“Analysis of tail dependence structure and risk spillover between cryptocurrencies”

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ANALYSIS OF TAIL DEPENDENCE STRUCTURE AND RISK SPILLOVER BETWEEN CRYPTOCURRENCIES

Abstract

Understanding the interconnectedness of cryptocurrencies based on their underlying technology is crucial for effective portfolio management and risk assessment. To establish the tail dependence structure and risk spillover between cryptocurrencies, this paper used the daily closing prices of the top eight proof-of-stake-based cryptocurrencies and the top ten proof-of-work-based cryptocurrencies from September 22, 2020 to April 7, 2023. This study applied the C-vine copulas and CoVaR measures. The outcome of the copula findings for the proof-of-stake cryptocurrencies illustrates that Ethereum exhibits strong resilience during market downturns, acting as a buffer for other proof-of-stake cryptocurrencies with pairwise tail dependence coefficients ranging from 0.45 to 0.67. Bitcoin Cash emerges as a portfolio diversifier within the proof-of-work ecosystem, absorbing 45% to 75% of volatility spillovers. However, from the proof-of-stake CoVaR analysis, ETH, DOT, and MATIC rank highest in systematic importance before April 2022, signifying their significant risk transmission role, and for the proof-of-work CoVaR analysis, Bitcoin (BTC) is the primary risk transmitter in the cryptocurrency portfolio, having a positive CoVaR of 0.15. Ethereum and Bitcoin are identified as the dominant risk transmitters within their respective groups, highlighting their potential to amplify systemic risk. This study provides valuable insights for investors and policymakers navigating the increasingly complex cryptocurrency landscape.

Keywords cryptocurrencies, blockchain, proof-of-work, proof-of-stake, CoVaR, systemic risk

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INTRODUCTION

Over the past decade, blockchain-based applications and virtual currencies, notably Bitcoin since its 2009 launch, have gained widespread attention and have popularized blockchain technology (Rehman et al., 2022). Cryptocurrencies offer innovative features like incentivization, cost-effective transfers, and decentralized systems, reducing single points of failure risk (Metelski & Sobieraj, 2022). These algorithms emulate traditional finance processes, fostering the development of a new financial services industry. Despite concerns and their speculative use, cryptocurrencies operate independently from government intervention, aiming to function as mediums of exchange (Trimborn & Hardle, 2018). While not widely adopted as currency substitutes, cryptocurrencies play a significant role in financial markets and portfolio management (Bouri et al., 2020).

Recent research explores interconnections in the cryptocurrency market, revealing positive but relatively small correlations compared to traditional assets (Aslanidis et al., 2019). Time-varying optimal copula analysis by Naeem and Karim (2021) exposes multiple tail-dependence regimes characterized by strong dependence among cryptocurrencies. The dependence structure is predominantly asymmetric and subject to temporal changes. Understanding tail dependence and risk

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spillover in proof-of-work (PoW) and proof-of-stake (PoS) cryptocurrencies aids investors and portfolio managers in constructing resilient portfolios. Identifying cryptocurrencies with low or negative tail dependence enables the creation of diversified portfolios, reducing vulnerability to simultaneous extreme events. This strategy can enhance overall portfolio resilience and risk-adjusted returns and inform policymakers in developing effective regulatory frameworks. Analyzing interconnectedness and risk transmission channels helps identify potential vulnerabilities and systemic risks, guiding the formulation of policies promoting stability, investor protection, and risk mitigation in the cryptocurrency ecosystem. For cryptocurrency investors that only focus on the cryptocurrency market, the market information about the fiat currency and Bitcoin is insufficient for decision-making because day-to-day cryptocurrency traders would need more information about the dependence structure and spillover among cryptocurrencies. In general, most of these studies that have assessed the dependence structure and risk spillover within the cryptocurrency market used selected cryptocurrencies based on their market capitalization. This approach may result in an unreliable finding, given that cryptocurrencies are diverse in their archetype.

