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RESEARCH ARTICLE

Has bitcoin been dethroned too quickly? The cryptocurrency return networks

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Abstract

This study aims to explore the dependencies on the cryptocurrency market using social network tools. We focus on the correlations observed in the cryptocurrency returns. Based on the sample of cryptocurrencies listed between January 2015 and December 2022 we examine which cryptos are central to the overall market and how often major players change. Static network analysis based on the whole sample shows that the network consists of several communities strongly connected and central, as well as a few that are disconnected and peripheral. Such a structure of the network implies high systemic risk. The day-by-day snapshots show that the network evolves rapidly. We construct the ranking of major cryptos based on centrality measures utilizing the TOPSIS method. We find that when single measures are considered, Bitcoin seems to have lost its first-mover advantage in late 2016. However, in the overall ranking, it still appears among the top positions. The collapse of any of the cryptocurrencies from the top of the rankings poses a serious threat to the entire market.

Keywords: Cryptocurrency; network; distance; centrality; ranking; TOPSIS; entropy

1. Introduction

Cryptocurrencies are a rapidly growing segment of the financial market, considered a separate class of investment assets (Pele et al., 2021). They differ from other financial assets regarding high volatility, extreme returns and memory factors Bouri et al. (2019). They are often weakly or negatively correlated with traditional assets such as stocks or bonds (Bouri. Vo, and Saced, 2021), and therefore they are perceived as promising alternatives in portfolios. Bitcoin is even called a digital gold (Baur and Hoang, 2021; Selmi, Bouoiyour, and Wohar, 2022). With this increased interest and opportunities to invest in the cryptocurrency market, the question arises as to what the interdependencies are between crypto assets, whether any currencies play a major role in the market, and whether their central position is changing as the market matures. Bitcoin is the oldest crypto asset with a first-mover advantage (Barabási and Pósfai, 2022) and overwhelming capitalization. Therefore, it is usually treated as the title star (Bonneau et al., 2015; Będowska-Sójka, Kliber and Rutkowska, 2021; Kayal and Rohilla, 2021; Bruzgė and Šapkauskienė, 2022; Zięba, Kokoszczyński, and Śledziewska, 2019; Kajtazi and Moro, 2019). Nevertheless, some studies show the declining importance of this crypto asset (Shahzad et al., 2022; Ho, Chiu, and Li, 2020).

Our study aims to identify the main cryptocurrencies and verify the stability of their position. We use the social network approach based on the similarities observed in the cryptocurrency returns measured by the correlations and distances (Marti et al., 2021). The high correlation among assets' returns implies high systemic risk. For highly correlated systems changes or shocks in one part of the financial system can affect the other parts (Fund, 2023). By main cryptocurrencies, we understand central coins in the correlation network.[1] We identify the key crypto assets (hubs) that play a pivotal role in shaping the overall stability and functioning of the financial system. Hubs facilitate communication among nodes. Identifying and understanding these central nodes is crucial both for assessing systemic risk, and the resilience of the financial network to shocks or disruptions. A drop in the prices of a hub and the consequent increase in volatility may result in a snowball effect and the turbulences of the whole market. On the contrary, a resilient system with low dependence on assets will enhance financial stability. The identification of the most influential nodes in complex networks is a nontrivial task. Different centrality measures indicate different nodes as the most central ones. Therefore, concerning the issue of cryptocurrency network evolution, we apply the ranking based on the information entropy and the technique for order preference by similarity to an ideal solution (TOPSIS) method (Ishfaq, Khan, and Ighal, 2022).

Networks have been used in economics and finance over the last two decades (Boginski et al., 2005; Onnela, Kaski and Kertész, 2004; Engel et al., 2021). They provide unique insights allowing one to investigate in depth the dependence in structures that consist of a large number of nodes (Giudici and Spelta, 2016). We apply them to explain multidimensional dependence in the coins as well as patterns observed within the transmission of valuable information. They also allow us to identify key nodes (Engel et al., 2021). Here, we utilize this approach to indicate the main cryptocurrencies and examine the stability of their position in the ranking over time. By exploiting the network approach we enrich the understanding of complex relations observed on the cryptocurrency markets. When returns are highly correlated, information circulates quickly between coins. For noncorrelated cryptocurrencies, there will be no information transfer.

Our sample consists of a wide spectrum of cryptocurrencies. We selected 765 coins traded within the period from January 2015 to December 2022. Cryptocurrencies considered in the study are of different types and perform various functions being tokens, payment tools, stablecoins, and decentralized finance. We carry out the analysis over three horizons. In the first approach, we construct a cryptocurrency dependence network for the whole sample period from 2015 to 2022. In the second, we build such networks for non-overlapping two-year periods, while in the last, we apply a moving window approach and obtain a separate graph (snapshot) for each day in the whole sample. In all approaches, cryptocurrencies are used as nodes and weights for edges (links) are derived from the correlations between the daily returns. We are interested in indicating the most relevant nodes in the networks, so we apply a filtering procedure, the winner-take-all (WTA), which restricts the number of connected nodes only to those of critical importance (Bonanno et al., 2004; Giudici et al., 2020). Our three-horizon approach allows us to compare networks built on the same market for which correlations are calculated in different periods. The first and the second are static, while the last one allows us to identify the changes in the centrality measures and the importance of particular cryptocurrencies over time.

