Systemic Risk Measurement of Native cryptocurrencies and Stable coins emerging from interconnectedness

An application of tail dependence-based MST and CoVaR approach

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Abstract

This paper analyses the dynamics of the interconnections of native cryptocurrencies and stable coins and their impact on their systemic risk contribution. Results obtained from MST analysis identify Ether and GUSD as the most central nodes, while CoVaR results indicate that Ether and GUSD are the highest-risk contributors. MATIC and USDT are identified as periphery nodes and contribute the least to the systemic risk. The risk contribution of native cryptocurrencies decreases with increase in interconnection, while that of stable coins increases and the difference in results could be attributed to their underlying properties of decentralization in their issuance, management and governance.

Keywords: Cryptocurrency, Stablecoins, systemic risk, spillover effects, CoVaR, network analysis.

JEL Classification codes: G01, G15, G32

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1. Introduction

The term "crypto asset" has been defined by the International Organization of Securities Commissions as "a type of private asset that depends primarily on cryptography and DLT or similar technology as part of its perceived or inherent value, and can represent an asset such as a currency, commodity or security, or be a derivative on a commodity or security" (IOSCO, 2020)

Blockchain was developed as a direct reaction to the 2008 financial crisis, which saw widespread fear and mistrust of big, centralized banks due to bank collapse. The goal of blockchain technology was to execute transactions without the need for a central middleman (Ganley, 2023). The idea behind the design of crypto assets was to improve and democratize the lending and payment systems. Crypto assets, specifically those built on distributed ledger technology (DLT), are utilized in many financial services, e.g. payments, lending, funding, trade, etc. Distributed ledger technology could be defined as "a set of technological solutions that enables a single, sequenced, standardized, and cryptographically secured record of activity to be safely distributed to, and acted upon, by a network of diverse participants" (Bains, 2022). The data is usually distributed across all networks through nodes and control of this data is managed by multiple participants in a decentralized manner.

In recent years the growth of crypto assets has been very volatile. The total market capitalization of crypto assets was almost $3 trillion in November 2021, before dropping to less than $1 trillion in July 2022, and currently, it stands at $1.27 trillion. As the crypto ecosystem is expanding, it is becoming more integrated and interdependent. According to (Arner, 2023) somehow the crypto ecosystem, having properties of decentralization and disintermediation is moving towards the traditional intermediaries-based financial system.

The growing interconnectedness and interdependencies observed within the crypto ecosystem are no different from traditional financial systems. These interdependencies can either be systematic or institutional, where the former refers to integration between two or more systems in which the performance of one inevitably effects the performance of others in the network. In institutional integration, the source of interdependence between market systems and market participants results from the complicated activities of central authorities that create direct and indirect relationships among them. The major factors responsible for increasing interdependencies in global crypto ecosystems are financial consolidation, regulatory flexibility, public policy, and technological innovation.

The interconnected financial structure has many benefits in terms of resilience and recovery during times of crisis. Antonio et al. (2016) proposed a framework to look at how interconnection might lead to both fragility and resilience. Chief Economist Andrew Hanldane said in his speech that “highly interconnected financial networks may be robust yet fragile in the sense that within a certain range, connections serve as shock absorbers and connectivity engenders robustness. However, beyond a certain range, interconnections start to serve as a mechanism for the propagation of shocks; the system flips to the wrong side of the knife edge, and fragility prevails.” (Bovy, 2022).

Crypto assets appeared and flourished after the Global Financial Crisis in 2008; however, they were not considered a threat to the financial system until recently (Board, 2018). FSB, in their recent report on crypto assets in 2022, acknowledged the escalated surge in their market capitalization of crypto assets, their deep interconnections with other financial markets, and their adoption in those markets. These developments have changed policymakers' perceptions to the point where it is now deemed necessary for them to make appropriate policies to avoid any future risk and to regulate them to harness their benefits.

A network of "systemically important crypto institutions" is formed in the crypto ecosystem as a result of these interdependencies. These institutions come in a multitude of shapes, including crypto conglomerates, crypto mediators, and crypto infrastructure. These deregulated interdependencies have shown poor risk management and are often involved in market misconduct, a lack of transparency, inadequate risk management, and market malpractice (Arner, 2023).

The cryptocurrency ecosystem is also susceptible to various risks through cyber-attacks, exchanges, and central authorities (Weaver, 2018). Nicholas Weaver identified four major areas related to the risks of cryptocurrencies, which include technical risks effecting participants in the ecosystem, economic risks to the participants, systemic risks to the crypto asset ecosystem, and lastly, risks to society. According to Houben (2020), these crypto assets incorporate macroeconomic risks, which can cause negative effects on monetary policy, risks to capital flow volatility, fiscal risks, legal risks, and risks related to consumer protection, market stability and the integrity of the financial system. Some of these risks stem from the technology on which crypto assets are built, while others are related to the law-enforcing system and regulatory policies. Systemic risk can arise because of the worms, as there are peer-to-peer systems in blockchain-based crypto assets. A worm can manipulate a P2P node, extend to all connected nodes, and eventually spread globally in a matter of seconds.

The World Bank defines contagion as a shock mechanism that spreads across nations while taking into consideration market co-movements that amplify the correlation between different economies. The analysis of the contagion effect is crucial for determining how certain financial assets are interconnected following unexpected events like crises or bubbles. The contagion channel among cryptocurrencies is amplified during times of crisis because of increased integration and interdependence. Researchers have empirically investigated the co-movement of price in native cryptocurrencies and systemic risk in the crypto currency market, e.g., Huynh (2018), Bouri (2019), Tiwari (2020), Bruhn (2022), Akhtaruzzaman (2022), and Arner (2023). All research confirms that due to high price volatility, price bubbles exist in the crypto market, which indicate high risk to the investors in these assets. Cryptocurrencies which have high market capitalization contains high contagion risk. The presence of co-explosivity during the period of crises and increased interconnectivity are also evident from these studies.

Stable coins emerged as the eventual solution to these issues. Cryptocurrencies referred to as "stable coins" are those that are fixed to a specific value and backed by fiat money, usually the US dollar or the euro. They keep their peg in different ways, depending on which stable coin is most prevalent. The non-volatile assets help cryptocurrency investors protect themselves from market volatility and are trusted globally as risk-free hedging options, with market capitalizations in the billions of US dollars (Ganley, 2023). While there are many potential benefits for the financial system from global stable coins, including lower transaction costs for global payments and increased inclusive finance, new risks are also emerging for monetary policy and financial stability (Group, 2019). Purchasing the safe assets that support a global stable coin may lessen the amount of liquid assets available in financial markets, which can lead to financial distress. It may seem from the word "stable" that the volatility of the SCs is zero, but it is not. In particular, Tether's median volatility is 2.3%, USD Coin's 1.5%, TrueUSD's 6.6%, and Dai's 7.1%, whereas Bitcoin's is 62.2% and Ether and XRP's is over 80%, as determined by Melachrinos, and Pfister (2020). This brings attention to the fact that stable coins share a major share of the traded coins in the cryptocurrency market and raises the question, “Are they affected by the changes in price movements of other assets?” If a stable coin collapses, it would erode confidence in the market overall as well as in that particular coin. The credibility of stable coins became a question when the ecosystems of Luna and Terra failed. (Briola et al., 2023).

There exists a very limited literature on the growing interconnections of stable coins and their systemic risk contribution during periods of turbulence. Our study contributes to the available literature by investigating the interconnectedness of native cryptocurrencies and stable coins in cryptocurrency market and how much they are impacted by the price changes of entire market by using network topologies generated from MST analysis for the period of 2020 to 2023. Also, by employing the CoVaR approach, we have measured the risk in isolation, spillover effects and systemic risk contribution of native cryptocurrencies and stable coins. To evaluate how time affects the degree of linkages and systemic risk contribution, simple linear regression is run between centrality values and time-varying ΔCoVaR.

The remainder of the research is arranged in the following manner. In Section 2, we present the relevant literature carried out in this field and how our research adds to it. In Section 3, data and the empirical methodology used in our study is discussed in section 4. In Section 5, we interpret the relevant empirical findings and discuss the corresponding results. Section 6 concludes research questions and findings.

2. Literature Review

There are yet no globally consistent definitions and taxonomy of crypto assets. These digital assets are based on the internet, advanced cryptography, blockchain and distributed ledgers. Blockchain and distributed ledger technology eliminates the need of intermediaries in any system. It facilitates direct peer to peer transactions among participants.

Cryptocurrency market carries many potential investment opportunities but it also pose greater risk for investors. A research study in 2020, used quantitative descriptive analysis, (Dasman, 2021) on the returns of 15 cryptocurrencies that had greatest market capitalization. The purpose of their research was to determine the returns and risks of investment in crypto assets. They used descriptive analysis by evaluating risk measures and Heteroscedastic model GARCH (1, 1) for empirical analysis. The results showed that investing in crypto assets is more profitable in terms of high returns than investing in other currencies or stock market. However, crypto currencies carries extreme risk of losses and volatility clustering or heteroscedasticity.

Similar results were generated by research conducted by Bruhn et al. (2022). They examined the financial risk features of the entire cryptocurrency market portfolio and individual cryptocurrencies. They made a portfolio carrying the 20 largest cryptocurrencies, with a market capitalization of almost 82.1% of the total cryptocurrency market. They applied extreme value theory to investigate extreme tail risks by using the returns of these currencies. They employed t-student Copula to look at potential portfolio diversification effects and the GARCH-EVT technique to predict the tail distribution. The empirical analysis revealed that, although Bitcoin was the most stable cryptocurrency, all cryptocurrencies exhibited significant price fluctuation. Every return distribution has a strong tail and a high tail risk. Particularly for Ethereum and Bitcoin, a significant positive intra-market correlation was discovered. The study came to the conclusion that there is a considerable chance of loss when investing in individual cryptocurrencies or a portfolio.

Empirical investigation by Huynh et al. (2018) explored the possibility of contagion risk among cryptocurrencies during periods of crises. It analyzed the movement of asset returns based on price dynamics and price volatility to see if it could spread to other cryptocurrencies of the same type. Using the Copulas approach, this research has generated empirical evidence of these crypto assets' mutual impact. It showed that all pairs have significant left tail dependence with Chi-plots. It also confirmed the presence of systemic risk in these crypto assets. The statistical techniques used e.g. Kendall-plots, Chi-plots, and Copulas estimation produced the same results showing the existence of contagion risk.

The existence of co-explosivity among cryptocurrencies is also confirmed by the research “Co-explosivity in the cryptocurrency market”, by Bouri (2019). The seven largest cryptocurrencies by market capitalization, with a period of over two years, were brought under consideration for the research. The logistic regression approach was used for empirical analysis. The research concluded with evidence of multiple periods of explosivity in all cryptocurrencies and the explosivity time period in one currency was found to be dependent on the presence of explosivity in another cryptocurrency, which shows the existence of co-explosivity among selected crypto assets.

Extreme price volatility in the cryptocurrency market indicates a high risk to investors in crypto assets. It also hints at the presence of bubbles in the price movement of crypto assets. The failure of one crypto currency can lead to the failure of other assets due to the integrated market structure. The empirical investigation to determine the co-explosivity of crypto assets was performed by Arianna and Alessia in 2020. They used the unit root testing approach to determine the co-explosivity of crypto assets and crisis transmission channels (Agosto et al., 2020). They included five cryptocurrencies with the largest market capitalization in their study to investigate the presence of bubbles in different phases of their price behavior. The research confirmed the presence of high interdependence among cryptocurrencies and a significant relationship between cryptocurrencies co-explosivity. They further added that increased interdependence makes them prone to higher risks.

Tiwari (2020) also confirmed the presence of contagion risk between large cryptocurrencies determined by market capitalization size, such as BTC, LTC and XRP. The quantitative analysis was carried out for the period of 04-08-2013 to 17-06-2018 by using non-parametric mixture copulas and full-range tail dependence copulas. Research findings from Chi-plots and Kendall plots showed that strong tail dependence exists in each pair of the cryptocurrencies. Upper tail dependence was found to be significant for the BTC-LTC pair, while for other pairs of crypto currencies, lower tail dependence was significant according to mixture copula results. However, extreme upper and lower tail dependence was found to be significant in all pairs of cryptocurrencies, as shown by the results of full-range copulas, which confirms the presence of high contagion risk among major cryptocurrencies. A research study by Ahelegbey (2021) was aimed to determine the relationship among crypto assets during turbulent times. He used the extreme downside hedge along with extreme downside correlation econometric modeling techniques and extended it to a multivariate networking model framework to find systemic risk tail dependence among them. Asset bubble interconnectedness was also investigated, as he indicate the existence of extreme risks. The study showed the existence of a significant and positive relationship among the tail risks of cryptocurrencies. On the basis of the results, all crypto assets were combined into two categories: speculative currencies, i.e., BTC, responsible for giving tail contagion, and technical currencies, i.e., ETH, that are receiving tail contagion.

The contagion channel among cryptocurrencies is amplified during times of crisis because of increased integration and interdependence. The empirical evidence was provided by Akhtaruzzaman (2022). He selected 17 cryptocurrencies, which have around 76.11% of the total market valuation for the time period of 1 January 2017 to 30 June 2021. Conditional Value-at-Risk approach was used to build the index of systemic contagion from a Principal component analysis of selected cryptocurrencies. The research findings showed that during pandemic, interconnections among cryptocurrencies were increased, that resulted in increased transmission channels of contagious shocks. High SCI value indicated presence of increased systemic channels of risk driven by pandemic, while Bitcoin performed as a more stable cryptocurrency during pandemic. Speculative bubble behavior of cryptocurrencies can create financial instability in the markets and can even lead to systemic risk. To calculate the systemic risk and identify the transmission channels across both crypto and non-crypto markets, Hakim, (2023) developed multivariate conditional value-at-risk model. By employing Delta MCoVaR he generated results which showed that the crypto assets are the major sources and channels of systemic risk and simultaneously spread it across crypto ecosystem and towards the S&P 500, oil, and gold. This transmission is more evident during pandemic and 2021 crypto bubble event. Arner et al. (2023) conducted a research to investigate the role played by interdependencies of the crypto ecosystem in effecting practices responsible for managing internal risk and crisis control in the crypto ecosystem. Market trends and significant events of the crypto market in the years 2022-2023 were used to evaluate the factors contributing to the increased interconnectedness in the crypto ecosystem and how these interdependencies disturb the mechanism to manage internal risk and crises while projecting known and unknown systemic risks. According to their research, the collapse of crypto assets in the years 2022-2023 was mainly due to poor internal risk management and a lack of supervision and regulatory policies. The situation even gets worse when there is a lack of understanding about the market participants, and the crypto ecosystem, and a lack of framework to understand the interconnectivity of services and entities in the system. They used case studies of recent market collapses in both centralized exchanges (CeFi) and decentralized assets and exchanges (DeFi). Market valuation of crypto assets increases during the period of high price volatility, however, it also poses threats to financial stability. Adverse effects of market shocks can cause risks to the financial ecosystem. Federal Reserve Bank of New York report published research on "Financial Implications of digital assets" (Azar, 2022) which examined the emerging vulnerabilities that could bring potential risks to financial stability, if the cryptosystem becomes more interconnected and systemic, in the absence of regulations. Federal Reserve uses a framework to examine vulnerabilities in traditional finance. In this research, the same framework was used to analyze vulnerabilities in the digital financial ecosystem. According to this research, as the crypto ecosystem gets bigger with increased interconnected with the traditional financial system, risks from asset valuations could move to the traditional financial sector. However, stablecoins that are backed by money market instruments indicate major financial stability risk which can be materialized if it becomes more interconnected with traditional financial system. Increased connectedness of crypto assets with regulated financial market increases systemic risks is also confirmed by ECB in Financial Stability Review 1 (Hermans, 2022). It states that systemic risk rises as interconnections grow higher between cryptocurrencies and the traditional finance, the usage of leverage and lending practices increases. It also focuses on gaps in available data and regulatory policies which needs to be resolved to reduce the possibility and impact of these risks.

Research study conducted by Ganley (2023) was focused on stable coins price movement and movement in the returns of entire crypto currency market and traditional finance market. He used a time-series OLS regression, and a Granger-Causal test to measure co movement of prices of four largest stable coins (USDT, USDC, BUSD and DAI) and cryptocurrency market. Results showed that both USDT and USDC have statistically significant correlation with SP500, while BUSD has significant price correlation with the price of cryptocurrency market. Only DAI has no correlation with either of the market. Thus identified DAI as most trustworthy stable coin for hedging against market risks.

