Correlations and Risks of DeFi with Capital Markets: The Terra Luna Case

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Abstract

In 2022, the collapse of Terra Luna, a decentralized finance (DeFi) protocol, caused a loss of 200 billion in just 24 hours. This study aims to investigate the effects of this collapse on the correlations between digital and traditional assets, as well as identify potential ways to minimize the inherent risks of such collapses in the future. As DeFi technologies continue to go unregulated, there is a potential for large exposure to traditional finance. Therefore, it is important to identify ways to minimize the inherent risks of such collapses and provide stakeholders with insights for hedging, portfolio management, and the formulation of regulation for consumer protection. The study applies a multivariate DCC GARCH model to answer the empirical research question. The results indicate increased volatility during the crash but do not provide sufficient evidence or statistical significance to reject the null hypothesis. Further findings highlight the difficulty in providing solutions for the minimization of risks to collapses such as that of Terra Luna outside of regulation and investor caution.

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List of Abbreviations

BTC……………………………………………………………………………………Bitcoin

CAKE………………………………………………………………..………SushiSwap

CBDC………………..…………………………………………Central Bank Digital Currency

COMP…………………………………………………………..………………Compound

CRV…………………………………………………………………………………..Curve

Crypto……………………………………………………………………...Cryptocurrency

DCC……………………………………………...…………Dynamic conditional correlation

DeFi………………………………..……………….………………Decentralized Finance

DXY…………………………………………………………………..U.S. Dollar Index

ETH……………………………………………………………………………Ethereum

FOREX……………………………………………………………..………Foreign exchange

GARCH………………………………Generalized autoregressive conditional heteroskedasticity

LFG………………………………………………………………… Luna Foundation Guard

MKR……………………………………………………………………………….…...Maker

mCap…………………………………………………………………...…Market Capitalization

MiCA……………………………………………………..Markets in Crypto-Assets Regulation

S&P500………………………………………………………...…Standard and Poor's 500

SUSHI……………………………………………………………………..………SushiSwap

TVL………………………………………………………………………Total Value Locked

UCT……………………………………………………………Coordinated Universal Time

UST…………………………………………………………………………………US Terra

USDT…………………………………………………………..……………USD Terra

USP…………………………………………………….…………Unique Selling Proposition

US10Y……………………………………………...………..U.S. 10-Year Treasury Bond

UNI…………………………………………………………………..……………Uniswap

YFI……………………………………………………………………..…Yearn Finance

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1 Introduction

Since 2018, the DeFi space has aimed to create an open, trustless and permissionless financial market, which provides an alternative to centralized financial institutions, third-party players, and the traditional financial system. In 2022, we have seen the collapse of many protocols, projects, and ecosystems due to the inherent vulnerabilities and fragility of such technologies. One of the most notable, was Terra Luna, which collapsed along with DeFi Protocol Anchor, its native token LUNA, and algorithmic stablecoin UST, wiping out 200 billion USD in just 24 hours, and will be examined as a case study for this paper. DeFi is still in its early stages and has massive implications for Web 3.0 development, and potentially the larger financial system. Therefore, reducing such risk and improving these vulnerabilities is essential for the DeFi space to continue making strides in the global economy and foster stability in the DeFi and Web 3.0 ecosystems. It is important to understand the impacts these risks can have on both digital and traditional asset classes, especially as they continue to go unregulated, leaving DeFi with potentially large exposure to traditional finance (Carapella et al., 2022). The inherent risks of Terra Luna primarily stem from the two-coin system of maintaining an algorithmic stablecoins peg known as seigniorage, which will be discussed in detail further in this study.

Motivation for this study stems from suggestions from previous research of Lee et al., (2022), Antonakakis et al., (2019); Yi et al., (2018); Bouri et al., (2021), who study the connectedness and spillover effects of the market, in some cases during the Terra Luna crash. The purpose of this study is to investigate the following two research questions: „Is there an increase in the correlation of volatility between digital and traditional assets during the Terra Luna crash?" and „How could the inherent risks of the Terra Luna ecosystem and algorithmic stablecoin UST have been identified or minimized?" The empirical question is answered by testing the following null hypothesis: "there is no increase in correlation of volatility between digital and traditional assets during the Terra Luna crash." This study aims to provide first insight to the volatility correlations between digital and traditional assets during a DeFi collapse through the case study of Terra Luna, as well as provide stakeholders and regulators with new insights for hedging, portfolio management, and the formulation of regulation for consumer protection.

In December 2021, investors began overestimating the power and value of demand created by network effects of the Terra Luna ecosystem (Kereiakes et al., 2019; Quast et al., 2021). As the lender to borrower ratio of anchor protocol, the primary DeFi protocol on of the ecosystem began to drop, founder Do Kwon provided a band-aid solution to Anchor reserves by adding an additional 450 million USD in the form of BTC and other assets. The LFG began filling its reserves as a backstop for stablecoin UST, unfortunately, this incentivized strategies for individuals to acquire BTC at a discounted price (Clements, 2021; Morris, 2022). On April 2nd, migration to a new liquidity pool was announced with partners which would leave Curve3pool in a liquidity crunch, and prone to potential attacks (Briola et al., 2022; Falk & Hammer, 2022; Kwon, 2022; Lee et al., 2022). As this research focuses on the inherent risks of the technology, not potential malpractice currently in ongoing investigation, the timeline of events focuses only on what is known for a fact. In context of this research, we refer to the following definition of inherent risk: “the level of risk in place in order to achieve an entity's objectives and before actions are taken to alter the risk's impact or likelihood” (Tennessee State Government, n.d). In April, reports by Swissborg and Coindesk began to surface indicating a bank run risk on the two-coin algorithmic stablecoin system (Bonato, 2022; Morris, 2022). On May 7th, Curve3pool suffered a liquidity attack, causes the first de-peg of UST below $0.99, and loss of investor confidence in UST’s future value causing a bank run (Briola et al., 2022). This loss of confidence in expectation for future returns led to the hyperinflation of the LUNA, primarily due to its lack of collateral or intrinsic value (European Central Bank, 2019; European Securities and Markets Authority, 2022). The following day, LFG began trading its reserves to restore the peg, which ultimately failed on May 10th. By the 12th, consumer trust had been lost and the Terra blockchain was officially halted (Lee et al., 2022). On May 13, 0:300 UTC, UST bottomed out at a price of $0.0583 from its 1$ peg, and LUNA had fallen by over 1100%. On the 18th, Terra governance proposed to rename LUNA to LUNC, and rebirth the ecosystem on Terra 2.0, which was approved by chain validators with 2/3 majority a week later. This marked the end of the original Terra Luna blockchain, which is the focus of this study. It should be noted that while LUNA has since been renamed LUNC, LUNA will refer to the asset prior to its renaming, as that was the current name during the period reference in this paper. In addition, the terms “digital assets” and “cryptocurrencies” are used interchangeably, as NFTs and other forms of digital assets are not considered for this research.

The structure of the remainder of this paper is as follows: A literature review is presented, which is divided into sections addressing the two research questions. The research design and methodology are described, including the sample, data, and the application of the multivariate DCC GARCH model to test the empirical research question. The results and discussion section presents the findings, which address the empirical research question and provide the outcome of the null hypothesis. The limitations of the study are then discussed. Finally, a conclusion is provided, summarizing the findings and answering the theoretical research question based on the literature review.

2 Literature Review

2.1 Cracks in the DeFi architecture

While DeFi provides many technological innovations and innovative financial solutions, the Terra Luna ecosystem is not the first collapse due to inherent risks. The idea of an algorithmic stablecoin has been heavily scrutinized and led to many collapses even prior to Terra Luna (Clements, 2021; European Securities and Markets Authority, 2022; Reserve Research Team, 2018). This technology will be the highlight of the inherent risks involved in the Terra Luna crash, as the broader risks of DeFi and cryptocurrencies as a whole are manifest. Thankfully, DeFi is not currently of systemic importance to the global financial markets, however close eye should be kept by regulators as the impact and frequencies of such collapses continue to increase. (European Securities and Markets Authority, 2022; Carapella et al., 2022). While some see cryptocurrencies in large as an ongoing experiment, policies in regulation must be well considered prior to the potential point of systemic risk (Carapella et al., 2022); Cermak, 2017).

A primary concern for stablecoins at large lies in the absence of mandatory disclosure of reserves, which can be difficult to value due to the volatile nature of certain collateral, which can take form in various asset classes both on and off chain (Bullmann et al., 2019; European Central Bank, 2019; Salami, 2021). In principle, this should not be an issue for maintaining the peg of an algorithmic stablecoin, as they are designed to maintain their peg algorithmically, without the need for collateral. However as seen in the collapse, speculation on the existence and state of reserves held by the LFG played a large role in losing investor confidence of the Terra Luna ecosystem at large.

The idea of algorithmic stablecoins is that their value can be maintained through user expectations on future purchasing power of their holdings (European Central Bank, 2019). In the case of IRON, an algorithmic stablecoin similar to UST created by TITAN which crashed on June 16, 2021, a two coin system known as seigniorage was used to maintain a stable peg (Reynolds, 2021). The idea that a native token such as TITAN can absorb volatility shocks holds true under normal market conditions, however in extreme cases, primarily a loss of confidence in expectation for future returns causes hyperinflation due to the lack of collateral or intrinsic value (European Securities and Markets Authority, 2022). Terra Luna attempted and failed to solve this issue, as their experiment of awarding funds accrued through transaction fees for ecosystem development together with network affects within that ecosystem did not provide enough intrinsic value to maintain stability in the face of skepticism in consumer trust (Kereiakes et al., 2019). At its core, this was the primary cause of the projects collapse.

There has been little to no success in the field of algorithmic stablecoins, with the exception of MakerDAO's DAI, which is only a pseudo-algorithmic stablecoin due to the mix of its decentralized seigniorage base coupled with overcollateralized on chain backing (Buterin, 2022; Bullmann et al., 2019). Thus far, it has proven its ability to endure multiple large periods of volatility affecting its underlying collateral (European Central Bank, 2019). No case of a fully algorithmic stablecoin based on the seigniorage principle of UST, IRON, or NuBits has proven to do the same. Therefore, the ECB attests that „algorithmic stablecoins are still a theoretical alternative rather than a practical solution"(European Central Bank, 2019).

Vitalik Buterin, the founder of ETH and one of the pioneers of blockchain development laid out a set of steady state conditions which could be applied to evaluate whether algorithmic stablecoins can remain stable under extreme market conditions. The primary aspect which Terra Luna's two-coin system proved unable to achieve, was the ability to slowly wind down, overcoming the fundamental issue of the feedback loop created in a two-coin system (Buterin, 2022). As UST's demand experienced a shock, hyperinflation led to what Vitalik coined a „self-fulfilling prophecy." The expectation of returns which hold the peg together was eliminated, pushing down the mCap and increasing fragility to the point of collapse (Buterin, 2022, 4).

It is important to note, the more centralized a project becomes the more susceptible to operational risk it becomes, leading to potential malpractice by issuers in the wake of a lack of regulation. There is significant and ongoing controversy regarding other aspects related to the Terra Luna crash however it is clear that regulation could significantly aid in the prevention of crashes in the future (Bullmann, 2019). The extent of these risks to the larger financial system depends primarily on the magnitude of potential losses (Carapella et al., 2022).

While some solution such as the use of third-party institutions creating stable infrastructure through a CBDC or granting full transparency to issuer balance sheets have been suggested, both solutions limit the USPs of DeFi through the limitation of privacy and decentralization (Chiu et al., 2022).

The most prominent proposed regulation to date is MiCA, which suggested standards based on the significance of a given stablecoin in October 2022. This significance is based on the value of issued tokens, size of issuer base, and interconnectedness with the traditional financial system have been given thus far. These regulations would address the issuance, disclosure, collateral, and authorization to release such tokens (General Secretariat of the Council of the Council, The European Union, 2022; Salami, 2021).

Further, without buy-in from industry participants and global policymakers, as well as a prioritization of strong consumer protections, it is unclear whether the implementation of such regulation will have as large of an impact in preventing crashes as needed (Falk & Hammer, 2022). With MiCA being the only proposed regulation by a systemically relevant body, little progress has been made in creating any sort of global regulatory standards which could minimize risks such collapses in future (Salami, 2021).

2.2 Relationship between digital and traditional assets

There has been debate in the literature about the role of BTC as a hedge, safe-haven, or diversifier against traditional financial assets for some time. Some studies have found that BTC can serve as a hedge or diversifier for investors (Rudolf et al., 2021; Stensås et al., 2019; Yi et al., 2018). However, other research has suggested that BTC is more volatile even in normal times and has downside risk spillover to traditional assets, making it important to monitor carefully for financial stability (Smales, 2019). It has also been suggested that it may be helpful for investors or portfolio managers to consider a range of cryptocurrencies rather than just focusing on BTC (Yi et al., 2018). It is important to consider the interdependencies between the cryptocurrency market and traditional financial markets, as the transmission of shocks from one system to the other is possible due to the existence of connections between both markets (European Securities and Markets Authority, 2022). These interdependencies, such as the use of assets as collateral for liabilities, can create a direct link between the two systems and lead to material value changes in one market spilling over into the other. As limited research exists regarding the DCC correlations between digital and traditional assets, the following section provides insight to the relationships, correlations, and hedging capabilities of crypto, often BTC, in relation to individual traditional asset classes, as well as existence of connectedness within the crypto space.