1. LITERATURE REVIEW

Understanding the tail dependence dynamics and the role of cryptocurrencies is crucial for investors aiming to safeguard their portfolios during market turbulence. However, the general assumption is that digital currencies are more commonly used as investment vehicles than as means of exchanging money for goods and services (Tiwari et al., 2020). Even though there is a growing body of study on cryptocurrencies, a large percentage of the works that have been published up to this point have focused on examining their market capitalization, evaluating their effectiveness, quantifying volatility, and looking into the formation of price bubbles. This emphasis frequently ignores the diversity that exists among different cryptocurrency archetypes. Numerous studies have examined the tail dependency patterns in the world of cryptocurrency using a variety of methodologies. Recent research on carbon prices and environmentally friendly and non-environmentally friendly cryptocurrencies was conducted by Pham et al. (2022). They used the GAS-DCS (Generalized Autoregressive Score-Dynamic Conditional Score) and GAS-Copula models to investigate spillover effects. The results revealed a significant relationship between carbon markets and environmentally friendly and non-green cryptocurrencies, with spillovers appearing at both lower and upper extreme quantiles. This highlights a strong tail dependence between various monetary assets. Additionally, asymmetric spillovers were shown in the study, with spillovers at the lower extreme quantiles being smaller than those at the upper quantiles. In a different study, Naeem et al. (2020) utilized GARCH-copula techniques to investigate the average and high dependence between trade volume and major cryptocurrencies (Bitcoin, Ethereum, and Litecoin) in various market dynamics. The findings indicated that tail dependence and excessive trading volume are more prominent when volumes and returns are high, whereas they are less prominent when volumes and returns are low. Moreover, when the student-t and time-varying symmetrized Joe Clayton (SJC) copulas were used to illustrate the dependence structure between bitcoin and green financial assets, Naeem et al. (2020) discovered that the tail connectivity of the return volume is asymmetric. Boako et al. (2019) employed daily data from September 2015 to June 2018, applying vine copula methodologies to analyze the interdependence and portfolio value-at-risk of six cryptocurrencies. The study demonstrates evidence of robust dependencies among the virtual currencies with a dynamic dependency structure. Using the efficient frontier, this paper discovers that Ethereum provides portfolio investors with the most optimal and economically sound risk-reward trade-off among the class of cryptocurrencies under consideration, provided that there is a no-shorting requirement. Additional research on the tail connectivity between bitcoin and green financial assets was done in 2021 by Naeem and Karim (2021). The study investigated the tail fusing Bitcoin and green financial assets using the time-varying optimal copula (TVOC) concept. It discovered multiple tail dependence regimes characterized by the high dependence between cryptocurrencies, and the connectedness structure is primarily asymmetric and time varying. Contrary to the finding by Naeem and Karim (2021), Chang (2022) assesses the diversification mechanisms for tail dependence structure among Bitcoin return and trading volume using a dynamic mixture copula technique with spillover effect and asymmetric volatility impact. The results demonstrate that positive and negative reliance cannot be compared in terms of strength. The positive dependence scenario is more common than the negative reliance condition. The positive dependence structure is characterized by an increase in co-movement strength as opposed to a decrease in co-movement strength. In the negative dependence structure, there are more examples of large returns with low volume than tiny returns with huge quantities. Numerous studies have investigated the risk spillover in various financial markets, including the cryptocurrency industry, in addition to the tail dependence analysis. Risk spillovers have been the subject of several research, such as Xu et al. (2021) and Zhang et al. (2021). A useful method for determining the dynamic time development of complex risk spillovers between Bitcoin and other asset classes, including stocks, bonds, currencies, and commodities, was put forth by Zhang et al. in 2021. They made use of Zhang and Ma's (2019) Extreme Value at Risk (EVaR) approach. However irregular they may be, the results point to the existence of considerable downward risk spillovers between Bitcoin and the assets under study. Additionally, Ozdemir (2022) used the EGARCH (Exponential Generalized Autoregressive Conditional Heteroscedasticity) and DCC-GARCH (Dynamic Conditional Correlation-GARCH) techniques to study volatility spillovers among eight major cryptocurrencies: Bitcoin, Ethereum, Stellar, Ripple, Tether, Cardano, Litecoin, and Eos. The findings show that over the sample period, Bitcoin, Ethereum, and Litecoin all show significant interdependence and high volatility. This research implies that disruptions in one market cause comparable investor actions in the other, which causes volatility spillovers. This implies that under normal and extreme market conditions, the benefits of diversification for various assets may vary significantly. Rehman et al. (2022) employed the time-varying Clayton copula technique to model the dependence structure and measured the risk spillover using VaR, CoVaR, and ΔCoVaR to assess upside and downside risk. The copula findings revealed that the COVID-19 pandemic increased dependence, revealing a time-varying relationship between Bitcoin and the foreign exchange market. Many of the above-mentioned studies that have investigated the dependence structure among assets have also accessed the risk spillover (Rehman et al., 2022). This paper believes that this combined approach is more informative in assisting investors, policymakers, and portfolio managers in making informed decisions. In a study by Bouri et al. (2023), Rotated Gumbel copula and GARCH copula quantile regression-based ΔCoVaR models were used to investigate the downside risk spillover and dynamic lower tail reliance between the FTX Token and seven major cryptocurrencies. It demonstrates how the examined cryptocurrencies differ greatly in terms of downside risk spillovers and dynamic lower tail dependency. The findings demonstrate that there are notable differences between the analyzed cryptocurrencies in terms of dynamic lower tail dependency and downside risk spillovers. In other words, there is substantial proof that FTX Token risk has an impact on cryptocurrency markets. Cardano trails Solana in showing the most downside risk spillover. With the least amount of negative risk spillovers from the FTX implosion, Tether and Bitcoin are the least impacted. Furthermore, each cryptocurrency has distinct dynamic risk spillover effects that vary over time. The dependence structure and risk spillover between Bitcoin and fiat currencies were examined by Rehman et al. in 2022. However, for cryptocurrency investors that only focus on the cryptocurrency market, the market information about the fiat currency and Bitcoin is insufficient for decision-making because day-to-day cryptocurrency traders would need more information about the dependence structure and spillover among cryptocurrencies. In general, most of these studies that have assessed the dependence structure and risk spillover within the cryptocurrency market used selected cryptocurrencies, based on their market capitalization. This approach may result in an unreliable finding, given that cryptocurrencies are diverse in their archetype. In this scenario, to obtain meaningful results, one should look beyond the global aspect of cryptocurrency and delve deeper into its building characteristics and chain features. Schwiderowski et al. (2023) used the text

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analysis on more than 509 blockchain white papers to build a cryptocurrency token classification around three archetypes. "Utility tokens, Payment tokens, and Assets tokens". This study focuses on the tail dependence of the payments token class. For further examples of the morphological classification of tokens (Freni et al., 2022).

In the study by Rehman et al. (2022), the tail dependence structures of each pair of assets were modelled using various individual copula selections. The study focuses on Bitcoin, a cryptocurrency that acts as proof of work. Cryptocurrencies that rely on proof of work have come under fire for their high energy usage and the pricey setup of the high-level competing facility that is needed, this complexity made the Ethereum coin switch from a proof of work to a proof of stake consensus method for this reason, among other reasons. It is important to consider the risk spillover between cryptocurrencies that use proof of stake and proof of work, which is the main focus of this study.

The affiliation between cryptocurrencies and other assets during eras of thrilling volatility is still largely unknown despite substantial research on the dependency structure in various market conditions across various markets and the rapid growth of literature on Bitcoin. To the authors' understanding, only Baumohl (2019) has inspected how cryptocurrencies and conventional currency interact in volatile market circumstances. In particular, Baumohl (2019) revealed considerable negative connections between cryptocurrencies and foreign exchange markets from both short- and long-term angles using the quantile cross-spectral technique. It should be noted that the primary focus of Baumohl (2019) was on developed country currencies. Furthermore, the spillover effects of sharp upward or downward movements in proof-of-work and proof-of-stake cryptocurrencies have never been examined in a previous study.

This study will follow a similar technique as that used by Rehman et al. (2022). The studies by Rehman et al. (2022), Naeem et al. (2020), Chang (2022), examined the tail-risk spillover using different individual copula selections to model the tail dependence structures of each pair of assets. However, there is a large family of copula with different specific dependence properties that one could take advantage of. In this regard, this study will utilize the vine copulas to capture the tail dependence of each pair of assets. The advantage of using the vine copulas is that it is capable of auto-selecting suitable copula for each pair of assets from a pool of copulas, and it is computationally less intensive. Examples of studies that used the vine copula are Tenkam et al. (2022), Mba et al. (2022), and Mba et al. (2021). Thus, the main aim of this paper is to access the tail dependence structure and the risk spillover between cryptocurrencies in the morphological classification framework based on the proof-of-stake and proof-of-work consensus mechanism.

2. METHODOLOGY

This paper will distinguish between two groups of assets, the first group consists of the proof-of-stake cryptocurrencies, and the second group consists of the proof-of-work cryptocurrencies.

2.1. Vine copula

To analyze the relationship between cryptocurrencies in both bullish and bearish market conditions, this paper utilizes copulas. Copulas are mathematical tools that provide a means to examine both the typical dependence and the extreme or tail dependence between variables. They enable us to assess the likelihood that two variables would move in an extreme way, either upwards or downwards, at the same time. Copulas serve as functions that connect the multivariate distribution of the variables of interest to each univariate variable distribution. In this section, this paper presents the essential characteristics that define a function as a copula, along with some noteworthy properties associated with copulas (Bedford et al., 2002).

Consider a vector $X = (X_1, \ldots, X_n)$ consisting of n random variables. Each of these variables is characterized by its marginal distribution.

The marginal distributions $F_1, \ldots, F_n$ are defined in such a way that $F_i(x_i) = P(X_i \leq x_i) = u_i$ represents the likelihood that the value of x_1 is less than or equal to x_1, which can be denoted as u_i. In other words, u_i corresponds to the probability that the measurement of x_1 is below the value x_1.

