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RESEARCH ARTICLE

Sectoral Analysis of the Cryptocurrency Market Using Minimum Spanning Tree[1]

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Abstract

This study examined the interaction dynamics and clustering characteristics of cryptocurrencies using MST (Minimum Spanning Tree) analysis based on the daily closing prices of 67 cryptocurrencies traded on Binance. The study included ten cryptocurrencies from the gaming sector and 56 high-market-cap cryptocurrencies. While cryptocurrencies have been analysed from various perspectives using MST in the literature, sectoral analysis has been neglected. This study focused on the categorization of cryptocurrencies and directly on crypto games. According to the MST analysis, crypto games and decentralized exchanges exhibited significant clustering within themselves. Ethereum emerged as the cryptocurrency with the most connections on the network. ENJ held a central position within crypto games, and most crypto games showed clustering among themselves. The intuitive expectation was that Bitcoin would have more connections, dominating the cryptocurrency market. However, the analysis indicated that Ethereum occupies a central position in the cryptocurrency sector.

Keywords: *Minimum Spanning Tree, Cryptocurrencies, Financial Networks, Blockchain, Cryptocurrency Market*
Jel Codes: *G17, C58, D85*

Kripto Para Piyasasının Minimum Kapsayan Ağaç ile Sektörel Analizi

Özet

Bu çalışma, Binance'de işlem gören 67 kripto paranın günlük kapanış fiyatları kullanılarak yapılan MST (Minimum Spanning Tree) analiziyle, kripto paraların etkileşim dinamiklerini ve kümelenme özelliklerini incelemiştir. Çalışma, oyun sektöründen 10 kripto parayı ve piyasa hacmi yüksek 56 kripto parayı analiz kapsamına almıştır. Literatürde MST analiziyle kripto paralar çeşitli veçhelerle incelenmiş ancak sektörel bir analiz ihmal edilmiştir. Bu çalışma kripto paraların kategorizasyonuna ve doğrudan kripto oyunlara odaklanmıştır. MST analizine göre, kripto oyunlar ve merkeziyetsiz borsalar kendi aralarında belirgin bir kümelenme sergilemiştir. Ethereum, ağ üzerinde en fazla bağlantıya sahip kripto para olarak öne çıkmıştır. ENJ, kripto oyunlar içinde merkezi bir konumda yer almış ve kripto oyunların çoğu kendi içinde bir kümelenme göstermiştir. İçsel öngörü Bitcoin'in kripto para piyasasında domine bir güce sahip olarak daha fazla bağlantıya sahip olacağıdır. Ancak analize göre Ethereum kripto para sektöründe merkezi bir konumda yer almaktadır.

Anahtar kelimeler: *Minumum Yayılan Ağaç, Kripto Paralar, Finansal Ağlar, Blok Zinciri, Kripto Para Piyasası*
Jel Kodu: *G17, C58, D85*

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1. INTRODUCTION

Financial markets are highly complex systems. By modelling the complex relationships within financial markets, it is possible to identify hierarchical structures and clusters. In this study, the hierarchical and clustering relationships of cryptocurrencies were analysed in the context of "Macrotokenomics," which included the financial magnitude of cryptocurrencies. Methodologically, the analysis was based on the literature focused on stock and financial networks built on correlation matrices. Modelling financial markets using Minimum Spanning Tree (MST) for complex networks involves the nodes of different financial assets in the network and their correlations forming the connections between them. MST consists of a subset that connects all nodes of a graph with minimum edge weights. In this study, the edge weights were derived from the distance calculated from the correlation of cryptocurrency pairs.