In October 2022, it was observed that BTC had become less volatile than stocks, though Bloomberg cautioned this may not necessarily be a positive development in a low-volume market (Hajric, 2022). Yi, Xu, and Wang (2018) point out that cryptocurrencies differ from traditional financial assets such as stocks, which are more influenced by economic fundamentals and corporate performance, which could have implications for the correlation between the two. Falk & Hammer (2022) find that BTC and other cryptocurrencies are often correlated with other risk assets such as stocks. In particular, BTC tends to be associated with tech stocks such as PayPal and CashApp (Falk & Hammer, 2022), as well as the NASDAQ. During the Terra Luna collapse, Arcane Research reported all-time highs in the 90-day correlation between BTC and the S&P 500 (Falk & Hammer, 2022), which contributed to the motivation for this research.

Several studies have explored the relationship between BTC and traditional assets such as gold and commodities, as well as hedging capabilities. In terms of volatility and the types of shocks that most influence BTC, there are similarities to gold and the US dollar (Dyhrberg, 2016). In 2018, Selmi et al. found BTC acts as a diversifier for commodities, which has since been supported by further findings that BTC and gold are highly correlated as a hedge, indicating that investors are increasingly holding BTC as a digital store of value like gold (Rudolf et al., 2021). This was particularly evident during the COVID-19 pandemic, when BTC's volatility decreased and returns increased as investors perceived it as a digital hedge against the economic recession (Rudolf et al., 2021). Some studies have also found that bitcoin is a better hedge and investment than gold and major stock indexes, exhibiting superiority in terms of returns (Bouri et al., 2020; Jareño et al., 2020). BTC's lack of intrinsic value, coupled with the fact that its value is driven solely by market forces, means that its variance is determined by external factors rather than endogenous factors like gold, making BTC an attractive option for portfolio diversification (Dyhrberg, 2016; Hatemi-J et al., 2021; Tully & Lucey, 2007),

Evidence suggests that BTC exhibits characteristics of a diversifier for currencies, particularly regarding its potential use as a medium of exchange. This is supported by the findings of Regaieg et al. (2020) which indicate the return on BTC is influenced more-so by demand for its use as a medium of exchange than temporary price shocks, indicating a similarity to a currency (Regaieg et al. 2020). Furthermore, the positive coefficient on the federal funds rate in the mean equation of Dyhrberg (2016) suggests an increase in the federal funds rate leading to appreciation of the American dollar may result in an increase in demand for BTC due to its usefulness in international online trade. The sensitivity of bitcoin returns to the value of the dollar relative to the pound, as opposed to the value of the dollar relative to the euro, suggests the presence of regional or country-specific effects (Dyhrberg 2016). Furthermore, research on the risk management capabilities of gold as a hedge against the dollar may be extended to suggest that bitcoin may also have some risk management capabilities against the dollar (Capie et al. 2005; Dyhrberg 2016).

2.3 Relationships amongst digital assets

While Bouri et al., (2021), Antonakakis et al., (2019), and Yi et al., (2018) all find the connectedness of cryptocurrencies increases during extreme market events and times of high volatility, it is less clear how these relationships change during calmer market periods. These findings support the possibility of a change in correlation between digital and traditional assets during the Terra Luna crash, providing reason for conducting this research. These findings have implications for hedging strategies and risk management for investors (Ji et al., 2018). Research shows cryptocurrency market is not solely influenced by BTC and other highly market capitalized currencies. This is supported by the granger causality approach applied by Bouri et al., (2019) as well as the T-MDS methodology of Papadimitriou et al., 2020. While both their findings state BTC, as the largest coin by mCap, is not the clear leader in terms of volatility connectedness, Yi et al., 2018 suggest that connectedness among cryptocurrencies does not necessarily depend on their size. This is supported by Bouri et al., (2019) and Bouri et al., (2021), making it plausible that this was the case for Luna and UST during the Terra Luna collapse, as connectedness has been found to be more pronounced through the TVP-FAVAR model by Antonakakis et al., (2019). This area is highly debated amongst literature, which attests this is due to the volatile and nature of the market. These findings support the possibility that BTC is losing its dominance (Ji et al., 2018), and is in line with the possibility that cryptocurrencies become increasingly homogenous in the eyes of investors, posing as potential substitutes to one another due to convergence in returns and volatility (Papadimitriou et al., 2020). Finally, no research was found investigating these relationships across more specific areas of the cryptocurrency space, such as DeFi, Web 3.0, or the Metaverse, providing further motivation to consider how the Terra Luna crash affected the DeFi space in its own context, removed from cryptocurrencies as a whole. As the previous section mentions, this space in particular is highly relevant for the context of regulation, making this research a valuable first step in understanding these relationships.

3 Research Design and Methodology

To answer the empirical research question and test the hypothesis, a multivariate DCC-GARCH model was utilized to examine the changes in dynamic correlations of volatility and overall volatility correlations between financial assets during the crash period. The data for this model was collected from various exchanges as 30-minute candle returns for the S&P500, US10Y, gold, oil, DXY, BTC, ETH, and various cryptocurrencies used to create a DeFi index from January 1, 2022, to May 31, 2022. Further details for these variables can be found in Table 1 on the following page.

3.1 Variable Selection

The variables included in the model were chosen to provide a sample of all primary participants of traditional markets, as well as the DeFi space where the crash occurred. The S&P500 was taken as a sample for the stock market due to its broad representation of the primary global market. The US10Y was chosen to represent the bond market as it is widely traded, highly liquid, and its role as an indicator for investor sentiment in the economy. Gold and oil were selected as samples of the most systemically relevant commodities, while DXY was selected to represent the USD in the FOREX market, as it considers a basket of currencies in its comparison with the USD. BTC and ETH were taken as samples of the cryptocurrency market, as they represent over half the mCap of the market, as well as for comparability to previous research. As BTC may have been manipulated during the sample period leading up to the crash (Briola et al., 2022, Falk & Hammer, 2022, Lee et al., 2022). These considerations together with Bouri et al.'s, (2021) findings of ETH's importance during extreme market conditions mentioned in section 2.1 of the literature review led to the inclusion of both BTC and ETH to provide a more accurate representation of the market and provide possibilities reference robustness in DCC analysis. Finally, LUNA and UST were included as the two main assets involved in the Terra Luna crash.

3.2 DeFi Index Construction

As no DeFi index with a complete dataset during the sample period currently exists, a price weighted DeFi index was constructed based on the following criteria. DeFi projects with the highest TVL as of Jan 1, 2022, the start period of the sample, were selected, excluding projects built on the Terra Luna Blockchain, such as Anchor Protocol, who played a direct role in the crash. Projects were included in this order, until the TVL of the smallest project no longer met a minimum of 10% of the largest project. In addition, to avoid the dominance of any given category e.g., lending, the index maintains a maximum dominance of 50% for any type of service provided by the DeFi project. Included assets must represent a token that services as a bearer instrument, to ensure tokens are liquid and provide a representative sample. Thus, this final point excludes tokens which are wrapped, synthetic, derived from other assets, tied to physical assets, or represent claims on other tokens. Further breakdown of constituents, their functions, and TVL can be found in Appendix A.

3.3 Data and Sample

30 min price data for the sample came from the Binance, Huobi, and KuCoin exchanges, and was retrieved through TradingView, as seen in Table 1.

Asset	Asset Category	Data Use	Data Retrieved	Price Calculated by	mCap Calculated by
S&P500	Traditional Index	Dependent Variable	Trading View	SPX	N/A
US 10-Year Treas. Bond	Traditional	Dependent Variable	Trading View	TradingView	N/A
DXY Dollar Index	Traditional Index	Dependent Variable	Trading View	TradingView	N/A
Gold	Traditional	Dependent Variable	Trading View	TradingView	N/A
Brent Crude Oil	Traditional	Dependent Variable	Trading View	TradingView	N/A
USD Tether	Digital (stablecoin)	Conversion Factor	Trading View	Binance	N/A
US Terra	Digital (stablecoin)	Dependent Variable	Trading View	Huobi	N/A
Luna	Digital	Dependent Variable	Trading View	Huobi	N/A
Ethereum	Digital	Dependent Variable	Trading View	Huobi	N/A
Bitcoin	Digital	Dependent Variable	Trading View	Huobi	N/A
DeFi Index (Components below)	Digital Index	Dependent Variable			
Curve	Digital	DeFI Index Comp.	Trading View	Kucoin	Trading View
Maker	Digital	DeFI Index Component	Trading View	Huobi	Trading View
Aave	Digital	DeFI Index Component	Trading View	Huobi	Trading View
Compound	Digital	DeFI Index Component	Trading View	Huobi	Trading View
UniSwap	Digital	DeFI Index Component	Trading View	Huobi	Trading View
Cake	Digital	DeFI Index Component	Trading View	Kucoin	Trading View
Yearn	Digital	DeFI Index Component	Trading View	Kucoin	Trading View
SushiSwap	Digital	DeFI Index Component	Trading View	Huobi	Trading View

Table 1. Asset Information Table

Data for missing datapoints was estimated using linear interpolation for the constituents of the DeFi Index and US10Y, however estimated data comprised of less than 1% and 1.6% of data for these assets respectively. Digital asset prices were retrieved in USDT and converted to USD using the 30-minute USDT/USD exchange rate calculated by Binance.

A sample period from Jan 3, 14:30 UTC, to May 31. 23:00 UTC, was taken, during opening times of US stock market, with a total of 1442 observations. This sample represents the largest frame of data available as prior data was unavailable for LUNA and UST as they were delisted from most major exchanges following the crash and halting of the Terra Luna blockchain. Key dates in the sample include the start and end of the crash period, which are reflected in the sample from May 9 14:30 UTC to May 16 14:30 UTC, the next available data from the actual dates mentioned in the introduction.

3.4 Multivariate DCC GARCH Model

The multivariate DCC-GARCH model was chosen as it is well-suited for analyzing the dynamic correlations between multiple time series and allows for the incorporation of various effects. The results of the multivariate DCC-GARCH model will be used to determine the changes in dynamic correlations and overall correlations between the assets during the crash period to evaluate whether there is an increase in correlation of volatility between digital and traditional assets. The primary benefit of a multivariate DCC GARCH model include its ability to focus on dynamic volatility relationships across multiple variables over time.

Multivariate DCC GARCH models assume changes in the conditional mean over time and have proven to be more a more appropriate approach in modelling traditional assets over time. Their flexible and dynamic structure (Rudolf et al., 2021) are derived from their considerations for past volatilities and standard errors of not just one, but all time series considered in the model. The model constructs individual univariate GARCH coefficients for each asset to compute standard residuals as well as alpha and beta parameters for each asset, which provide insight to the long-term volatility and impact of past volatility of time series respectively (Bauwens et al., 2006; Engle et al., 2006). The univariate coefficients are estimated using maximum likelihood estimation, and the estimated values indicate the strength of the relationships between the variance of the variables and their past values. The multivariate DCC GARCH model's primary outputs are the dcca1 and dccb1 parameters. These coefficients reflect the extent to which past dynamic correlations and current and past errors, respectively, impact current correlations. For this study, they were calculated using maximum likelihood estimation and provide information about the strength of the relationships between the variables in the model. High value for the dcca1 coefficient might indicate that past dynamic correlations have a significant effect on current correlations, while a low value for the dccb1 coefficient might suggest that current and past errors have a minimal impact on current correlations. (Bauwens et al., 2006; Engle et al., 2006; Rudolf et al., 2021,)

As this research is a case study involving an economic crash period, this model provides the ideal approach to investigate changes in the DCC of assets considered, as traditional volatility models such as moving average deviation or standard deviation do not take into account the fact that the variance covariance of returns can be highly volatile during such periods (Rudolf et al., 2021). Further, the DCC pairings derived with the model can be plotted to draw relative conclusions about changes in the DCC over the sample period.

All modelling was conducting in the programming language R. The code for this can be found in Appendix E. The analysis was conducted using the zoo, PortfolioAnalytics, xts, rugarch, rmgarch, and quantmod packages in R build a multivariate DCC GARCH model.

4 Results and Discussion

4.1 Digital and Traditional Asset Correlations Pairs

As the focus of this paper is on the relationship between digital and traditional assets, further volatility correlations which can be derived from the model will not be addressed, particularly between traditional assets, and between digital asset, other than the DeFi index. The following section describes the findings of the DCC plots created using the multivariate DCC-GARCH model in relation to the volatility correlations for the entire sample, as shown in Table 2. Please note once again, the correlations described and plotted in the table and figures below refer to volatility correlations, not return correlations.