There is currently little research on the contagion networks and systemic risk among crypto assets with contradicting results and how they behave as a result of changes in interconnections of crypto assets under normal conditions and in turbulent times. Many studies and analyses conducted so far have concentrated on a single cryptocurrency or a small number of cryptocurrencies; thus, an in-depth investigation of the cryptocurrency market for spillovers and systemic risk channels is still lacking. Further, there exists a very limited literature on the growing interconnections of stable coins and their systemic risk contribution during periods of turbulence. Our study contributes to the existing research by investigating the interconnectedness of native cryptocurrencies and stable coins in cryptocurrency market and how much they are impacted by the price changes of large native cryptocurrencies and entire market by using network topologies generated from MST analysis for the period of 2020 to 2023 and ΔCoVaR approach to estimate risk contribution of each native cryptocurrency and stable coin to the market distress. It also provides insights into the evolution of interconnection and how they affect risk contribution or absorption properties of digital assets.

3. Data

Data for the daily adjusted closing prices of 27 native cryptocurrencies and 8 stable coins have been collected from the webpage *www.coinmarketcap.com* for the time period of January 1st, 2020, to September 18, 2023. Cryptocurrencies are defined as "digital representations of a value or contractual rights that use some form of distributed registry technology and that can be transferred, stored or traded electronically" Стойка (2021), and stable coins could be defined as "digital units of value that are not a form of any specific currency (or basket thereof) but rely on a set of stabilization tools which are supposed to minimize fluctuations of their price in such currency(ies)" as defined by Bullmann el al. (2019). Native cryptocurrencies and stable coins and their codes are given in Table 1 and 2, respectively.

The chosen crypto currencies and stable coins have the highest market capitalization and are included in top-ranked 100 crypto coins, which cover more than 88% of total market capitalization. Those stable coins are included in our analysis that are pegged to either fiat currency, i.e., the dollar, euro or gold.

The macro variables chosen for the analysis of ΔCoVaR include those variables that affect the cryptocurrency market. Although each cryptocurrency and stable coin behave differently in response to changes in those variables, there is some common trend or behaviour. The returns of the SP500 Index, CBOE VIX volatility index, fear and greed index of the cryptocurrency market, and market capitalization of cryptocurrencies are chosen as state variables for our study. The Fear and Greed Index is an indicator that analyses and generates a number between '0' and '100', where 1 is the indication of extreme fear and 100 is the indication of extreme greed. Extreme fear implies that the investors in the market are selling, and extreme greed implies that the traders are in a mood to buy more.

While Index of SP500 and CBOE volatility index covers the traditional financial market behaviour and events while fear and greed index and market capitalization of cryptocurrencies and stable coins are specific to cryptocurrency market. Data for returns of SP500 index and

CBOE volatility Index has been collected for the same time period from Yahoo Finance website *www.finanace.yahoo.com* and data for fear and greed index (FIG) has been collected from alternative.me https://alternative.me/crypto/fear-and-greed-index/. Data for market capitalization of cryptocurrencies has been collected form *www.coinmarketcap.com.* These chosen variables represent investor sentiment, trend and expectations, and business cycles. Cryptocurrencies prices data is then transformed in to log returns values in percentage form.

The total daily observation are 1357. Figure 1 and 2 displays the entire period's price fluctuations for the chosen currencies. The daily rate of return for each currency was determined for the purpose of studying correlations, and it was defined as ri (t) = ln. Pi (t) – ln Pi (t-1), which represents the price of the cryptocurrency at t and t-1, respectively, where Pi (t) and Pi (t-1) are the corresponding prices. The statistical summary of returns for each currency is displayed in Table 2.

4. Methodology

The previous studies on the subject of systemic risk utilized the network analysis approach, which focuses on the collective loss sharing of all market players, and the micro-evidence approach, which involves the individual contribution of institutions to systemic risk (Krygier, 2014). This study takes into account both approaches to investigating interconnectedness and systemic risk. While network analysis is used in order to investigate the interconnections of the systematically important market participants, and micro-evidence approach is used to assess the systemic risk caused by each participant individually and lastly, we will analyse if there is any relationship between the centrality measures of network participants and the contribution to the systemic loss in cryptocurrency market.

4.1 Network Analysis for the measurement of interconnectedness

In network analysis, centrality metrics have gained popularity as a metric for determining influential nodes in a network. It also determines the effect of changes in influential nodes on other nodes within the network. Numerous studies have evaluated market dynamics and performance using the values of centrality indicators. (Tariq, 2023). Networks based on correlation are very useful in identifying links between assets and institutions. They are compatible with the MST algorithm and are simple to calculate and evaluate. By identifying the major participants in the market and observing their actions during periods of volatility, MST analysis provides a detailed understanding of the trends of the market. Additionally, it issues warnings regarding the assets and firms that fuel market instability. It also provides information on portfolio diversification for risk mitigation. Peripheral nodes may be seen as safe havens during market distress. Economists, investors, and regulators can all benefit from MST graphs, weights, and centrality values (Tomeczek, 2022).

4.2 Minimum Spanning Tree Analysis

Creating the matrix of correlations between the daily returns of all the cryptocurrencies under study is the first step in building the "Minimum Spanning Tree" (MST). This yields the coefficients of the Pearson correlations between each pair of currencies, i and j, which are defined as:

$$C_{ij} = \frac{n(\sum r_i r_j) - (\sum r_i)(\sum r_j)}{\sqrt{[n\sum r_i^2 - (\sum r_i)^2]\,[n\sum r_i^2 - (\sum r_i)^2]}} \tag{1}$$

A correlation matrix is obtained:

$$C = \begin{bmatrix} C_{11} & \cdots & C_{1N} \\ \vdots & \ddots & \vdots \\ C_{N1} & \cdots & C_{NN} \end{bmatrix} \tag{2}$$

N is the total number of currencies (36 in our study), and C_ij values range between -1 and 1. The elements of the correlation matrix C_ij can be converted into distances, according to Mantegna (1999), to create a distance matrix where

$$d_{ij} = \sqrt{2(1 - C_{ij})} \tag{3}$$

The value ranges from 0 to 2, so if the correlation is high among cryptocurrencies, the distance will be short among them. To construct MST, combine nodes N (which are the native cryptocurrencies and stable coins) with links N–1, and thus the total of all the distances of the links will be the smallest. So the most relevant data will be taken out of the correlation matrix using the N–1 linkages. We have created the MST that employs the Kruskal algorithm (1956) by following Mantegna (1999) and Mantegna and Stanley (2000). We followed the following steps for creating the MST graph. First of all, using the distance matrix, we selected N (N – 1) / 2 elements in ascending order, then selected the cryptocurrency pair with the shortest distance and included the link to the graph. After that, we added the link to the next pair of cryptocurrencies, which has the smallest distance between them. The same process is repeated until all the currencies are linked together in the MST graph.

We first examined the N (N – 1) / 2 descriptors, components of the correlation matrix created prior to displaying the MST, which was created using the algorithm previously explained. Furthermore, a comparison was made between the correlation coefficients' significance values. From MST, different centrality measures were collected, which indicate different aspects of the interconnectedness of cryptocurrencies. These four centrality measures include degree centrality, betweenness centrality, closeness centrally, and eigenvector centrality.

4.2.1 Degree centrality

Degree centrality counts the total number of edges, a node is linked to in a network. It is the primary centrality metric and could be regarded as the instant risk that is circulating through the network and that a node can contract.

$$\text{Degree centrality of Node } (i) = \text{Total number of edges connected to node } (i) \qquad (4)$$

4.2.2 Closeness centrality

The distance of a node from another node in the network is calculated by its closeness centrality. This centrality metric shows a node's level of impact within a network. Its closeness to other nodes in the network is shown by its closeness centrality.

Centrality and closeness could be determined as

$$\text{Closeness Centrality (i)} = \frac{N-1}{\sum_{j=1}^{N} d(i,j)} \qquad (5)$$

While N is the total number of nodes in the graph and *d (i, j)* is the shortest path between node *i* and node (*j*). While $\sum_{j=1}^{N} d(i,j)$ denotes the total of the shortest distances between node (i) and all other nodes (j) in the network.

4.2.3 Betweenness centrality

The shortest distance between two nodes is measured by this centrality. It detects the nodes that serve as a link between various nodes. The information flow in the network can be significantly influenced by the node with a high betweenness centrality. It displays the most significant vertex that joins several vertex pairs.

$$\text{Betweenness Centrality} = \sum_{s \neq v \neq t \in V} \frac{\sigma st(v)}{\sigma st} \qquad (6)$$

Whereas Σst is the total number of shortest paths from node (s) to node (v) and $\sigma st(v)$ is the total number of shortest paths from node (s) to node (t) that pass through node (v).

4.2.4 Eigenvector centrality

Another term for it is Broncich's centrality. It calculates a node's connections within its local network. The node with the highest eigenvector value is the one that is most powerful, and its power originates from its relationships with other strong or weak nodes.

$$\text{Eigenvector Centrality (v)} = \frac{1}{\lambda} \sum_{j=1}^{n} \alpha\, j, v\ (centrality\ j) \qquad (7)$$

4.3 An application of CoVaR for the measurement of Systemic Risk

The micro-evidence approach provides numerous ways to gauge systemic risk. Adrian and Brunnermeier (2011) developed CoVaR, which is one of the measures of systemic risk, in their paper of the same name.

Conditional, contagion, or co-movement is what the Co stands for, highlighting the systemic aspect of their risk assessment. According to their definition, CoVaR is the VaR of a financial system conditional on various institutions being in distress. In this context, "distress" is defined as an institution falling below its 1%-VaR level. VaR is the highest loss that can occur with a given probability during a given time frame.1.

Further, ΔCoVaR could be defined as CoVaR conditional on the institution *(i)* which is under distress (at its 1%- VaR) minus the CoVaR that is conditional on the institution *(i)* which is in its median state (at its 50%-VaR). CoVaR and ΔCoVaR are estimated, conditionally and unconditionally, for 36 cryptocurrencies including native cryptocurrencies and stable coins during the period January 1st, 2020, to September 18, 2023. Whereas the conditional evaluation produces CoVaR values based on market indicators (traditional financial markets and crypto currency markets), the unconditional estimation yields a CoVaR value that stays constant across time. In contrast to the unconditional estimate approach, which is a static approach, the conditional estimation of CoVaR can be thought of as a dynamic approach. The term CoVaR always refers to two entities of some kind. When discussing CoVaR in this article, is the cryptocurrency market (CCM) and certain cryptocurrencies return i. The additional macro variables include the SP500 index, the CBOE Volatility Index, the market cap and fear and greed index of crypto market, serving as proxies for traditional and crypto market short-term risks and sentiments.

One of the most common measures of systemic risk is VaR.

$$VaR_a(L) = \{l\colon \Pr(L > l) \leq 1 - a\} \qquad (8)$$

is the smallest loss *l* for which the probability of a future loss L greater than loss *l* is equal to or less than 1 - a.

Adrian and Brunnermeier first presented the concept of CoVaR as a risk measure in 2011. It is the VaR of a company, institution, nation, or portfolio conditional on another organization experiencing financial crises. As demonstrated in this study, CoVaR can also be used to analyse the risk exposure of one entity to another, such as the systemic risk contribution of a corporation to a financial system (or market).

$$\Delta \mathrm{CoVaR}_q^{J|i} = \mathrm{CoVaR}_q^{J|X^i=VaR_q^i} - \mathrm{CoVaR}_q^{J|X^i=VaR_{Median}^i} \quad (9)$$

In order to check the robustness of the results generated from the CoVaR analysis, a time-varying CoVaR analysis is performed by including the state variable. The derivation of equations for estimation of unconditional and conditional VaR, CoVaR and ΔCoVaR is given in Appendix. Further, the conditional time-varying values are then regressed against centrality values calculated from MST analysis. The frequency of observations is reduced to 45 months, and the results still hold valid and are in line with the results generated from the high frequency of daily observations.

4.4 Multiple Linear Regression Analysis for measuring the Relationship between Centrality Measures and contribution to systemic risk Values

Multiple linear regression is employed to predict the dependent variable y (which in our research is the time-varying ΔCoVaR values) and a number of independent variables. This relationship could be explained with the following formula

$$y = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots + \varepsilon \quad (24)$$

The regression equation parameters were estimated by the ordinary least square method (OLS) where the sum of the root square error is minimized. The regression coefficients, and, contain the slope coefficient for the independent variables, whereas is the predictor and ε is the error term.

5. Research Findings

In this section results obtained from MST, ΔCoVaR, and multiple linear regression are interpreted and discussed.

5.1 Results of MST analysis

Figure 3 of MST 2020 shows the summary of most central and periphery nodes for the year 2020. Centrality values of all cryptocurrencies and stable coins calculated from MST are shown in Table 4. Tables 5, 6, and 7 show the centrality values calculated for the years 2021, 2022, and 2023 respectively. Table 8 shows the centrality values calculated for the entire period 2020-2023.

5.1.1 MST 2020

For the MST 2020, ETH is the most influential node, with the highest values of all centrality measures. Influential currencies other than ETH are WBTC, BNB, MKR, XTZ, USDP, PAXG, THETA, SNX, RPL, BCH, and ADA, according to Table 4. In 2020, the amount of BTC on Ethereum (represented by tokenized BTC such as wrapped BTC) surpassed the amount of BTC on the lightening network, the Bitcoin layer 2 scaling network.

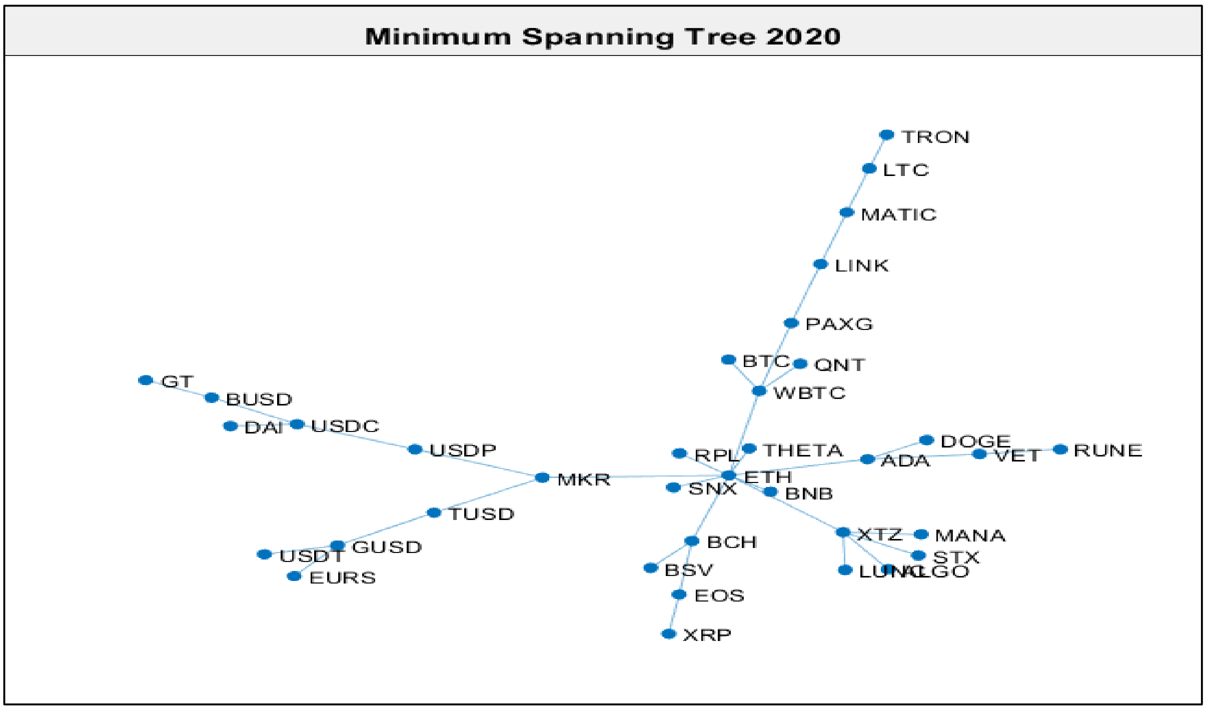

FIGURE 3. Minimum spanning tree is plotted by using data of log return values of selected native cryptocurrencies and stable coins. Pearson correlation matrix was generated by using log return values which was then transformed by using distance matrix. This matrix was employed in MATLAB to create MST for the year 2020.

Therefore, WBTC saw increased trading volume and an increase in price during 2020. XTZ has experienced significant volatility since its launch in 2018. Soon after its launch, its price and the entire crypto landscape went down. However, in 2020 as the bear market was in full swing the price of XTZ touched new heights but the increase was short-lived, as by the end of 2020, its price was decreased to even less than half. Due to COVID-19 and the bear market, many currencies experienced increasing trading volume and high prices. BNB also experienced price appreciation due to increased trading volume, resistance levels, and correlation with market trends and indicators. Research conducted by Kumar et al. (2022), to measure return and volatility connectedness provided evidence for Ether being the most influential and central cryptocurrency. Another research by Katsiampa et al. (2022) confirmed these results. They measured network structured changes after COVID-19 in the cryptocurrency market by using MST and PMFG graphs from January 2019 to December 2020. Research findings showed that those currencies that involve the DAaps protocol became more attractive to investors in 2020.

