particular circumstances. Bitcoin performs more effectively as a safe-haven during the most extreme tail of the distribution, while Tether excels in offering protection during less volatile market conditions.

7. Conclusion

Despite existing for over 15 years, the role of cryptocurrencies within the modern financial landscape remains uncertain and highly debated. While some authors perceive cryptocurrencies as a form of “digital gold”, others argue that they are merely speculative assets lacking intrinsic value, characterized by high volatility and risk. A clearer understanding of cryptocurrencies’ potential role can be gained by examining their relationship with well-established asset classes, particularly in terms of their ability to provide diversification, hedging, and safe-haven benefits for investors and others alike. With the existing literature on this topic presenting mixed conclusions regarding the role of cryptocurrencies in financial markets, this research aimed to contribute to this ongoing debate by analyzing whether, based on their correlations with traditional financial assets, cryptocurrencies can be considered a financial safe-haven across different market conditions.

With the aforementioned objective in mind, two cryptocurrencies with distinctly different properties were picked: Bitcoin and Tether. Bitcoin was chosen due to its status as the leading cryptocurrency in the market. Tether, on the other hand, was selected because it is a stablecoin, designed to maintain a relatively stable price by being pegged, in this case, to the US dollar. For the safe-haven analysis, this research sought to explore potential differences in the behavior of digital assets across various regions. As such, the two cryptocurrencies were compared to five regional indices, which were picked as proxies for global equity markets, as well as two commodities – gold and oil - due to their common association with safe-haven analysis.

Regarding the methodology, a Dynamic Conditional Correlation GARCH model was employed to extract the time-varying dynamic correlations between the selected cryptocurrencies and the other variables in the analysis. This approach specifically focused on the periods in which the market exhibited its lowest percentile returns, enabling a precise assessment of correlation dynamics during extreme market conditions.

Through the values obtained for the correlations, it was concluded that both Bitcoin and Tether can be perceived as safe-havens for the North American, European, Asian, Pacific, and World proxies during certain market conditions, with Bitcoin excelling as a protective asset for market variations in the most extreme instances of negative returns in the markets, and Tether showing a more pronounced role as a safe-haven during moderate downturns. As for the commodities, Tether demonstrated hedging and safe-haven capabilities, while Bitcoin presented a more limited protective role, only serving as a weak safe-haven for oil in one of the analyzed quantiles.

While both cryptocurrencies exhibited varying degrees of safe-haven behavior across different asset classes, their effectiveness remains asset-specific and market-dependent. These findings contribute to the ongoing debate on cryptocurrency integration into traditional finance, emphasizing the need for further research on their evolving role, regulatory impact, and long-term stability as financial instruments.

The findings of this study also carry significant implications for investors, financial institutions, and policymakers. For investors, the identification of Bitcoin and Tether as safe-havens under specific market conditions provides useful insights for portfolio construction and risk management. Their differing behaviors - Bitcoin offering protection during extreme downturns and Tether during more moderate stress - highlight the need for a nuanced approach to crypto asset allocation based on market context and asset exposure.

Financial institutions may also find these results relevant when assessing the integration of digital assets into their investment offerings and risk strategies. As demand for cryptocurrencies continues to grow, understanding their safe-haven potential can inform the development of more resilient financial products. For policymakers and central banks, the evidence that decentralized assets may serve a stabilizing role during periods of market stress suggests a need to further explore their impact on systemic risk and financial stability. As the boundary between traditional finance and digital assets continues to blur, this study contributes to a clearer understanding of how cryptocurrencies may function within the broader financial system.

In terms of limitations, it is worth mentioning this study is primarily centered on stock markets and a selected set of commodities, which inherently narrows the scope of the conclusions. While the focus on equity market proxies provides valuable insights into the safe-haven behavior of Bitcoin and Tether during periods of extreme market stress, it overlooks the potential interactions these digital assets may have with other important asset classes. Future research could broaden the analytical framework by incorporating fixed-income securities, such as sovereign and corporate bonds, as well as major fiat currencies. This expanded scope would allow for a more comprehensive assessment of the hedging and diversification potential of cryptocurrencies across a wider financial landscape.