	SP500	US10Y	GOLD	OIL	DXY	BTC	ETH	DEFI INDEX	UST	LUNA
SP500	1	0.15572329	-0.112592	0.02064038	-0.3583189	0.53669709	0.5507646	0.16235651	0.00888976	0.33576627
US10Y	0.15572329	1	-0.2363632	0.01076662	-0.005109	0.20865058	0.22784228	0.07810719	0.00900826	0.13626981
GOLD	-0.112592	-0.2363632	1	0.40279464	-0.0773017	-0.1199797	-0.0910203	-0.0556915	-0.0405705	-0.0112463
OIL	0.02064038	0.01076662	0.40279464	1	0.07284319	0.02961076	0.03471215	-0.0472775	-0.0685867	0.02373832
DXY	-0.3583189	-0.005109	-0.0773017	0.07284319	1	-0.2308676	-0.2252285	-0.0831747	0.05831128	-0.1547968
BTC	0.53669709	0.20865058	-0.1199797	0.02961076	-0.2308676	1	0.92308304	0.33954415	0.05405455	0.54176215
ETH	0.5507646	0.22784228	-0.0910203	0.03471215	-0.2252285	0.92308304	1	0.42571673	0.06504723	0.54680703
DEFI INDEX	0.16235651	0.07810719	-0.0556915	-0.0472775	-0.0831747	0.33954415	0.42571673	1	-0.0080144	0.22297572
UST	0.00888976	0.00900826	-0.0405705	-0.0685867	0.05831128	0.05405455	0.06504723	-0.0080144	1	0.42323266
LUNA	0.33576627	0.13626981	-0.0112463	0.02373832	-0.1547968	0.54176215	0.54680703	0.22297572	0.42323266	1

Table 2. Traditional and Digital Asset Return Correlation

As shown in figures 1 and 2, the S&P500 and BTC maintain relatively stable positive DCCs in a corridor between 44% and 67.27%, both prior to and during the crash of Terra Luna, as seen in figures 1 and 2. We do not see any significant deviation from the positive correlation at moderate strength of 53.67% for the full sample in Table 2. It should be noted that there is a new low in the conditional correlation at 26% at after the crash period on May 31st which will be addressed in the limitations of this paper.

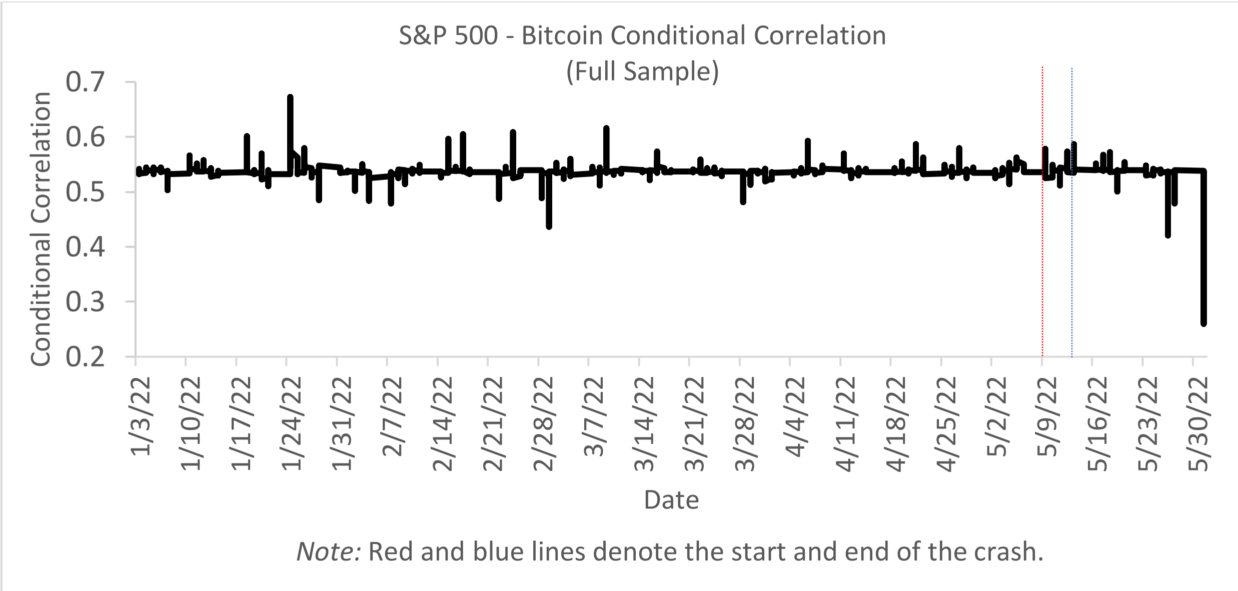


Figure 1. S&P 500 - Bitcoin Conditional Correlation

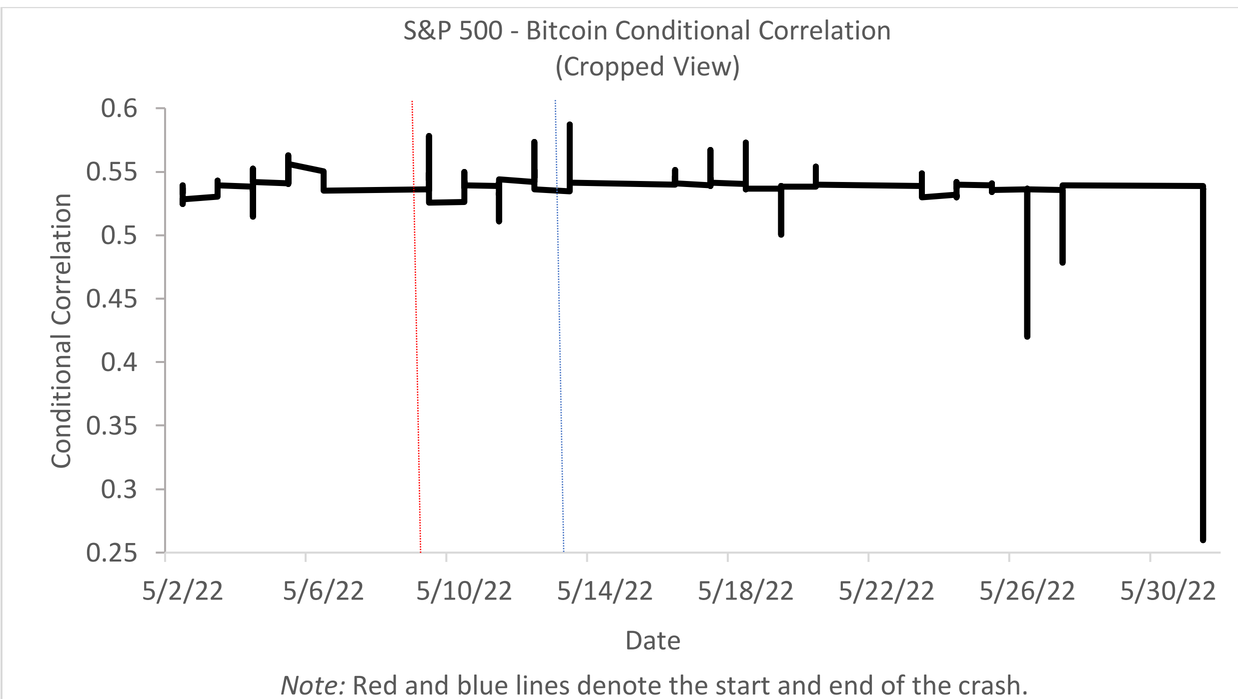


Figure 2. May 2022 S&P 500 – Bitcoin Conditional Correlation

US10Y and BTC are positively correlated with weak strength at 20.87% during the sample period, as shown in Table 2. While figures 3 and 4 indicate volatile DCCs in a corridor from 3.66% and 42.55%, we do not see any significant change during the crash of Terra Luna.

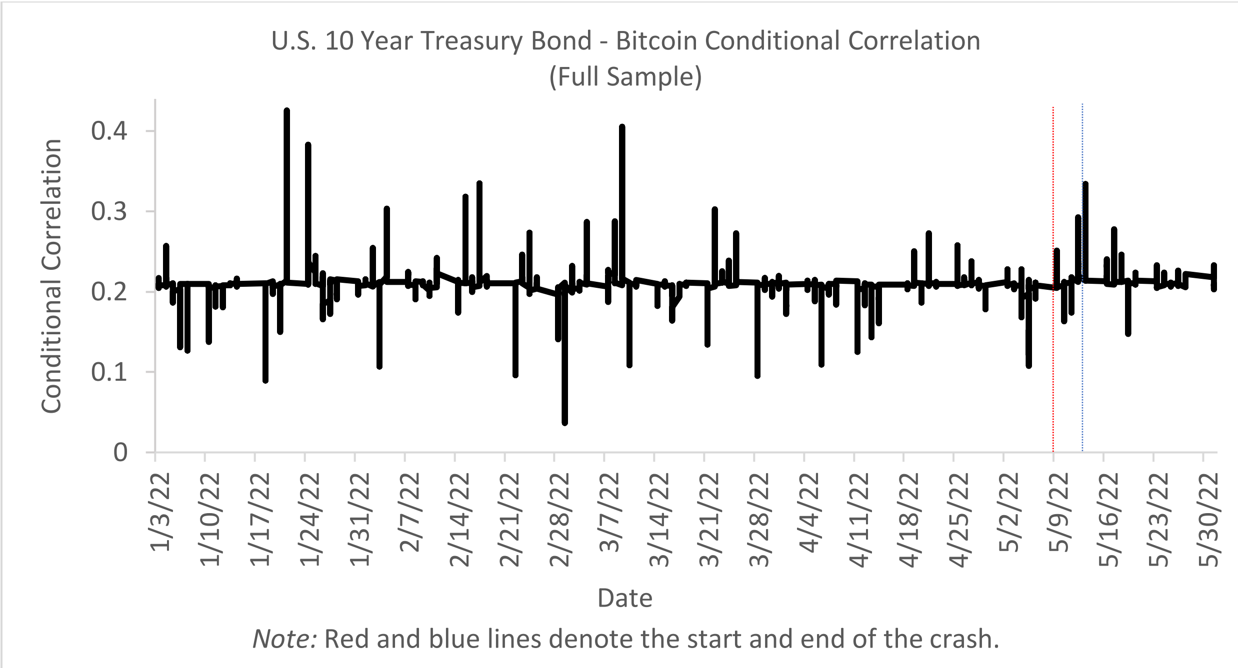


Figure 3. U.S. Treasury Bond - Bitcoin Conditional Correlation

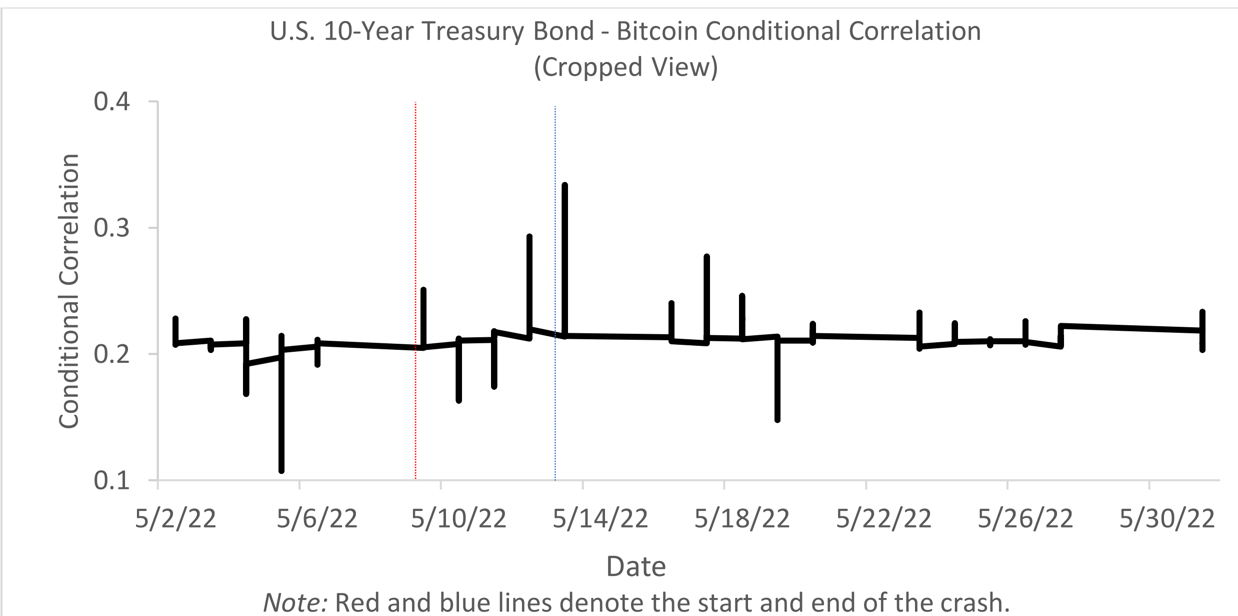


Figure 4. May 2022 U.S. Treasury Bond - Bitcoin Conditional Correlation

Gold and BTC are negative correlated with very weak strength at -12.00% during the sample period, as seen in Table 2. Figures 5 and 6 indicate the DCCs regularly oscillate between positive and negative, peaking at 11.73% during the Terra Luna crash, with previous limits at 5.62% and

-47.03% during the sample. This indicates a significant change during the crash period, as it marks a new high in correlation between the two assets.