Our study contributes to the existing research in several ways. First, some papers indicate that Bitcoin has already lost its position as the leading coin (Al-Shboul et al., 2022; Ho, Chiu, and Li, 2020; Vidal-Tomás, 2021), the others, on the contrary, indicate its dominance in the cryptocurrency market as the forrunner and the largest crypto asset by market capitalization (Kayal and Rohilla, 2021; Będowska-Sójka, Kliber and Rutkowska, 2021; Bonneau et al., 2015). We propose a study which reconciles two contradictory results. By investigating the centralization dynamics of cryptocurrencies and introducing different horizons of the analysis, we show that for the whole period, Bitcoin and major capitalized cryptocurrencies are the most important. When the sequence of snapshots, namely day-by-day changes are considered, the results are different. The answer to the question of whether a crypto is central depends on the investment horizon. The dependencies between the majority of coins are weak showing some potential for diversification in the portfolios. We indicate that hubs arise around one major or several major cryptocurrencies. In our dataset, we find several such "leaders," which are featured by high capitalization and stronger relationships with other coins expressed by the high-ranking places in centrality measures horse races.

Second, while Shahzad et al. (2022) found that the transmission from and to Bitcoin is rather weak and taken by smaller cryptocurrencies, we indicate that in two-year periods communities arise around one or several hubs. Such key players are featured by relatively high capitalization and stronger relationships with other cryptocurrencies expressed by the high-ranking places in centrality measures' horse races. Third, we describe the structure of the cryptocurrency market from the network perspective. Similarly, as described in the stock markets (Mahmoud et al., 2015; Tse, Liu, and Lau, 2010), we find communities in the cryptocurrency market that arise around hubs. The structure of the market consists of connected and disconnected groups of crypto assets. There is no single key cryptocurrency, but there are several smaller communities, most of which are linked to Bitcoin. Fourth, we enrich the study of Ho, Chiu, and Li (2020) by examining networks built for each day separately and by adding the ranking of crypto assets relying on objective criteria.

Bouri et al. (2019) show that herding behavior in the cryptocurrency market occurs as the uncertainty grows. For our data, we observe fast changes in the rankings of centrality measures suggesting that the market is constantly evolving. Bitcoin is losing its key position as indicated by the networks' centrality measures at the end of 2016 to other frequently changing cryptocurrencies. We also extend the results of Ma et al. (2023) in two key ways. Firstly, we conduct very careful filtering and preprocessing of the data to exclude cryptocurrencies with small market capitalization. Secondly, we employ random matrix theory (RMT) to remove noise correlations from the correlation matrix. Both of these factors appear to be important from the point of view of portfolio management. Small capitalization is usually linked to low liquidity and high transaction costs (Cakici et al., 2024), while in large matrices we often observe noise correlations (Laloux et al., 2000). These refinements in our methodology allow for a more precise analysis of the cryptocurrency market structure, potentially leading to a more robust identification of the main cryptocurrencies.

The conclusions from the study may improve portfolio construction and risk management, enriching the analysis of correlation with broader dependence structures. The network approach allows us to indicate hubs, that are closely connected to crypto assets and the most peripheral, which are not related. When managing a portfolio, we try to avoid highly correlated assets and prefer those peripheral ones. Our approach allows for a multidimensional analysis of dependencies and the identification of such assets. The dependencies between the majority of cryptocurrencies are weak showing some potential for diversification in the portfolios.

The remaining part of the article is structured in the following way. Section 2 provides a review of the existing literature. We describe the dataset in section 3.1 while our methodological framework is shown in section 3.2. Section 4 presents empirical results both for the static and dynamic approach. Finally, section 5 summarizes the main conclusions.

2. Literature review

Analyzing and measuring dependence in financial markets is crucial for portfolio diversification, risk management, systemic risk assessment, and understanding the transmission channels of financial shocks. Network analysis is one of the tools employed in financial asset dependence studies, which are usually considered for simultaneous dependencies (Ho, Chiu, and Li, 2020; Mahmoud et al., 2015; Vidal-Tomás, 2021; Bouri. Vo, and Saced, 2021; Giudici, Sarlin and Spelea, 2020) or casual ones (Aslanidis, Bariviera, and Perez-Lahorda, 2021; Wen et al., 2023; Poddar et al., 2023; Ahelegbey and Giudici, 2022). Here, we utilize the first approach in which the main input to the network is taken from the returns correlation matrix.

Within this strand of literature, in the early work of Bonanno et al. (2004), they investigated correlation-based networks built on the cross-section dependence between stocks on the US market. They applied the minimum spanning trees (MSTs) as a filtration technique that removes nonrelevant information by omitting the weakest links. Di Matteo, Pozzi, and Aste (2010) applied two kinds of filtered networks, MSTs and planar maximally filtered graphs (PMFGs) for the dynamic correlations in returns. It was aimed at detecting the hierarchical organization of financial market sectors. Mahmoud et al. (2015) propose an approach for constructing the similarity between stock company profiles within the Fuzzy Spectral Modularity method. They calculate distances between stocks based on stock return correlations and detect network hubs and their communities in the Italian stock market. To determine which nodes are most strongly connected Tse, Liu, and Lau (2010) applied a WTA approach. They find that the variation of stock prices is influenced by a relatively small number of stocks. Heiberger (2014) indicates the relations between the network structure and the market conditions. He finds that the stock network changed its composition and became more centralized in times of financial turmoil such as the dot-com bubble or the Global Financial Crisis in 2008.