The sample period was from October 2017 to 5th January 2021. Another research showed that those stable coins which are pegged with gold experienced high volatility during 2020 however the increase was insignificant (Wasiuzzaman et al., 2021).

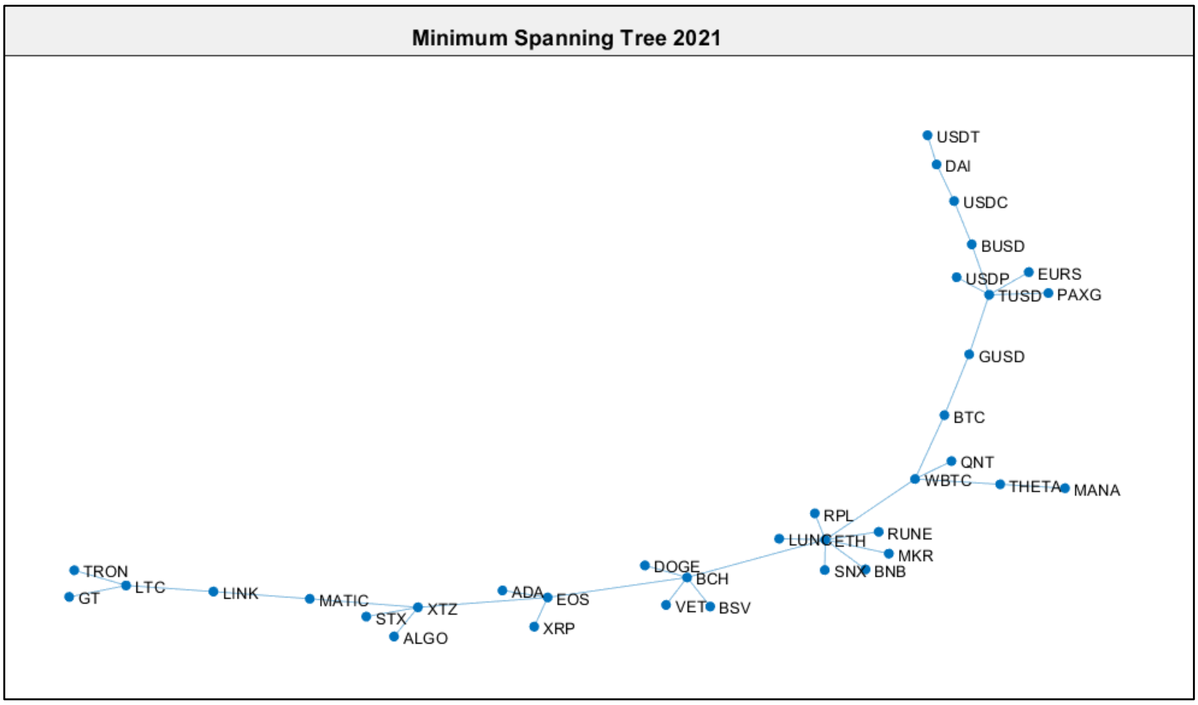

FIGURE 4. Minimum spanning tree is plotted by using data of log return values of selected native cryptocurrencies and stable coins for the year 2021.

5.1.2 MST 2021

The cryptocurrency market matured and boomed in 2021, with a number of currencies exceeding the market leader, bitcoin, and flourishing. The total market capitalization of the cryptocurrency industry increased by 187.5%, even though bitcoin only managed to yield a 59.8% return. Still, in November 2021, it reached a peak of over $69000 (Kamau, 2022). Many of the leading coins offered four or even five-digit percentage returns. Returns on Ethereum increased to 399.2 percent as a result of the development of DeFi 2.0 protocols such as Olympus (OHM) and the popularity explosion of NFTs. The currencies with the highest returns were BNB 1268.9%, XRP 277.8%, BCH 25.7%, ADA 621.8%, and DOGE 3546.5%. Earlier in the year, prominent financial institutions and large institutional investors started endorsing cryptocurrencies. When businesses like Tesla and Square began purchasing bitcoin with their balance sheets, the value of the cryptocurrency surpassed $1 trillion. NFT interest skyrocketed following Beeple's 2021 $69 million sale. Crypto-assets trended higher for the majority of 2021, despite volatile movements and periods of speculation (Hermans et al., 2022). Also, China banned the use and trading of cryptocurrencies in May 2021 since it was illegal for any kind of cryptocurrency activity. TrueUSD (TUSD), a stable coin based on the US dollar, claimed to have a $1.5 billion supply at its height in 2021. Additionally, it made achievements in the implementation of multi-chains, collaborations with banks, DeFi ecosystem projects, and cryptocurrency exchanges. As the cryptocurrency market entered a new bullish cycle in April 2021, EOS broke above $14.71. It was the highest price in nearly three years. For the MST 2021, ETH is the most influential mode with all high centrality measures, as shown in figure 4. Influential currencies except ETH are, BTC, TUSD, WBTC, BCH, EOS, XTZ, MATIC, and GUSD. The centrality values of all currencies and stable coins are shown in Table 5.

5.1.3 MST 2022

In 2022, the rising trend of cryptocurrency got reversed when the values of numerous crypto assets crashed, following a peak in November 2021. Almost $1.8 trillion in cryptocurrency value vanished as values plummeted. Almost $450 billion was wiped out in the market turbulence that followed the failure of Terra/Luna in May 2022 alone; an additional $200 billion was lost following the collapse of FTX in November 2022 (Cornelli et al., 2023). Ethereum lost 66% of his value from the start to the end of the year. Ethereum also transitioned form proof of work to proof of stake and its price was down by 25% falling from $1635 to $1209. Its price was also badly hit by the market crash triggered by the collapse of FTX exchange.

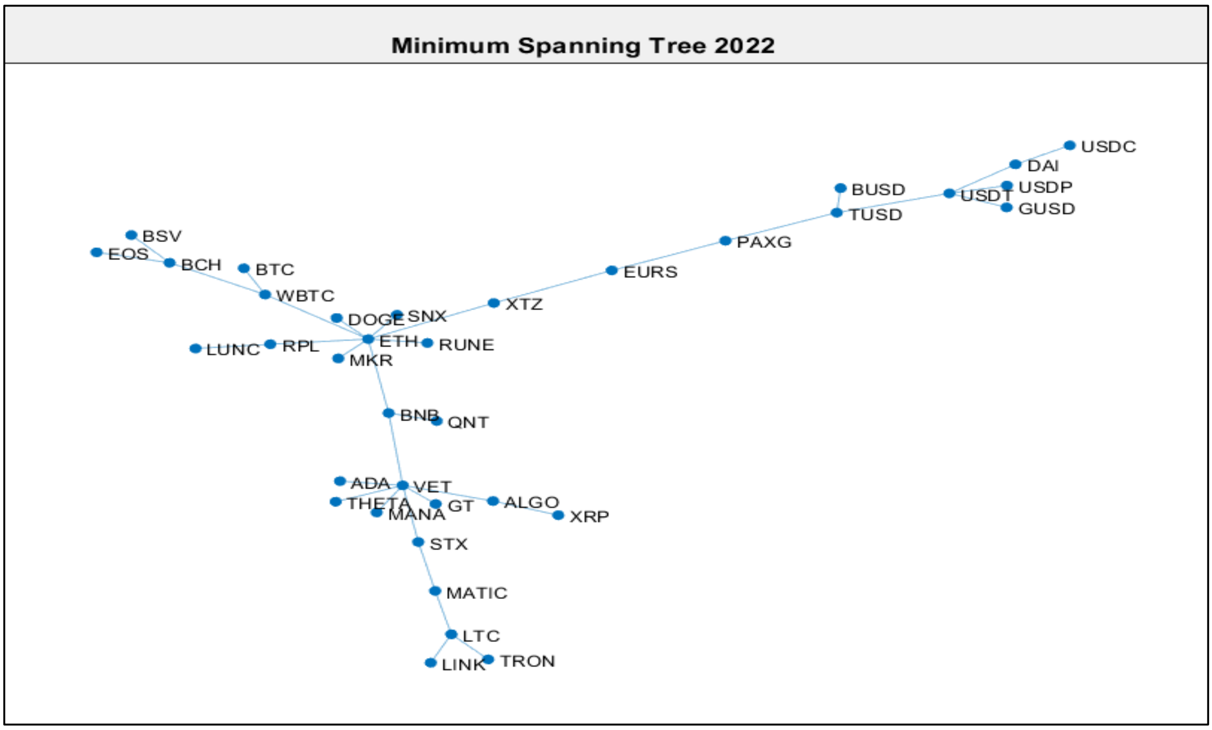

FIGURE 5. Minimum spanning tree is plotted by using data of log return values of selected native cryptocurrencies and stable coins for the year 2022.

The two least impacted by the FTX collapse, in terms of downside risk spillovers, are Tether and Bitcoin (Bouri et al., 2023). Tether (USDT), the world's largest stablecoin, achieved a ground-breaking milestone by surpassing its previous all-time high market cap of $83.2 billion, a record set back in May 2022. After the FTX crash, stablecoins were the most adversely affected tokens, whereas USDC was found to be a net receiver from the system (Esparcia et al., 2023) While USDT continues to gain market dominance, other stablecoins like BUSD and USDC struggle to sustain their market share. BNB price saw many ups and downs during the year and in response to market crashes however, at the end of the year, it saw some recovery. Centrality values of all currencies and stablecoins are given in Table 6.

For MST 2022 as shown in Figure 5, ETH contains the highest values for all centrality measures. BNB, WBTC, EURS, XTZ, USDT, and TUSD also contain high centrality values compared to other cryptocurrencies and stable coins included in our dataset.

5.1.4 MST 2023

For MST 2023 as shown in figure 6, again ETH has the highest centrality values among all cryptocurrencies. The prominent currencies other than ETH are BNB, DAI, WBTC, VET, THETA, ALGO, ADA, DOGE, and SNX.

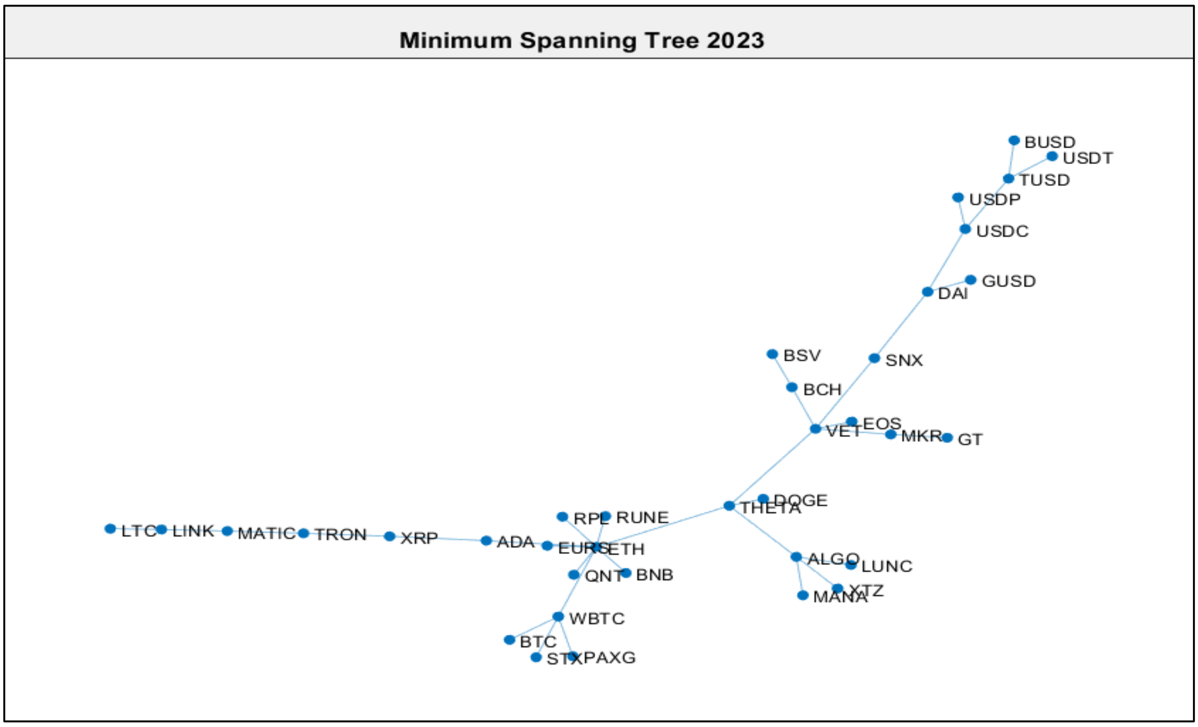

FIGURE 6. Minimum spanning tree is plotted by using data of log return values of selected native cryptocurrencies and stable coins for the year 2023.

In 2023, despite the difficult macroeconomic conditions, the overall market capitalization of cryptocurrencies climbed to almost $1.4 trillion. The sector was probably greatly fueled by an upsurge in confidence about spot Bitcoin and Ether exchange-traded funds in the second half of 2023. Ethereum has seen an 85% increase in market cap in 2023. While this growth is substantial, it slightly underperforms compared to other major assets in the blockchain space. Our findings are consistent with the research of Ali et al. (2023), which suggests that there was an increase in the return and volatility connectivity across cryptocurrencies after the collapse of SVB. This is in line with the findings of (Yi et al., 2018) and (Kumar et al., 2022) and implies a high sensitivity of crypto returns to major economic and financial events in traditional markets. Centrality values of all currencies and stable coins are given in Table 7.

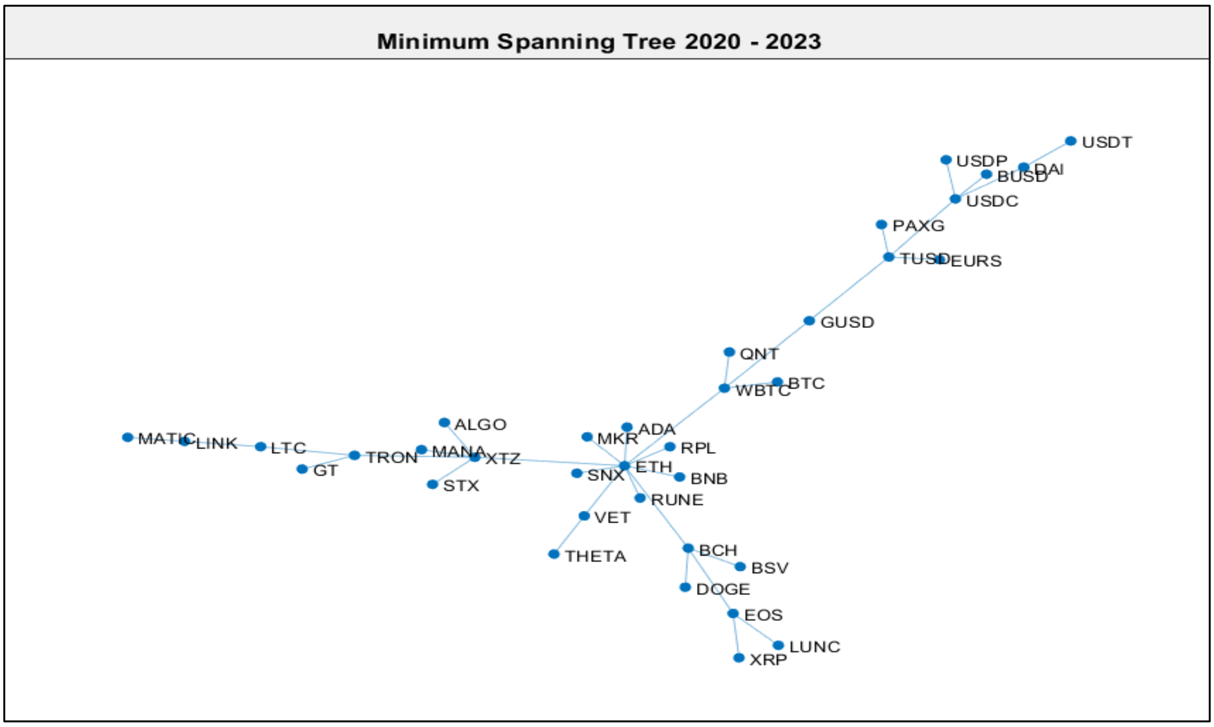

FIGURE 7. Minimum spanning tree is plotted by using data of log return values of selected native cryptocurrencies and stable coins for time period of 2020-2023.

5.1.5 MST 2020 – 2023

ETH is the most influential crypto currency, with high values for all centrality measures. Other than ETH, currencies with high centrality values are USDC, TUSD, WBTC, BCH, XTZ, and GUSD in the cryptocurrency network.