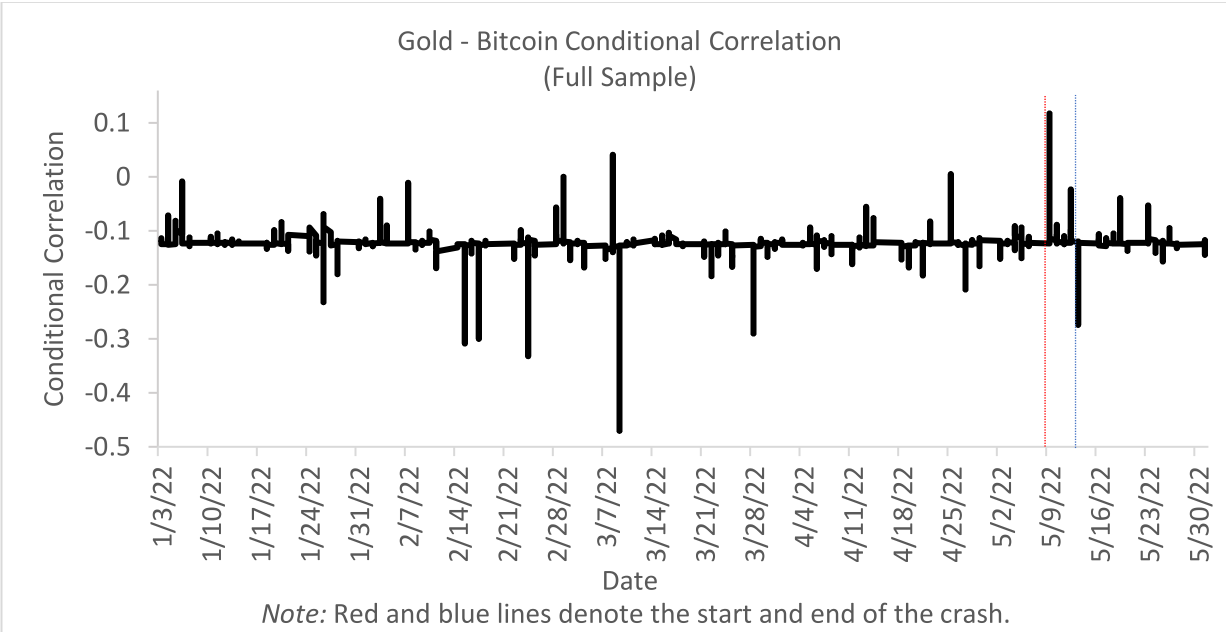


Figure 5. Gold - Bitcoin Conditional Correlation

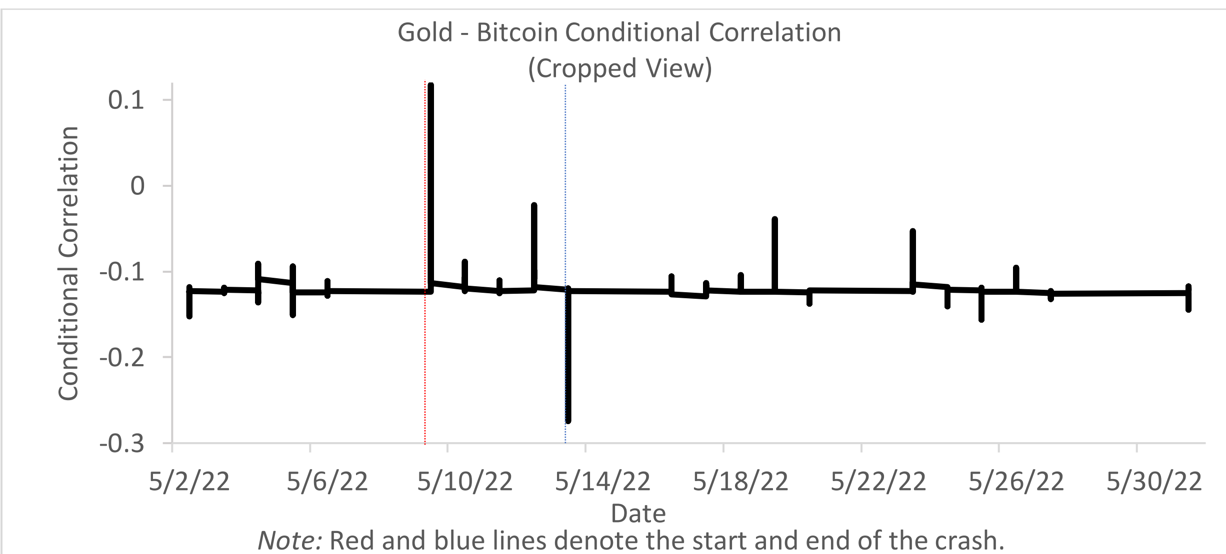


Figure 6. May 2022 Gold - Bitcoin Conditional Correlation

As seen in Table 2, Oil and BTC are positively correlation with very weak strength at 2.96%, the weakest of traditional assets compared to BTC as seen in Table 2. Like Gold, the DCCs in figures 7 and 8 further indicate this correlation periodically experiences large periods of volatility oscillating between 30.94% and -26.38%. unlike Gold, although we do see an increase in the correlation peaking at 26%, this does not break the corridor of conditional correlation mentioned above, indicating no significant change during the crash period.

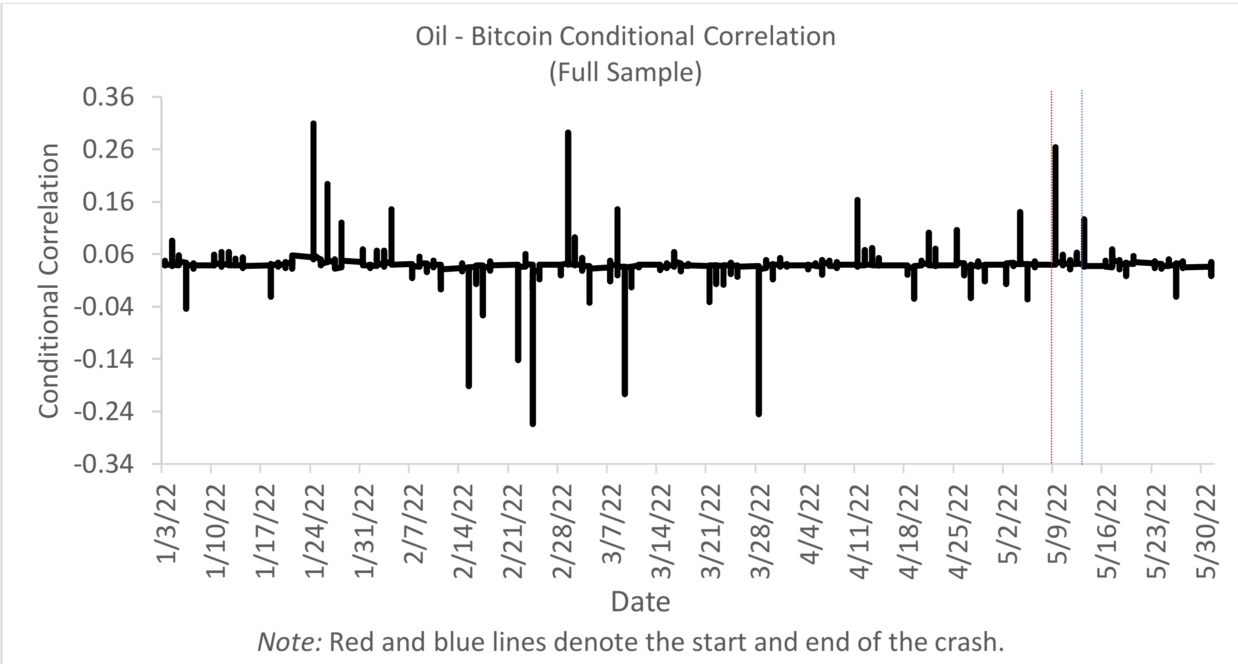


Figure 7. Oil - Bitcoin Conditional Correlation

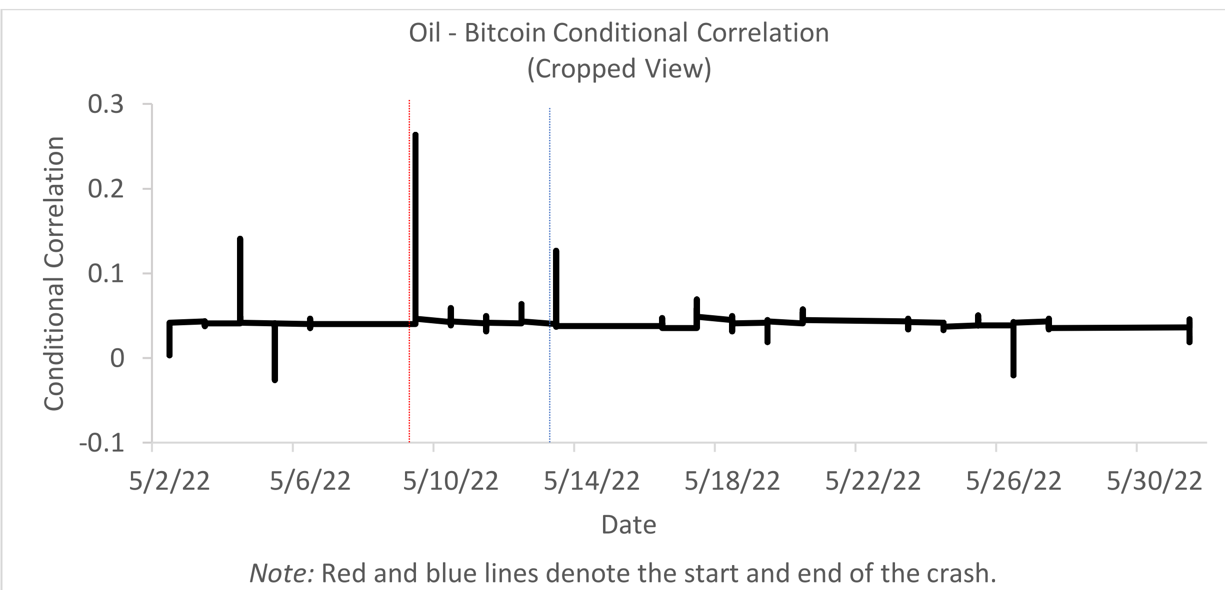


Figure 8. May 2022 Oil - Bitcoin Conditional Correlation

DXY and BTC have a negative correlation with weak strength of -20.87% during the sample period, as shown in Table 2. While figures 9 and 10 indicate occasionally volatile DCCs in a corridor from -47.83% and 2.84%, we do not see any significant change during the crash of Terra Luna.