Following that, the joint distribution function is provided by:

$$F(x_i,\ldots,x_n) = P\left(X_1 \le x_1,\ldots,X_n \le x_n\right). \quad (1)$$

A copula is a function C: $I^n \to I$ that operates in n-dimensional space where ($n \ge 2$) and maps from the unit hypercube C: $I^n \to I$. It should adhere to the following characteristics:

1. C is non-decreasing that is $C(0,\ldots,x_i,\ldots,0) = 0$, for all $x_i \in I = [0, 1]$

2. The copula C must have uniform margins in one dimension on each component C_i, which means that:

$C_i(x_i) = C(1,\ldots,1,x_i,1,\ldots,1) = x_i$ for all $x_i \in I$. C_i is an invariant non-decreasing transformation of the marginal.

Copula was introduced by Bedford and Cooke (2022) as outlined in the following theorem.

Theorem 3.1. Assume $F = (F_1,\ldots,F_n)$ is an n dimensional joint distribution function with marginal distribution function F_i ($i = 1,\ldots,n$). Then there exists a copula C such that for all $x = (x_1,\ldots,x_n) \in I^n$

$$F(x) = C\left(F_1(x_1),\ldots,F_n(x_n)\right). \quad (2)$$

If $F_1,\ldots,F_n$ are continue, then C is unique. Otherwise, C is non-unique on I^n.

In addition, if $F_1,\ldots,F_n$ are distribution functions on I and if C is a copula, then the function $F(x) = C\left(F_1(x_1),\ldots,F_n(x_n)\right)$ is a joint distribution function on I^n.

The standard presentation of the copula density function is provided as:

$$c(u_1,\ldots,u_n) = \frac{\partial^n C(u_1,\ldots,u_n)}{\partial u_1 \ldots \partial u_n}. \quad (3)$$

To calculate the density of the n-dimensional distribution F, the following equation is employed.

$$f(x_1,\ldots,x_n) = C\begin{pmatrix} F_1(x_1), \\ \ldots,F_n(x_n) \end{pmatrix} \prod_{i=1}^{n} f_i(x_i), \quad (4)$$

where f_i is the density of the marginal distribution F_i.

The literature on copula approaches presents different types of various kinds of density functions, which have the potential to be broadly classified into two families: elliptical copulas (such as Gaussian or Student's t copula) and Archimedean copulas such as Clayton, Gumbel, or Frank copula (Bedford & Cooke, 2001). When considering the modeling of dependence among three or more random variables, multivariate copulas have been developed. In a d-dimensional scenario (where d represents the number of random variables), the multivariate density is constructed by employing d(d – 1) / 2 bivariate (conditional) copulas. This procedure, known as Pair-Copula Construction (PCC), utilizes these copulas as fundamental elements. Moreover, the application of vine copula models utilizes the AIC criteria to choose the suitable bivariate copula for capturing the pairwise dependence structure.

It is essential to recognize that there is no single unique way to construct the joint density. Different structures can be represented by a set of nested trees, denoted as $T_i = (v_i, E_i)$, where v_i represents the nodes and E_i represents the edges. This set of trees is known as a vine. Therefore, vine copulas, originally introduced by Bedford and Cooke in 2002, provide flexible graphical models for representing multivariate copulas. These models are created by utilizing a sequence of bivariate copulas. The advancements in statistical modeling using copulas with vines have been highlighted by Tenkam et al. (2022). There are two commonly used types of vine copula models: Canonical vine (C-vine) and Drawable vine (D-vine). For this study, the C-vine copula specification will be utilized.

2.2. Risk measures VaRs, CoVaRs and delta CoVaR

Value at Risk (VaR) quantifies the maximum potential loss an investor may face over a specific period and confidence level, whether holding a long or short position. Conditional Value at Risk (CoVaR) for a portfolio is its VaR given the VaR of one of its assets. Quantile regressions are employed to estimate CoVaR, enabling the examination of relationships between PoS and PoW cryptocurrencies' returns or prices across different distribution

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quantiles. This is crucial for understanding tail dependence during extreme events, as relationships may vary in the tails of the distribution.

$$\hat{X}_q^{system,i} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i. \quad (5)$$

The symbol $\hat{X}_q^{system,i}$ represents the estimated value for a specific quantile, considering the condition of institution *i*. In theory, this regression analysis can be expanded to incorporate nonlinearity by considering higher-order dependence of the system's return based on the returns of institution *i*. Building on the definition of value at risk, this paper can deduce the following relationship directly:

$$VaR_q^{system} \mid X^i = \hat{X}_q^{system,i}. \quad (6)$$

Stated differently, the conditional value at risk of the financial system based on X^i is represented as the outcome predicted by quantile regression for the entire system, with institution *i* as a variable, because the VaR_q given X^i is just the conditional quantile. Employing a predicted value of $X^i = VaR_q^{\ i}$ yields our $CoVaR_q^{\ i}$ measure (for the conditioning event $\{X^i = VaR_q^{\ i}\}$). To put it formally, this specific *CoVaR* measure is simply given by:

$$\begin{aligned} CoVaR_q^i &= (VaR_q^{system} \mid X^i = VaR_q^i) \\ &= \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i. \end{aligned} \quad (7)$$

The $\Delta CoVaR_q^{\ i}$ is then given by

$$\begin{aligned} \Delta CoVaR_q^i &= CoVaR_q^i - CoVaR_{50\%}^i \\ &= \hat{\beta}_q^i \left(VaR_q^i - VaR_{50\%}^i \right). \end{aligned} \quad (8)$$

The calculated unconditional $VaR_q^{\ i}$ and $\Delta CoVaR_q^{\ i}$ values are obtained where the *VaR* estimate for the asset $VaR_q^{\ i}$ corresponds to the q-th quantile of its returns. In the following sections of this paper, the conditional *VaR* and $\Delta CoVaR$ estimates that consider the temporal variations in the joint distribution of asset returns will be employed, considering lagged systematic state variables. To account for the time-dependent nature of *VaR* and *CoVaR*, the study introduces a set of state variables M_t in our estimation process. These state variables are commonly acknowledged as indicators of the evolving conditional characteristics of asset returns and possess high liquidity and tradability. To avoid overfitting the data, this study deliberately restricted to a limited number of risk factors, ensuring a more focused and robust analysis.