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9. Appendix

Figure 2: Stock Indexes Returns
Source: RStudio

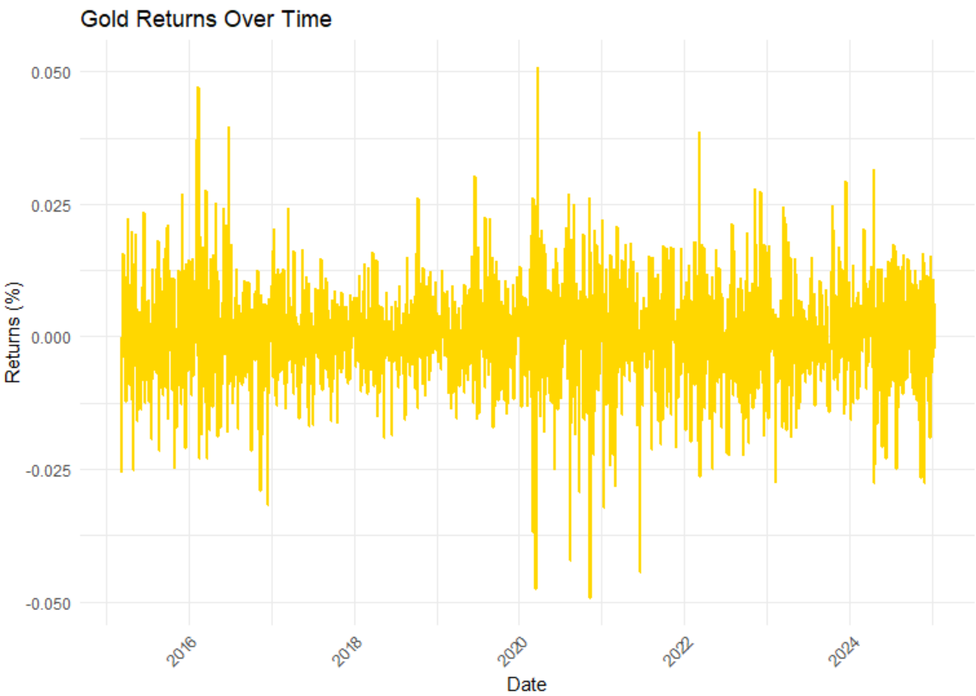

Figure 3: Gold Returns
Source: RStudio

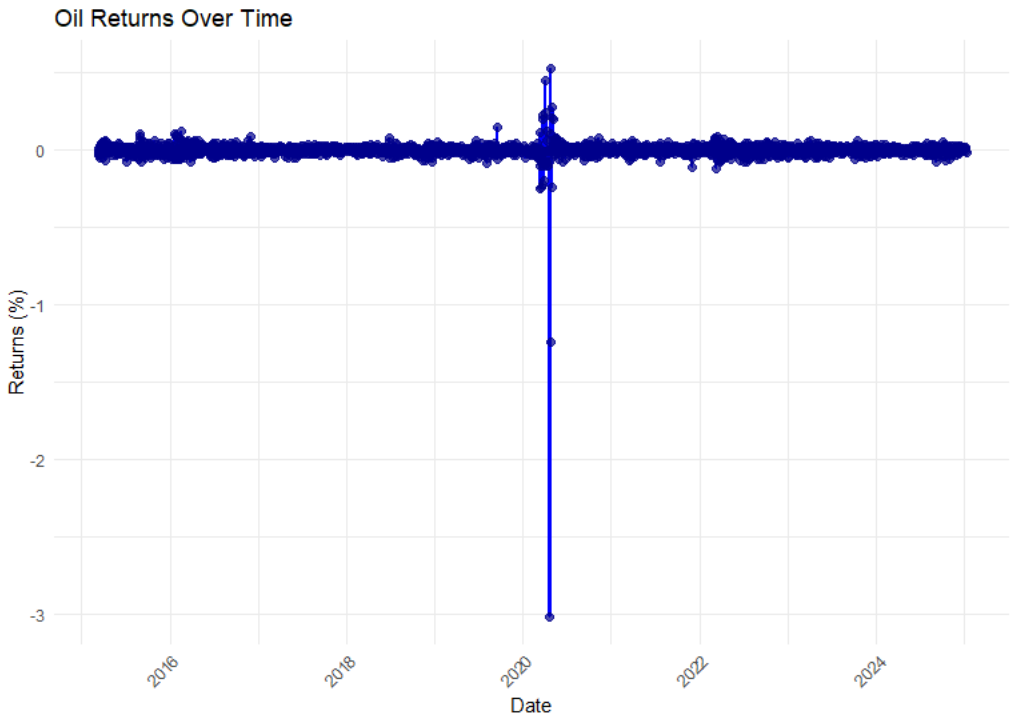

Figure 4: Oil Returns
Source: Rstudio

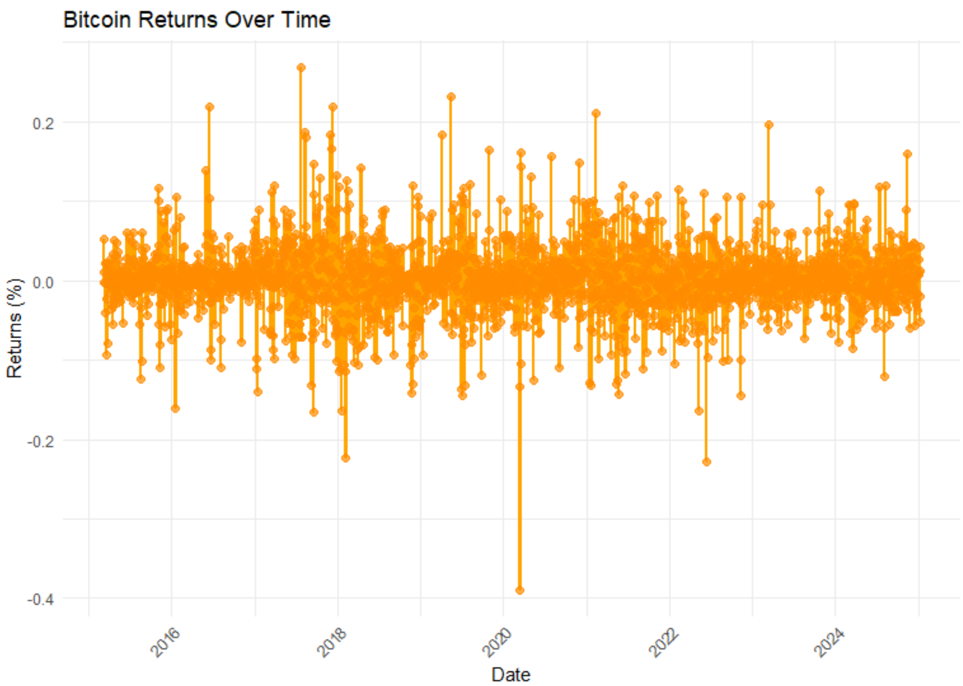

Figure 5: Bitcoin Returns
Source: Rstudio

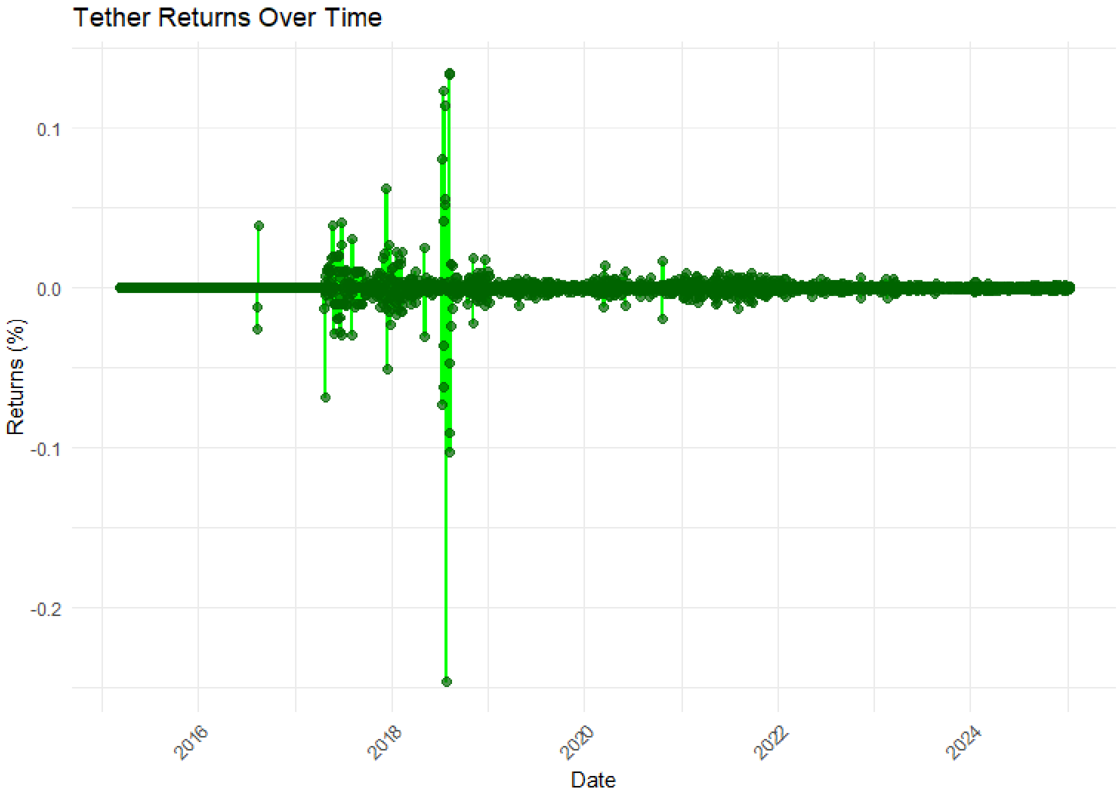

Figure 6: Tether Returns
Source: RStudio

```
        Augmented Dickey-Fuller Test

data:  df$`MSCI Asia Ex Japan`
Dickey-Fuller = -13.756, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(df$`MSCI Asia Ex Japan`, alternative = "stationary") :
  p-value smaller than printed p-value
> adf.test(df$`MSCI World`, alternative = "stationary")

        Augmented Dickey-Fuller Test

data:  df$`MSCI World`
Dickey-Fuller = -13.536, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(df$`MSCI World`, alternative = "stationary") :
  p-value smaller than printed p-value
```

```
        Augmented Dickey-Fuller Test

data:  df$.STOXX
Dickey-Fuller = -14.081, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(df$.STOXX, alternative = "stationary") :
  p-value smaller than printed p-value
> adf.test(df$`MSCI Pacific`, alternative = "stationary")

        Augmented Dickey-Fuller Test

data:  df$`MSCI Pacific`
Dickey-Fuller = -14.27, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(df$`MSCI Pacific`, alternative = "stationary") :