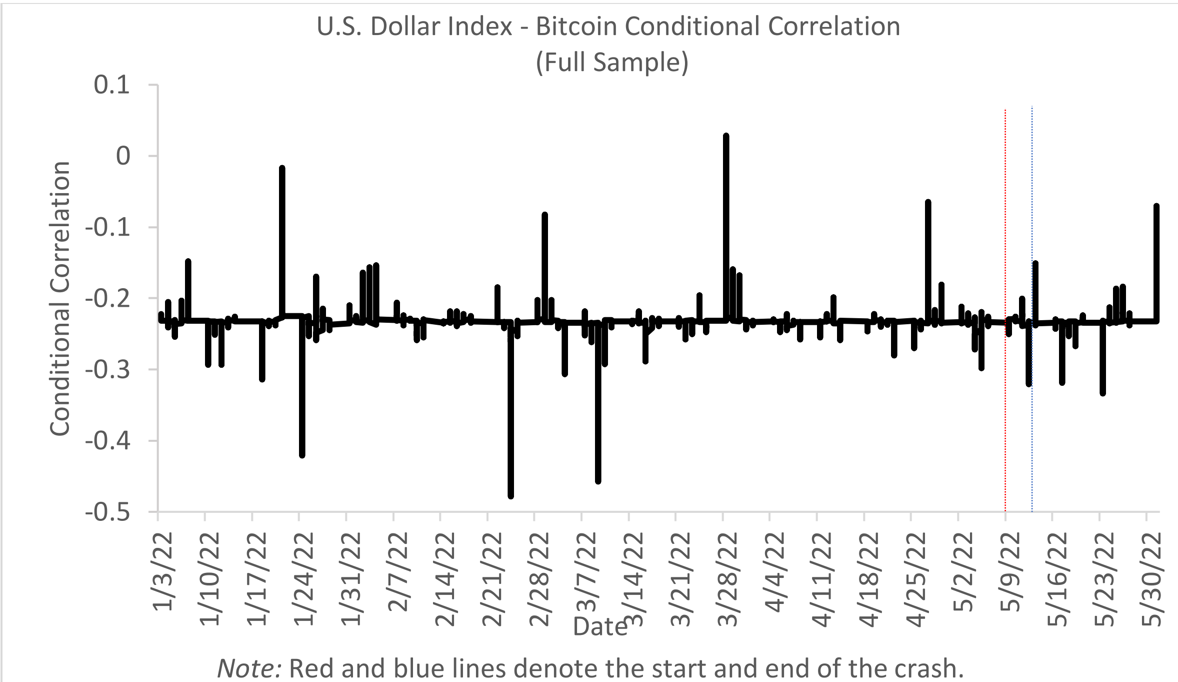


Figure 9. U.S. Dollar Index- Bitcoin Conditional Correlation

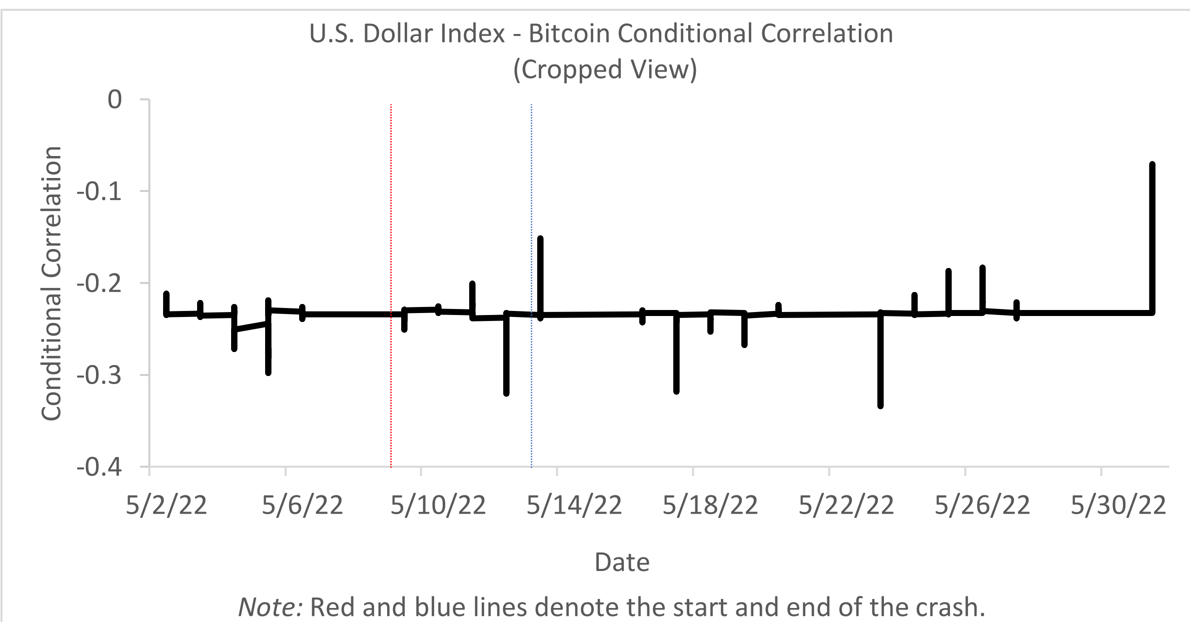
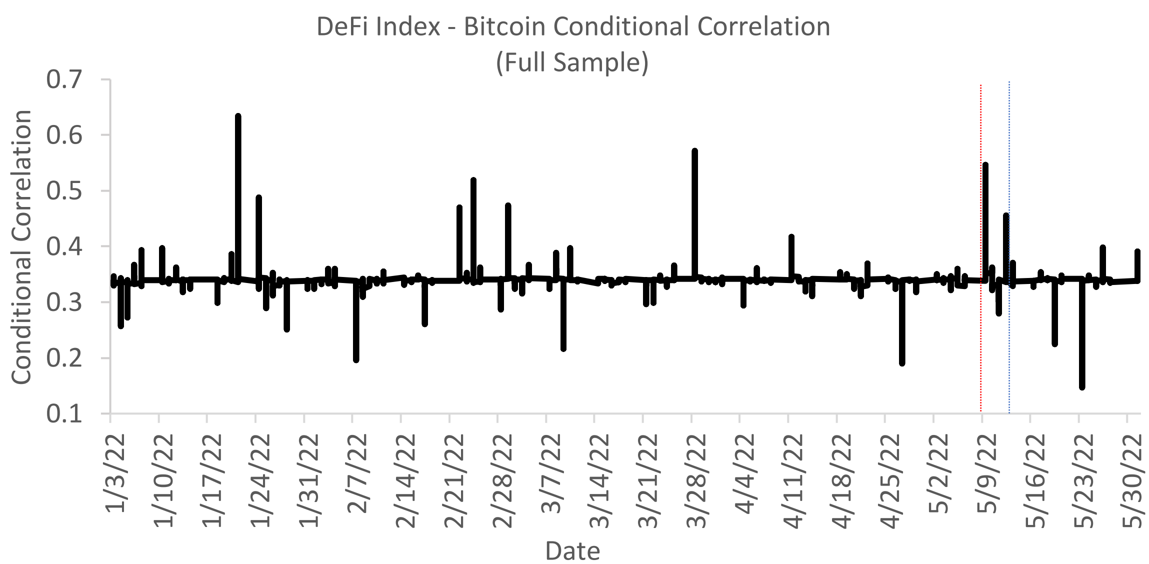


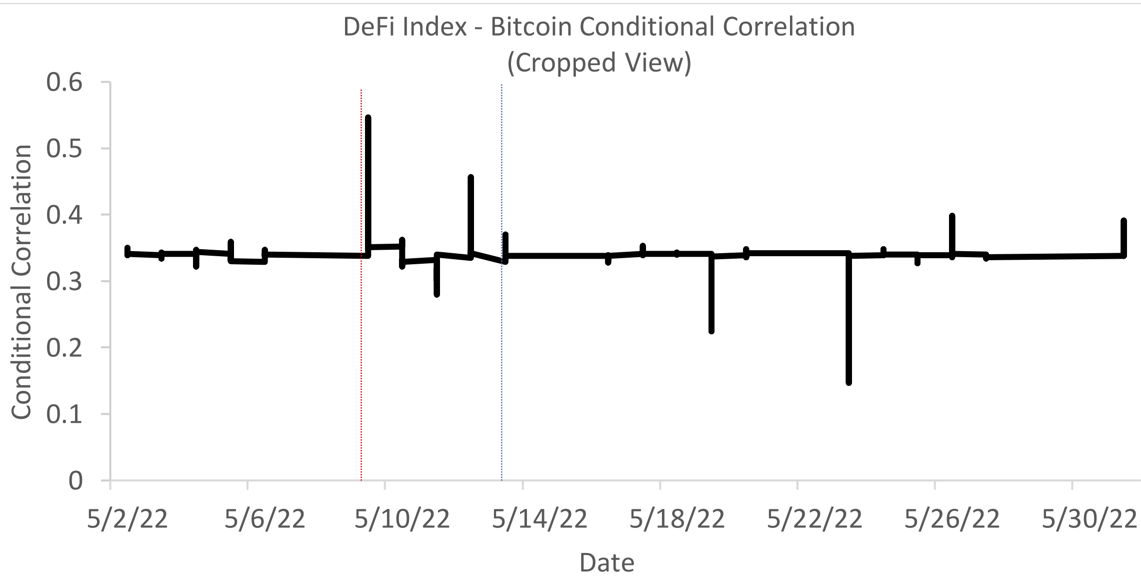
Figure 10. May 2022 U.S. Dollar Index- Bitcoin Conditional Correlation

The DeFi Index and BTC have a positive correlation with weak strength of 33.95% during the sample period, as shown in Table 2. While figures 11 and 12 indicate occasionally large increases in DCCs by up to 30%, with a corridor between 63.42% and 14.69%, we do not see any change during the crash of Terra Luna which would significantly differentiate it from other increases in the conditional correlation.



Note: Red and blue lines denote the start and end of the crash.

Figure 11. DeFi Index- Bitcoin Conditional Correlation



Note: Red and blue lines denote the start and end of the crash.

Figure 12. May 2022 DeFi Index- Bitcoin Conditional Correlation

The aforementioned results were further confirmed through a robustness analysis using the DCCs of ETH compared to each asset, which can be found in Appendix B.

In addition, while not all assets show a correlation with Luna during the entire sample, see Table 2, this changes during the crash period. Appendix C shows the DCC for each variable with LUNA referenced below in further detail.

The S&P 500 sees a very high amount of volatility in DCCs with LUNA during the crash period, which break out to a new low of 11.24% from its pre-crash corridor and significantly below the positive moderate correlation of 33.57% in Table 2.

While US10Y does see some volatility with LUNA during the crash period, it is the only variable which does not break out from its pre-crash DCC corridor, ranging from 35.17% to -0.031%, with a positive correlation with weak strength of 13.63% for the full sample period. This is in line with what was found in the literature review, as US10Y are considered the most stable asset class of those selected.

Gold, Oil, DXY, and the DeFi Index all break out of their DCC corridors with LUNA reaching new highs in positive DCC of 26.9%, 32.55%, 7.89%, and 53.55% respectively, significantly above their respective correlations of -1.12%, -2.37%, -15.48%, and -22.30% for the full sample as seen in Table 2. In addition, Oil and the DeFi Index show new lows in the later days of the crash period, of -31.77% and -16.49% respectively.

Finally, it is worth noting, that the DCC between BTC and LUNA, as well as the DCC between ETH and LUNA reach new highs of 73.81% and 75.11% respectively, which can be seen in Appendix D, from a correlation of 54.18% and 54.68% for the entire sample as seen in Table 2, suggesting digital assets saw a significant increase with LUNA during the crash period. In addition, ETH's DCC with LUNA reached new lows of 28.76% during the crash.

As correlations do not describe a directional relationship between variables, a quantile VAR model could be applied to determine the directional spillovers, such as those conducted by Bouri et al., (2021), Bouri et al., (2021) or Diebold (2012) to further explain the changes in DCC during the crash period.

4.2 Multivariate DCC GARCH Outputs

	Output
Distribution	Normal
Model	DCC (1,1)
No. Parameters	97
VAR GARCH DCC Unc0	0+50+2+45
No. Series	10
No. Observations	1442
Log-Likelihood	54138.92
Av. Log-Likelihood	37.54

Optimal Parameters

Variable	Parameter	Coefficient Estimate	Std. Error	t value	p value
Joint	dcca1	0.009004	0.006774	1.329161	0.183795
Joint	dccb1	0.688297	0.064923	10.601789	0.000000

Table 3. Multivariate DCC GARCH Output Table

The dcca1 coefficient of 0.009004 shown in Table XYZ suggests that the past dynamic correlations have a weak influence on the current correlations, indicating either that the variables have relatively independent dynamics, or that the relationships between the variables are not persistent over time. However, as the p-value of the dcca1 parameter shown in Table 3 is 18.37%, significantly outside the 95% confidence interval, a conditional relationship between the variables included in the model is likely. This indicates the autoregressive component of the DCC is not statistically significant, and further supports that all variables may not be related to one another in the short term, as past dynamic correlations between the variables do not have a strong influence on the current dynamic correlations. An inconsistency in the relationships between the variables over time is plausible, as the DCC pairings including LUNA in section 4.1 above showed significant change during the crash period, however further investigation both between the pairings of all variables and additional research methodology is needed confirmed or denied this possibility.

The dccb1 coefficient of 0.688297 shown in Table 3 indicates current and past errors have a moderate to strong influence on the current dynamic correlations, suggesting the existence of lagged effects of the variables on each other, or that the relationships between the variables are persistent over time. The p-value for the dccb1 is highly significant, at 0.00. This indicates all variables are related to one another in the long run, as the current dynamic correlations between the variables are influenced by the past dynamic correlations. This also explains why an increase in correlation may not be apparent in the plots.

4.3 Univariate GARCH Coefficients

The alpha and beta coefficients for the univariate GARCH models used as inputs to the multivariate DCC GARCH model above shown in Table 3. The alpha1 coefficients of all variables suggest that the past variance has a weak influence on the current variance, with values less than 7%. In addition, all univariate GARCH coefficients, apart from LUNA, are statistically significant at both the 95% and 99% significance level. LUNA's alpha coefficient being 10% could be explained by the crash period included in the sample, as probability that the estimated value of the alpha parameter occurred by chance is quite high considering the black swan even of the crash is unlikely to be replicated in a sample of another period.