With the rapid growth of the cryptocurrency market (Ji et al., 2019), the question is posed as to what is the relationship between these instruments and whether any of the currencies are central to the market. Ho, Chiu, and Li (2020) studied the evolution of the cryptocurrency market and analyzed the network structure over a relatively long period from 2013 to 2020 for 120 cryptocurrencies. They found after a period of an initial weakening of the dependencies, since 2016 the network has been getting denser. The main player in the cryptocurrency market is changing, Bitcoin was dominating till mid-2016, replaced then by MAID and FCT. Since mid-2017 Ethereum together with its closed network has overtaken that position.

Vidal-Tomás (2021) obtain the centrality measures such as the degree centrality and betweenness for 69 long-lived cryptocurrencies in the period between 1 August 2019 and 1 August 2020. He focuses on the market dynamic of these measures over time and finds that the synchronization of markets increased during the short period of the financial panic related to the pandemic outbreak, from March 12, 2020, to April 1, 2020. Shahzad et al. (2022) focus on the dependence in tails of returns' distribution and its impact on the trading strategy. They combine the LASSO technique with quantile regression and examine 50 major capitalized cryptocurrencies. According to their results, Bitcoin is neither a major receiver nor a major transmitter, but smaller cryptocurrencies are.

Giudici and Polinesi (2021) analyze the price behavior of cryptocurrency assets. Their research explores the mechanisms of price information transfer across various Bitcoin trading platforms, as well as the interaction between Bitcoin markets and conventional financial markets. Ahelegbey et al. (2021) investigate the phenomenon of contagion among cryptocurrencies under conditions of extreme tail risk. Their findings reveal two primary categories of assets: speculative assets, which act as sources of contagion, and technical assets, which predominantly serve as recipients of contagion. Their results indicate that Bitcoin falls within the speculative group.

Papadimitriou et al. (2020) propose a novel approach which allows to indicate the so-called dominant cryptocurrencies. They define dominance on the basis of the adequate description of the behavior of the coins' neighborhood. Their sample consists of 112 coins and tokens, out of which 6 are fixed and the remaining 106 are chosen from different capitalization baskets. The sample period covers three years from 2016 to 2018 and for each year, a separate network is built and several "dominant" nodes are indicated. The number of dominant cryptos changes over time and with the change of the threshold. They provide evidence that there is a tendency to synchronize within the cryptocurrency market, but the dominant nodes (coins) are not always those that are mostly capitalized. Ma et al. (2023) examine the portfolios consisting of tokens and stocks. They find that the correlation structure of cryptocurrencies resembles that of the stock market. Also similarly to the stock market, correlations increase as the market is in the downturn. The most useful tokens in terms of portfolio construction are those which have a high Sharpe ratio and low centrality measures. In the closing of this section, it is worth mentioning that the same network approach is also applied when studying the dependencies between cryptocurrency exchanges (Bruzgė and Šapkauskienė, 2022).

3. Data and methods

3.1 Data

The cryptocurrency data are obtained from the website www.coinmarketcap.com. We take into account daily prices and volumes. We initially considered all available coins listed within the sample period from January 1, 2015, till December 31, 2022 (2922 days). Several filters are applied to consider a given cryptocurrency in the final dataset: (1) each crypto included in the dataset was among 100 cryptocurrencies with the highest capitalization on any day during the sample period. Such a filter allowed us to omit small—in terms of market capitalization—assets; (2) we introduced the condition related to the number of days a crypto is required to be listed. It differentiates between the three approaches. In the case of one network built over the whole period, the minimum was 2338 days, which accounts for 80% of the full sample period. In the case of two-year periods, we required the data for the whole period, while for the networks based on daily snapshots 180 days of returns were taken into account; (3) price data are available with no more than 30 missing observations. These steps allowed us to include both active and inactive coins, thus avoiding the survivorship bias. Such an approach allows us to include those cryptos that were most active in trading, even if this activity was only temporary and later they were no longer available on the market.

The coin selection procedure enables us to focus on the main players in the market without narrowing the circle of currencies to the most well known among them. We take into account all cryptocurrencies, among them those which are performing different roles as payment cryptocurrencies (coins), utility tokens, decentralized finance and stablecoins (we follow here the division of crypto assets provided by the Corporate Finance Insitute[2]). Stablecoins are often removed from academic studies because of their special features—they are pegged to a stable asset such as traditional currencies, commodities (e.g. gold) or financial algorithms. Due to that fact, their volatility is much smaller than the remaining crypto assets. Taking stablecoins into account allows us to improve the interpretation of the network structure (Ling et al., 2022).

The full list of cryptocurrencies is available upon request. The list of digital currencies which appear on the graphs in the paper is in Table 2 in the Appendix. Each network consists of nodes, which are individual cryptocurrencies, and the edges are calculated as distances based on returns' correlations. We have 755 different crypto assets in the database, which follow the mentioned criteria. For all cryptocurrencies in the dataset, we calculate returns and the Kendall τ correlations between returns of each pair of crypto assets. Based on these, we calculate the Euclidean distances. In each of the approaches, the whole period, two-year periods or each day networks, the number of cryptocurrencies in networks differs.

3.2 Methods

We construct weighted undirected networks within three approaches: first, a one-time approach where one network for the entire sample period is constructed. Second, we obtain four networks, each based on two years of data. Third, we apply a day-by-day approach in which each network is created every day in the sample.