  p-value smaller than printed p-value
```

```
        Augmented Dickey-Fuller Test

data:  df$`Crude Oil WTI Cushing U$/BBL`
Dickey-Fuller = -16.867, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(df$`Crude Oil WTI Cushing U$/BBL`, alternative = "stationary")
:
  p-value smaller than printed p-value
> adf.test(df$`Gold`, alternative = "stationary")

        Augmented Dickey-Fuller Test

data:  df$Gold
Dickey-Fuller = -13.511, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(df$Gold, alternative = "stationary") :
  p-value smaller than printed p-value


        Augmented Dickey-Fuller Test

data:  df$Bitcoin
Dickey-Fuller = -12.175, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(df$Bitcoin, alternative = "stationary") :
  p-value smaller than printed p-value
> adf.test(df$`Tether`, alternative = "stationary")

        Augmented Dickey-Fuller Test

data:  df$Tether
Dickey-Fuller = -17.792, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(df$Tether, alternative = "stationary") :
  p-value smaller than printed p-value
```

Figure 7: Augmented Dickey-Fuller test results
Source: RStudio

```
        Phillips-Perron Unit Root Test

data:  df$.SP500
Dickey-Fuller Z(alpha) = -2915.8, Truncation lag parameter = 9, p-value = 0.01
alternative hypothesis: stationary
```

```
        Phillips-Perron Unit Root Test