Many studies have analysed financial networks using the MST method. Additionally, analyses targeting the cryptocurrency market have been conducted using this method. Briola and Aste (2022) analysed 25 cryptocurrencies traded on the FXT exchange over different time periods. They concluded that Ethereum acted as a hierarchical reference node for other cryptocurrencies and maintained its position over time. Chaudhari and Crane (2020) used Random Matrix Theory to analyse the price changes of 119 and 59 cryptocurrencies with cross-correlations and revealed the community structures of these cryptocurrencies using MST. Accordingly, significant groups among cryptocurrencies were observed. It was argued that forming various portfolios from these community groups would provide better diversification for investors and reduce portfolio risk. Dönmez et al. (2020) examined cross-correlations between different cryptocurrencies in terms of changes in market capitalization value. They concluded that some cryptocurrency pairs were highly correlated and that BTC had a central and significant role in the cryptocurrency network. Dönmez et al. (2021) analysed the cross-correlation, Hierarchical Tree, and MST methods by including Bitcoin in the currencies of 50 different countries. It was concluded that Bitcoin did not have a central role in the MST. Frances et al. (2018) analysed the daily price series of 16 different cryptocurrencies from July 2017 to February 2018 using MST and Dendrogram methods. It was observed that Ethereum was the most central cryptocurrency, having more connections than other cryptocurrencies and serving a binding role among cryptocurrencies. Giudici and Polinesi (2021) analysed the price dynamics of cryptocurrencies and how price information was transmitted between cryptocurrency exchanges and traditional exchanges using the MST method. It was found that Bitcoin had a positive relationship with exchange rates and that major exchanges influenced prices, while traditional asset prices did not affect Bitcoin's price. Giudici et al. (2020) analysed the top 10 cryptocurrencies by market size using the MST method to generate a portfolio strategy and created the Markowitz model. It was argued that the use of network models in the portfolio construction process would improve the risk-return profiles of portfolios and reduce losses during market downturns. Similarly, Kitanovski et al. (2022) investigated the correlation between cryptocurrencies and community behaviour based on mutual information for portfolio diversification. Ho et al. (2020) conducted a network analysis using centrality measures to examine the characteristics and dynamic development of the cryptocurrency market, using the daily closing prices of the top 120 cryptocurrencies between 2013 and 2020. The cross-correlation among cryptocurrencies weakened from 2013 to 2016 and then strengthened again. Until mid-2016, Bitcoin dominated the MST, after which it was replaced by Ethereum. Kwapień et al. (2021) analysed the dependencies between the cryptocurrency market and some traditional markets, such as commodity markets, stock markets, and Forex, using the MST method. During periods when the cryptocurrency market had strong internal cross-correlation, it showed higher levels of cross-correlation with other markets. Şensoy et al. (2021) examined the returns and volatility of cryptocurrencies in different sub-periods. The analysis conducted with MST concluded that Bitcoin, Litecoin, and Ethereum had the highest connectivity and became central to other cryptocurrencies. Throughout the examined period, Bitcoin, Litecoin, and Ethereum maintained their central roles. Song et al. (2019) studied the structure and collective behaviour of the cryptocurrency market using correlation-based clustering and MST methods. It was observed that most cryptocurrencies had a high correlation with Bitcoin and Ethereum. Stosic et al. (2018) measured collective behaviour among cryptocurrencies by analysing cross-correlations between price changes of 119 publicly traded cryptocurrencies from August 26, 2016, to January 18, 2018, using Random Matrix Theory and MST. The analysis revealed stable community structures among cryptocurrencies. Zieba et al. (2019) analysed the dependencies between the daily returns of cryptocurrencies using MST with 78 cryptocurrencies in two consecutive periods. It was observed that cryptocurrencies formed hierarchical clusters in both periods. In addition, using the Vector Autoregression model, the transmission of demand shocks within clusters was examined, concluding that changes in Bitcoin's price did not affect the prices of other cryptocurrencies. Finally, there were also studies in the literature that addressed the impact of the pandemic on cryptocurrencies and the change in their hierarchical structure (Hong and Yoon, 2022; Katsiampa et al., 2022).

In the literature, cryptocurrencies have been analysed using the MST method from various perspectives. However, there is no study focusing on the categorization of cryptocurrencies or directly on crypto games. In this context, this study conducted an analysis focusing on the categorization of cryptocurrencies and directly on crypto games.

2. DATA

As part of the analysis, the daily closing prices of 67 cryptocurrencies traded on Binance were obtained. Ten cryptocurrencies from Binance's gaming sector were included in the analysis, while the remaining 56 cryptocurrencies were selected based on market capitalization. Although there were 25 cryptocurrencies in Binance's gaming sector, only ten tokens that were introduced before or on November 4, 2020, including the AXS token, were included in the analysis due to AXS starting to trade on that date. Price data was sourced from CoinGecko (www.coingecko.com). Stablecoins were excluded from the analysis due to their price stability and lack of determinability in the context of this study.