2.3. Time variation associated with systematic state variables

An approach for calculating CoVaR that remains constant over time was described in the section before this one. This paper estimates the conditional distribution as a function of state variables in order to represent time variation in the joint distribution of X^i and X^{system}. This paper estimates the time variation conditional on a vector of delayed state variables and denotes time-varying $CoVaR_t$ and VaR_t with a subscript *t*. Utilizing the daily data (where *i* denotes an institution), the following quantile regressions:

$$x_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i, \quad (9)$$

$$\begin{aligned} x_t^{system} &= \alpha^{system,i} + \beta^{system,i} x_t^i \\ &+ \gamma^i M_{t-1} + \varepsilon_t^{system,i}. \end{aligned} \quad (10)$$

The predicted values are generated from the regression to obtain.

$$VaR_t^i(q) = \hat{\alpha}_q^i + \gamma^i M_{t-1}, \quad (11)$$

$$\begin{aligned} CoVaR_t^i(q) &= \alpha^{system,i} + \beta^{system,i} VaR_t^i(q) \\ &+ \gamma^i M_{t-1}. \end{aligned} \quad (12)$$

Finally, the $CoVaR_t^{\ i}$ for each institution is computed:

$$\begin{aligned} CoVaR_t^i(q) &= CoVaR_t^i(q) - CoVaR_t^i(50\%) \\ &= \hat{\beta}^{system|i}(VaR_t^i(q) - VaR_t^i(50\%). \end{aligned} \quad (13)$$

To establish the tail dependence structure and risk spillover between cryptocurrencies, this paper used the daily closing prices of the top eight proof-of-stake-based cryptocurrencies, namely, Ethereum (ETH), Solana (SOL), Cardano (ADA), Algorand (ALGO), Polkadot (DOT), Avalanche (AVAX), Tronix (TRX), and Polkadot (DOT); and top ten proof of work based currencies Bitcoin (BTC), Litecoin (LTC), Bitcoin Cash (BCH),

Table 1. Descriptive statistics for PoS cryptocurrencies

Assets	Mean	Median	Max	Min	Skewness	Kurtosis	Std Dev
ETH	0.0018222805	1.830669e–03	0.2306952	–0.3174590	–0.41267629	7.229896	0.04810481
SOL	0.0021023836	–3.046869e–04	0.3088670	–0.5495821	–0.39047193	9.353731	0.07408149
MATIC	0.0043495213	3.508608e–04	0.4577552	–0.3914188	1.02180813	9.357624	0.07626374
AVAX	0.0013095915	–1.657094e–04	0.5596235	–0.4540522	0.42335503	9.915023	0.07333106
ALGO	–0.0003621015	1.356816e–03	0.4182027	–0.3700606	0.04193157	8.053348	0.06180003
DOT	0.0004240623	–5.247919e–04	0.3191911	–0.4769641	–0.12118213	9.810750	0.06153869
TON	–0.0006188880	2.363401e–03	0.7022853	–0.3319798	1.04607777	20.517432	0.06597556
TRX	0.0010471749	2.314603e–03	0.3342172	–0.3832707	–0.12896781	12.110155	0.04958337

Ripple (XRP), Dogecoin (DOGE), Tether (USDT), Monero (XMR) and Biance (BNB). These cryptocurrency data were extracted from Yahoo Finance and spanning the period from September 22, 2020 to April 7, 2023. The selected period was based on the availability of the data since some of these cryptocurrencies were introduced or became active during the second half of 2020. Additionally, this paper aims to capture the crises that the cryptocurrency market experienced in the second quarter of 2022. For the time frame selected, the top ten proof of stake cryptocurrencies were selected. Two of the ten were omitted because they were recently introduced, which caused the unavailability of data. The state variable components are: The VIX Index, TED Spread, Term Spread, Gold Price, and Oil Price. These state variables are chosen based on two criteria: (i) they are easily marketable and liquid, and (ii) are widely acknowledged for their efficacy in capturing the chronological changes in the conditional moments of asset returns.

Table 1 presents the statistical features of all proof-of-stake cryptocurrencies in this study. All observed cryptocurrencies have positive means and standard deviations, with positive skewness and fat tails in their data series. These traits, common in financial assets, suggest a deviation from normal distribution. Traditional statistical techniques may yield biased results, overlooking informational flow patterns and assuming specific distributions. Notably, all cryptocurrencies in the dataset show positive returns, except for ALDO and TON, which exhibit average negative returns.

Table 2 provides a summary of data for proof-of-work cryptocurrencies. Kurtosis values range from 5.82 to 93.91, suggesting leptokurtosis and a higher likelihood of significant oscillations in distribution tails. Six assets exhibit left-skewed returns, deviating from normal distribution, except for XRP, DOGE, BNB, and XLM. Eight proof-of-work cryptocurrencies, excluding USDT and ZEC, show positive average daily gains. This trend aligns with investor preference for cryptocurrencies and has a high correlation with the US dollar, particularly USDT. The analysis reveals notable volatility, with Bitcoin exhibiting the highest volatility. XRP has the highest average daily returns, while USDT and DOGE show the highest and lowest volatility at 0.0007327592 and 0.0926142786, respectively.

3. RESULTS

The study automatically selected copulas, such as Survival Gumbel (SG), t-copula (t), SBB6, and SBB8, to model dependence between cryptocur-

Table 2. Descriptive statistics for PoW cryptocurrencies

Assets	Mean	Median	Max	Min	Skewness	Kurtosis	Std Dev
BTC	1.051264e–03	3.512057e–04	0.171820562	–0.17405255	–0.21544271	5.817038	0.0364456502
LTC	7.663174e–04	1.537109e–03	0.248433868	–0.44118863	–0.83481998	10.026696	0.0528946020
BCH	–6.127292e–04	1.144027e–03	0.420814193	–0.43461229	–0.06897915	14.051208	0.0544583779
XRP	8.510064e–04	9.833046e–04	0.444755603	–0.55050253	0.10312424	16.359935	0.0648341158
DOGE	3.705980e–03	–9.946451e–04	1.516327930	–0.51511793	5.50701608	87.037877	0.0926142786
USDT	–8.739576e–07	–9.999645e–07	0.009121781	–0.01136004	–1.80561458	93.905003	0.0007327592
BNB	2.757911e–03	1.251270e–03	0.529217870	–0.40445009	0.76569789	19.484274	0.0538922823
XLM	4.221070e–04	8.435616e–04	0.559183801	–0.36232800	1.10695297	18.353447	0.0576126112
ZEC	–3.759045e–04	1.342119e–03	0.252789933	–0.53943348	–0.77534547	10.818391	0.0615903100
XMR	5.639259e–04	3.493628e–03	0.344953945	–0.53419602	–1.07254814	19.005313	0.0519249716

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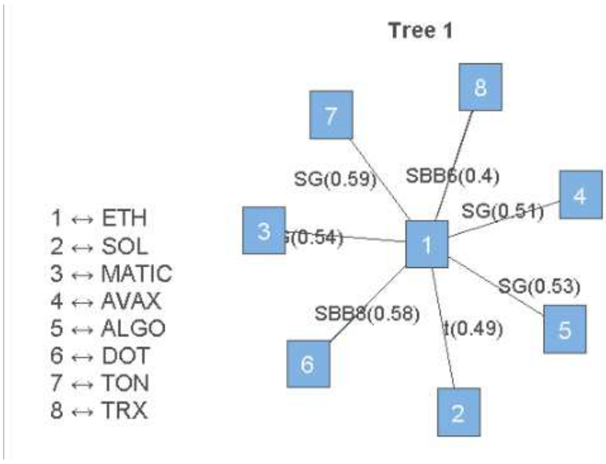

Figure 1. C-vine proof-of-stake tree 1 for the dependence structure

rency pairs. Survival Gumbel (SG) suggests randomness in data, making risk contributions nondeterministic. Kendall Tau coefficients in Table 3 reveal positive correlations among proof-of-stake cryptocurrencies, ranging from 0.49 to 0.59, indicating a moderate positive correlation. Lower tail coefficients (LTC) measure the probability of one asset losing value conditional on others losing value. Higher LTC implies riskier portfolio inclusion. ETH and DOT show the highest LTC, indicating faster price drops during extreme conditions. Overall, a strong correlation is observed among ETH, MATIC, DOT, AVAX, and ALGO, with SOL, TON, and TRX less affected by ETH distress. The portfolio is moderately diversified, with lower tail dependence between Ethereum and the other seven acceptable assets. CoVaR analysis is essential to understand the portfolio's exposure to risk during distress.