The most widely used cryptocurrency in the cryptocurrency ecosystem, BTC, does not seem to be the most central. The ETH platform is a large project that is home to several decentralized applications, while Bitcoin is only a payment method that is primarily utilized for speculative purposes (Francés et al., 2018). ETH being the most central and influential crypto currency is also confirmed by the research conducted by Hong et al. (2022), which confirms that Ethereum platform is the most famous platform for employing smart contracts rather than acting only as a store of wealth or a competitive alternative to traditional fiat money (Peng et al., 2018). Unlike Bitcoin, Ethereum has an endless supply of currencies. Eth can host both decentralized applications and tokens or coins. The emergence of decentralized applications running on blockchain, handling many of the financial tasks without involving intermediaries became very popular and many of these decentralized applications are running on the Ethereum blockchain, which makes it the most central, popular and influential node in the crypto currency network (Ciaian et al., 2018). It is also observed that Ethereum serves as a benchmark node with a hierarchical structure for most other assets. It continues to play this role over time, however, losing its centrality over turbulent time periods (Briola et al., 2022). MATIC is the periphery node with the smallest centrality values, which shows it is least affected by changes in large cryptocurrency prices and thus can provide hedging against volatile currencies, while GUSD has the highest centrality values among stable coins and USDT has the lowest centrality values. Research findings from a study also confirmed the position of USDT as a peripheral node in the network structure of cryptocurrencies and ETH as one of the central nodes in the network (Polovnikov et al., 2020). The centrality values of all currencies and stable coins are given in Tables 9 and 10.

5.1.6 MST Weight

MST 2022 has an MST weight of 12.6528, which is the smallest of all MSTs. It suggests the emergence of nodes during periods of crisis. (Tomeczek, 2022).

Table 11: MST Weight for individual years

Year	MST Weight
2020	13.6353
2021	13.5954
2022	12.6528
2023	13.3544

During the period of market turmoil not the whole market moves in unison; instead, some nodes become more prominent while connections with other nodes become weak. The high MST weight in 2023 shows a market recovery.

5.2 Empirical Results of CoVaR Analysis

The results are structured as follows: The unconditional estimates of VaR, CoVaR, and ΔCoVaR are given at 1%, 5%, and 10% percentile in Tables 12, 13, and 14 respectively. As unconditional estimations are not time-varying but are constant over time.

In order to provide an overview of each cryptocurrency's loss in terms of VaR, the summary of VaR values at 1%, 5%, and 10% are given in Tables 15 and 16. From these figures, it can be concluded that LUNC has the highest VaR value at 1%, and at 5% and 10%, RUNE has the highest value, while BTC and WBTC have the lowest value at risk at different quantiles.

Table 15: Summary of VaR values for Native cryptocurrencies 2020-2023

Highest VaR			**Lowest VaR**		
Unconditional			Unconditional		
At 1%	**At 5%**	**At 10%**	**At 1%**	**At 5%**	**At 10%**
LUNC	RUNE	RUNE	BTC	WBTC	BTC

Table 16: Summary of VaR values for Stable Coins 2020-2023

Highest VaR			**Lowest VaR**		
Unconditional			Unconditional		
At 1%	**At 5%**	**At 10%**	**At 1%**	**At 5%**	**At 10%**
EURS	EURS	EURS	USDT	USDC	USDT

Among stable coins, EURS has the highest VAR value according to unconditional estimates, while USDT has the lowest value at risk at 5 and 10, and USDC has the lowest value at 5% quantiles, as shown in Table 20.

CoVaR estimation involves running quantile regression, in which cryptosystem returns are dependent variables and are regressed on the returns of each cryptocurrency. CoVaR estimation provides information about the spillover effects of the system on cryptocurrencies when it is in distress. ΔCoVaR quantifies the contribution of an institution's shift (from a median state of 50% VaR to financial distress of 1% VaR) to the VaR of the cryptocurrency market.

Table 17: 5.2.3 Summary of ΔCoVaR results for 2020-2023

Highest ΔCoVaR			**Lowest ΔCoVaR**		
Unconditional			Unconditional		
At 1%	**At 5%**	**At 10%**	**At 1%**	**At 5%**	**At 10%**
ETH	BTC	ETH	GT	MATIC	GT

ΔCoVaR values are highest for BTC and ETH in unconditional results at different quantile levels. Our results are in line with the results generated by Chen et al. (2024). They analyzed the risk-connectedness of five cryptocurrencies (BTC, ETH, ADA, LTC, and BNB) during periods of extreme events by using returns, volatility, skewness, and kurtosis. The time-varying connectedness was found to be higher among all cryptocurrencies during periods of high volatility. During 2018 and the first half of 2019, Bitcoin showed high volatility spillovers, but Ether leads in risk spillover at all order moments, whereas BNB is the net receiver. Another study showed that the market observes how Ethereum and Bitcoin move to respond. The overarching altcoins decline along with Bitcoin and Ethereum, and vice versa. While new cryptocurrency assets might still be introduced to the market, it is highly likely that they will follow the price movements of Ethereum and Bitcoin, which control the majority of the market for all cryptocurrencies with the exception of stablecoins (Obeng, 2022). Ethereum was identified as the most influential cryptocurrency in the post-COVID period (Hong et al., 2022). Bruhn and Ernst also found Bitcoin and Ethereum to have strong and positive intra-market correlations with altcoins in the cryptocurrency market, and all 20 currencies were heavy-tailed and prone to extreme risks (Bruhn et al., 2022). Extreme tail risk in BTC, ETH, LTC, and XRP was also found in the ΔCoVaR analysis conducted by (Borri, 2019) for the period of 2015 to 2018. Results showed that all 4 cryptocurrencies were found to be highly correlated both conditionally and unconditionally. Some other studies which confirm BTC and ETH as net transmitters of risk in the cryptocurrency market are Mensi et al. (2021); Hasan et al. (2021), and Koutmos (2018). A summary of the results of ΔCoVaR values is shown in Tables 17 and 18.

Table 18: Summary of ΔCoVaR values for Stable coins for 2020-2023

Highest ΔCoVaR			**Lowest ΔCoVaR**		
Unconditional			Unconditional		
At 1%	**At 5%**	**At 10%**	**At 1%**	**At 5%**	**At 10%**
GUSD	GUSD	GUSD	BUSD	USDP	USDT

ΔCoVaR values are highest for GUSD in unconditional results at all quantile levels. While USDT, BUSD, and USDP have the lowest ΔCoVaR values at different quantile levels, According to the research conducted by Kołodziejczyk (2023) among stablecoins, Gemini Dollar exhibited the highest volatility, with daily returns varying between -11% and +13%. Not only that, but it is the only stablecoin with a negative mean return. For monthly investment horizons, it acts as a weak hedge, and the price of GUSD moves with the price of Bitcoin, so the relationship between the Gemini Dollar and Bitcoin could be referred to as a co-movement rather than a contagion because it is present in both regular and distressed market conditions. From a risk management standpoint, GUSD is sometimes a hedge and other times a diversifier. Also, research findings (Ma et al., 2023) confirmed our results and showed that GUSD has the highest price deviation from its peg value of $1 when examining the run risk of all USD-backed stablecoins. For each stablecoin, the magnitude of these price deviations was different. The average discount at USDC was just 1 bps, compared to an average of 55bps of USDT. The average discount of GUSD was the highest at 78 bps, while that of BUSD, TUSD, and USDP is likewise lower than that of USDT at 1 bps, 11 bps, and 18 bps, respectively.

Our results are also compatible with research (Wang et al., 2020), in which researchers examined stable coins by using time-varying copula models for mixed cryptocurrency-stable coin portfolios. They discovered that USDT shows the best characteristics of a strong hedge for risk diversification. Another research (Xie et al., 2021) confirms our results which used new data from the COVID-19 pandemic outbreak and examined if stablecoins have safe haven properties for traditional native cryptocurrencies. The findings confirm Tether's status as a safe haven before, during, and after the pandemic and further, when Tether is added to the portfolio, it outperforms both the naked portfolio and the portfolio which includes assets backed by traditional assets i.e., gold. Another study (Baur et al., 2021) provided evidence for the safe haven properties of stablecoins, specifically Tether. Not all stable coins remain stable in case of high price volatility, and some of them respond negatively as well. However, Tether, in response to extreme price volatility and negative returns of bitcoin, behaves positively and thus offers investors security and protection, lowering overall risk in the cryptocurrency market. Tether also provides hedging against bitcoin volatility. Results also showed that stablecoins are not stable all the time but they offer hedging against negative returns. Specifically, Tether, among all stablecoins, has the strongest positive response to extreme negative returns, thus offering investors a safe haven.

It is clear from the results that some cryptocurrencies have a higher VaR than their ΔCoVaR value, which means that although their individual losses are higher, their spillover effect and contribution to systemic risk are very small. Some cryptocurrencies which have a small VaR value than their ΔCoVaR value indicate that their individual risk is small but their contribution to systemic risk is large. Research results show that all native cryptocurrencies have high VaR values when compared with their ΔCoVaR values in unconditional estimation. On the other hand, those stable coins that have a higher CoVaR value than their VaR values are USDT, USDC, TUSD, BUSD, PAXG, and GUSD at different quantiles (1%, 5%, and 10%), which means that though their individual losses are small in case of crises, their risk contribution to cryptocurrency market distress is high.

5.3 Robustness check and Extension of CoVaR analysis

In order to check the robustness of the results of CoVaR analysis, time-varying ΔCoVaR analysis was performed by including lagged state variables in the CoVaR analysis. As conditional estimates are time-varying, they also capture the aspect of time in analysis. According to conditional estimates, LUNC, RUNE, and SNX have the highest value at risk at different quantiles, while BTC and WBTC have the lowest value at risk at different quantiles. These results confirm our unconditional results discussed in Section 5.2.

Table 19: Summary of VaR values for Native cryptocurrencies 2020-2023

Highest VaR			**Lowest VaR**		
Conditional			Conditional		
At 1%	**At 5%**	**At 10%**	**At 1%**	**At 5%**	**At 10%**
LUNC	RUNE	RUNE/ SNX	WBTC	BTC	BTC/ WBTC

Table 20: Summary of VaR values for Stable Coins 2020-2023

Highest VaR			**Lowest VaR**		
Conditional			Conditional		
At 1%	**At 5%**	**At 10%**	**At 1%**	**At 5%**	**At 10%**
EURS	EURS	EURS	USDT/ USDC/ TUSD	USDT/ USDC/ TUSD/ BUSD	USDT

Table 21: Summary of ΔCoVaR values for Stable coins for 2020-2023

Highest ΔCoVaR			**Lowest ΔCoVaR**		
Conditional			Conditional		
At 1%	**At 5%**	**At 10%**	**At 1%**	**At 5%**	**At 10%**
BTC	ETH	ETH	MATIC	MATIC	GT/ MATIC/ LINK/ TRON

Table 22: Summary of ΔCoVaR values for Stable coins for 2020-2023

Highest ΔCoVaR			**Lowest ΔCoVaR**		
Conditional			Conditional		
At 1%	**At 5%**	**At 10%**	**At 1%**	**At 5%**	**At 10%**
GUSD/ PAXG	GUSD	GUSD	BUSD	USDC	USDT

The detailed conditional estimates of VaR, CoVaR, and ΔCoVaR at 0.01, 0.05, and 0.10 quantiles are presented in Tables 23, 24, and 25 respectively.

5.4 Empirical results of regression analysis between time-varying ΔCoVaR and centrality measures:

To analyze the interconnections in the cryptocurrency market and its impact on the systemic risk contribution of cryptocurrencies over time a simple linear regression is run between centrality values and time-varying ΔCoVaR values. The ΔCoVaR value of native cryptocurrencies and stable coins are regressed against centrality values i.e. betweenness, closeness, degree, and eigenvector. The control variables are the SP500 index returns, VIX index, and fear and greed index (FIG) of the cryptocurrency market.

The results of simple linear regression for native cryptocurrencies are shown in Tables 26, 27, 28, and 29. Results show that there exists a significant negative relationship between each centrality value and ΔCoVaR of the index of native cryptocurrencies. The coefficient value of regression between betweenness and ΔCoVaR is -.0000692 with 0.0543, -8.233668 with 0.0664 for closeness, -.0072127 with 0.0574 for degree centrality, and -.3772624 with 0.0738 for eigenvector. The relationship of SP500 and VIX with ΔCoVaR in all regression analyses is significant and negative while with fear and greed index is positive, however, this positive relationship is insignificant.

The results of the simple linear regression between time-varying ΔCoVaR values of stablecoins and centrality values are shown in Tables 29, 30, 31, and 32. The results indicate a positive and significant relationship between ΔCoVaR and the betweenness and degree measure of stablecoins. The relationship between closeness and eigenvector is negative and insignificant. The coefficient values of betweenness and degree are .0000159, 0.0970, and .0016264, 0.1007, respectively. The relationship with SP500, VIX, and FIG is negative and significant in all regression analyses. The significance of all coefficient values was checked by the Wald test. All coefficient values were found to be significant for native cryptocurrencies however for stable coins the centrality values for closeness and eigenvector centrality were found to be insignificant.

Contradicting views are found in literature when it comes to the causes of risk and contagion behavior of financial assets and institutions and how their network structure impacts them. According to Freixas et al. (2000), a more integrated network structure makes the system more resilient to any bank's insolvency. For instance, Allen and Gale (2000) contend that in a financial network with a greater density of connections, the losses of a bank in trouble are distributed among multiple nodes, lessening the effect of adverse shocks to specific institutions of the remainder of the framework. However, some researchers have argued that the more interconnected and concentrated a network is, the more it is vulnerable to contagions and shocks (Blume et al., 2011). Both views hold in the case of our research results of regression analysis between native cryptocurrencies and different centrality values to gauge the relationship between interconnections (degree, closeness, betweenness, and eigenvector) and systemic risk. Results show that the systemic risk contribution of native cryptocurrencies decreases with the increase in interconnections as shown by a negative relationship with each centrality measure. However, In the case of stablecoins, the systemic risk contribution increases with the increase in interconnections as indicated by positive results of regression analysis. There can be various reasons for the difference in the behavior of native currencies and stablecoins in response to changes in connectivity in the network.

According to Melachrinos and Pfister (2020), the emergence of very large issuers of stablecoins could give their initiatives a potentially systemic impact because they can reach a wider public and offer users a better degree of confidence. This worldwide spread of stablecoins would put monetary policy and financial stability at risk, especially in less developed nations. Aramonte et al. (2021) also mentioned in their research that the way that different designs ensure a constant value of stablecoins differs. Since they are administered off-chain, centrally managed, like USD Tether, make up the bulk of stablecoins. A designated intermediary oversees the reserve assets that underpin centralized stable coins as well as their issuance and redemption. Therefore, an increase in the concentration of stablecoins can cause an increase in risk contribution.

Also, counterparty risk is very low for native cryptocurrencies because most of the native cryptocurrencies are managed, issued, and governed in a decentralized manner whereas it is high for stablecoins as they are issued, managed, and governed by some centralized entities. Failure of a single central counterparty of any major stable coin that is highly integrated can be a potential source of systemic risk. However, if governance and issuance of currencies are operated through a distributed and decentralized system it can greatly reduce the counterparty risk. According to Colombo (2023) a blockchain-based distributed and decentralized system could run on a single node, meaning that even if all but one node failed, the network would survive and continue to operate. Since all nodes participate in validating and recording transactions in the blockchain and they have the same set of data, for the network to fail, it would mean that all nodes have failed. This is less likely to happen the more nodes are present in the network.

The negative relationship between the systemic risk contribution of both native cryptocurrencies and stablecoins and stock market returns is confirmed by Xu (2022) who investigated the connections between cryptocurrencies and crypto-exposed US companies and discovered that when major cryptocurrencies experience significant increases in returns, significant increases in stock returns of blockchain and crypto-exposed US companies are more likely to occur. A recent research investigation carried out by Dong (2023) empirically investigated the contagion risk and systemic risk in crypto stocks. The study observed co-movements in crypto and stock markets. When there is an increase in stock market returns investors, also increase their investment in crypto assets which reduces systemic risk in this market and vice versa. Niyitegeka (2023) investigated by employing the DDC GARCH model and Wavelet analysis method, to measure the presence of financial contagion between cryptocurrency and equity markets during the black swan event of COVID-19. The generated results showed that in the first and second quarters of 2020, which correlate to times of financial unrest, were when the growing conditional correlation was most frequently observed. The presence of the pure form of financial contagion is also indicated by the rise in conditional correlation during times of financial turmoil according to Iyer (2022).

The relationship of native cryptocurrencies with FIG is positive but insignificant in our study. The Crypto Fear and Greed Index may give investors some idea of the current perception of some aspects of the cryptocurrency market but it is not useful as a tool for making investment decisions. Johnson (2023). FIG coefficients were negatively related to the systemic risk of stable coins and the relationship was significant which indicates that when there is fear in the cryptocurrency market people take a flight towards stable coins for their investment and in case of a greedy environment people withdraw from stable coins and invest in native cryptocurrencies which increases risk contribution of stable coins.