Table 1. Sectoral Distribution of Cryptocurrencies

Gaming	AXS, SLP, BURGER, ENJ, COCOS, GALA, GHST, MANA, SAND, WAXP
Decentralized Finance	AAVE, UNI, RPL, CRV, MKR, SNX, INJ, KAVA, KLAY, WOO, RUNE, LRC, CAKE
Layer 1-2	BNB, ADA, MATIC, SOL, TRX, DOT, AVAX, ATOM, ETC, ETH, XLM, HBAR, VET, NEAR, ALGO, EOS, EGLD, FTM, XTZ, CFX, NEO, CHZ, IOTA, ZIL
Storage	FIL, STX
PoW	BTC, DOGE, BCH, DASH, LTC, XMR, ZEC
Infrastructure	LINK, QNT, BAT, TWT, RNDR
Innovation	FTT
NFT	THETA
Others	NEXO, PAXG, XRP, AGIX

Source: Binance (2023).

Table 1 shows the sectors categorized by Binance. According to this categorization, the gaming sector includes crypto games. Decentralized finance refers to an ecosystem of blockchain-based financial applications that operate transparently and without requiring permission. Layer 1 cryptocurrency projects represent foundational blockchain networks that host decentralized applications, meaning the projects have their own blockchain. Layer 2 cryptocurrency projects run on top of an existing foundational network. Storage tokens specialize in blockchain-based cloud storage/data storage, providing alternatives to centralized storage platforms. Proof of Work (PoW) tokens are projects that have their own blockchain and utilize the PoW protocol. Infrastructure tokens specialize in providing components and systems for blockchains, ensuring their smooth operation. Innovation encompasses projects that involve innovative token offerings. NFTs include tokens related to collections. The "Other" category includes projects that do not fall under any other categories within Binance's classification. A token can belong to multiple categories in Binance's categorization. For example, crypto games that are NFT-based are included in both the NFT and gaming categories. This study uses Binance's categorization as specified in Table 1.

3. METHODOLOGY

The method used in this study, the Minimum Spanning Tree (MST), has a wide range of applications in optimization and data analysis. MST was first proposed by Mantegna (1999) to explain the relationships between financial products. In this study, MST was used to identify the interactions between games in the crypto gaming sector and high-market-cap cryptocurrencies. Following Mantegna's (1999) steps, each cryptocurrency was defined as N, and the number of days was T in the analysis.

- The price return of the i-th cryptocurrency on day t, $p_i(t)$, was calculated from the closing price of the i-th stock on day t as follows:

$$r_i(t) = lnp_i(t) - lnp_i(t-1)$$

- The correlation coefficient between the price return series of the i-th and j-th cryptocurrencies, denoted as $\bar{r}_i = \frac{1}{T-1}\sum_{t=2}^{T} r_i(t)$, was calculated using the following formula:

$$c_{ij} = \frac{\sum_{t=2}^{T}(r_i(t)-\bar{r}_i)(r_j(t)-\bar{r}_j)}{\sqrt{\sum_{t=2}^{T}(r_i(t)-\bar{r}_i)^2}\sqrt{\sum_{t=2}^{T}(r_j(t)-\bar{r}_j)^2}}$$

- The distance between cryptocurrencies, or the weights of the edges on the tree, was calculated using the following formula:

$$d(i,j) = \sqrt{2(1-c_{ij})}$$

Here, the distance between cryptocurrencies is inversely proportional to the correlation coefficient. To analyse the correlation structure of cryptocurrencies in tree form, it is necessary to calculate the matrix of all pairwise distances. By calculating the minimum spanning tree of this complete graph distance matrix, a sub-ultrametric space network was obtained. Similar to Bonanno et al. (2000; 2001), Mantegna (1999), Guidici and Polinesi (2021), it was assumed that the sub-ultrametric space network was a meaningful pattern of economic information implicitly found within time series.

Prim's MST Algorithm (1957) was used to obtain minimum spanning trees. To derive numerical information from the minimum spanning trees, measures such as betweenness centrality and degree centrality, used by Mirzaei et al. (2019), were also calculated. For a cryptocurrency represented by node v_i in the tree, the degree centrality value, $\alpha_{\deg}(v_i)$, was calculated as follows, where $\deg(v_i) =$ was the number of directly connected nodes (cryptocurrencies):

$$\alpha_{\deg}(v_i) = \deg(v_i)/n$$

Betweenness centrality, $\alpha_{\text{bet}}(v_i)$, was calculated as follows, where σ_i was the number of times node v_i was visited on the paths from node v_j to node v_k (Freeman,1977):