data:  df$.STOXX
Dickey-Fuller Z(alpha) = -2579.8, Truncation lag parameter = 9, p-value = 0.01
alternative hypothesis: stationary


        Phillips-Perron Unit Root Test

data:  df$`MSCI Pacific`
Dickey-Fuller Z(alpha) = -2606.1, Truncation lag parameter = 9, p-value = 0.01
alternative hypothesis: stationary


        Phillips-Perron Unit Root Test

data:  df$`MSCI Asia Ex Japan`
Dickey-Fuller Z(alpha) = -2396.1, Truncation lag parameter = 9, p-value = 0.01
alternative hypothesis: stationary


        Phillips-Perron Unit Root Test

data:  df$`MSCI World`
Dickey-Fuller Z(alpha) = -2623.8, Truncation lag parameter = 9, p-value = 0.01
alternative hypothesis: stationary


        Phillips-Perron Unit Root Test

data:  df$`Crude Oil WTI Cushing U$/BBL`
Dickey-Fuller Z(alpha) = -1696.8, Truncation lag parameter = 9, p-value = 0.01
alternative hypothesis: stationary


        Phillips-Perron Unit Root Test

data:  df$Gold
Dickey-Fuller Z(alpha) = -2576.7, Truncation lag parameter = 9, p-value = 0.01
alternative hypothesis: stationary


        Phillips-Perron Unit Root Test

data:  df$Bitcoin
Dickey-Fuller Z(alpha) = -2769.7, Truncation lag parameter = 9, p-value = 0.01
alternative hypothesis: stationary


        Phillips-Perron Unit Root Test

data:  df$Tether
Dickey-Fuller Z(alpha) = -2716.2, Truncation lag parameter = 9, p-value = 0.01
alternative hypothesis: stationary
```