Variable	Parameter	Coefficient Estimate	Std. Error	t value	p value
S&P500r	alpha1	0.026208	0.005403	4.850590	0.000001
S&P500r	beta1	0.964118	0.005087	189.507740	0.000000
US10Yr	alpha1	0.005373	0.000676	7.944642	0.000000
US10Yr	beta1	0.991951	0.000176	5621.386195	0.000000
GOLDr	alpha1	0.015756	0.002886	5.459639	0.000000
GOLDr	beta1	0.979077	0.002076	471.690234	0.000000
OILr	alpha1	0.015546	0.001621	9.592163	0.000000
OILr	beta1	0.983147	0.001337	735.390592	0.000000
DXYr	alpha1	0.012169	0.003917	3.107009	0.001890
DXYr	beta1	0.984828	0.001751	562.552208	0.000000
BTCr	alpha1	0.000431	0.000049	8.745975	0.000000
BTCr	beta1	0.995250	0.000529	1881.879915	0.000000
ETHr	alpha1	0.010593	0.001552	6.823254	0.000000
ETHr	beta1	0.971767	0.005636	172.414375	0.000000
DEFIINDEXr	alpha1	0.015152	0.002329	6.505398	0.000000
DEFIINDEXr	beta1	0.957237	0.006820	140.365941	0.000000
USTr	alpha1	0.070681	0.025742	2.745778	0.006037
USTr	beta1	0.912028	0.032607	27.969995	0.000000
LUNAr	alpha1	0.069408	0.042192	1.645067	0.099956
LUNAr	beta1	0.929592	0.015240	60.998089	0.000000

Table 3. Univariate GARCH Output Table

These alpha coefficients could potentially influence the dynamic correlations between the variables and therefore explain the high p-value for the dcca1 term mentioned above, however the dcca1 parameter and the alpha parameters are not directly related, as they are calculated and used in different contexts.

The beta coefficients for the univariate GARCH models used as inputs to the multivariate DCC GARCH model range between 91.20% and 99.53%, suggesting that the current and past errors have a strong influence on the current variance. This could indicate that there are lagged effects of the errors on the variance, or that the relationships between the errors and the variance are persistent over time. In addition, all univariate GARCH coefficients are statistically significant at both the 95% and 99% significance level.

4.3 Evidence for empirical research question

The interpretation of the DCC plots, in addition to the p-values and coefficients of the multivariate DCC GARCH model indicate there is insufficient evidence and statistical significance to reject the null hypothesis. Therefore, to answer the research question, we do not see an increase in correlation of volatility between digital and traditional assets during the Terra Luna crash.

5 Limitations and Future Research

One limitation of this study is that the model has not been tested for skewness and kurtosis, which could potentially affect the results. Additionally, further analysis of the coefficients and DCC correlations of each variable would provide a more comprehensive understanding of the relationships between the variables.

Data limitations include the short sample period, as data prior to Jan 1st, 2022, was unavailable on major exchanges for certain assets considered. A more extensive and broader study of correlations between digital and traditional assets during crashes in DeFi could be constructed on a larger time frame, including digital assets on a rolling bases based on mCap over time. This would also allow for deeper insight into whether the changes in DCC are increasing or decreasing over time, which could aid regulators in setting standards for market stability, as well as provide a baseline for estimates to be made for at which point these crashes may become relevant systemic stability.

A limitation in the DCC interpretation lies in the definition of the DCC corridor, as other major market events such as but not limited to the escalation of the Russo-Ukrainian War on Feb 24 may have caused large changes in the DCC. This leads to complication in what is considered normal level of DCC. It should be noted that the data presented in the DCC plots can still provide value in determining relative changes compared to other market events.

A related limitation lies in what is considered a significant increase. For this study achieving new highs or lows during the crash period was considered significant when compared to the DCC corridor of the prior to the crash. This is a limitation due to the limited definition of the corridor described above.

A deeper look into subcategories of digital assets, such as those related to Web 3.0 and NFTs, different services of DeFi would provide a more detailed understanding of the relationships between different types of digital assets. The consideration of changes in TVL across DeFi could provide more insight than those conducted on returns such as this study, as TVL is a more relevant metric in the DeFi space. This would provide value for stakeholders in identifying their exposure, and insight to the development of regulation for the space. To provide maximum value, this could also be applied in a larger time frame encompassing multiple crashes,

A final limitation is the lack of literature and proposed regulation surrounding digital asset space mentioned in the literature review, making it difficult to provide solutions for the minimization of risks to crashes such as that of Terra Luna.

6 Conclusion

Regarding the theoretical research question, “How could the inherent risks of the Terra Luna ecosystem and its algorithmic stablecoin UST have been identified and minimized?”, it is difficult to provide solutions for the minimization of risks to crashes such as that of Terra Luna outside of regulation and investor caution. Further, as Terra Luna was not the first algorithmic stablecoin based on seigniorage to collapse, and the risks of the ecosystem were identified some such as SwissBorg and Coindesk, it is possible to identify such risks beforehand (Bonato, 2022; Morris, 2022). With limited options available, stakeholders should be weary of such algorithmic stablecoin systems, and DeFi projects at large, while regulators should strongly and swiftly consider proposals such as MiCA to help avoid such events in future.

While the DCC plots of the multivariate DCC GARCH model reflect increased volatility during the Terra Luna crash, the empirical results do not indicate an increase in correlation of volatility between digital and traditional assets during the Terra Luna crash. Further, the DCC plots, p-values, and coefficients of the DCC GARCH model provide both insufficient evidence and statistical significance to reject the null hypothesis, “there is no increase in correlation of volatility between digital and traditional assets during the Terra Luna crash.”

Despite limitations, the results provide valuable information to the market dynamics during the Terra Luna crash. Additional research of market events during the sample period would allow for relative inferences to be made regarding the exposure of investors, institutions, projects, and businesses to collapses in the DeFi space.

Further research considering a longer time frame encompassing multiple crashes in the digital asset space could allow for an even more insightful comparability to other major market events for the aforementioned stakeholders.

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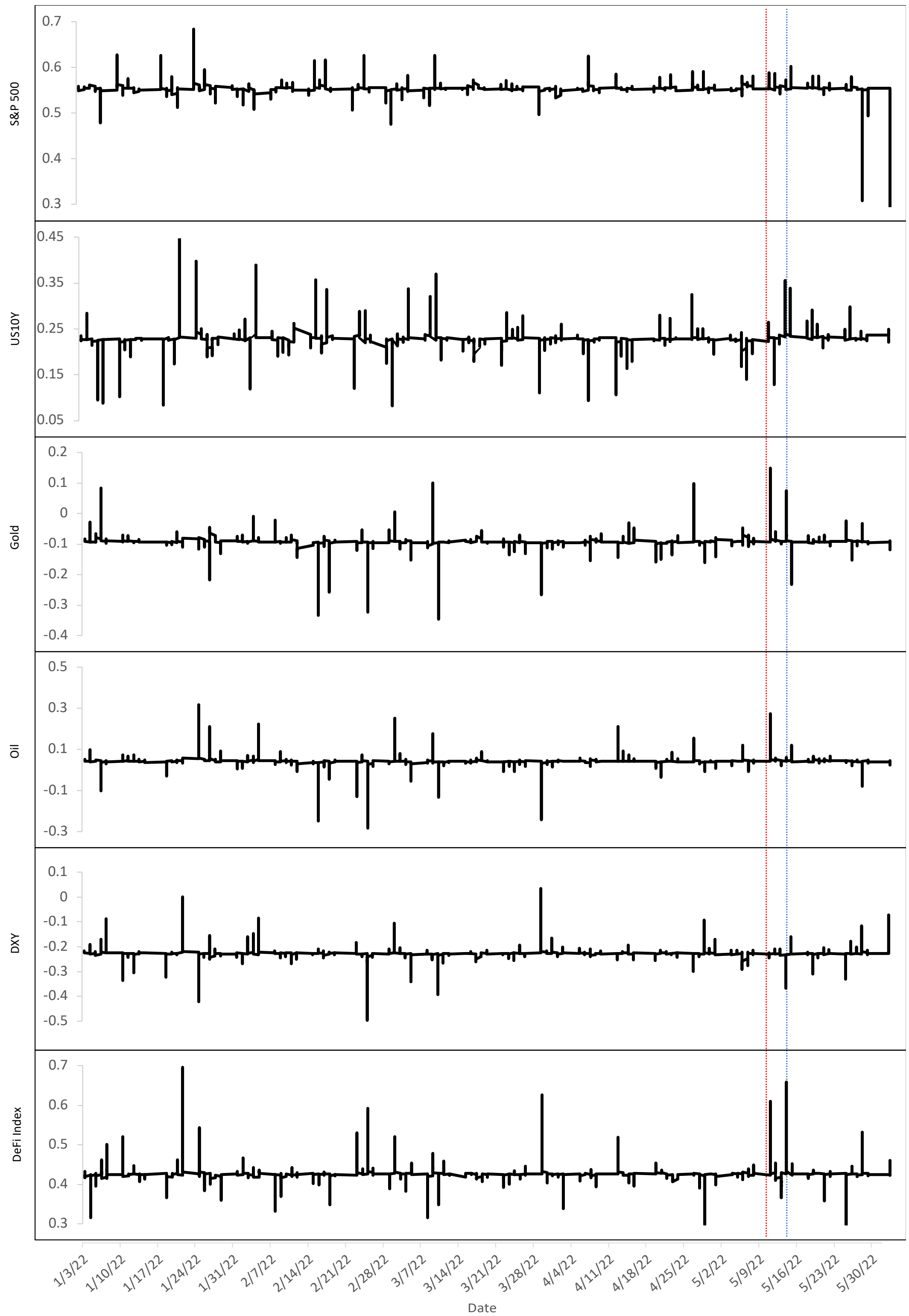
Appendix

Appendix A. DeFi Index Constituents

Asset	Category	Jan 1 2022 TVL
Curve	DEX	23.25
Maker	CDP	17.5
Aave	decentralized money market with lending and governance	14.2101
Compound	Lending	8.9
Uniswap	DEX	8.36455
PancakeSwap	DEX	5.53
Yearn Finance	Yield Aggreagtor	4.12
SushiSwap	DEX	3.91

Appendix B. Full Sample Conditional Correlations Between ETH and Modeled Assets.