While various econometric tools exist for analyzing financial time series dependencies, network analysis offers a uniquely comprehensive perspective. Though traditionally more prevalent in other disciplines, this approach provides deep insights into complex systems with multiple interconnected elements in finance. When constructing a network, we rely on the correlation matrices and distances for crypto returns as this is a standard solution for networks in the financial series (Boginski et al., 2005; Wu et al., 2021). We assume that for a currency to be considered as the central one, it must be highly connected to other crypto assets. The stronger the relationships with other cryptos, measured by correlations, the more important (and more central) a given cryptocurrency is in the network. We consider a weighted network using an undirected graph $G = (V, E, d)$, where V is the set of N nodes, E the set of $N \times N$ edges, and d is the weight function assigned to the edges. Here, the nodes correspond to different cryptocurrencies, and the edges between them carry weights indicative of the strength of connections between these cryptocurrencies.

The procedure of constructing a network consists of several steps. First, we obtain Kendall's correlations τ_{ij} between two series of returns of cryptocurrencies, i and j. The returns are calculated as $r_i = \ln(P_t/P_{t-1})$, where r_i stands for the daily return of asset i, while P_t and P_{t-1} are the coin's prices on day t and $t-1$, respectively. Then we filter significant correlations, thus leaving only those that are nonzeros from the statistical point of view.

Additionally, following Plerou et al. (2002) and Giudici and Polinesi (2021), we apply the RMT approach, which allows us to remove noise from the correlation matrix. There is a general agreement that the correlation matrix might contain not only information but also noise (Onnela, Kaski and Kertész, 2004) and that RMT is a well-performing tool to handle the complexity of high-dimensional data as it analyses the distribution of eigenvalues. Specifically, the presence of large eigenvalues indicates dominant patterns, that is, the "market" component (Laloux et al., 2000; M. Potters, 2005).

We test the null hypothesis that the eigenvalues of the correlation matrix match those of a symmetric random Wishart matrix of equal size (Miceli and Susinno, 2004), against the alternative hypothesis that the eigenvalues differ. For $N, T \to \infty$, where N is a number of variables (cryptocurrencies) and T is a length of the time series, with $Q = T/N \geq 1$, the spectral density P_{rm} of eigenvalues λ is given by:

$$P_{rm} = T/2\pi \frac{\sqrt{(\lambda_+ - \lambda)(\lambda - \lambda_-)}}{\lambda}$$

where

$$\lambda_-^+ = 1 + 1/Q \pm 2 * \sqrt{1/Q}.$$

From the P_{rm}, it follows that if $\lambda_k \geq \lambda_+$, then the k-th empirical eigenvalue cannot be an eigenvalue from a random Wishart matrix, and the null hypothesis is rejected. For every correlation matrix of crypto returns, we obtain λ_+ and verify if the highest eigenvalues exceed this value.

We then retain only those eigenvalues that are equal or exceed λ_+ and reconstruct the correlation matrix through singular value decomposition (Plerou et al., 2002). To preserve the sum of all the eigenvalues, we replace all the eigenvalues lower than λ_+ with their average. This allows us to "clean" the correlation matrix of noise while maintaining the same trace of the matrix (Plerou et al., 2002; Miceli and Susinno, 2004). The matrices, "filtered" in this way, are used in the next steps.

Since the correlation coefficient of a pair of crypto returns itself is not a proper measure of the distance between the two series,[3] we calculate distances based on the "filtered" matrices for all pairs of cryptocurrencies. For this transformation, we calculate Euclidean distances based on the following formula: $d_{ij} = \sqrt{2 * (1 - \tau_{ij})}$ (Onnela, Kaski and Kertész, 2004; Di Matteo, Pozzi, and Aste, 2010). In the next step, the matrix of distances d_{ij} is used as the weighted adjacency matrix of the network G.

To obtain a complex system with several centers, we apply the MST approach, proposed in a similar framework by Mantegna (1999), which limits the number of connections between the nodes. A spanning tree is a simply connected acyclic graph that connects all N nodes (cryptocurrencies) with $N-1$ edges in such a way that the sum of all edges' weights, $\sum_{ij} d_{ij}$, is minimized.

MST allows selecting the most relevant connections between the crypto assets in the set (Ho, Chiu, and Li, 2020 ; Zięba, Kokoszczyński, and Śledziewska, 2019; Vidal-Tomás, 2021). Moreover, to obtain a clear structure we set the limit for a correlation, for which the dependence between crypto assets is considered (Karim et al., 2022). In the literature, this is known as the WTA approach, which requires establishing a correlation threshold. The WTA method allows us to reduce the number of edges in the network by omitting those of minor importance and focusing on the significant (highly correlated) ones. As explained by Giudici et al. (2020) the detection of patterns requires such a representation of the network, which replaces complexity with scarcity. It is achieved here by reducing the number of edges and leaving only those of the greatest importance. In our study, following Tse, Liu, and Lau (2010) and Heiberger (2014), we apply the threshold of $\tau \geq 0.4$.

For the obtained networks, we calculate standard centrality measures such as degree, betweenness, closeness and eigenvector centrality. It offers us a description in several dimensions: degree indicates highly connected nodes, betweenness highlights nodes that are right in the middle, closeness indicates how quickly information can spread from a node to all others, while eigenvector centrality takes into account the importance of nodes' neighbors (Oggier and Datta, 2021). In our framework, those measures combine correlation information into four metrics.