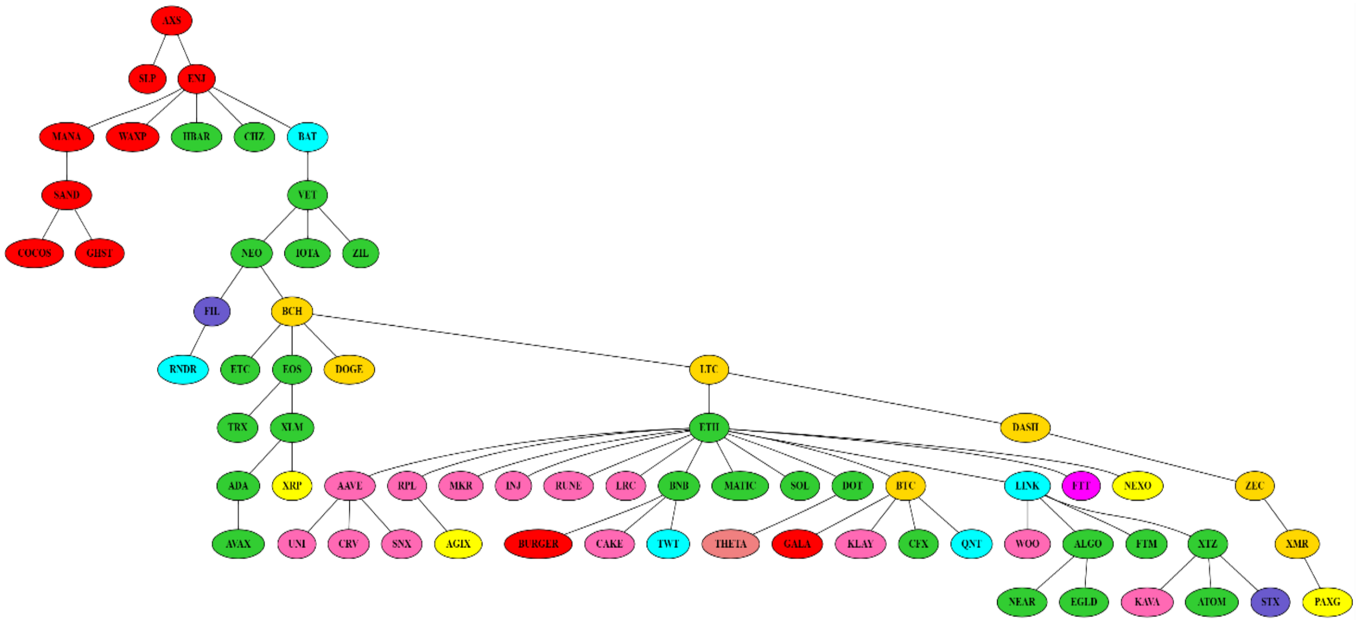
$$\alpha_{\text{bet}}(v_i) = \frac{\sum_{j=1}^{n}\sum_{k=1}^{n}\sigma_i}{n(n-1)}$$

Unlike the original calculation, in the minimum spanning tree, there is only one path between any two nodes, and there is no need to search for the shortest path. The total number of paths is n(n-1).

4. RESULTS

With MST analysis, it is possible to observe the connection dynamics of products in financial markets. The tree visual created with MST analysis is shown in Figure 1. The tree is color-coded according to Binance's categorization distinctions. Accordingly, red represents the gaming sector, pink represents decentralized finance applications, green represents Layer 1 and Layer 2 cryptocurrencies, navy blue represents storage tokens, gold represents proof-of-work cryptocurrencies, blue represents infrastructure tokens, purple represents innovation tokens, brown represents NFT tokens, and yellow represents tokens that do not fall into any specific category.

Figure 1. Cryptocurrencies Minimum Spanning Tree



Source: Prepared by the authors

Figure 1 shows the MST. According to this, crypto games and decentralized exchanges cluster within themselves. This indicates that the clusters exhibit similar characteristics among themselves. On the other hand, an intuitive prediction is that Bitcoin has the most connections in terms of market volume and capitalization. However, consistent with the MST literature on cryptocurrencies, Ethereum is the cryptocurrency with the most connections in the tree (Briola and Aste, 2022; Dönmez et al., 2021; Frances et al., 2018; Ho et al., 2020). Contrary to the view that Bitcoin's dominant position has a global impact on the entire cryptocurrency market, the analysis showed the opposite. It seems understandable that Ethereum dominates the market with smart contracts that contribute to the blockchain ecosystem. The emergence of many cryptocurrencies with smart contracts supports this. Moreover, it can be said that the fact that smart contracts form the basis of decentralised exchanges causes them to be located close to Ethereum in the tree. The proximity of cryptocurrencies in the tree indicates a high correlation among them. In the crypto games sector, ENJ is in the central position. This is not surprising given ENJ's infrastructure, which can be integrated into every crypto game due to its wallet, storage, and exchange infrastructure for NFTs. Other than BURGER and GALA, other crypto games have clustering within themselves, indicating a similar dynamic among them. Layer 1 and Layer 2 cryptocurrencies have a scattered clustering feature. Although proof-of-work tokens do not have complete clustering among themselves, they are connected to each other. It is observed that cryptocurrencies in other categories do not have clustering. Notably, eight cryptocurrencies have more connections than Bitcoin. This allows us to infer that Bitcoin may lose its position in the cryptocurrency market over time.