Note: Red and blue lines denote the start and end of the crash

Appendix C. Full Sample Conditional Correlations Between LUNA and Modeled Assets

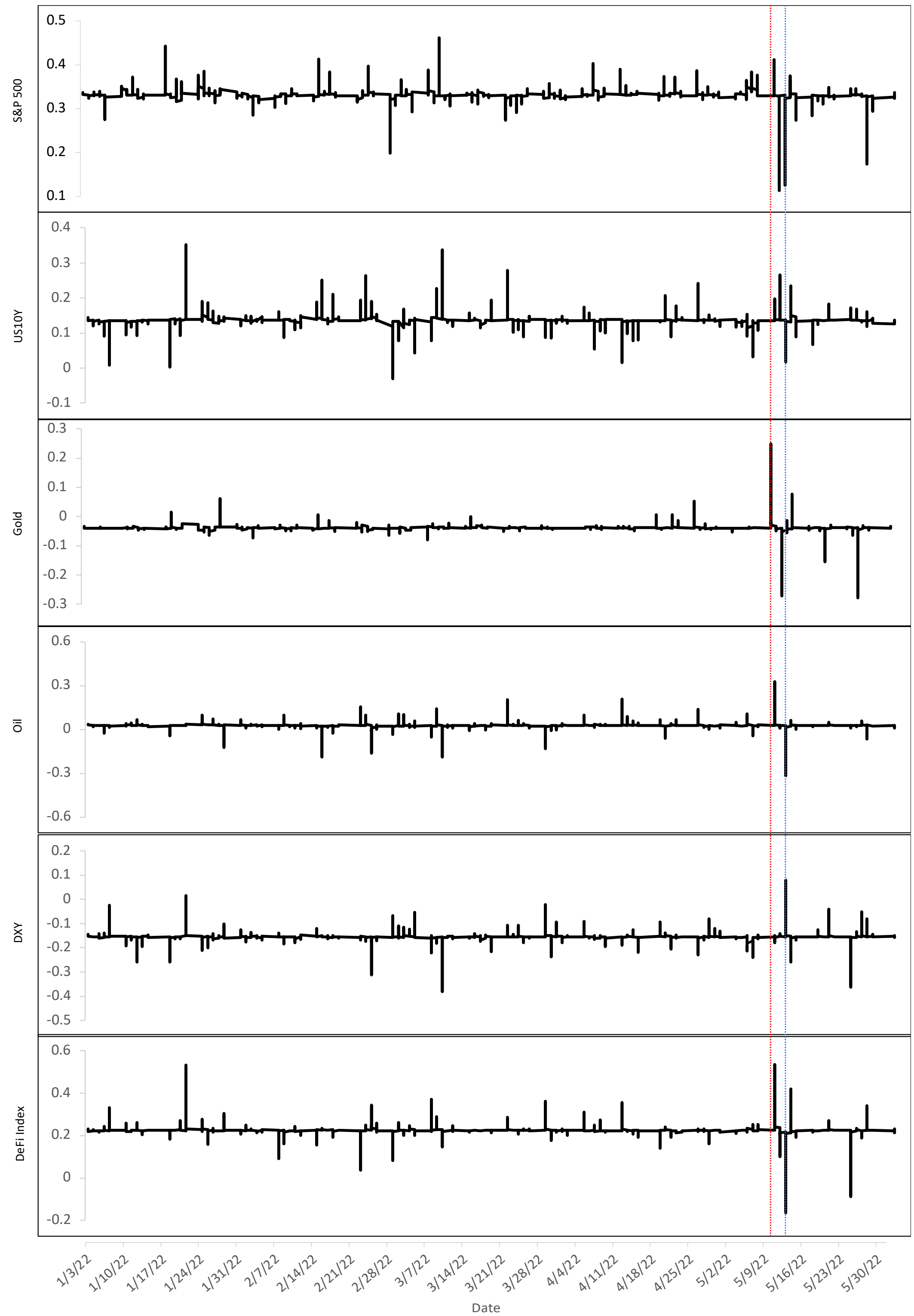
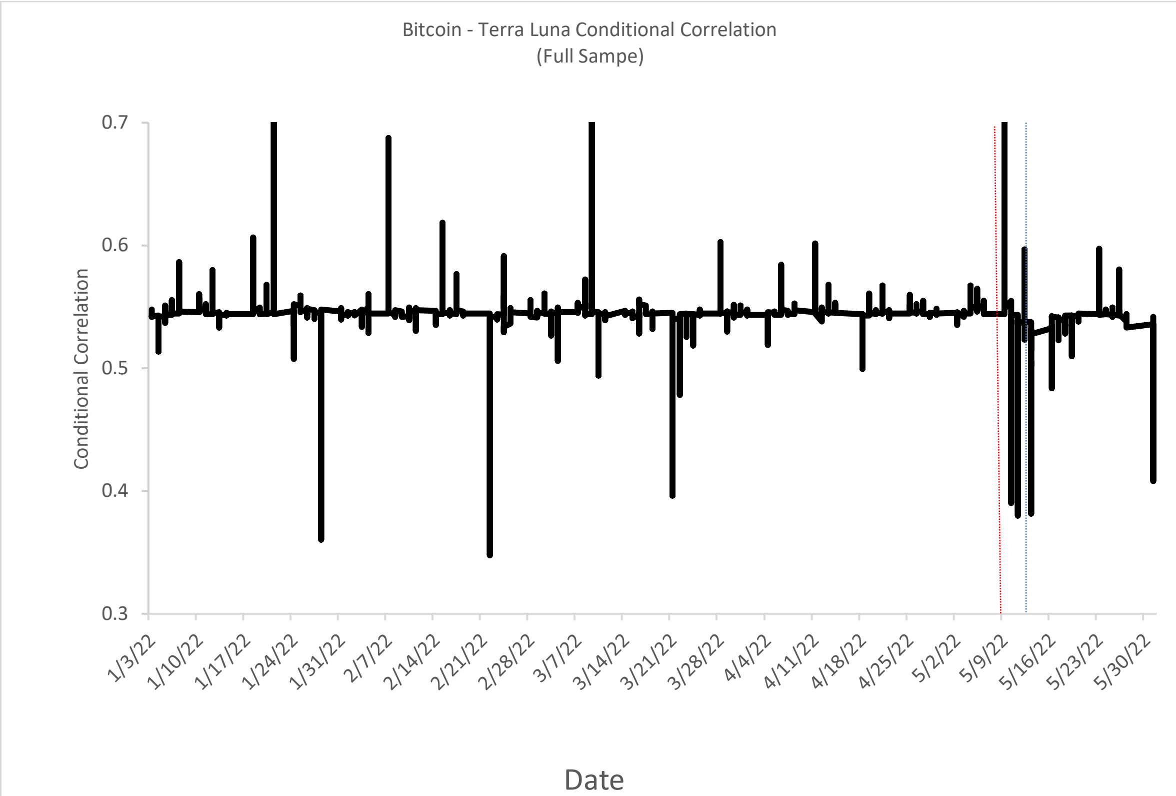


Figure X. *Note:* Red and blue lines denote the start and end of the crash

Appendix D. Full Sample Bitcoin – Terra Luna Conditional Correlation Plots



Note: Red and blue lines denote the start and end of the crash.