Conclusion

In recent years, the cryptocurrency market has observed ups and downs in the market, and many real-world phenomena have marked their impact on the cryptocurrency ecosystem. To investigate how topology structures based on interconnections of crypto assets change in response to these events, we have used the Minimum Spanning Tree methodology obtained from the Pearson correlation of daily returns for the period 2020–2023. It estimates the correlation between the prices of cryptocurrencies and the relationship between them. Further, to measure the systemic risk contribution and spillover effect of cryptocurrencies and stablecoins, we have used the unconditional and conditional CoVaR and ΔCoVaR approaches. This approach identifies the risk of assets in isolation and as a whole for the market. The state variables for the estimation of the conditional ΔCoVaR estimate are the SP500 index, the CBOE volatility index, which captures real-world market changes, and the market capitalization of cryptocurrencies, which is used as a market indicator of the crypto ecosystem. Lastly, simple linear regression is run between the centrality measures obtained from MST analysis and the time-varying ΔCoVaR values of native cryptocurrencies and stablecoins. The control variables used in our regression analysis are SP500, the CBOE volatility index, and the fear and greed index of the cryptocurrency market. Results obtained from centrality values identify Ether as the central, most interconnected, and most influential node in the cryptocurrency market and GUSD as the most interconnected node in the MST analysis of 2020–2023. While results obtained from unconditional ΔCoVaR at 1% and 10% and conditional ΔCoVaR at 5% and 10% analysis indicate that Ether has the highest risk contribution in systemic risk, both unconditional and conditional estimates of ΔCoVaR at 1%, 5%, and 10% confirm GUSD as the highest risk contributor. MATIC is the periphery node among native cryptocurrencies, and USDT is the periphery node among stable coins with the lowest centrality values. MATIC is also the least risk contributor according to the unconditional estimation of ΔCoVaR at 5% and the conditional estimation at 1%, 5%, and 10% while Tether is the least risk contributor according to the unconditional estimation of ΔCoVaR at 1% and 10% and according to the conditional estimation at 10%.

For a thorough analysis, we employed both approaches for each year from 2020 to 2023 to examine the impact of significant events that occurred in the crypto market on native cryptocurrencies and stablecoins. The emergence of important nodes during periods of crises was observed in the cryptocurrency market in different years, as indicated by the MST weight calculated for each year. MST weight was lowest for MST 2022, which marks the collapse of two major cryptocurrencies. Results from unconditional and conditional time-varying ΔCoVaR estimates calculated for each year at 1%, 5%, and 10% showed that individual losses calculated by value at risk (VaR) were higher for native cryptocurrencies and lower for stablecoins. However, ΔCoVaR values of BTC and stable coins were higher than their VaR values which indicates that their spillover effect and risk contribution are higher than their risk in isolation. In addition, the results of the linear regression between centrality values and time-varying ΔCoVaR values showed that the systemic risk contribution of native cryptocurrencies decreases with the increase in interconnections while that of stablecoins increases with the increase in interconnections. This could be attributed to the decentralized nature of the underlying blockchain technology of native cryptocurrencies which makes them risk absorbers with the increase in their interconnection. On the other hand, all stablecoins included in our study except DAI are centralized in their issuance, management, and governance. The relationship with SP500 and the Volatility Index VIX is negative for both native cryptocurrencies and stablecoins and is statistically significant which hints that when investors see high returns in traditional markets they also increase their investment in the crypto market which reduces their risks. Also, the relationship with fear and greed index is positive but is statistically insignificant and this result is in line with the research carried out by Johnson (2023) who confirmed that investors don’t take into account the fear and greed index while making investment decisions. Our research has important implications for risk managers, policymakers, and portfolio managers.

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Table 1. List of Native Cryptocurrencies

Name	Code
Bitcoin	BTC
Ethereum	ETH
BNB	BNB
Ripple	XRP
Cardano	ADA
DogeCoin	DOGE
Wrapped Bitcoin	WBTC
Bitcoin Cash	WBTC
Algorand	ALGO
ThorChain	RUNE
Rocket Pool	RPL
Terra Classic	LUNC
Tron	TRON
ChainLink	LINK
LiteCoin	LTC
Polygon	MATIC
Maker	MKR
VeChain	VET
Quant	QNT
Stacks	STX
Synthetix	SNX
Theta Network	THETA
EOS	EOS
Bitcoin SV	BSV
Decentraland	MANA
Gate Token	GT
Tezos	XTZ

Table 2. List of Stable Coins:

Name	Code
Tether	USDT
USD Coin	USDC
True USD	TUSD
Binanace USD	BUSD
DAI	DAI
USDP	USDP
Pax Gold	PAXG
Statis Euro	EURS
Gemini Dollar	GUSD

Table 3: Descriptive Statistics of Native cryptocurrencies and Stable coins

Variable	Obs	Mean	Std. Dev.	Min	Max
BTC	45	.024	.2	-.474	.391
ETH	45	.049	.253	-.599	.578
BNB	45	.055	.328	-.566	1.555
XRP	45	.017	.374	-1.106	1.02
ADA	45	.034	.344	-.442	1.333
DOGE	45	.072	.47	-.419	2.072
WBTC	45	.024	.202	-.478	.39
BCH	45	-.01	.279	-.684	.991
ALGO	45	-.019	.298	-.77	.668
RUNE	45	.06	.48	-.671	1.129
LUNC	45	-.178	2.07	-13.435	1.298
RPL	45	.085	.393	-.56	1
TRON	45	.035	.216	-.542	.704
LINK	45	.024	.287	-.593	.696
LTC	45	-.001	.221	-.399	.454
MATIC	45	.075	.435	-.611	1.788
MKR	45	.023	.292	-.688	.925
VET	45	.025	.341	-.592	.826
QNT	45	.068	.306	-.613	1.005
SNX	45	.012	.362	-.598	.898
STX	45	.036	.362	-.783	1.16
THETA	45	.041	.391	-.633	1.374
EOS	45	-.044	.216	-.474	.368
BSV	45	-.048	.193	-.615	.399
MANA	45	-.048	.193	-.615	.399
XTZ	45	-.02	.256	-.534	.536
GT	45	.048	.234	-.34	.845
USDT	45	0	.016	-.076	.077
USDC	45	-.001	.017	-.081	.075
TUSD	45	0	.016	-.074	.076
BUSD	45	0	.016	-.075	.077
DAI	45	0	.017	-.085	.068
USDP	45	-.001	3.488	-16.118	16.59
PAXG	45	.004	.043	-.08	.104
EURS	45	-.001	.028	-.063	.053
GUSD	45	0	.018	-.076	.078

Table 4. shows the centrality values of all crypto currencies during the year 2020. Centrality measures include degree, betweenness, closeness and eigenvector centrality and **Table 5** represents centrality measures for the year 2021. **Table 6** for the year 2022, **Table 7** for the year 2023 and **Table 8** for the entire period of 2020-2023 respectively.

Table 4: MST Centrality Values 2020

Node	Degree	Closeness	Betweenness	Eigenvector
BTC	1	0.007142857	0	0.020616002
ETH	9	0.011627907	500	0.15744034
USDT	1	0.005154639	0	0.002391204
BNB	1	0.008333333	0	0.048013123
XRP	1	0.005555556	0	0.006119777
USDC	3	0.006410256	98	0.00794612
TUSD	2	0.007692308	96	0.020929173
BUSD	2	0.005319149	34	0.002671728
ADA	3	0.00877193	98	0.059683532
DOGE	1	0.006756757	0	0.018201134
WBTC	4	0.009433962	207	0.067602149
BCH	3	0.00877193	98	0.059683532
DAI	1	0.005263158	0	0.002423255
ALGO	1	0.006849315	0	0.023315631
RUNE	1	0.005555556	0	0.006119777
RPL	1	0.008333333	0	0.048013123
LUNC	1	0.006849315	0	0.023315631
TRON	1	0.00390625	0	0.000272672
LINK	2	0.00625	96	0.00782585
LTC	2	0.004504505	34	0.000894121
MATIC	2	0.005263158	66	0.002659249
USDP	2	0.0078125	124	0.020961223
PAXG	2	0.007575758	124	0.023002579
EURS	1	0.005154639	0	0.002391204
MKR	3	0.009803922	254	0.06078805
VET	2	0.006849315	34	0.020067426
QNT	1	0.007142857	0	0.020616002
STX	1	0.006849315	0	0.023315631
SNX	1	0.008333333	0	0.048013123
THETA	1	0.008333333	0	0.048013123
EOS	2	0.006849315	34	0.020067426
BSV	1	0.006756757	0	0.018201134
MANA	1	0.006849315	0	0.023315631
GT	1	0.004504505	0	0.000814772
XTZ	5	0.008928571	130	0.076454532
GUSD	3	0.00625	67	0.007841023

Table 5: MST Centrality Values 2021

Node	Degree	Closeness	Betweenness	Eigenvector
BTC	2	0.006993007	234	0.02919058
ETH	8	0.008403361	399	0.157423635
USDT	1	0.003278689	0	0.000108343
BNB	1	0.006535948	0	0.051165052
XRP	1	0.005780347	0	0.016620482
USDC	2	0.0041841	66	0.000917294
TUSD	5	0.005524862	211	0.006740702
BUSD	2	0.004784689	96	0.002488964
ADA	1	0.005780347	0	0.016620482
DOGE	1	0.006289308	0	0.032252174
WBTC	4	0.007874016	318	0.078134799
BCH	5	0.008	330	0.099232861
DAI	2	0.003690037	34	0.000333347
ALGO	1	0.005181347	0	0.008081587
RUNE	1	0.006535948	0	0.051165052
RPL	1	0.006535948	0	0.051165052
LUNC	1	0.006535948	0	0.051165052
TRON	1	0.003610108	0	0.000462611
LINK	2	0.004694836	96	0.003454125
LTC	3	0.004115226	67	0.001423354
MATIC	2	0.005405405	124	0.00920423
USDP	1	0.004651163	0	0.00219083
PAXG	1	0.004651163	0	0.00219083
EURS	1	0.004651163	0	0.00219083
MKR	1	0.006535948	0	0.051165052
VET	1	0.006289308	0	0.032252174
QNT	1	0.00621118	0	0.025394986
STX	1	0.005181347	0	0.008081587
SNX	1	0.006535948	0	0.051165052
THETA	2	0.006289308	34	0.028394425
EOS	4	0.007194245	267	0.051137576
BSV	1	0.006289308	0	0.032252174
MANA	1	0.005181347	0	0.009228616
GT	1	0.003610108	0	0.000462611
XTZ	4	0.006289308	207	0.024865271
GUSD	2	0.00621118	216	0.011678208

Table 6: MST Centrality Values 2022

Node	Degree	Closeness	Betweenness	Eigenvector
BTC	1	0.005847953	0	0.020207778
ETH	8	0.009009009	448	0.142835479
USDT	4	0.004694836	129	0.001676196
BNB	3	0.008403361	298	0.082250395
XRP	1	0.005076142	0	0.00978708
USDC	1	0.003584229	0	0.000200964
TUSD	3	0.005347594	179	0.00341182
BUSD	1	0.004524887	0	0.001116334
ADA	1	0.006060606	0	0.026709674
DOGE	1	0.006896552	0	0.046735215
WBTC	3	0.00729927	127	0.061760443
BCH	3	0.005988024	67	0.02571339
DAI	2	0.004081633	34	0.000614199
ALGO	2	0.006134969	34	0.029911969
RUNE	1	0.006896552	0	0.046735215
RPL	2	0.006993007	34	0.052338426
LUNC	1	0.005649718	0	0.01712493
TRON	1	0.004016064	0	0.001573258
LINK	1	0.004016064	0	0.001573258
LTC	3	0.004651163	67	0.004808303
MATIC	2	0.005405405	96	0.011548961
USDP	1	0.004048583	0	0.000548445
PAXG	2	0.006060606	196	0.007634916
EURS	2	0.006896552	216	0.019922551
MKR	1	0.006896552	0	0.046735215
VET	7	0.007633588	308	0.081632001
QNT	1	0.006535948	0	0.026912011
STX	2	0.006369427	124	0.03048845
SNX	1	0.006896552	0	0.046735215
THETA	1	0.006060606	0	0.026709674
EOS	1	0.004975124	0	0.008413322
BSV	1	0.004975124	0	0.008413322
MANA	1	0.006060606	0	0.026709674
GT	1	0.006060606	0	0.026709674
XTZ	2	0.007874016	234	0.053253797
GUSD	1	0.004048583	0	0.000548445

Table 7: MST Centrality Values 2023

Node	Degree	Closeness	Betweenness	Eigenvector
BTC	1	0.005848	0	0.023412
ETH	8	0.009174	384	0.151003
USDT	1	0.004082	0	0.000518
BNB	1	0.006993	0	0.049122
XRP	2	0.006289	124	0.020647
USDC	3	0.005525	127	0.003856
TUSD	3	0.004739	67	0.001591
BUSD	1	0.004082	0	0.000518
ADA	2	0.007519	150	0.055838
DOGE	1	0.007194	0	0.02953
WBTC	4	0.007299	99	0.071969
BCH	2	0.006897	34	0.020102
DAI	3	0.006452	179	0.009008
ALGO	4	0.007519	99	0.043265
RUNE	1	0.006993	0	0.049122
RPL	1	0.006993	0	0.049122
LUNC	1	0.005988	0	0.014074
TRON	2	0.005348	96	0.007633
LINK	2	0.004016	34	0.001025
LTC	1	0.003534	0	0.000333
MATIC	2	0.004608	66	0.002816
USDP	1	0.004651	0	0.001254
PAXG	1	0.005848	0	0.023412
EURS	1	0.006993	0	0.049122
MKR	2	0.006897	34	0.020102
VET	5	0.00885	334	0.055257
QNT	1	0.006993	0	0.049122
STX	1	0.005848	0	0.023412
SNX	2	0.007519	196	0.020906
THETA	4	0.009524	378	0.090777
EOS	1	0.006803	0	0.017975
BSV	1	0.005587	0	0.006539
MANA	1	0.005988	0	0.014074
GT	1	0.005587	0	0.006539
XTZ	1	0.005988	0	0.014074
GUSD	1	0.005291	0	0.00293

Source: Author’s own calculations

Table 8: MST Centrality Values 2020-2023				
Node	Degree	Closeness	Betweenness	Eigenvector
BTC	1	0.007407407	0	0.01945752
ETH	10	0.011235955	477	0.161641912
USDT	1	0.004329004	0	0.000360597
BNB	1	0.008130081	0	0.047772257
XRP	1	0.005649718	0	0.007027304
USDC	4	0.006060606	129	0.003767774
TUSD	4	0.007194245	207	0.009301419
BUSD	1	0.005025126	0	0.001113542
ADA	1	0.008130081	0	0.047772257
DOGE	1	0.006802721	0	0.019623791
WBTC	4	0.00990099	283	0.065836345
BCH	4	0.008849558	157	0.066398938
DAI	2	0.005076142	34	0.001220114
ALGO	1	0.007092199	0	0.02237781
RUNE	1	0.008130081	0	0.047772257
RPL	1	0.008130081	0	0.047772257
LUNC	1	0.005649718	0	0.007027304
TRON	3	0.007518797	127	0.027421651
LINK	2	0.005128205	34	0.002902159
LTC	2	0.006134969	66	0.008962013
MATIC	1	0.004366812	0	0.000857715
USDP	1	0.005025126	0	0.001113542
PAXG	1	0.005780347	0	0.002748976
EURS	1	0.005780347	0	0.002748976
MKR	1	0.008130081	0	0.047772257
VET	2	0.008264463	34	0.05234433
QNT	1	0.007407407	0	0.01945752
STX	1	0.007092199	0	0.02237781
SNX	1	0.008130081	0	0.047772257
THETA	1	0.006451613	0	0.01547004
EOS	3	0.006993007	67	0.023777543
BSV	1	0.006802721	0	0.019623791
MANA	1	0.007092199	0	0.02237781
GT	1	0.005988024	0	0.008104298
XTZ	5	0.009345794	234	0.07571742
GUSD	2	0.008403361	216	0.022206496

Table 9: Summary of highest and lowest centrality values Index for native crypto currencies and Stable coins for individual years from 2020-2023

Native Cryptocurrencies 2020	Highest Centrality Values	Lowest Centrality Values
Centrality Index	ETH	TRON
Stable Coins 2020		
Centrality Index	PAXG	USDT/EURS
Native Cryptocurrencies 2021		
Centrality Index	ETH	TRON/GT
Stable Coins 2021		
Centrality Index	GUSD	USDT
Native Cryptocurrencies 2022		
Centrality Index	ETH	TRON/LINK
Stable Coins 2022		
Centrality Index	EURS	USDC
Native Cryptocurrencies 2023		
Centrality Index	ETH	LTC
Stable Coins 2023		
Centrality Index	DAI	BUSD/USDT

Table 10: Summary of highest and lowest centrality values Index for native crypto currencies and Stable coins for entire period of 2020-2023

Native Cryptocurrencies 2020-2023	Highest Centrality Values	Lowest Centrality Values
Centrality Index	ETH	MATIC
Stable Coins 2020 - 2023		
Centrality Index	GUSD	USDT