In our weighted network framework, the **degree** centrality of a node is a crucial attribute. It considers the sum of weights associated with edges incident to a node. It is computed using the formula:

$$D_i = \sum_j d_{ij}.$$

When it comes to **betweenness** centrality, the concept of shortest paths is necessary. The shortest path between two nodes is the path with the shortest length calculated as the minimum total weight among all possible paths connecting those nodes. Formally, the betweenness centrality B_i of a node i is calculated as the fraction of shortest paths between all pairs of nodes h and j that pass through node i (say $s_{hj}(i)$), divided by the total number of shortest paths between h and j (say s_{hj}):

$$B_i = \sum_{h,j} \frac{s_{hj}(i)}{s_{hj}}.$$

This measure considers both the presence and the strength of connections between nodes when evaluating the influence of a node within the network.

Closeness centrality is the inverse of the average shortest length from one node to each other node. Specifically, for node i it is the inverse of the average length of the shortest paths between node i and any other node j:

$$C_i = \frac{N-1}{\sum_j d_{ij}}.$$

The inverse is used so that a higher closeness centrality indicates a more desirable centrality score.

In a weighted network, **eigenvector** centrality measures the influence of a node based on both the number and the importance of its neighbors. It assigns higher centrality to nodes that are connected to other nodes that themselves have high centrality. Mathematically, eigenvector centrality E_i for a node i is calculated using the formula:

$$E_i = \frac{1}{\lambda} \sum_j d_{ij} e_j$$

where λ represents the largest eigenvalue of the distance matrix, d_{ij} represents the weight of the edge between node i and node j, and e_j represents the corresponding eigenvector component associated with node j.

Each of those four measures captures a different feature of centrality. As a result, each measure indicates different nodes as the most central and important ones. Therefore, we applied a procedure which captures information gathered by these measures and allows us to indicate a unified ranking. This ranking is applied to the series of centrality measures obtained for daily networks.

For all cryptocurrencies listed in a given period, we compute four centrality measures based on the distances obtained in the moving window of 180 days. Then we apply the Technique for Order of Preference by Similarity to an Ideal Solution (TOPSIS) with entropy weights for identifying the most influential nodes in a similar vein as described by Dwivedi and Sharma (2023) and Alao et al. (2020), among others. Entropy-weighted TOPSIS method is a multi-criteria decision-making approach that allows us to find the best option from a set of node alternatives (here cryptocurrencies, $i = 1, \ldots, N$) based on predefined criteria (here the four centrality measures, $j = 1, \ldots, 4$). This approach helps ensure that the most informative measures contribute more to the decision-making process, leading to more robust rankings. The applied algorithm consists of six steps:

(1) The normalization of the centrality measures in the decision matrix

$$x_{ij}^* = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{N} (x_{ij})^2}}$$

where x_{ij} represents the value of centrality measure j for node i and N is the total number of nodes.

(2) The calculation of weights based on the information entropy for each centrality measure, so that the bigger the value of the entropy weight of the measure, the more useful the information of the measure

$$w_j = \frac{1 - H_j}{\sum_{j=1}^{4} (1 - H_j)}$$

where $H_j = -\frac{1}{\log(N)} \sum_{i=1}^{N} p_{ij} \log(p_{ij})$ is the entropy of centrality measure j and $p_{ij} = \frac{x_{ij}^*}{\sum_{i=1}^{N} x_{ij}^*}$. Note that $\sum_j w_j = 1$.

(3) The computation of the entries of the weighted normalized decision matrix:

$$v_{ij} = x_{ij}^* \times w_j.$$

(4) The determination of the best and the worst solution

$$A_j^+ = \max_i v_{ij}, \quad A_j^- = \min_i v_{ij}$$

(5) The calculation of the distances of each alternative to the ideal (the best) solution and anti-ideal (the worst) one

$$S_i^+ = \sqrt{\sum_{j=1}^{4} (v_{ij} - A_j^+)^2}, \quad S_i^- = \sqrt{\sum_{j=1}^{4} (v_{ij} - A_j^-)^2}.$$

(6) The calculation of the relative closeness degree to an ideal solution for every alternative

$$RC_i = \frac{S_i^-}{S_i^- + S_i^+}.$$

(7) The determination of the final ranking by sorting the alternatives from the largest RC_i. It reveals the most important nodes in the network, see Opricovic and Tzeng (2004) among others.

In the empirical part, we present rankings in line with each of the four centrality measures separately and the final ranking which combines all the considered measures through the entropy-weighted TOPSIS method.

The graphs were drawn using the igraph R package https://igraph.org/r/html/1.3.4/mst.html.

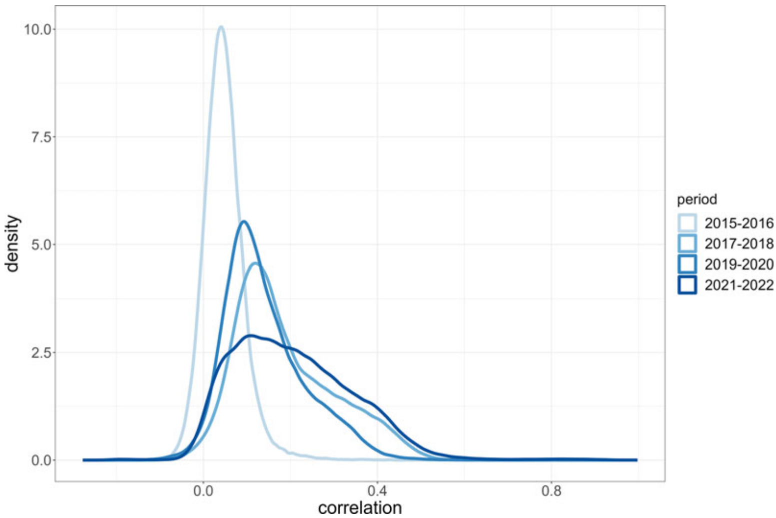

Figure 1. The density of correlation coefficients in subsequent 2-yearly periods.
Note: The density functions are based on daily correlations.