Table 3. C-vine dependence analysis for proof-of-stake cryptocurrencies

Asset pairs	Copula	Tau	UTC	LTC
ETH-SOL	T	0.49	0.45	0.45
ETH-MATIC	SG	0.54	–	0.62
ETH-TON	SBB6	0.59	–	0.54
ETH-DOT	SG	0.58	–	0.67
ETH-AVAX	SG	0.51	–	0.60
ETH-ALGO	SG	0.53	–	0.61
ETH-TRX	SG	0.40	–	0.58

Figure 1 depicts the C-vines' configuration, showcasing the node chosen as the root to optimize cumulative pairwise dependence. Ethereum serves as the central node (Tree 1), with all virtual currencies connected to it. The selection process employs a range of five and the Akaike Information Criterion (AIC). To construct a maximum dependence tree, one copula is chosen from Independent copula I(0), Student-t copula (t-copula), Survival BB6 (18), Survival Gumbel SG (14), and Survival BB8 (20). The C-vine copula model utilizes this tree, emphasizing Ethereum's distinct role compared to the other nine connected proof-of-stake cryptocurrencies. Changes in Ethereum can impact other proof-of-stake cryptocurrencies, as detailed in Table 3.

Table 4. C-vine dependence analysis for proof-of-work cryptocurrencies

Asset Pairs	Copula	Tau	UTC	LTC
BCH, XRP	SBB6	0.54		0.68
BCH, USDT	1	0		0
BCH, ZEC	SG	0.53		0.62
BCH, DOGE	SBB6	0.52		0.69
BCH, BNB	SBB8	0.53		0
BCH, LTC	SSBB6	0.64		0.75
BCH, XLM	SBB6	0.59		0.72
BCH, BTC	SG	0.59		0.67
XMR, BCH	SG	0.47		0.56

Table 4 reveals strong connections between Bitcoin Cash (BCH) and other cryptocurrencies, with Litecoin (LTC) having the highest lower tail dependence at 75%. Tau and LTC values for BCH and LTC indicate independence, making them suitable for portfolio pairing. The lower tail dependence coefficients show that during BCH distress, BTC, LTC, XRP, DOGE, and XMR are likely to follow a similar trend, while USDT and BNB are less affected. The lower tail dependence between Bitcoin Cash and the other nine cryptocurrencies is considered acceptable

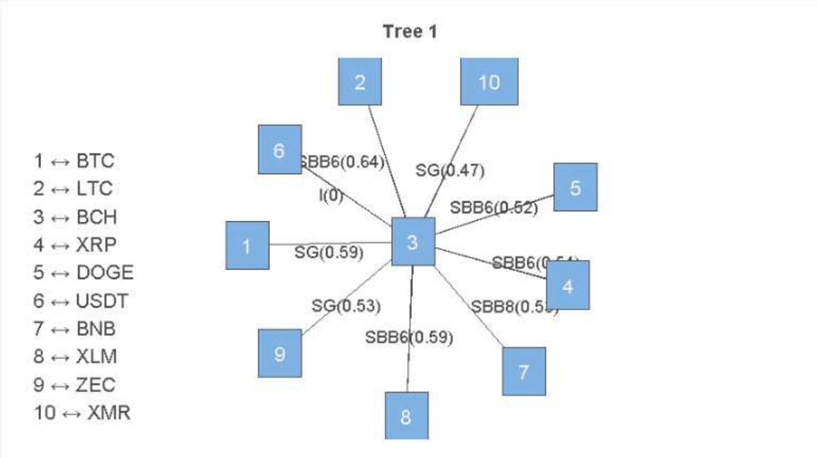

Figure 2. C-vine tree dependence structure for proof-of-stake cryptocurrencies

risk-sharing. Comparing proof-of-work (PoW) and proof-of-stake (PoS) cryptocurrencies, PoW assets show a stronger positive correlation with LTC (0, 0.56 to 0.75) than PoS assets (0.45 to 0.67).

The structure begins with Bitcoin Cash as the central node (Tree 1). Various copulas, including the independent copula I(0), Student-t copula (t-copula), Survival BB6 (18), Survival Gumbel SG (14), and Survival BB8 (20), are employed to construct a maximum dependence tree based on total pair-wise dependencies. The selection criterion is the AIC. The C-Vine copula model, as shown in Figure 2, highlights the distinctive role of the central node "Bitcoin Cash" compared to the other nine connected Proof of Work cryptocurrencies. Notably, Litecoin (LTC), Ripple (XRP), Dogecoin (DOGE), Tether (USDT), Monero (XMR), and Binance (BNB) are the most connected to Bitcoin Cash in Tree 1, with Monero (XMR) having the sole direct dependence.

Figure 3 illustrates the autocorrelation function of Proof of Stake cryptocurrencies. A higher autocorrelation function indicates strong autocor-