Table 12: Results of unconditional VaR, CoVaR, DCoVaR at 0.01 for native cryptocurrencies and stable coins

`x'	a_`x'	b_`x'	`x'_VaR	CoVaR_`x'	`x'_median	DCoVaR_`x'
Bitcoin	-0.04191	0.664228	-0.10405	-0.11102	0.000472	-0.06942
Ether	-0.04574	0.558138	-0.13644	-0.12189	0.001577	-0.07703
BNB	-0.05755	0.412822	-0.13998	-0.11533	0.001824	-0.05854
XRP	-0.06398	0.31348	-0.15108	-0.11134	0.000509	-0.04752
ADA	-0.06588	0.454764	-0.12891	-0.1245	0.000632	-0.05891
DOGE	-0.07825	0.144831	-0.17054	-0.10295	-0.00032	-0.02465
WBTC	-0.04172	0.667594	-0.10512	-0.1119	0.000587	-0.07057
BCH	-0.05512	0.379487	-0.15752	-0.11489	0.000983	-0.06015
ALGO	-0.05662	0.402749	-0.15815	-0.12031	0.001222	-0.06419
RUNE	-0.05607	0.296504	-0.20169	-0.11587	0.000132	-0.05984
RPL	-0.07342	0.305319	-0.21287	-0.13841	0.003408	-0.06603
LUNC	-0.0717	0.155704	-0.24481	-0.10982	-0.00209	-0.03779
TRON	-0.09328	-0.0226	-0.13708	-0.09018	0.002428	0.003154
LINK	-0.09275	-0.01817	-0.15446	-0.08995	0.003011	0.002862
LTC	-0.09398	-0.02808	-0.16172	-0.08944	0.001396	0.00458
MATIC	-0.09123	0.05328	-0.18042	-0.10084	0.000861	-0.00966
MKR	-0.06264	0.294252	-0.13868	-0.10344	-0.00015	-0.04076
QNT	-0.06731	0.287932	-0.15193	-0.11105	-0.00139	-0.04334
STX	-0.07535	0.225492	-0.16634	-0.11286	0.000258	-0.03757
SNX	-0.06532	0.326238	-0.18054	-0.12422	-0.00126	-0.05849
Theta	-0.06336	0.313582	-0.15696	-0.11258	0.001093	-0.04956
EOS	-0.05	0.405804	-0.16867	-0.11845	0.00038	-0.0686
BSV	-0.06692	0.257414	-0.14747	-0.10488	-0.00015	-0.03792
MANA	-0.06521	0.237231	-0.16619	-0.10464	0.001116	-0.03969
GT	-0.09105	0.005262	-0.13767	-0.09177	0.001137	-0.00073
XTZ	-0.05475	0.376939	-0.16728	-0.11781	0.001654	-0.06368
USDT	-0.08807	3.61484	-0.00741	-0.11486	2.92E-05	-0.0269
USDC	-0.08905	1.802337	-0.00908	-0.10542	0.00004	-0.01644
TUSD	-0.08972	3.717363	-0.00969	-0.12575	-6.6E-05	-0.03577
BUSD	-0.09102	0.218559	-0.00873	-0.09292	7.13E-06	-0.00191
DAI	-0.09228	0.461264	-0.01198	-0.09781	5.95E-05	-0.00555
USDP	-0.09023	0.207306	-0.01286	-0.0929	-2.4E-05	-0.00266
PAXG	-0.08633	1.03791	-0.02864	-0.11605	0.000167	-0.0299
EURS	-0.09105	0.656494	-0.05036	-0.12411	-0.00012	-0.03298
VETUSD	-0.0558	0.396798	-0.17641	-0.1258	0.0013	-0.07051
GUSD	-0.09626	1.231217	-0.03289	-0.13675	-2.4E-05	-0.04047

Table 13: Results of unconditional VaR, CoVaR, DCoVaR at 0.05 for native cryptocurrencies and stable coins

`x'	a_`x'	b_`x'	`x'_VaR	CoVaR_`x'	`x'_median	DCoVaR_`x'
BTC	-0.0246	0.682794	-0.05719	-0.06365	0.00047182	-0.0393713
ETH	-0.02183	0.518678	-0.07169	-0.05902	0.00157664	-0.03800408
BNB	-0.02862	0.396372	-0.06699	-0.05517	0.00182377	-0.02727516
XRP	-0.03156	0.307348	-0.07915	-0.05589	0.00050889	-0.0244826
ADA	-0.02706	0.360284	-0.07891	-0.05549	0.00063202	-0.02865926
DOGE	-0.03732	0.17745	-0.08124	-0.05173	-0.00032166	-0.01435887
WBTC	-0.02363	0.653418	-0.05717	-0.06099	0.00058669	-0.03773746
BCH	-0.02701	0.375261	-0.0779	-0.05625	0.00098337	-0.02960264
ALGO	-0.02729	0.334743	-0.09091	-0.05772	0.0012217	-0.03083895
RUNE	-0.03269	0.242263	-0.11361	-0.06022	0.00013191	-0.02755591
RPL	-0.03241	0.249816	-0.10565	-0.0588	0.00340822	-0.02724355
LUNC	-0.03799	0.126452	-0.11087	-0.05201	-0.00208611	-0.01375568
TRON	-0.04415	0.055206	-0.06871	-0.04794	0.00242823	-0.0039271
LINK	-0.04404	0.055541	-0.09585	-0.04937	0.00301142	-0.00549103
LTC	-0.04361	0.070355	-0.0783	-0.04912	0.00139644	-0.00560684
MATIC	-0.04495	0.037226	-0.09216	-0.04838	0.0008613	-0.00346282
MKR	-0.03029	0.308807	-0.07879	-0.05462	-0.00014807	-0.02428465
QNT	-0.03538	0.255883	-0.08661	-0.05754	-0.00139269	-0.02180689
STX	-0.03311	0.227345	-0.10098	-0.05607	0.0002576	-0.02301494
SNX	-0.03045	0.264023	-0.10951	-0.05937	-0.00125506	-0.02858147
THETA	-0.03222	0.294804	-0.09917	-0.06146	0.00109301	-0.02955819
EOS	-0.02458	0.403781	-0.08775	-0.06001	0.00037988	-0.03558513
BSV	-0.0302	0.329341	-0.08267	-0.05743	-0.00015302	-0.02717594
MANA	-0.03171	0.243173	-0.09694	-0.05529	0.00111637	-0.02384562
GT	-0.04452	0.086313	-0.06068	-0.04976	0.0011368	-0.005336
XTZ	-0.02564	0.357406	-0.09568	-0.05984	0.00165379	-0.03478713
USDT	-0.04537	1.148445	-0.00383	-0.04977	0.00002915	-0.00443424
USDC	-0.04531	-0.23233	-0.00367	-0.04446	0.00004	0.0008615
TUSD	-0.04565	2.388944	-0.00399	-0.05519	-0.000066	-0.00938071
BUSD	-0.04491	-0.26781	-0.00435	-0.04375	7.13E-06	0.00116666
DAI	-0.04584	-0.9134	-0.00508	-0.0412	0.00005946	0.00469553
USDP	-0.04668	0.742768	-0.00488	-0.0503	-0.00002424	-0.00360824
PAXG	-0.04557	0.555865	-0.01438	-0.05357	0.00016729	-0.00808846
EURS	-0.04448	0.362989	-0.02014	-0.05178	-0.00012014	-0.007266
VET	-0.02503	0.365686	-0.08872	-0.05747	0.00129968	-0.03291951
GUSD	-0.04329	0.899588	-0.01383	-0.05574	-0.00002437	-0.01242383

Table 14: Results of unconditional VaR, CoVaR, DCoVaR at 0.10 for native cryptocurrencies and stable coins

`x'	a_`x'	b_`x'	`x'_VaR	CoVaR_`x'	`x'_median	DCoVaR_`x'
Bitcoin	-0.01698	0.66716301	-0.03510787	-0.04040204	0.00047182	-0.02373746
Ether	-0.0158	0.50875764	-0.04754868	-0.03999455	0.00157664	-0.02499289
BNB	-0.01925	0.43783993	-0.04803762	-0.04028222	0.00182377	-0.02183131
XRP	-0.02128	0.35860385	-0.05187419	-0.03988652	0.00050889	-0.01878477
ADA	-0.01744	0.38824224	-0.05630449	-0.03929869	0.00063202	-0.02210516
DOGE	-0.02413	0.2230779	-0.05575504	-0.03657216	-0.00032166	-0.01236596
WBTC	-0.01683	0.63714548	-0.03575474	-0.03960603	0.00058669	-0.02315478
BCH	-0.0173	0.39982997	-0.05265689	-0.03835458	0.00098337	-0.02144698
ALGO	-0.01897	0.34191528	-0.06600758	-0.04154239	0.0012217	-0.02298672
RUNE	-0.02094	0.24669058	-0.08258394	-0.04131468	0.00013191	-0.02040522
RPL	-0.02254	0.26458988	-0.07426051	-0.04219073	0.00340822	-0.02055036
LUNC	-0.02564	0.12882509	-0.07731011	-0.03560204	-0.00208611	-0.00969074
TRON	-0.02954	0.06887386	-0.04549939	-0.03267219	0.00242823	-0.00330096
LINK	-0.03013	0.05507327	-0.06475732	-0.03369498	0.00301142	-0.00373225
LTC	-0.02929	0.08052271	-0.05403033	-0.03364128	0.00139644	-0.00446311
MATIC	-0.0295	0.04548424	-0.07268563	-0.03280592	0.0008613	-0.00334523
MKR	-0.02124	0.31758865	-0.06012089	-0.04032976	-0.00014807	-0.01904669
QNT	-0.02482	0.26797919	-0.06332713	-0.0417931	-0.00139269	-0.01659714
STX	-0.02308	0.23493663	-0.07420884	-0.04051067	0.0002576	-0.0174949
SNX	-0.02204	0.2631451	-0.08207073	-0.04363302	-0.00125506	-0.02126625
Theta	-0.02224	0.29611005	-0.06751943	-0.04223751	0.00109301	-0.02031683
EOS	-0.01657	0.41842356	-0.05930971	-0.04138749	0.00037988	-0.02497553
BSV	-0.02031	0.35665081	-0.05344594	-0.03936895	-0.00015302	-0.01900696
MANA	-0.02055	0.2612247	-0.07207019	-0.0393752	0.00111637	-0.01911814
GT	-0.02926	0.04468565	-0.03713866	-0.03092292	0.0011368	-0.00171036
XTZ	-0.01755	0.38543498	-0.06143952	-0.04123407	0.00165379	-0.02431837
USDT	-0.02942	0.22728439	-0.00239472	-0.02996258	0.00002915	-0.00055091
USDC	-0.02919	-0.07540565	-0.00257191	-0.02899899	0.00004	0.00019695
TUSD	-0.03006	1.4656462	-0.00282145	-0.03419723	-0.000066	-0.00403851
BUSD	-0.02936	-0.18059846	-0.00295489	-0.02883026	7.13E-06	0.00053494
DAI	-0.0303	-0.59260689	-0.00346391	-0.02824524	0.00005946	0.00208797
USDP	-0.0292	0.52711782	-0.00315142	-0.03086052	-0.00002424	-0.00164839
PAXG	-0.03008	0.34024812	-0.01025808	-0.03356731	0.00016729	-0.00354721
EURS	-0.0291	0.38868402	-0.01346985	-0.0343383	-0.00012014	-0.00518882
VETUSD	-0.01734	0.35598393	-0.06437083	-0.04025927	0.00129968	-0.02337765
GUSD	-0.02882	0.72107364	-0.00759791	-0.03429844	-0.00002437	-0.00546108

Table 23: Conditional Descriptive Statistics of VaR, CoVaR, and DCoVaR at 0.01 for native cryptocurrencies and stable coins

Variable	Obs	Mean	Std. Dev.	Min	Max
tVaR BTC	1357	-.103	.025	-.195	-.026
tCoVaR BTC	1357	-.124	.027	-.23	-.05
tDCoVaR BTC	1357	-.078	.018	-.149	-.023
tVaR ETH	1357	-.132	.044	-.327	-.049
tCoVaR ETH	1357	-.115	.032	-.257	-.049
tDCoVaR ETH	1357	-.075	.025	-.185	-.027
tVaR BNB	1357	-.134	.032	-.278	-.063
tCoVaR BNB	1357	-.106	.03	-.245	-.039
tDCoVaR BNB	1357	-.056	.013	-.121	-.026
tVaR XRP	1357	-.145	.024	-.204	-.066
tCoVaR XRP	1357	-.101	.021	-.175	-.038
tDCoVaR XRP	1357	-.044	.007	-.063	-.021
tVaR XTZ	1357	-.164	.029	-.285	-.092
tCoVaR XTZ	1357	-.11	.017	-.172	-.058
tDCoVaR XTZ	1357	-.059	.01	-.1	-.038
tVaR ADA	1357	-.138	.032	-.264	-.064
tCoVaR ADA	1357	-.122	.033	-.26	-.042
tDCoVaR ADA	1357	-.065	.014	-.121	-.037
tVaR DOGE	1357	-.181	.059	-.436	-.04
tCoVaR DOGE	1357	-.106	.034	-.249	-.022
tDCoVaR DOGE	1357	-.026	.008	-.064	-.007
tVaR WBTC	1357	-.097	.023	-.188	-.036
tCoVaR WBTC	1357	-.117	.024	-.218	-.056
tDCoVaR WBTC	1357	-.073	.017	-.143	-.03
tVaR BCH	1357	-.166	.063	-.462	-.039
tCoVaR BCH	1357	-.112	.03	-.254	-.045
tDCoVaR BCH	1357	-.062	.023	-.176	-.014
tVaR ALGO	1357	-.17	.049	-.377	-.089
tCoVaR ALGO	1357	-.125	.021	-.216	-.09
tDCoVaR ALGO	1357	-.069	.019	-.152	-.038
tVaR RUNE	1357	-.205	.045	-.38	-.095
tCoVaR RUNE	1357	-.123	.026	-.237	-.066
tDCoVaR RUNE	1357	-.064	.012	-.116	-.037
tVaR RPL	1357	-.208	.085	-.593	-.07
tCoVaR RPL	1357	-.13	.049	-.355	-.038
tDCoVaR RPL	1357	-.062	.025	-.179	-.02
tVaR LUNC	1357	-.291	.107	-.747	-.06
tCoVaR LUNC	1357	-.11	.03	-.237	-.036
tDCoVaR LUNC	1357	-.046	.017	-.118	-.009
tVaR TRON	1357	-.131	.049	-.382	-.024
tCoVaR TRON	1357	-.081	.023	-.168	-.017
tDCoVaR TRON	1357	.007	.003	.002	.021
tVaR LINK	1357	-.154	.056	-.413	-.032
tCoVaR LINK	1357	-.084	.02	-.16	-.023
tDCoVaR LINK	1357	.001	0	0	.004
tVaR LTC	1357	-.141	.04	-.335	-.049
tCoVaR LTC	1357	-.066	.022	-.159	-.02
tDCoVaR LTC	1357	.013	.004	.005	.032
tVaR MATIC	1357	-.174	.062	-.462	-.033
tCoVaR MATIC	1357	-.089	.026	-.198	-.024
tDCoVaR MATIC	1357	-.002	.001	-.006	0
tVaR MKR	1357	-.136	.048	-.345	-.034
tCoVaR MKR	1357	-.104	.02	-.184	-.048

tDCoVaR MKR	1357	-.039	.013	-.098	-.01
tVaR VET	1357	-.169	.063	-.445	-.035
tCoVaR VET	1357	-.118	.042	-.313	-.024
tDCoVaR VET	1357	-.066	.024	-.179	-.013
tVaR QNT	1357	-.142	.024	-.235	-.096
tCoVaR QNT	1357	-.104	.014	-.159	-.066
tDCoVaR QNT	1357	-.038	.007	-.064	-.026
tVaR STX	1357	-.156	.025	-.262	-.092
tCoVaR STX	1357	-.105	.025	-.217	-.049
tDCoVaR STX	1357	-.033	.005	-.054	-.02
tVaR SNX	1357	-.188	.036	-.332	-.117
tCoVaR SNX	1357	-.123	.022	-.22	-.079
tDCoVaR SNX	1357	-.061	.011	-.106	-.041
tVaR THETA	1357	-.155	.022	-.213	-.079
tCoVaR THETA	1357	-.111	.029	-.238	-.049
tDCoVaR THETA	1357	-.05	.006	-.07	-.028
tVaR EOS	1357	-.171	.024	-.27	-.11
tCoVaR EOS	1357	-.111	.025	-.222	-.055
tDCoVaR EOS	1357	-.058	.008	-.094	-.039
tVaR BSV	1357	-.147	.037	-.321	-.088
tCoVaR BSV	1357	-.102	.025	-.228	-.055
tDCoVaR BSV	1357	-.039	.01	-.089	-.022
tVaR GT	1357	-.116	.03	-.198	-.05
tCoVaR GT	1357	-.09	.027	-.202	-.022
tDCoVaR GT	1357	-.004	.001	-.006	-.002
tVaR USDT	1357	-.008	.003	-.019	-.002
tCoVaR USDT	1357	-.11	.028	-.235	-.049
tDCoVaR USDT	1357	-.025	.009	-.063	-.005
tVaR USDC	1357	-.008	.002	-.019	-.002
tCoVaR USDC	1357	-.101	.027	-.222	-.046
tDCoVaR USDC	1357	-.019	.006	-.048	-.005
tVaR TUSD	1357	-.008	.003	-.021	-.003
tCoVaR TUSD	1357	-.111	.02	-.191	-.055
tDCoVaR TUSD	1357	-.028	.009	-.073	-.009
tVaR BUSD	1357	-.01	.004	-.028	-.002
tCoVaR BUSD	1357	-.078	.021	-.157	-.018
tDCoVaR BUSD	1357	.011	.004	.002	.033
tVaR USDP	1357	-.012	.004	-.03	-.005
tCoVaR USDP	1357	-.081	.023	-.176	-.021
tDCoVaR USDP	1357	.006	.002	.003	.016
tVaR PAXG	1357	-.029	.01	-.078	-.01
tCoVaR PAXG	1357	-.127	.027	-.249	-.077
tDCoVaR PAXG	1357	-.044	.016	-.123	-.014
tVaR EURS	1357	-.043	.011	-.085	-.01
tCoVaR EURS	1357	-.137	.034	-.265	-.03
tDCoVaR EURS	1357	-.043	.011	-.085	-.011
tVaR DAI	1357	-.01	.004	-.027	-.005
tCoVaR DAI	1357	-.085	.019	-.148	-.022
tDCoVaR DAI	1357	.003	.001	.001	.008
tVaR GUSD	1357	-.03	.017	-.105	-.004
tCoVaR GUSD	1357	-.132	.035	-.286	-.07
tDCoVaR GUSD	1357	-.044	.025	-.156	-.005