Table 2 shows the top 20 cryptocurrencies with the highest centrality measures. The interpretation of centrality measures can be made as follows: cryptocurrencies with a high degree of centrality have a high number of direct interactions with other cryptocurrencies, while those with a high betweenness centrality have a high number of indirect interactions with other cryptocurrencies. If there are no direct connections between cryptocurrencies in the tree, access to cryptocurrencies is indirectly achieved by following a path through other cryptocurrencies. Accordingly, betweenness indicates how many times a cryptocurrency is visited on the selected indirect paths and is obtained by dividing the number of times a cryptocurrency is visited by the total number of paths.

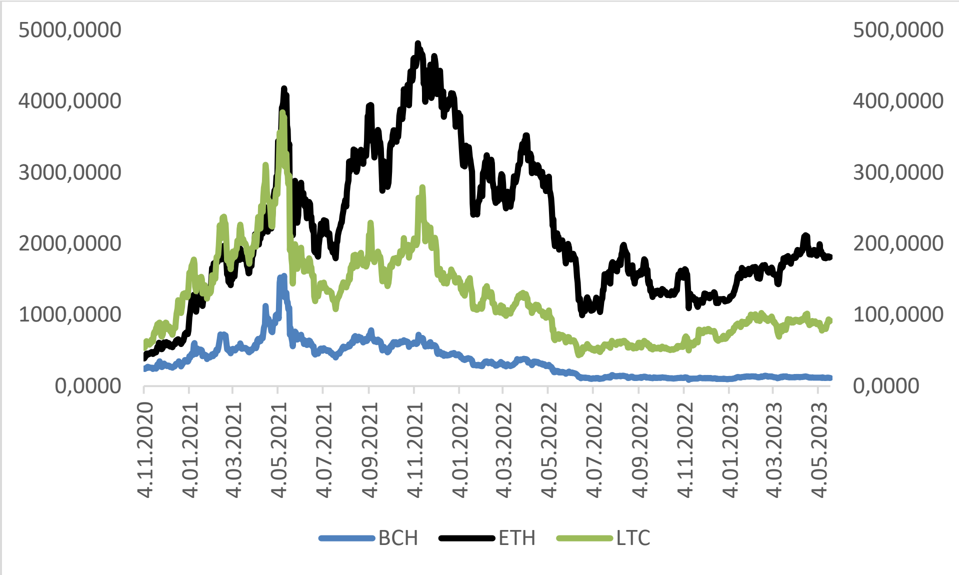
Table 2. MST Centrality Measures

	DEGREE	**BETWEENNESS**
ETH	0.224	0.729
LTC	0.045	0.536
BCH	0.075	0.531
NEO	0.045	0.374
VET	0.060	0.322
BAT	0.030	0.253
ENJ	0.090	0.245
LINK	0.075	0.244
EOS	0.045	0.140
BTC	0.075	0.115
AAVE	0.060	0.087
BNB	0.060	0.087
XTZ	0.060	0.087
XLM	0.045	0.086
MANA	0.030	0.085
DASH	0.030	0.085
SAND	0.045	0.058
ALGO	0.045	0.058
ZEX	0.030	0.058
AXS	0.030	0.029

Source: Prepared by the authors

According to Table 2, as seen in the tree, the cryptocurrency with the most connections, both directly and indirectly, was Ethereum. After Ethereum, LTC, BCH, NEO, ENJ, LINK, BTC, and VET were the cryptocurrencies with the most direct connections. Although ENJ had higher direct connections compared to others, its indirect connections were weaker. On the other hand, LTC, which had fewer direct connections, had more indirect connections, meaning it was more frequently visited when accessing other cryptocurrencies in the tree.