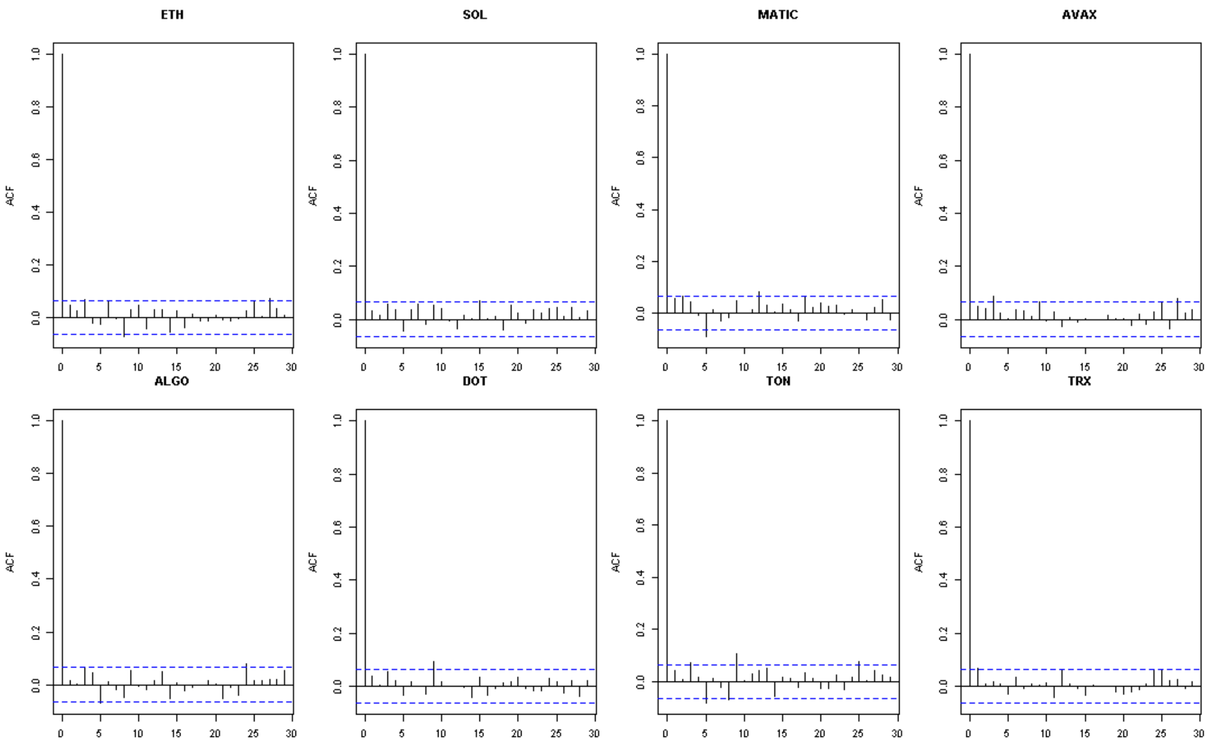

Figure 3. Copula ACF plot (proof-of-stake)

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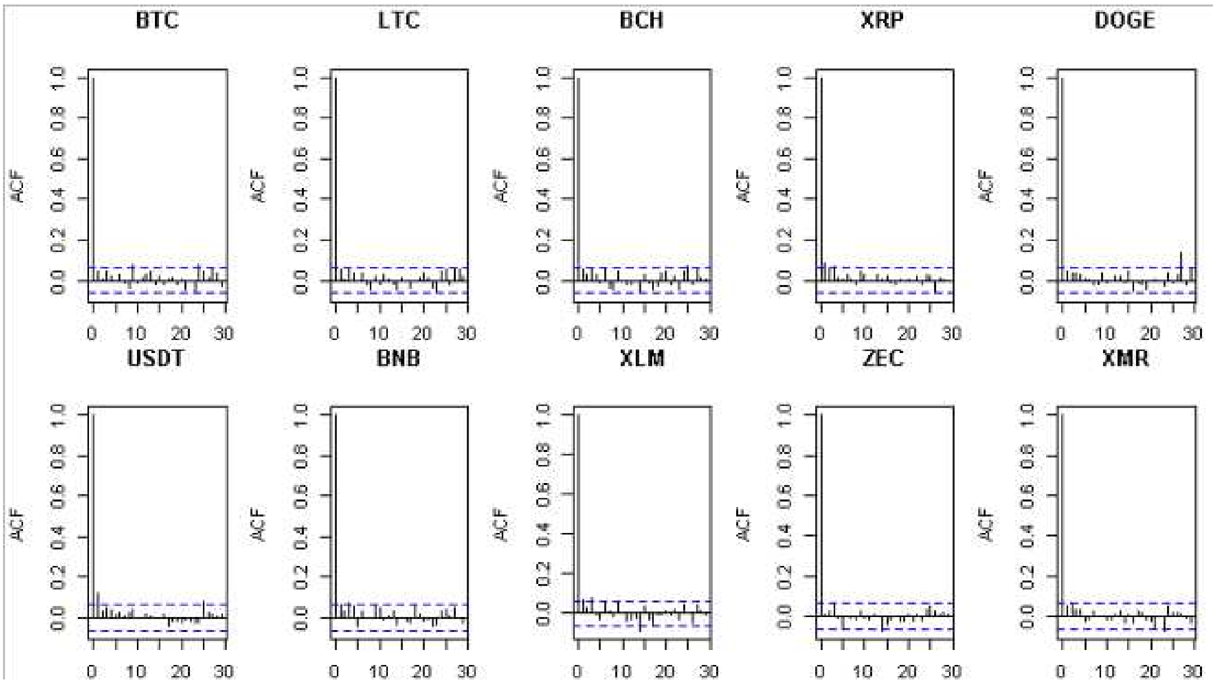


Figure 4. Copula ACF plot (proof-of-work)

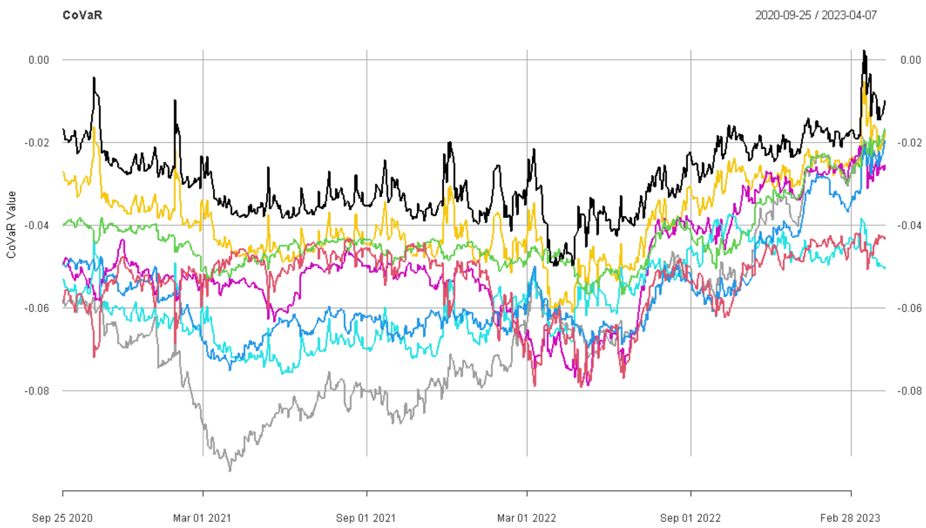
relation between lag returns. Values above the blue line are statistically significant, while those below are not. ETH, SOL, ALGO, TON, and TRX in Figure 3 show no significant autocorrelation at specific lags, while Matic, Avax, and DOT exhibit strong positive autocorrelation at certain lags. Autocorrelation measures previous states' impact on a time series's current state. A more vulnerable asset displays high positive or negative autocorrelation, indicating a strong dependence on past performance and a higher risk of reversal or continuation. Ethereum, the central node in the C-Vine tree (Figure 1), is statistically significant at lag 9. Table 3 reveals moderate associations (tau values: ETH-SOL 0.49, ETH-ALGO 0.53, ETH-TON 0.59, ETH-TRX 0.4). While not a perfect correlation, it suggests that changes in ETH's price are moderately related to changes in SOL's price.