Table 24: Conditional Descriptive Statistics of VaR, CoVaR, and DCoVaR at 0.05 for native cryptocurrencies and stable coins

Variable	Obs	Mean	Std. Dev.	Min	Max
tVaR BTC	1357	-.054	.011	-.088	-.015
tCoVaR BTC	1357	-.06	.012	-.105	-.026
tDCoVaR BTC	1357	-.035	.007	-.06	-.013
tVaR ETH	1357	-.069	.015	-.121	-.021
tCoVaR ETH	1357	-.06	.012	-.106	-.023
tDCoVaR ETH	1357	-.038	.007	-.067	-.016
tVaR BNB	1357	-.066	.012	-.121	-.037
tCoVaR BNB	1357	-.057	.013	-.112	-.025
tDCoVaR BNB	1357	-.029	.006	-.057	-.016
tVaR XRP	1357	-.077	.017	-.124	-.026
tCoVaR XRP	1357	-.057	.013	-.098	-.022
tDCoVaR XRP	1357	-.025	.006	-.042	-.01
tVaR XTZ	1357	-.092	.018	-.151	-.03
tCoVaR XTZ	1357	-.059	.01	-.095	-.029
tDCoVaR XTZ	1357	-.033	.006	-.054	-.015
tVaR ADA	1357	-.077	.012	-.115	-.035
tCoVaR ADA	1357	-.059	.013	-.108	-.024
tDCoVaR ADA	1357	-.031	.004	-.045	-.02
tVaR DOGE	1357	-.083	.021	-.158	-.029
tCoVaR DOGE	1357	-.051	.011	-.091	-.021
tDCoVaR DOGE	1357	-.015	.004	-.03	-.007
tVaR WBTC	1357	-.055	.011	-.093	-.018
tCoVaR WBTC	1357	-.059	.011	-.1	-.026
tDCoVaR WBTC	1357	-.036	.007	-.063	-.014
tVaR BCH	1357	-.076	.014	-.132	-.04
tCoVaR BCH	1357	-.054	.008	-.085	-.031
tDCoVaR BCH	1357	-.029	.006	-.054	-.016
tVaR ALGO	1357	-.091	.013	-.141	-.055
tCoVaR ALGO	1357	-.058	.009	-.096	-.035
tDCoVaR ALGO	1357	-.031	.004	-.049	-.021
tVaR RUNE	1357	-.116	.019	-.168	-.06
tCoVaR RUNE	1357	-.061	.01	-.104	-.042
tDCoVaR RUNE	1357	-.029	.003	-.038	-.021
tVaR RPL	1357	-.104	.022	-.2	-.068
tCoVaR RPL	1357	-.058	.013	-.119	-.031
tDCoVaR RPL	1357	-.027	.006	-.055	-.017
tVaR LUNC	1357	-.112	.015	-.154	-.057
tCoVaR LUNC	1357	-.053	.011	-.094	-.017
tDCoVaR LUNC	1357	-.015	.002	-.021	-.008
tVaR TRON	1357	-.072	.024	-.183	-.018
tCoVaR TRON	1357	-.044	.008	-.066	-.015
tDCoVaR TRON	1357	-.003	.001	-.007	-.001
tVaR LINK	1357	-.091	.024	-.188	-.025
tCoVaR LINK	1357	-.044	.008	-.069	-.015
tDCoVaR LINK	1357	-.002	.001	-.005	-.001
tVaR LTC	1357	-.079	.016	-.136	-.032
tCoVaR LTC	1357	-.046	.008	-.066	-.015
tDCoVaR LTC	1357	-.004	.001	-.007	-.002
tVaR MATIC	1357	-.092	.022	-.185	-.041
tCoVaR MATIC	1357	-.043	.009	-.074	-.015
tDCoVaR MATIC	1357	-.001	0	-.003	-.001
tVaR MKR	1357	-.077	.016	-.133	-.025
tCoVaR MKR	1357	-.053	.009	-.086	-.027
tDCoVaR MKR	1357	-.024	.004	-.04	-.01
tVaR VET	1357	-.09	.015	-.142	-.043
tCoVaR VET	1357	-.062	.014	-.126	-.03
tDCoVaR VET	1357	-.037	.007	-.063	-.022

tVaR QNT	1357	-.088	.018	-.17	-.053
tCoVaR QNT	1357	-.059	.011	-.105	-.032
tDCoVaR QNT	1357	-.023	.006	-.049	-.013
tVaR STX	1357	-.1	.014	-.145	-.052
tCoVaR STX	1357	-.057	.011	-.1	-.027
tDCoVaR STX	1357	-.024	.003	-.034	-.013
tVaR SNX	1357	-.114	.013	-.165	-.091
tCoVaR SNX	1357	-.06	.01	-.104	-.043
tDCoVaR SNX	1357	-.03	.003	-.042	-.026
tVaR THETA	1357	-.099	.019	-.162	-.032
tCoVaR THETA	1357	-.062	.014	-.126	-.029
tDCoVaR THETA	1357	-.031	.007	-.055	-.012
tVaR EOS	1357	-.085	.014	-.121	-.041
tCoVaR EOS	1357	-.055	.009	-.079	-.023
tDCoVaR EOS	1357	-.03	.005	-.045	-.017
tVaR BSV	1357	-.082	.015	-.137	-.052
tCoVaR BSV	1357	-.056	.004	-.069	-.049
tDCoVaR BSV	1357	-.026	.006	-.047	-.013
tVaR GT	1357	-.057	.02	-.12	-.012
tCoVaR GT	1357	-.05	.01	-.087	-.019
tDCoVaR GT	1357	-.006	.002	-.013	-.001
tVaR USDT	1357	-.004	.001	-.008	-.001
tCoVaR USDT	1357	-.048	.01	-.085	-.016
tDCoVaR USDT	1357	-.005	.001	-.011	-.002
tVaR USDC	1357	-.004	.001	-.008	-.002
tCoVaR USDC	1357	-.043	.009	-.077	-.013
tDCoVaR USDC	1357	-.001	0	-.002	0
tVaR TUSD	1357	-.004	.001	-.01	-.002
tCoVaR TUSD	1357	-.055	.011	-.1	-.024
tDCoVaR TUSD	1357	-.011	.004	-.028	-.004
tVaR BUSD	1357	-.004	.001	-.01	-.002
tCoVaR BUSD	1357	-.041	.009	-.074	-.011
tDCoVaR BUSD	1357	.001	0	0	.002
tVaR USDP	1357	-.005	.001	-.009	-.003
tCoVaR USDP	1357	-.048	.01	-.082	-.015
tDCoVaR USDP	1357	-.005	.001	-.009	-.003
tVaR PAXG	1357	-.015	.004	-.034	-.007
tCoVaR PAXG	1357	-.053	.012	-.1	-.021
tDCoVaR PAXG	1357	-.011	.003	-.026	-.004
tVaR EURS	1357	-.021	.005	-.045	-.01
tCoVaR EURS	1357	-.051	.01	-.086	-.018
tDCoVaR EURS	1357	-.008	.002	-.017	-.003
tVaR DAI	1357	-.005	.002	-.013	-.002
tCoVaR DAI	1357	-.039	.008	-.061	-.008
tDCoVaR DAI	1357	.003	.001	.001	.007
tVaR GUSD	1357	-.014	.007	-.046	-.003
tCoVaR GUSD	1357	-.055	.013	-.111	-.03
tDCoVaR GUSD	1357	-.015	.007	-.048	-.003

Table 25: Conditional Descriptive Statistics of VaR, CoVaR, and DCoVaR at 0.10 for native cryptocurrencies and stable coins

Variable	Obs	Mean	Std. Dev.	Min	Max
tVaR BTC	1357	-.036	.008	-.064	-.011
tCoVaR BTC	1357	-.041	.009	-.075	-.017
tDCoVaR BTC	1357	-.024	.005	-.045	-.01
tVaR ETH	1357	-.048	.009	-.076	-.015
tCoVaR ETH	1357	-.04	.007	-.063	-.019
tDCoVaR ETH	1357	-.025	.004	-.042	-.012
tVaR BNB	1357	-.046	.009	-.082	-.021
tCoVaR BNB	1357	-.039	.009	-.067	-.013
tDCoVaR BNB	1357	-.02	.005	-.04	-.011
tVaR XRP	1357	-.052	.011	-.081	-.018
tCoVaR XRP	1357	-.039	.008	-.059	-.01
tDCoVaR XRP	1357	-.018	.004	-.029	-.008
tVaR XTZ	1357	-.065	.013	-.104	-.022
tCoVaR XTZ	1357	-.041	.007	-.059	-.016
tDCoVaR XTZ	1357	-.025	.005	-.042	-.013
tVaR ADA	1357	-.056	.011	-.094	-.019
tCoVaR ADA	1357	-.04	.008	-.068	-.015
tDCoVaR ADA	1357	-.022	.004	-.038	-.013
tVaR DOGE	1357	-.057	.014	-.094	-.02
tCoVaR DOGE	1357	-.036	.008	-.058	-.011
tDCoVaR DOGE	1357	-.012	.003	-.019	-.006
tVaR WBTC	1357	-.036	.008	-.067	-.013
tCoVaR WBTC	1357	-.04	.009	-.075	-.017
tDCoVaR WBTC	1357	-.023	.005	-.046	-.011
tVaR BCH	1357	-.052	.008	-.073	-.03
tCoVaR BCH	1357	-.037	.005	-.048	-.019
tDCoVaR BCH	1357	-.021	.004	-.034	-.012
tVaR ALGO	1357	-.064	.01	-.095	-.03
tCoVaR ALGO	1357	-.041	.007	-.064	-.018
tDCoVaR ALGO	1357	-.023	.003	-.034	-.014
tVaR RUNE	1357	-.082	.009	-.105	-.054
tCoVaR RUNE	1357	-.042	.006	-.066	-.027
tDCoVaR RUNE	1357	-.02	0	-.022	-.019
tVaR RPL	1357	-.076	.015	-.139	-.052
tCoVaR RPL	1357	-.043	.009	-.085	-.024
tDCoVaR RPL	1357	-.021	.004	-.04	-.013
tVaR LUNC	1357	-.079	.014	-.112	-.025
tCoVaR LUNC	1357	-.036	.008	-.057	-.007
tDCoVaR LUNC	1357	-.01	.002	-.014	-.003
tVaR TRON	1357	-.045	.014	-.103	-.017
tCoVaR TRON	1357	-.031	.006	-.047	-.01
tDCoVaR TRON	1357	-.002	0	-.004	-.001
tVaR LINK	1357	-.065	.016	-.115	-.014
tCoVaR LINK	1357	-.032	.006	-.05	-.009
tDCoVaR LINK	1357	-.002	0	-.004	-.001
tVaR LTC	1357	-.052	.013	-.088	-.013
tCoVaR LTC	1357	-.032	.006	-.048	-.011
tDCoVaR LTC	1357	-.003	.001	-.005	-.001
tVaR MATIC	1357	-.069	.018	-.131	-.024
tCoVaR MATIC	1357	-.031	.006	-.049	-.01
tDCoVaR MATIC	1357	-.002	0	-.004	-.001
tVaR MKR	1357	-.057	.01	-.086	-.019
tCoVaR MKR	1357	-.039	.007	-.06	-.016
tDCoVaR MKR	1357	-.017	.003	-.025	-.008
tVaR VET	1357	-.065	.011	-.101	-.027
tCoVaR VET	1357	-.041	.009	-.076	-.018
tDCoVaR VET	1357	-.024	.004	-.041	-.014

tVaR QNT	1357	-.061	.012	-.116	-.037
tCoVaR QNT	1357	-.04	.009	-.073	-.015
tDCoVaR QNT	1357	-.015	.004	-.032	-.008
tVaR STX	1357	-.074	.012	-.113	-.035
tCoVaR STX	1357	-.04	.007	-.06	-.016
tDCoVaR STX	1357	-.017	.003	-.026	-.008
tVaR SNX	1357	-.082	.007	-.108	-.068
tCoVaR SNX	1357	-.044	.007	-.071	-.026
tDCoVaR SNX	1357	-.021	.001	-.026	-.019
tVaR THETA	1357	-.069	.014	-.112	-.019
tCoVaR THETA	1357	-.044	.01	-.086	-.02
tDCoVaR THETA	1357	-.022	.005	-.041	-.008
tVaR EOS	1357	-.062	.013	-.097	-.024
tCoVaR EOS	1357	-.04	.008	-.062	-.012
tDCoVaR EOS	1357	-.025	.006	-.041	-.012
tVaR BSV	1357	-.053	.011	-.098	-.031
tCoVaR BSV	1357	-.039	.005	-.056	-.026
tDCoVaR BSV	1357	-.018	.005	-.037	-.007
tVaR GT	1357	-.039	.013	-.083	-.011
tCoVaR GT	1357	-.032	.006	-.049	-.008
tDCoVaR GT	1357	-.002	.001	-.004	0
tVaR USDT	1357	-.002	.001	-.006	-.001
tCoVaR USDT	1357	-.031	.006	-.048	-.008
tDCoVaR USDT	1357	-.001	0	-.002	0
tVaR USDC	1357	-.003	0	-.005	-.001
tCoVaR USDC	1357	-.03	.006	-.047	-.007
tDCoVaR USDC	1357	0	0	0	0
tVaR TUSD	1357	-.003	.001	-.006	-.001
tCoVaR TUSD	1357	-.036	.007	-.055	-.011
tDCoVaR TUSD	1357	-.005	.002	-.013	-.002
tVaR BUSD	1357	-.003	.001	-.006	-.001
tCoVaR BUSD	1357	-.03	.006	-.048	-.007
tDCoVaR BUSD	1357	0	0	0	.001
tVaR USDP	1357	-.003	0	-.005	-.002
tCoVaR USDP	1357	-.032	.006	-.048	-.01
tDCoVaR USDP	1357	-.002	0	-.003	-.001
tVaR PAXG	1357	-.01	.003	-.023	-.004
tCoVaR PAXG	1357	-.033	.007	-.052	-.007
tDCoVaR PAXG	1357	-.004	.001	-.009	-.001
tVaR EURS	1357	-.013	.003	-.029	-.007
tCoVaR EURS	1357	-.034	.007	-.052	-.009
tDCoVaR EURS	1357	-.005	.001	-.012	-.002
tVaR DAI	1357	-.004	.001	-.009	-.002
tCoVaR DAI	1357	-.027	.006	-.042	-.005
tDCoVaR DAI	1357	.003	.001	.001	.007
tVaR GUSD	1357	-.009	.004	-.03	-.002
tCoVaR GUSD	1357	-.038	.008	-.071	-.02
tDCoVaR GUSD	1357	-.008	.004	-.028	-.001