4. Empirical results

The empirical part is threefold. First, we consider the whole sample period, from 2015 to 2022, and we build networks utilizing the MST and the WTA approach separately. Second, we construct networks based on non-overlapping two-year samples, that enable us to observe the changes in the networks over time. Third, based on the daily snapshots we calculate centrality measures and verify which cryptocurrencies are the most central and if these centrality features change over time.

In the case of the WTA approach, one should justify the choice of the threshold. Mantegna (1999) finds the highest correlations between the stock of $\tau = 0.55$ (and $d = 0.95$), and the minimum taken into account is $\tau = 0.4$ ($d = 1.1$). We analyzed the statistical properties of correlations obtained for the two-year periods for daily data. Figure 1 presents the distribution of correlation coefficients measured with Kendall's τ starting from 2015 to 2016, and ending at 2021–2022. The correlations in the first two-year period are lower and less dispersed. They tend to increase in the subsequent years as distributions shift to the right. This represents a strengthening of correlations and dependencies in a maturing cryptocurrency market. Lower density tends to gather above 0.4 as shown in Figure 1. Therefore, going forward, we will implicitly use a minimum correlation threshold of 0.4 when applying the WTA approach. This result is also in line with that one obtained on stock markets (Mantegna, 1999; Boginski et al., 2005; Wu et al., 2021; Giudici and Spelta, 2016).

4.1 Static networks based on the whole sample period

First, we show the static network created for cryptos that were listed within the period 2015–2022 for at least 2338 days (80% of the whole sample). For such crypto assets, we obtained correlations, that were a basis for distances calculations. We present three scenarios: (1) the MST with N nodes and $N-1$ edges; (2) the network constructed with the WTA approach with 0.4 threshold, and (3) the mix of the MST with the WTA approach. The number of nodes changes depending on the scenarios. In the case of the whole sample, the full graph would consist of 755 nodes, which represent all crypto assets included in our database. As the correlation matrix is symmetric,

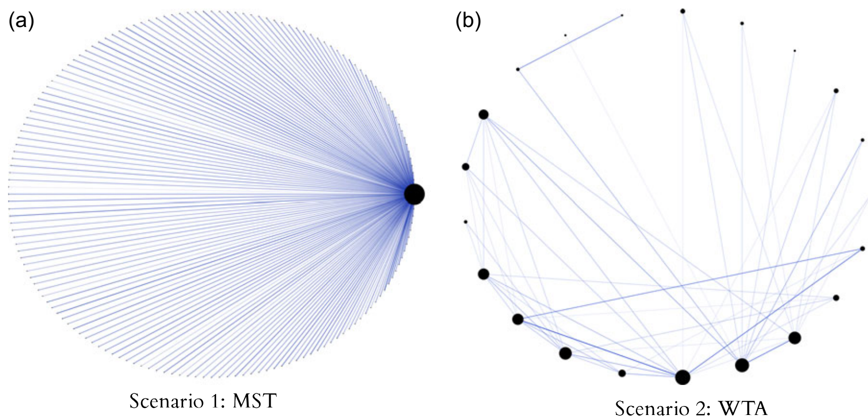

Figure 2. Networks with either MST filter or the WTA approach.
Note: For a graph on the left we used the MST filter, while that on the right utilizes the WTA approach with the threshold for correlation coefficient equal to 0.4. The size of the node depends on the centrality degree of a particular node. The width of links represents the strength of the dependence between two nodes measured by the correlation coefficients. The higher the correlation is, the darker the color of the edge. A graph on MST has 160 nodes and 159 edges, while the WTA graph has 21 nodes and 49 edges.

there would be 284635 edges. By application of the filters (MST or WTA) we remove nonrelevant edges, leaving only those that are the most informative (MST) or represent the strongest dependence (WTA). If we were trying to create a graph based on all cryptocurrencies, which were listed for 8 years uninterruptedly, then we would obtain a graph with several nodes only. Thus when building the first four graphs, we consider all cryptocurrencies, that were listed at least for a given period.

Figure 2 presents networks from scenarios (1) and (2). On the left, we show the graphs built with MST, and on the right, we show the WTA approach. Every node on the circle represents one cryptocurrency. The node size represents the degree – the higher the degree, the bigger the node. The width of edges represents correlations of returns between every pair of nodes, the corresponding weight is the distance between the two nodes inversely proportional to the correlation. The more intense the color of an edge, the higher the correlation. The widths of the edges in the graph range from 0.0 to 0.98. A graph built as MST has only one distinctive node, that is Bitcoin, which has the highest degree (a black dot on the right side of a circle). For the WTA approach, a greater diversity of nodes is obtained. There are more prominent nodes in this case. Also, some areas in the circle are empty suggesting a lack of correlations between some nodes.

Such separate approaches give only a general picture and do not allow one to observe the hierarchical structure. To deepen the analysis, we have combined both approaches (scenario 3). Reducing the multidimensionality of the dataset within the MST approach and the WTA allows us to make visible several communities (hubs) with central nodes. Figure 3 presents a network with combined MST and WTA approaches. The network exhibits a hierarchical structure, with Bitcoin (BTC) occupying the central position as the node with the highest degree and XRP being the connecting (bridge) node with the LTC community. XRP is designed for fast and low-cost international money transfers, while LTC offers faster and cheaper transactions compared to Bitcoin. Other cryptocurrencies, such as ETC and ETH, form distinct communities around themselves, each serving slightly different purposes within the ecosystem. The ETC community emphasizes immutability and supports decentralized applications, while the ETH stands out as a major hub for smart contracts and decentralized applications.