Figure 4 depicts the autocorrelation function of proof-of-work cryptocurrencies, with values above the blue line indicating statistically significant autocorrelation. BTC, BCH, XRP, DOGE, BNB, XLM, ZEC, USDT, and XRM exhibit significant autocorrelation at specific lags, while LTC lacks autocorrelation at any lag. BCH is statistically significant at lag 9, and Table 4 shows moderate to strong associations between BCH and other connected assets. Ethereum, Bitcoin, Litecoin, and Solana display varying significance levels in their autocorrelation functions. Generally, proof-of-stake cryptocurrencies exhibit more significant autocorrelation, suggesting a stronger influence of past returns on their future returns compared to proof-of-work counterparts. Investors should consider previous returns up to fifteen days backward for informed decision-making.

3.1. CoVaR analysis for proof-of-stake cryptocurrencies

The analysis focuses on the dynamics of CoVaR among selected proof-of-stake cryptocurrencies before and after the second quarter of 2022. Figure 5 illustrates changes in CoVaR dynamics, notably during the first quarter of 2021, influenced by global lockdowns due to COVID-19. Another shift occurred in March 2022, marked by blockchain protocol hacks and crypto exchange bankruptcy, leading to a loss of confidence in the market. CoVaR estimations increase significantly towards the end of March 2022, indicating heightened risk. The risk transmission characteristics undergo a complete shift, with TRX and DOT changing positions as major risk contributors.

Regular risk assessments are crucial for crypto investors and portfolio managers, especially dur-



Note: ETH – black, SOL – yellow, MATIC – green, AVAX – purple, ALGO – blue, TON – turquoise, DOT – brown, TRX – gray.

Figure 5. CoVaR for proof-of-stake cryptocurrencies

ing market turmoil. ETH, DOT, and MATIC rank highest in systematic importance before April 2022, signifying their significant risk transmission role. Ethereum consistently emerges as the top risk transmitter, aligning with the C-Vine estimation, highlighting its central node role in dependence structure. The changing dynamics emphasize the importance of monitoring risk interconnectedness over time, as larger cryptocurrencies do not always maintain the highest systemic risk contributions. Elevated CoVaR levels in the second quarter of 2022 signify a period of financial contagion and reduced diversification benefits. The analysis reveals time-variation in risk spillovers and tail dependence, urging portfolio managers to adapt strategies to changing risk landscapes. Policymakers are encouraged to consider stability mechanisms during periods of sustained high CoVaR levels in cryptocurrencies.

3.2. Delta CoVaR analysis for proof-of-stake cryptocurrencies

The "Delta CoVaR" is the difference between the system's CoVaR (Conditional Value at Risk) at a 5% and 50% confidence level, respectively. This means that

Figure 6. Delta CoVaR for proof-of-stake cryptocurrencies

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it is an additional risk incurred by the portfolio during market distress. As shown in Figure 6, there are several spike peaks in Delta CoVaR, suggesting periods of particularly high vulnerability when portfolio risk increased sharply. This highlights vulnerability to extreme market moves. The highest spike appears in the second quarter of 2021, at the heart of the COVID-19 pandemic. This implies the portfolio became most vulnerable and prone to losses during the COVID-19 crisis. From the second quarter of 2022 through the end of the fourth quarter, there is an overall decreasing trend in Delta CoVaR, meaning portfolio risk and vulnerability were generally lower over this period as a whole.

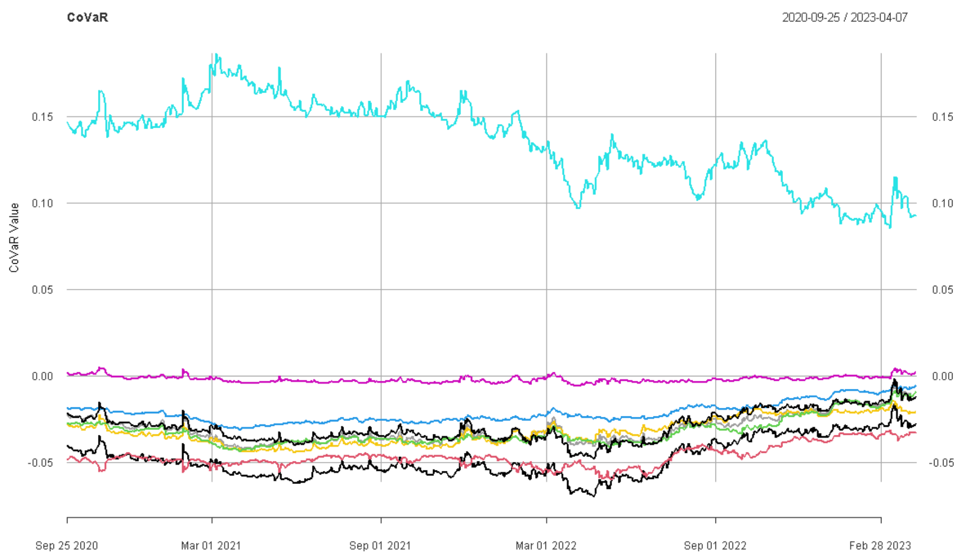
From Figure 6, in 2023, the portfolio was less vulnerable at the beginning of 2023, corresponding to the period when the cryptocurrency market started picking from the distress experienced during 2022. The fluctuations and spikes in Delta CoVaR over the period of study signify considerable variability in portfolio vulnerability. The portfolio appears prone to sudden surges in risk and an elevated risk profile in general. This analysis underscores the importance of risk monitoring and mitigation for such a crypto portfolio."

3.3. CoVaR analysis for proof-of-work cryptocurrencies

Figure 7 illustrates that Bitcoin (BTC) is the primary risk transmitter in the proof-of-work (PoW) cryptocurrency portfolio, having a positive CoVaR of 0.15. In contrast, the CoVaR for other PoW cryptocurrencies is around zero, with Litecoin (LTC) at zero and others below zero or negative, signifying their role as shock absorbers. The risk dynamics of these PoW cryptocurrencies remain relatively stable throughout the study period, except for occasional spikes in the second half of 2022.

The risk profile of the selected PoW cryptocurrencies shows consistent behavior, without significant shifts observed in the dynamics compared to the more variable patterns noted in PoS cryptocurrencies. In the PoW portfolio, BTC stands out with a positive CoVaR, indicating its significant contribution to systemic risk. A positive CoVaR suggests that the distress of an asset is associated with a higher value at risk for the entire portfolio, implying that the asset is exposed to common shocks or contagion effects that can affect other assets in the portfolio. On the other hand, PoS cryptocurrencies, including Ethereum, exhibit negative CoVaR values, indicating that their distress is associated with a lower value at risk for the portfolio. This implies that these assets reduce systemic risk, are diversified, or are hedged against common shocks or contagion effects.

A negative CoVaR suggests that these assets are not too big, interconnected, or complex to fail, and their failure would have limited spillover ef-



Note: BTC – turquoise, LTC – purple, BCH – blue, XRP – gray, DOGE – black, USDT – yellow, BNB – green, XLM – red, ZEC – black.