Table 26: Regression Results of tDCoVaR_NC and Betweenness Centrality for Native Cryptocurrencies

tDCoVaR_NC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Betweenness_NC	-.0000692	0	-4.54	0	0	0	***
SP500	-.238	.035	-6.78	0	-.307	-.169	***
VIX	-.022	.006	-3.40	.001	-.034	-.009	***
FIG	.004	.004	0.98	.328	-.004	.011	
Constant	.002	.026	0.06	.951	-.05	.053	

Mean dependent var	-0.061	SD dependent var	0.062
R-squared	0.054	Number of obs	1170
F-test	16.734	Prob > F	0.000
Akaike crit. (AIC)	-3237.357	Bayesian crit. (BIC)	-3212.033

*** *p<.01, *** *p<.05, ** *p<.1*

Table 27: Regression Results of tDCoVaR_NC and Closeness Centrality for Native Cryptocurrencies

tDCoVaR_NC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Closeness_NC	-8.234	1.374	-5.99	0	-10.93	-5.537	***
SP500	-.248	.035	-7.10	0	-.317	-.18	***
VIX	-.022	.006	-3.43	.001	-.034	-.009	***
FIG	.004	.004	1.20	.232	-.003	.012	
Constant	.04	.027	1.47	.143	-.013	.093	

Mean dependent var	-0.061	SD dependent var	0.062
R-squared	0.066	Number of obs	1170
F-test	20.702	Prob > F	0.000
Akaike crit. (AIC)	-3252.337	Bayesian crit. (BIC)	-3227.013

*** *p<.01, *** *p<.05, ** *p<.1*

Table 28: Regression Results of tDCoVaR_NC and Degree Centrality for Native Cryptocurrencies

tDCoVaR_NC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Degree_NC	-.007	.001	-4.94	0	-.01	-.004	***
SP500	-.237	.035	-6.75	0	-.306	-.168	***
VIX	-.021	.006	-3.33	.001	-.034	-.009	***
FIG	.004	.004	1.03	.301	-.003	.011	
Constant	.008	.026	0.29	.768	-.044	.059	

Mean dependent var	-0.061	SD dependent var	0.062
R-squared	0.057	Number of obs	1170
F-test	17.731	Prob > F	0.000
Akaike crit. (AIC)	-3241.141	Bayesian crit. (BIC)	-3215.818

*** *p<.01, *** *p<.05, ** *p<.1*

Table 29: Regression Results of tDCoVaR_NC and Eigenvector Centrality for native cryptocurrencies

tDCoVaR_NC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Eigenvector_NC	-.377	.056	-6.75	0	-.487	-.268	***
SP500	-.242	.035	-6.94	0	-.31	-.173	***
VIX	-.022	.006	-3.43	.001	-.034	-.009	***
FIG	.004	.004	1.00	.32	-.004	.011	
Constant	.008	.026	0.31	.757	-.043	.059	

Mean dependent var	-0.061	SD dependent var	0.062
R-squared	0.074	Number of obs	1170
F-test	23.211	Prob > F	0.000
Akaike crit. (AIC)	-3261.711	Bayesian crit. (BIC)	-3236.387

*** *p<.01, *** *p<.05, ** *p<.1*

Table 23: Regression Results of tDCoVaR_SC and Betweenness Centrality for stable coins

tDCoVaR_SC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Betweenness_SC	.0000204	0	3.73	0	0	0	***
SP500	-.031	.008	-3.67	0	-.047	-.014	***
VIX	-.007	.002	-4.32	0	-.01	-.004	***
FIG	-.002	.001	-2.48	.014	-.004	0	**
Constant	.022	.006	3.47	.001	.009	.034	***

Mean dependent var	-0.006	SD dependent var	0.009
R-squared	0.102	Number of obs	405
F-test	11.341	Prob > F	0.000
Akaike crit. (AIC)	-2707.156	Bayesian crit. (BIC)	-2687.136

**** p<.01, ** p<.05, * p<.1*

Table 24: Regression Results of tDCoVaR_SC and Closeness Centrality for stable coins

tDCoVaR_SC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Closeness_SC	-.062	.451	-0.14	.891	-.948	.824	
SP500	-.029	.009	-3.42	.001	-.046	-.012	***
VIX	-.006	.002	-4.06	0	-.009	-.003	***
FIG	-.003	.001	-2.87	.004	-.004	-.001	***
Constant	.024	.007	3.62	0	.011	.037	***

Mean dependent var	-0.006	SD dependent var	0.009
R-squared	0.071	Number of obs	405
F-test	7.610	Prob > F	0.000
Akaike crit. (AIC)	-2693.350	Bayesian crit. (BIC)	-2673.330

**** p<.01, ** p<.05, * p<.1*

Table 25: Regression Results of tDCoVaR_SC and Degree Centrality for stable coins

tDCoVaR_SC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Degree_SC	.002	0	3.87	0	.001	.003	***
SP500	-.029	.008	-3.47	.001	-.046	-.013	***
VIX	-.006	.002	-4.16	0	-.009	-.003	***
FIG	-.002	.001	-2.55	.011	-.004	-.001	**
Constant	.019	.006	3.01	.003	.007	.032	***

Mean dependent var	-0.006	SD dependent var	0.009
R-squared	0.104	Number of obs	405
F-test	11.641	Prob > F	0.000
Akaike crit. (AIC)	-2708.243	Bayesian crit. (BIC)	-2688.224

**** p<.01, ** p<.05, * p<.1*

Table 26: Regression Results of tDCoVaR_SC and Eigenvector Centrality for stable coins

tDCoVaR_SC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Eigenvector_SC	-.03	.036	-0.83	.406	-.101	.041	
SP500	-.029	.009	-3.33	.001	-.045	-.012	***
VIX	-.006	.002	-4.04	0	-.009	-.003	***
FIG	-.003	.001	-2.92	.004	-.004	-.001	***
Constant	.024	.006	3.74	0	.011	.036	***

Mean dependent var	-0.006	SD dependent var	0.009
R-squared	0.072	Number of obs	405
F-test	7.791	Prob > F	0.000
Akaike crit. (AIC)	-2694.032	Bayesian crit. (BIC)	-2674.013

**** p<.01, ** p<.05, * p<.1*

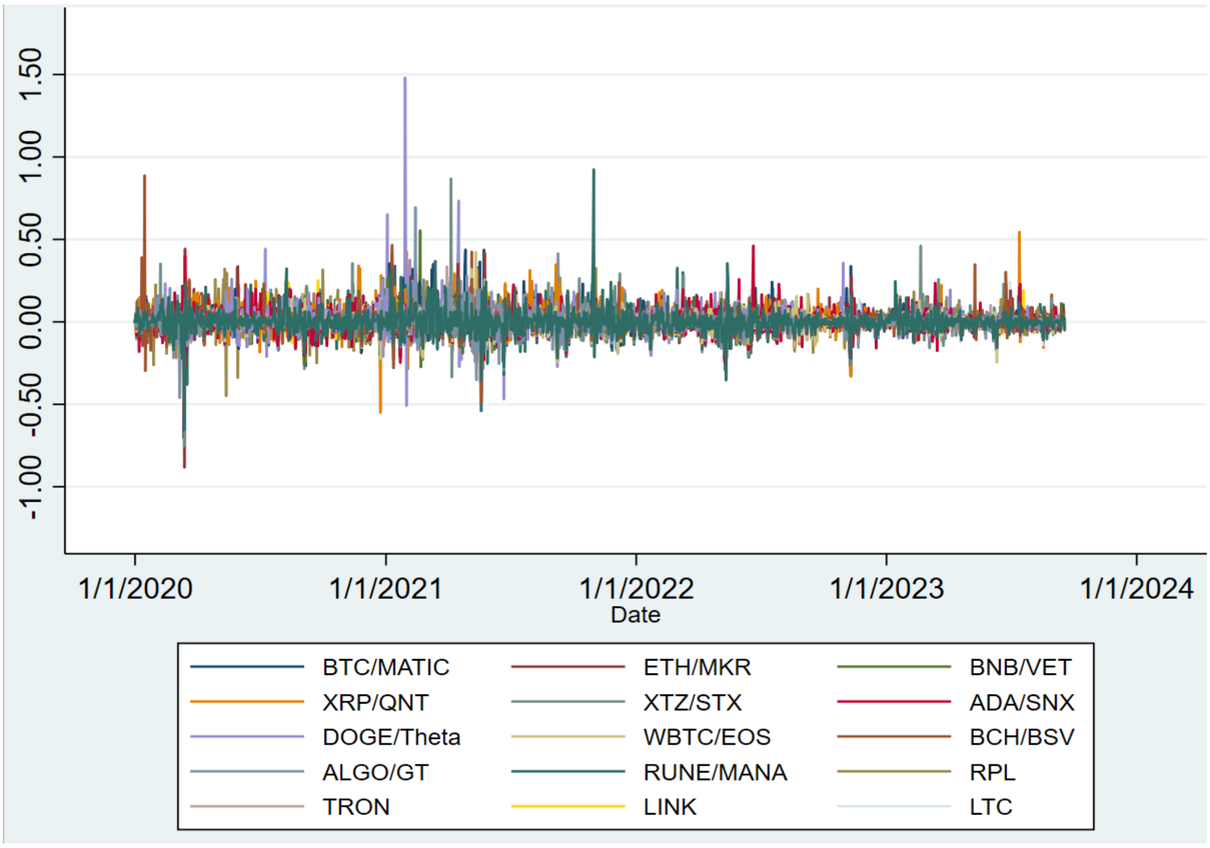

Fig 1: Changes in Prices of Cryptocurrencies 2020-2023

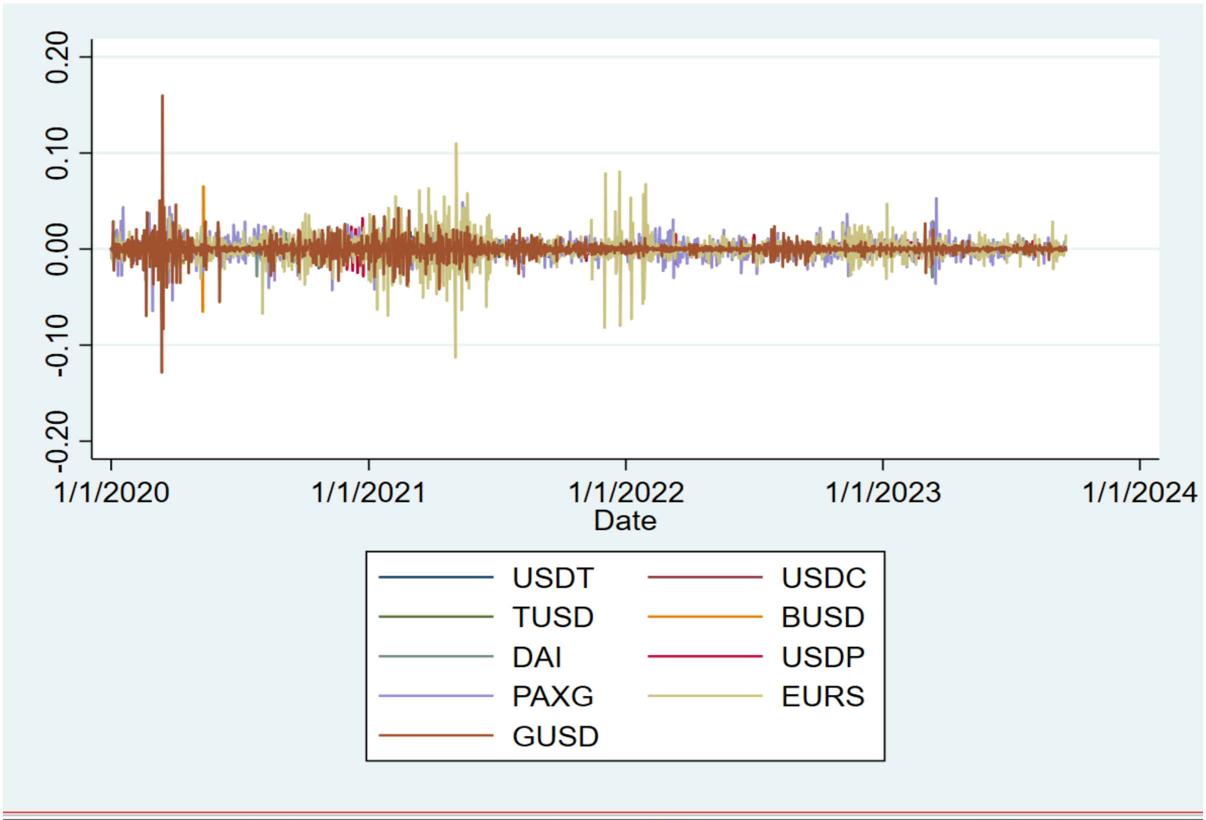

Fig 2: Changes in Prices of Stable coins 2020-2023

Appendix

ΔCoVaR is calculated as the 1% CoVaR minus the 50%-CoVaR. Adrian and Brunnermeier (2011) propose referring to $\Delta\mathrm{CoVaR}_q^{J|i}$ where i is the definition of the financial system, as "exposure CoVaR" since it quantifies an institution's vulnerability to systemic financial events. The $\Delta\mathrm{CoVaR}_q^{J|i}$ metric is interesting because it can assist with determining the most critical enterprises in terms of being most at risk during financial crises. CoVaR methodology is implemented using the quantile regression (QR) method (Koenker and Bassett, 1978). The base of QR is the minimization of the absolute value of the sum of the residuals, which are weighted asymmetrically through the quantile dependent on whether they are positive or negative.

Unconditional estimation of VaR, CoVaR, and ΔCoVaR

The QR approach makes it simple to estimate CoVaR. To obtain $CoVaR^{CCM|i}$ we need to calculate 1% and 50%-VaR of cryptocurrency returns i, for i = 1, 2,…, 36, QR is run of i's returns on a constant only, (with q=1% and q=50%) for median state VaR:

$$X_q^i = \alpha_q^i + \varepsilon_q^i \tag{10}$$

$$VaR_q^i = \hat{a}_q^i \tag{11}$$

Similarly for the system,

$$X_q^{system} = \alpha_q^{system} + \varepsilon_q^{system} \tag{12}$$

$$VaR_q^{system} = \hat{a}_q^{system} \tag{13}$$

In order to get the $CoVaR^{CCM|i}$, we (quantile) regress the cryptosystem's returns on a constant and on the returns of cryptocurrency i:

$$X_q^{CCM|i} = a_q^i + \beta_q^i X^i + \varepsilon_q^i \tag{14}$$

After getting coefficients of α and β from QR, we construct $CoVaR^{CCM|i}$, by putting them together with VaR_q^i,

$$CoVaR_q^{CCM|X^i=VaR_q^i} = VaR_q^{CCM} |\, VaR_q^i = \hat{a}_q^i + \hat{\beta}_q^i VaR_q^i \tag{15}$$

and further construct ΔCoVaR

$$\Delta CoVaR_{q=1\%}^{CCM|i} = \hat{\beta}_{q=1\%}^i \; (VaR_{q=1\%}^i - VaR_{q=50\%}^i\,) \tag{16}$$

Conditional estimation of VaR, CoVaR, and ΔCoVaR

Unconditional estimation is incorporated with some additional macro variables in order to get more refined ΔCoVaR values.

Then QR is run for all cryptocurrency returns (*i* = 36) for quantile q=1% and q=50%. This will yield time-varying 50%-VaR and 1%-VaR series, conditioned on the vector M's macro variables.

$$X_t^i(q) = \alpha_q^i + \beta_q^i M_t + \varepsilon_t^i \tag{17}$$

Using estimates of α and β we can generate a conditional VaR series for i,

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\beta}_q^i M_t \tag{18}$$

Time varying cryptosystem VaR series is also generated the same way,

$$X_t^{system}(q) = \alpha_q^{system} + \beta_q^{system} M_t + \varepsilon_t^{system} \tag{19}$$

$$VaR_t^{system}(q) = \hat{\alpha}_q^{system} + \hat{\beta}_q^{system} M_t$$

For calculating CoVaR and ΔCoVaR, following regressions for q=1% and q=50%, are run,

$$X_t^{system|i}(q) = \alpha_q^{system|i} + \beta_{q,1}^{system|i} X_t^i + \beta_{q,2}^{system|i} M_t + \varepsilon_t^{system|i} \tag{20}$$

$$CoVaR_t^i(q) = \hat{\alpha}_0^{system|i} + \hat{\beta}_{q,1}^{system|i} VaR_t^i(q) + \hat{\beta}_{q,2}^{system|i} M_t \tag{21}$$

Where X_t^i, are the cryptocurrency returns i. Each cryptocurrency's systemic risk contribution is estimated as follows:

$$\Delta CoVaR_t^i(q) = CoVaR_t^i(q) - CoVaR_t^i(q = 50\%) \tag{22}$$

$$\Delta CoVaR_t^{system}(q) = CoVaR_t^{system}(q) - CoVaR_t^{system}(q = 50\%) \tag{23}$$

Thus, this approach calculates time varying risk contribution of each cryptocurrency to overall market systemic risk in times of distress.