Figure 2. BCH-ETH-LTC Price Chart



Source: Prepared by the authors

Figure 2 shows the prices of the top three cryptocurrencies with the highest centrality measures. Ethereum entered the market in 2015 by introducing smart contracts to the blockchain ecosystem. Smart contracts allow not only value transfer but also the exchange of any asset. Ethereum, which provides infrastructure to the blockchain ecosystem through smart contracts, has enabled the creation of many tokens using this infrastructure. Thanks to this innovation within the market, Ethereum became the focus of users. Additionally, when it first launched, Ethereum had an unlimited supply. In a scenario where it was not of interest to the user base, it could have had an inflationary structure. However, Ethereum's design expanded its user base and maintained a sustainable structure. As seen in Figure 2, despite having cyclical fluctuations, Ethereum has not lost its sustainability.

Bitcoin Cash (BCH) emerged in 2017 following a hard fork in the Bitcoin network. Due to the 1 MB block size limit in Bitcoin, transaction limits were restricted. Miners who wanted to increase block sizes to 8 MB separated from the Bitcoin network, resulting in the creation of Bitcoin Cash. It aimed to establish a more efficient system by addressing Bitcoin's efficiency problems. Following its inception, it became the cryptocurrency used by those dissatisfied with Bitcoin's scalability issues. It was demanded by users because it was faster and cheaper. By solving an existing problem in the blockchain ecosystem early on, the project has its own sustainability. As seen in Figure 2, it has a stable price structure.

Litecoin (LTC) was launched in 2011. While BCH approached Bitcoin's scalability issue by changing block sizes, LTC addressed this issue by changing the hardware used in mining. Although it operates on the same principles as Bitcoin, its mining structure differs. Additionally, it has a supply limit of 84 million. Being one of the first cryptocurrencies and providing a solution to a market problem, LTC is also in demand by users.

Cryptocurrency projects naturally become in demand by users if they solve a problem within the blockchain ecosystem and/or offer a useful approach for users. Although Ethereum has an unlimited supply, it has not turned into an inflationary structure. When designing the token economy of cryptocurrency projects, planning incentive mechanisms around the developed business idea ensures the continuity of the user base. For a sustainable cryptocurrency design, the benefit it creates within the ecosystem is as important as the token economy. The measurement of this benefit can be seen through its user base and market price.

5. CONCLUSION

This study examined the interaction dynamics and clustering characteristics of cryptocurrencies using the daily closing prices of 67 cryptocurrencies traded on Binance through MST (Minimum Spanning Tree) analysis. The analysis included ten cryptocurrencies from the gaming sector and 56 high-market-cap cryptocurrencies, excluding stablecoins. The daily returns of the cryptocurrencies were calculated from the collected data, and a distance matrix was created using correlation coefficients. Prim's MST Algorithm was employed to visualize and analyse the connections among the cryptocurrencies.

According to the analysis conducted within the study, crypto games and decentralized exchanges exhibited significant clustering among themselves. Ethereum emerged as the cryptocurrency with the most connections on the network. Notably, ENJ held a central position within crypto games, and it was observed that most crypto games exhibited clustering within their group. The scattered clustering of Layer 1 and Layer 2 cryptocurrencies indicated their diversity and lack of consolidation into a specific group. Although proof-of-work tokens did not show complete clustering among themselves, they still maintained certain connections.

The centrality measures shown in Table 2 revealed that Ethereum had the highest values in terms of both direct and indirect connections. This underscores Ethereum's central role in the market and the importance of the infrastructure provided by its smart contracts. Additionally, the analysis suggests that Bitcoin's dominance in the market may decrease over time, as eight cryptocurrencies have more connections than Bitcoin, hinting that Bitcoin could lose its position in the cryptocurrency market.

Sectoral analyses are generally neglected in the MST literature on crypto assets. In the context of the findings, Bitcoin is in the central position in the correlation analyses in the literature. In this study, on the other hand, Ethereum is in the central position, and the price of Ethereum is more determinant in sectoral price dynamics. The main reason for this finding is that Ethereum creates an ecosystem for Defi, crypto games, the NFT market, and other sectors where smart contracts are used.

The market dynamics and interactions of cryptocurrencies provide valuable insights for investors and researchers, aiding in understanding the future potential and market impact of these projects. The central role of Ethereum and the potential diminishing influence of Bitcoin highlight the dynamic and volatile nature of the cryptocurrency market, forming a crucial foundation for future research.

Further studies will expand these empirical results with hierarchical clustering approaches (Average Linkage, Ward Method, etc.) frequently used in machine learning.

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