Figure 8: Phillips Perron test results
Source: RStudio

```
> kpss_test_result <- kpss.test(df$`.SP500`)
Warning message:
In kpss.test(df$.SP500) : p-value greater than printed p-value
> print(kpss_test_result)

        KPSS Test for Level Stationarity

data:  df$.SP500
KPSS Level = 0.056883, Truncation lag parameter = 9, p-value = 0.1
```

```
> kpss_test_result <- kpss.test(df$`.STOXX`)
Warning message:
In kpss.test(df$.STOXX) : p-value greater than printed p-value
> print(kpss_test_result)

        KPSS Test for Level Stationarity

data:  df$.STOXX
KPSS Level = 0.059223, Truncation lag parameter = 9, p-value = 0.1
```

```
> kpss_test_result <- kpss.test(df$`MSCI Pacific`)
Warning message:
In kpss.test(df$`MSCI Pacific`) : p-value greater than printed p-value
> print(kpss_test_result)

        KPSS Test for Level Stationarity

data:  df$`MSCI Pacific`
KPSS Level = 0.065618, Truncation lag parameter = 9, p-value = 0.1
```

```
> kpss_test_result <- kpss.test(df$`MSCI Asia Ex Japan`)
Warning message:
In kpss.test(df$`MSCI Asia Ex Japan`) :
  p-value greater than printed p-value
> print(kpss_test_result)

        KPSS Test for Level Stationarity

data:  df$`MSCI Asia Ex Japan`
KPSS Level = 0.05372, Truncation lag parameter = 9, p-value = 0.1
```

```
> kpss_test_result <- kpss.test(df$`MSCI World`)
Warning message:
In kpss.test(df$`MSCI World`) : p-value greater than printed p-value
> print(kpss_test_result)

        KPSS Test for Level Stationarity

data:  df$`MSCI World`
KPSS Level = 0.058695, Truncation lag parameter = 9, p-value = 0.1
```

```
> kpss_test_result <- kpss.test(df$`Crude Oil WTI Cushing U$/BBL`)
Warning message:
In kpss.test(df$`Crude Oil WTI Cushing U$/BBL`) :
  p-value greater than printed p-value
> print(kpss_test_result)

        KPSS Test for Level Stationarity

data:  df$`Crude Oil WTI Cushing U$/BBL`
KPSS Level = 0.048074, Truncation lag parameter = 9, p-value = 0.1
```

```
> kpss_test_result <- kpss.test(df$`Gold`)
Warning message:
In kpss.test(df$Gold) : p-value greater than printed p-value
> print(kpss_test_result)

        KPSS Test for Level Stationarity

data:  df$Gold
KPSS Level = 0.13596, Truncation lag parameter = 9, p-value = 0.1
```

```
> kpss_test_result <- kpss.test(df$`Bitcoin`)
Warning message:
In kpss.test(df$Bitcoin) : p-value greater than printed p-value
> print(kpss_test_result)

        KPSS Test for Level Stationarity

data:  df$Bitcoin
KPSS Level = 0.15606, Truncation lag parameter = 9, p-value = 0.1
```

```
> kpss_test_result <- kpss.test(df$`Tether`)
Warning message:
In kpss.test(df$Tether) : p-value greater than printed p-value
> print(kpss_test_result)

        KPSS Test for Level Stationarity

data:  df$Tether
KPSS Level = 0.02313, Truncation lag parameter = 9, p-value = 0.1
```

Figure 9: *Kwiatkowski–Phillips–Schmidt–Shin* Test Results
Source: RStudio

```
        Box-Ljung test

data:  residuals_normalgjr
X-squared = 7.0616, df = 10, p-value = 0.7196
```

Figure 10: Ljung-Box test for Bitcoin using the GJR-GARCH with a normal distribution
Source: RStudio