The above graphs show that over the whole sample period, from 2015 to 2022, Bitcoin is the undisputable center in the network. There are other important crypto assets in the network, which

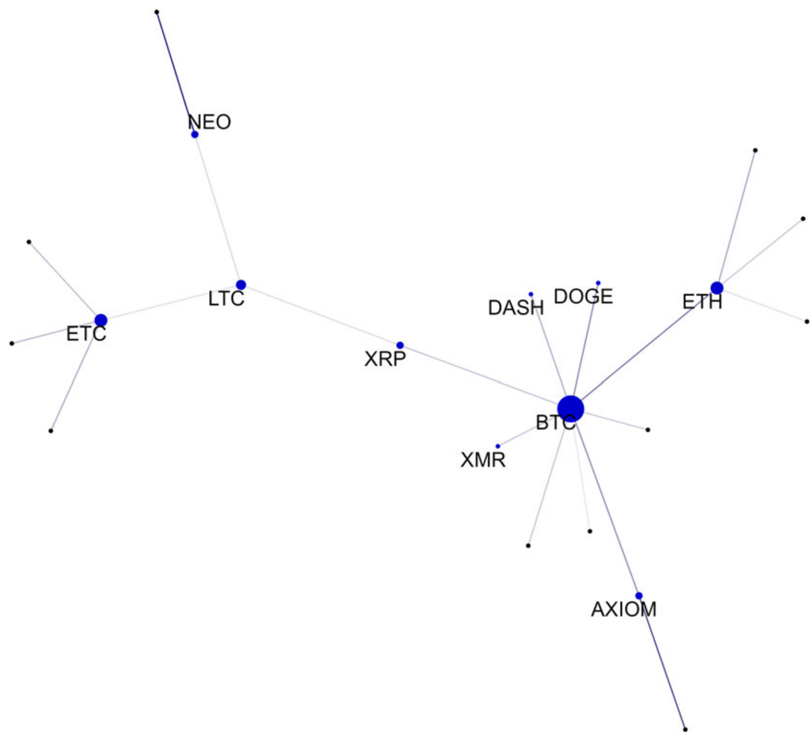

Figure 3. The network based on the combination of MST and WTA built for the data listed for at least 2338 days of the sample.
Note: The size of nodes is proportional to the degree of each coin. The higher the correlation, the darker the color of the edges. Only the first five crypto assets with the highest degree are labeled with a cryptocurrency ticker. The remaining nodes are plotted as black dots.

gather around themselves smaller communities distinct from the rest of the structure. We examine the robustness of these results by looking at graphs built for two-year periods.

4.2 Static networks based on two-year periods

In this part, we rely on crypto assets that were listed for the whole two-year period. The analysis of networks built in two-year periods enables us to assess the dependence between cryptocurrencies in several snapshots. Each of them reflects different steps in the evolution of the cryptocurrency market. The number of cryptocurrencies listed on the markets increased steadily. As shown in Figure 1, the correlations also increased (at least when one compares 2015-2016 with later periods).

Figure 4 shows four networks built based on two-year periods of daily observations when both MST and the WTA approach with the threshold of 0.4 are applied. The network obtained for 2015-2016 is the simplest one among these four, with BTC as a hub and five nodes, CRT, PPC, LTC, NMC, and DOGE linked closely. Each of these cryptos serves different purposes. CRT focuses on multi-currency wallet services, PPC is known for its energy-efficient proof-of-stake mechanism, LTC was already mentioned as a tool for fast and cheap transactions, NMC provides decentralized domain name system and identity services, and DOGE, initially a joke coin, has developed a strong community for tipping and donations. Later, at every two-year period, the network is hierarchical with BTC as the central node with different hubs forming their communities. In the second period, the hubs are LTC, ETH, XMR, SC, and LSK. ETH introduces smart contracts and decentralized