Appendix E. Multivariate DCC MGARCH Code

```
getwd()


library(zoo)

library(PortfolioAnalytics)

library(xts)

library(rugarch)

library(rmgarch)

library(quantmod)


# import data from csv

SP500PriceDataUNIX <- read.csv("SP500PriceDataUNIX.csv")

US10YPriceDataUNIX <- read.csv("US10YPriceDataUNIX.csv")

GoldPriceDataUNIX <- read.csv("GoldPriceDataUNIX.csv")

OilPriceDataUNIX <- read.csv("OilPriceDataUNIX.csv")

DXYPriceDataUNIX <- read.csv("DXYPriceDataUNIX.csv")

BTCPriceDataUNIX <- read.csv("BTCPriceDataUNIX.csv")

ETHPriceDataUNIX <- read.csv("ETHPriceDataUNIX.csv")

DeFiIndexPriceDataUNIX <- read.csv("DeFiIndexPriceDataUNIX.csv")

USTPriceDataUNIX <- read.csv("USTPriceDataUNIX.csv")

LUNAPriceDataUNIX <- read.csv("LUNAPriceDataUNIX.csv")
```

```
# convert UNIX to POSIXct date-time object
SP500PriceDataUNIX[, 1] <- as.POSIXct(SP500PriceDataUNIX[, 1],
                                      origin = "1970-01-01",
                                      tz = "UTC")
US10YPriceDataUNIX[, 1] <- as.POSIXct(US10YPriceDataUNIX[, 1],
                                      origin = "1970-01-01",
                                      tz = "UTC")
GoldPriceDataUNIX[, 1] <- as.POSIXct(GoldPriceDataUNIX[, 1],
                                     origin = "1970-01-01",
                                     tz = "UTC")
OilPriceDataUNIX[, 1] <- as.POSIXct(OilPriceDataUNIX[, 1],
                                    origin = "1970-01-01",
                                    tz = "UTC")
DXYPriceDataUNIX[, 1] <- as.POSIXct(DXYPriceDataUNIX[, 1],
                                    origin = "1970-01-01",
                                    tz = "UTC")
BTCPriceDataUNIX[, 1] <- as.POSIXct(BTCPriceDataUNIX[, 1],
                                    origin = "1970-01-01",
                                    tz = "UTC")
ETHPriceDataUNIX[, 1] <- as.POSIXct(ETHPriceDataUNIX[, 1],
                                    origin = "1970-01-01",
                                    tz = "UTC")
DeFiIndexPriceDataUNIX[, 1] <- as.POSIXct(DeFiIndexPriceDataUNIX[, 1],
```

```
                       origin = "1970-01-01",
                       tz = "UTC")
USTPriceDataUNIX[, 1] <- as.POSIXct(USTPriceDataUNIX[, 1],
                    origin = "1970-01-01",
                    tz = "UTC")
LUNAPriceDataUNIX[, 1] <- as.POSIXct(LUNAPriceDataUNIX[, 1],
                     origin = "1970-01-01",
                     tz = "UTC")


# reformat date-time object to "YYYY-MM-DD HH:MM"
SP500PriceDataUNIX[, 1] <- format(SP500PriceDataUNIX[, 1],
                    format = "%d-%m-%Y %H:%M")
US10YPriceDataUNIX[, 1] <- format(US10YPriceDataUNIX[, 1],
                    format = "%d-%m-%Y %H:%M")
GoldPriceDataUNIX[, 1] <- format(GoldPriceDataUNIX[, 1],
                   format = "%d-%m-%Y %H:%M")
OilPriceDataUNIX[, 1] <- format(OilPriceDataUNIX[, 1],
                  format = "%d-%m-%Y %H:%M")
DXYPriceDataUNIX[, 1] <- format(DXYPriceDataUNIX[, 1],
                  format = "%d-%m-%Y %H:%M")
BTCPriceDataUNIX[, 1] <- format(BTCPriceDataUNIX[, 1],
                  format = "%d-%m-%Y %H:%M")
ETHPriceDataUNIX[, 1] <- format(ETHPriceDataUNIX[, 1],
```

```
                             format = "%d-%m-%Y %H:%M")
DeFiIndexPriceDataUNIX[, 1] <- format(DeFiIndexPriceDataUNIX[, 1],
                                  format = "%d-%m-%Y %H:%M")
USTPriceDataUNIX[, 1] <- format(USTPriceDataUNIX[, 1],
                             format = "%d-%m-%Y %H:%M")
LUNAPriceDataUNIX[, 1] <- format(LUNAPriceDataUNIX[, 1],
                              format = "%d-%m-%Y %H:%M")

# convert first column to a POSIXct date-time object
SP500PriceDataUNIX[, 1] <- as.POSIXct(SP500PriceDataUNIX[, 1],
                                  format = "%d-%m-%Y %H:%M")
US10YPriceDataUNIX[, 1] <- as.POSIXct(US10YPriceDataUNIX[, 1],
                                  format = "%d-%m-%Y %H:%M")
GoldPriceDataUNIX[, 1] <- as.POSIXct(GoldPriceDataUNIX[, 1],
                                 format = "%d-%m-%Y %H:%M")
OilPriceDataUNIX[, 1] <- as.POSIXct(OilPriceDataUNIX[, 1],
                                format = "%d-%m-%Y %H:%M")
DXYPriceDataUNIX[, 1] <- as.POSIXct(DXYPriceDataUNIX[, 1],
                                format = "%d-%m-%Y %H:%M")
BTCPriceDataUNIX[, 1] <- as.POSIXct(BTCPriceDataUNIX[, 1],
                                format = "%d-%m-%Y %H:%M")
ETHPriceDataUNIX[, 1] <- as.POSIXct(ETHPriceDataUNIX[, 1],
                                format = "%d-%m-%Y %H:%M")
```

```
DeFiIndexPriceDataUNIX[, 1] <- as.POSIXct(DeFiIndexPriceDataUNIX[, 1],
                                          format = "%d-%m-%Y %H:%M")
USTPriceDataUNIX[, 1] <- as.POSIXct(USTPriceDataUNIX[, 1],
                                    format = "%d-%m-%Y %H:%M")
LUNAPriceDataUNIX[, 1] <- as.POSIXct(LUNAPriceDataUNIX[, 1],
                                     format = "%d-%m-%Y %H:%M")

# convert data frame to xts object
xtsSP500PriceData <- as.xts(SP500PriceDataUNIX[,-1],
                            order.by = SP500PriceDataUNIX[, 1])
xtsUS10YPriceData <- as.xts(US10YPriceDataUNIX[,-1],
                            order.by = US10YPriceDataUNIX[, 1])
xtsGoldPriceData <- as.xts(GoldPriceDataUNIX[,-1],
                           order.by = GoldPriceDataUNIX[, 1])
xtsOilPriceData <- as.xts(OilPriceDataUNIX[,-1],
                          order.by = OilPriceDataUNIX[, 1])
xtsDXYPriceData <- as.xts(DXYPriceDataUNIX[,-1],
                          order.by = DXYPriceDataUNIX[, 1])
xtsBTCPriceData <- as.xts(BTCPriceDataUNIX[,-1],
                          order.by = BTCPriceDataUNIX[, 1])
xtsETHPriceData <- as.xts(ETHPriceDataUNIX[,-1],
                          order.by = ETHPriceDataUNIX[, 1])
xtsDeFiIndexPriceData <- as.xts(DeFiIndexPriceDataUNIX[,-1],
```

```
                  order.by = DeFiIndexPriceDataUNIX[, 1])
xtsUSTPriceData <- as.xts(USTPriceDataUNIX[,-1],
                order.by = USTPriceDataUNIX[, 1])
xtsLUNAPriceData <- as.xts(LUNAPriceDataUNIX[,-1],
                order.by = LUNAPriceDataUNIX[, 1])

# re name first column of time series price data
colnames(xtsSP500PriceData)[1] <- "SP500p"
colnames(xtsUS10YPriceData)[1] <- "US10Yp"
colnames(xtsGoldPriceData)[1] <- "Goldp"
colnames(xtsOilPriceData)[1] <- "Oilp"
colnames(xtsDXYPriceData)[1] <- "DXYp"
colnames(xtsBTCPriceData)[1] <- "BTCp"
colnames(xtsETHPriceData)[1] <- "ETHp"
colnames(xtsDeFiIndexPriceData)[1] <- "DeFiIndexp"
colnames(xtsUSTPriceData)[1] <- "USTp"
colnames(xtsLUNAPriceData)[1] <- "LUNAp"


# calculate returns
SP500returns = CalculateReturns(xtsSP500PriceData)
US10Yreturns = CalculateReturns(xtsUS10YPriceData)
Goldreturns = CalculateReturns(xtsGoldPriceData)
```

```
Oilreturns = CalculateReturns(xtsOilPriceData)

DXYreturns = CalculateReturns(xtsDXYPriceData)

BTCreturns = CalculateReturns(xtsBTCPriceData)

ETHreturns = CalculateReturns(xtsETHPriceData)

DeFiIndexreturns = CalculateReturns(xtsDeFiIndexPriceData)

USTreturns = CalculateReturns(xtsUSTPriceData)

LUNAreturns = CalculateReturns(xtsLUNAPriceData)


# rename col from price to returns

colnames(SP500returns)[1] <- "SP500r"

colnames(US10Yreturns)[1] <- "US10Yr"

colnames(Goldreturns)[1] <- "Goldr"

colnames(Oilreturns)[1] <- "Oilr"

colnames(DXYreturns)[1] <- "DXYr"

colnames(BTCreturns)[1] <- "BTCr"

colnames(ETHreturns)[1] <- "ETHr"

colnames(DeFiIndexreturns)[1] <- "DeFiIndexr"

colnames(USTreturns)[1] <- "USTr"

colnames(LUNAreturns)[1] <- "LUNAr"


# replace blanks in first column of returns

SP500returns$SP500r[1] <- ifelse(is.na(SP500returns$SP500r[1]),

                                 0.00, SP500returns$SP500r[1])
```

```
US10Yreturns$US10Yr[1] <- ifelse(is.na(US10Yreturns$US10Yr[1]),
                                  0.00, US10Yreturns$US10Yr[1])
Goldreturns$Goldr[1] <- ifelse(is.na(Goldreturns$Goldr[1]),
                                0.00, Goldreturns$Goldr[1])
Oilreturns$Oilr[1] <- ifelse(is.na(Oilreturns$Oilr[1]),
                              0.00, Oilreturns$Oilr[1])
DXYreturns$DXYr[1] <- ifelse(is.na(DXYreturns$DXYr[1]),
                              0.00, DXYreturns$DXYr[1])
BTCreturns$BTCr[1] <- ifelse(is.na(BTCreturns$BTCr[1]),
                              0.00, BTCreturns$BTCr[1])
ETHreturns$ETHr[1] <- ifelse(is.na(ETHreturns$ETHr[1]),
                              0.00, ETHreturns$ETHr[1])
DeFiIndexreturns$DeFiIndexr[1] <- ifelse(is.na(DeFiIndexreturns$DeFiIndexr[1]),
                                          0.00, DeFiIndexreturns$DeFiIndexr[1])
USTreturns$USTr[1] <- ifelse(is.na(USTreturns$USTr[1]),
                              0.00, USTreturns$USTr[1])
LUNAreturns$LUNAr[1] <- ifelse(is.na(LUNAreturns$LUNAr[1]),
                                0.00, LUNAreturns$LUNAr[1])

# plot returns
plot(SP500returns)
plot(US10Yreturns)
plot(Goldreturns)
```

```
plot(Oilreturns)

plot(DXYreturns)

plot(BTCreturns)

plot(ETHreturns)

plot(DeFiIndexreturns)

plot(USTreturns)

plot(LUNAreturns)


str(LUNAreturns)


# DCC MGARCH Model

# Consolidate data into data frame for multivariate model


rX <- data.frame(SP500returns, US10Yreturns,

        Goldreturns, Oilreturns,

        DXYreturns,

        BTCreturns, ETHreturns,

        DeFiIndexreturns, USTreturns,

        LUNAreturns)


names (rX) [1] <- "SP500r"

names (rX) [2] <- "US10Yr"

names (rX) [3] <- "GOLDr"
```

```
names (rX) [4] <- "OILr"

names (rX) [5] <- "DXYr"

names (rX) [6] <- "BTCr"

names (rX) [7] <- "ETHr"

names (rX) [8] <- "DEFIINDEXr"

names (rX) [9] <- "USTr"

names (rX) [10] <- "LUNAr"


# Model Specification


ug_spec = ugarchspec()


# Review Overview


ug_spec


# Change Mean Model to AR(1) Model


ug_spec <- ugarchspec(mean.model = list (armaOrder = c(1,0)))


# Base Univariate GARCH Model Estimation for SP500 to be replicated


ugfit = ugarchfit(spec = ug_spec, data = SP500returns)
```

```
ugfit

names(ugfit@model)

names(ugfit@fit)

ugfit@fit$coef

ug_var <- ugfit@fit$var # to save estimated conditional variances

ug_res2 <- (ugfit@fit$residuals)^2 # to save estimated square residuals

# DCC Model Preparation

uspec.n = multispec(replicate(10, ugarchspec(mean.model = list(armaOrder = c(1,0)))))

# Results of estimated parameters for all 10 models are saved in multf, prior to DCC
specification

multf = multifit(uspec.n, rX)

# enter multf to consol to view estimated alpha and beta parameters per asset

spec1 = dccspec(uspec = uspec.n, dccOrder = c(1, 1), distribution = 'mvnorm')
```

```
# Multiariate DCC GARCH Model Estimation

# fit1 contains DCC MGARCH results of estimated parameters

fit1 = dccfit(spec1, data = rX, fit.control = list(eval.se = TRUE), fit = multf)

# Covariance and Correlation Matrices

# Extract model based time varying covariance (arrays) and correlation matrices

cov1 = rcov(fit1)  # extracts the covariance matrix

cor1 = rcor(fit1)  # extracts the correlation matrix

dim(cor1) # output is 10 10 1442 meaning we have a 10 by 10 matrix for each of 1442
observation periods

# format as time series of dynamic conditional correlation for selected assets

DCC <- "Conditional Correlation"

# SP500

# SP500 and UST

cor_SP500UST <- cor1[1,9,]   # first row, ninth column, blank last dimension implies we want
all observation periods
```

```
cor_SP500UST <- as.xts(cor_SP500UST)  # redefine as time series for plotting
colnames(cor_SP500UST)[1] <- DCC


# SP500 and LUNA
cor_SP500LUNA <- cor1[1,10,]   # row, column, all observation periods
cor_SP500LUNA <- as.xts(cor_SP500LUNA)  # redefine as time series
colnames(cor_SP500LUNA)[1] <- DCC


# SP500 and BTC
cor_SP500BTC <- cor1[1,6,]   # row, column, all observation periods
cor_SP500BTC <- as.xts(cor_SP500BTC)  # redefine as time series
colnames(cor_SP500BTC)[1] <- DCC


# SP500 and ETH
cor_SP500ETH <- cor1[1,7,]   # row, column, all observation periods
cor_SP500ETH <- as.xts(cor_SP500ETH)  # redefine as time series
colnames(cor_SP500ETH)[1] <- DCC



# US10Y
# US10Y and UST
cor_US10YUST <- cor1[2,9,]   # row, column, all observation periods
cor_US10YUST <- as.xts(cor_US10YUST)  # redefine as time series
```

```
colnames(cor_US10YUST)[1] <- DCC


# US10Y and LUNA
cor_US10YLUNA <- cor1[2,10,]   # row, column, all observation periods
cor_US10YLUNA <- as.xts(cor_US10YLUNA)  # redefine as time series
colnames(cor_US10YLUNA)[1] <- DCC


# US10Y and BTC
cor_US10YBTC <- cor1[2,6,]   # row, column, all observation periods
cor_US10YBTC <- as.xts(cor_US10YBTC)  # redefine as time series
colnames(cor_US10YBTC)[1] <- DCC


# US10Y and ETH
cor_US10YETH <- cor1[2,7,]   # row, column, all observation periods
cor_US10YETH <- as.xts(cor_US10YETH)  # redefine as time series
colnames(cor_US10YETH)[1] <- DCC



# Gold
# Gold and UST
cor_GoldUST <- cor1[3,9,]   # row, column, all observation periods
cor_GoldUST <- as.xts(cor_GoldUST)  # redefine as time series
colnames(cor_GoldUST)[1] <- DCC
```

```
# Gold and LUNA
cor_GoldLUNA <- cor1[3,10,]   # row, column, all observation periods
cor_GoldLUNA <- as.xts(cor_GoldLUNA)  # redefine as time series
colnames(cor_GoldLUNA)[1] <- DCC

# Gold and BTC
cor_GoldBTC <- cor1[3,6,]   # row, column, all observation periods
cor_GoldBTC <- as.xts(cor_GoldBTC)  # redefine as time series
colnames(cor_GoldBTC)[1] <- DCC

# Gold and ETH
cor_GoldETH <- cor1[3,7,]   # row, column, all observation periods
cor_GoldETH <- as.xts(cor_GoldETH)  # redefine as time series
colnames(cor_GoldETH)[1] <- DCC


# Oil
# Oil and UST
cor_OilUST <- cor1[4,9,]   # row, column, all observation periods
cor_OilUST <- as.xts(cor_OilUST)  # redefine as time series
colnames(cor_OilUST)[1] <- DCC
```

```
# Oil and LUNA

cor_OilLUNA <- cor1[4,10,]   # row, column, all observation periods

cor_OilLUNA <- as.xts(cor_OilLUNA)  # redefine as time series

colnames(cor_OilLUNA)[1] <- DCC


# Oil and BTC

cor_OilBTC <- cor1[4,6,]   # row, column, all observation periods

cor_OilBTC <- as.xts(cor_OilBTC)  # redefine as time series

colnames(cor_OilBTC)[1] <- DCC


# Oil and ETH

cor_OilETH <- cor1[4,7,]   # row, column, all observation periods

cor_OilETH <- as.xts(cor_OilETH)  # redefine as time series

colnames(cor_OilETH)[1] <- DCC



# DXY

# DXY and UST

cor_DXYUST <- cor1[5,9,]   # row, column, all observation periods

cor_DXYUST <- as.xts(cor_DXYUST)  # redefine as time series

colnames(cor_DXYUST)[1] <- DCC


# DXY and LUNA
```

```
cor_DXYLUNA <- cor1[5,10,]   # row, column, all observation periods
cor_DXYLUNA <- as.xts(cor_DXYLUNA)  # redefine as time series
colnames(cor_DXYLUNA)[1] <- DCC

# DXY and BTC
cor_DXYBTC <- cor1[5,6,]   # row, column, all observation periods
cor_DXYBTC <- as.xts(cor_DXYBTC)  # redefine as time series
colnames(cor_DXYBTC)[1] <- DCC

# DXY and ETH
cor_DXYETH <- cor1[5,7,]   # row, column, all observation periods
cor_DXYETH <- as.xts(cor_DXYETH)  # redefine as time series
colnames(cor_DXYETH)[1] <- DCC



# DeFiIndex
# DeFiIndex and UST
cor_DeFiIndexUST <- cor1[8,9,]   # row, column, all observation periods
cor_DeFiIndexUST <- as.xts(cor_DeFiIndexUST)  # redefine as time series
colnames(cor_DeFiIndexUST)[1] <- DCC

# DeFiIndex and LUNA
cor_DeFiIndexLUNA <- cor1[8,10,]   # row, column, all observation periods
```

```
cor_DeFiIndexLUNA <- as.xts(cor_DeFiIndexLUNA)  # redefine as time series
colnames(cor_DeFiIndexLUNA)[1] <- DCC

# DeFiIndex and BTC
cor_DeFiIndexBTC <- cor1[8,6,]   # row, column, all observation periods
cor_DeFiIndexBTC <- as.xts(cor_DeFiIndexBTC)  # redefine as time series
colnames(cor_DeFiIndexBTC)[1] <- DCC

# DeFiIndex and ETH
cor_DeFiIndexETH <- cor1[8,7,]   # row, column, all observation periods
cor_DeFiIndexETH <- as.xts(cor_DeFiIndexETH)  # redefine as time series
colnames(cor_DeFiIndexETH)[1] <- DCC



# BTC
# BTC and UST
cor_BTCUST <- cor1[6,9,]   # row, column, all observation periods
cor_BTCUST <- as.xts(cor_BTCUST)  # redefine as time series
colnames(cor_BTCUST)[1] <- DCC

# BTC and LUNA
cor_BTCLUNA <- cor1[6,10,]   # row, column, all observation periods
cor_BTCLUNA <- as.xts(cor_BTCLUNA)  # redefine as time series
```

```
colnames(cor_BTCLUNA)[1] <- DCC


# BTC and ETH
cor_BTCETH <- cor1[6,7,]   # row, column, all observation periods
cor_BTCETH <- as.xts(cor_BTCETH)  # redefine as time series
colnames(cor_BTCETH)[1] <- DCC



# ETH
# ETH and UST
cor_ETHUST <- cor1[7,9,]   # row, column, all observation periods
cor_ETHUST <- as.xts(cor_ETHUST)  # redefine as time series
colnames(cor_ETHUST)[1] <- DCC


# ETH and LUNA
cor_ETHLUNA <- cor1[7,10,]   # row, column, all observation periods
cor_ETHLUNA <- as.xts(cor_ETHLUNA)  # redefine as time series
colnames(cor_ETHLUNA)[1] <- DCC


# crash variables
# LUNA and UST
cor_LUNAUST <- cor1[10,9,]   # row, column, all observation periods
cor_LUNAUST <- as.xts(cor_LUNAUST)  # redefine as time series
```

```
colnames(cor_LUNAUST)[1] <- DCC
```

Declaration of Authorship

I hereby declare that I have written this paper myself and used no other sources or resources than those indicated, have clearly marked verbatim quotations as such, and clearly indicated the source of all paraphrased references, and have observed the General Study and Examination Regulations of Reutlingen University for bachelor and master programs, the specific regulations for study and examinations of my study program, and the Regulations for Ensuring Good Academic Practice of Reutlingen University.
Neither this paper nor any part of this paper is a part of any other material presented for examination at this or any other institution.

Reutlingen, 03 January 2023

Viktor Santiago