Figure 7. CoVaR for proof-of-work cryptocurrencies

fects on the rest of the portfolio. The observation concludes that the PoS portfolio appears well-diversified and hedged against common shocks or contagion effects among its assets, contrasting with BTC's more concentrated risk profile in the PoW portfolio. The commonality between the portfolios is that the leading cryptocurrency in each group remains the highest risk transmitter throughout the study period. The study raises the question of whether market capitalization can indicate a cryptocurrency's risk profile, especially in the PoW context, suggesting the need for further investigation.

3.4. Delta CoVaR analysis for proof-of-work cryptocurrencies

Figure 8 shows that in the second quarter of 2021, the portfolio was highly vulnerable, and this also corresponded to the COVID period, but afterward, the effects were neutralized. In the second quarter of 2022, the portfolios were also vulnerable, corresponding to the period when cryptocurrency prices started decreasing significantly. Similar to the proof-of-stake Delta CoVaR, there are several spike peaks in Delta CoVaR, suggesting there were periods of particularly high vulnerability when portfolio risk increased sharply. This highlights vulnerability to extreme market moves. The highest spike appeared in the 2nd quarter of 2021, at the heart of the COVID-19 pandemic, which was also observed from the PoS Delta CoVaR. From the second quarter of 2022 through the end of the 4th quarter, there is an overall decreasing trend in Delta CoVaR, meaning portfolio risk and vulnerability were generally lowering over this period as a whole. However, in terms of CoVaR, the PoS and PoW display noticeable differences. The Delta CoVaR of their Portfolio displays similar characteristics and trends.

This study examined the tail dependence structure and risk spillover between Proof of Stake (PoS) and Proof of Work (PoW) cryptocurrencies, providing crucial insights for investors and policymakers navigating this complex and evolving asset class. The findings reveal distinct patterns of interconnectedness and risk transmission within these two cryptocurrency ecosystems. Specifically, Ethereum emerged as a stabilizing force within the PoS space, exhibiting resilience during market downturns and acting as a buffer for other PoS cryptocurrencies. Conversely, Bitcoin Cash was identified as a key diversifier within the PoW group, absorbing a significant portion of volatility spillovers. However, both Ethereum and Bitcoin were found to be dominant risk transmitters within their respective groups, highlighting their potential to amplify systemic risk. These find-

Figure 8. Delta CoVaR for proof-of-work cryptocurrencies

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ings have significant implications for portfolio management. Investors seeking to diversify their cryptocurrency holdings should consider the distinct risk profiles of PoS and PoW assets. Including both asset types in a portfolio could potentially mitigate downside risk, but careful consideration should be given to the potential for risk transmission from dominant players like Ethereum and Bitcoin.

Furthermore, the findings underscore the need for policymakers to develop nuanced regulatory frameworks that account for the interconnectedness and specific risk characteristics of different cryptocurrency ecosystems. Understanding the tail dependence and risk spillover dynamics within and between PoS and PoW cryptocurrencies is crucial for fostering financial stability and investor protection.

4. DISCUSSION

Investigating the tail dependence structure and risk spillover between Proof-of-Stake (PoS) and Proof-of-Work (PoW) cryptocurrencies reveals important nuances within the broader cryptocurrency market. While previous research has often analyzed cryptocurrencies as a homogenous group, the findings of this study highlight the distinct risk profiles and interconnectedness patterns that emerge when considering their underlying technological foundations. The resilience of Ethereum during market downturns, acting as a buffer for other proof of stake cryptocurrencies, suggests a potential "flight-to-quality" phenomenon within this segment. As investors seek refuge from volatility, Ethereum's established position, larger market capitalization, and active development community may be perceived as offering relative stability. This finding aligns with previous research highlighting Ethereum's growing importance within the decentralized finance (DeFi) ecosystem, which could further solidify its role as a safe haven during turbulent market periods (e.g., Schär, 2021). Conversely, Bitcoin Cash's emergence as a portfolio diversifier within the PoW space, absorbing a significant portion of volatility spillovers, presents a more nuanced picture. While often overshadowed by Bitcoin, Bitcoin Cash's larger block size and focus on peer-to-peer transactions might attract investors seeking alternatives within the PoW space, particularly during periods of Bitcoin network congestion or high transaction fees. This finding challenges the notion that Bitcoin's dominance inherently translates to higher risk absorption capacity and suggests that intra-group diversification within PoW cryptocurrencies can be an effective risk management strategy. However, identifying Ethereum and Bitcoin as dominant risk transmitters within their respective groups raises concerns about systemic risk. This finding aligns with concerns about the increasing concentration of market power within the cryptocurrency market, where a few dominant players can disproportionately influence overall market sentiment and volatility (e.g., Giudici et al., 2020; Stylianou et al., 2021).

CONCLUSION

This study examined the tail dependence structure and risk spillover between Proof-of-Stake (PoS) and Proof-of-Work (PoW) cryptocurrencies, providing crucial insights for investors and policymakers navigating this complex and evolving asset class. The findings reveal distinct patterns of interconnectedness and risk transmission within these two cryptocurrency ecosystems. Specifically, Ethereum emerged as a stabilizing force within the PoS space, exhibiting resilience during market downturns and acting as a buffer for other PoS cryptocurrencies. Conversely, Bitcoin Cash was identified as a key diversifier within the PoW group, absorbing a significant portion of volatility spillovers. However, both Ethereum and Bitcoin were found to be dominant risk transmitters within their respective groups, highlighting their potential to amplify systemic risk. These findings have significant implications for portfolio management. Investors seeking to diversify their cryptocurrency holdings should consider the distinct risk profiles of PoS and PoW assets. Including both asset types in a portfolio could potentially mitigate downside risk, but careful consideration should be given to the potential for risk transmission from dominant players like Ethereum and Bitcoin.

Furthermore, our findings underscore the need for policymakers to develop nuanced regulatory frameworks that account for the interconnectedness and specific risk characteristics of different cryptocurrency ecosystems. Understanding the tail dependence and risk spillover dynamics within and between PoS and PoW cryptocurrencies is crucial for fostering financial stability and investor protection.

It is important to acknowledge that this study has limitations. The sample period and selection of cryptocurrencies may influence the generalizability of the findings. Future research could expand on this study by incorporating a wider range of cryptocurrencies, exploring different time periods, and investigating the impact of external events on risk transmission dynamics.

Despite these limitations, this study provides valuable insights into the complex interplay between PoS and PoW cryptocurrencies, offering practical guidance for investors and informing the development of effective regulatory frameworks for this rapidly evolving asset class.

AUTHOR CONTRIBUTIONS

Conceptualization: Jules Clement Mba, Abieyuwa Ohonba.
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Investigation: Abdulrazak Abdulrahman Abubakar.
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Project administration: Jules Clement Mba, Abieyuwa Ohonba.
Supervision: Jules Clement Mba, Abieyuwa Ohonba.
Validation: Abieyuwa Ohonba.
Visualization: Abdulrazak Abdulrahman Abubakar.
Writing – original draft: Abdulrazak Abdulrahman Abubakar.
Writing – review & editing: Abdulrazak Abdulrahman Abubakar, Jules Clement Mba, Abieyuwa Ohonba.

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