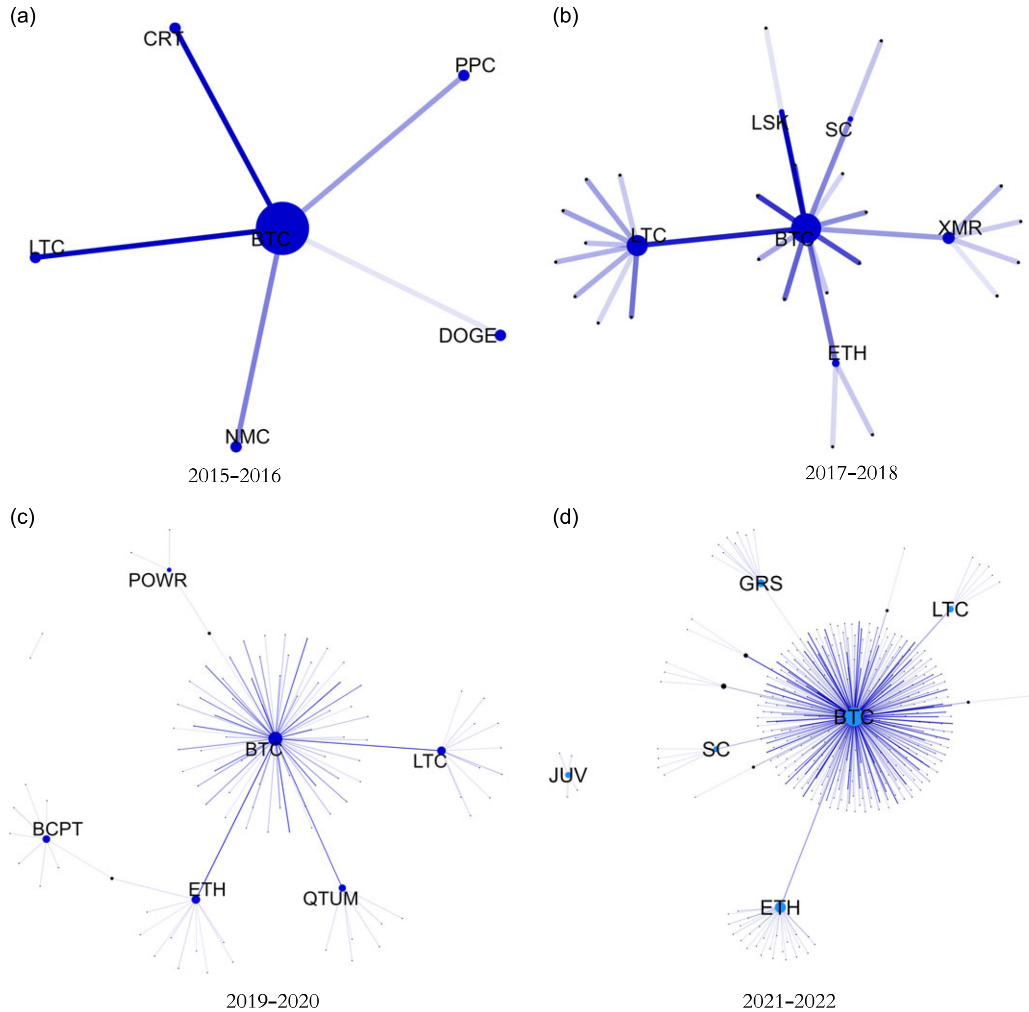

Figure 4. Networks with both MST filter and the WTA approach in two-year periods based on daily data.
Note: We label only the first five cryptocurrencies in the degree ranking. The higher the correlation, the darker the edge. The higher the degree, the larger the size of a node.

applications, XMR focuses on privacy and untraceable transactions, SC provides decentralized cloud storage, and LSK enables decentralized application development with a focus on JavaScript. During the third period, the hubs include again BTC, LTC, and ETH, but the new ones are BCPT, which facilitates blockchain-based credit and debt management, QTUM which combines Bitcoin's security with Ethereum's smart contracts for business applications, and POWR which promotes energy trading and sustainability solutions via blockchain. In the fourth period, the hubs are again LTC and SC, but among the new ones are: GRS which focuses on privacy, fast transactions, and low fees, BTH that addresses Bitcoin's scalability with larger block sizes and faster transactions, and JUV which represents a trend toward sports and entertainment tokens, enhancing fan engagement and interactions.

As the market develops, the number of nodes and edges increases. The density of the networks is calculated as the number of actual edges to the number of potential ones decreases in the subsequent periods. It signifies the decreasing connectivity of the market. In the first graph 4(a) representing the network for 2015–2016, we have only 5 nodes and 4 edges. The last one shows

Table 1. The degree of the major players among cryptocurrencies in two-year periods

Ticker	2015–2016	2017–2018	2019–2020	2021–2022
BTC	5	13	62	318
LTC	2	9	11	6
ETH		3	11	26
Number of nodes	6	30	102	375
Number of edges	5	29	1003	373
Graph density	0.400	0.067	0.019	0.005

Note: This list presents all cryptocurrencies (in alphabetical order) which tickers appeared on the plots, starting from Figure 3 and ending at Figure 6. The letters, D, B, C, and E display if a given crypto was among the first 10 cryptocurrencies in the daily networks' ranking presented at Figure 5 and Figure 6 based on the degree, betweenness, closeness, and eigenvector, respectively.

411 nodes and 406 edges. The density decreases from 0.4 in the first subperiod to 0.005 in the last one. Two tickers are present on all four graphs, BTC and LTC, another one, ETH appears in the last two, and the remaining cryptocurrencies change over time. BTC is always lying in the center of the graphs as it is featured by the highest degree (see Table 1). The next is LTC (in 2015–2016, 2017–2018, and 2019–2020) and ETH (in 2021–2022).

In subsequent two-year periods, the networks get more nodes and edges as we observe more connections between nodes. Thus the nature of the organization of cryptocurrencies changes from a very simple five-node network in the first period, to hierarchical networks with several clusters around nodes. In the last network for the period 2021–2022, we find BTC is taking over most of the connections. It means that the correlations with BTC are on average the highest among all nodes. In the arrangement of the MST, a cryptocurrency network moves from a structured snowflake-like graph to a simpler egocentric graph with BTC as the main node.

4.3 Central nodes in day-by-day snapshots

In this section, we analyze all four measures of cryptocurrencies' network centrality separately and combined. We consider networks obtained in a moving 180-day window under the condition that pairs of crypto assets have been listed together for at least 90 days. For each day and each coin in the sample, we calculate four centrality measures and create the ranking from the highest value of the centrality measures to the lowest. Figures 5(a)-5(d) report the ranking of cryptocurrencies starting from those with the highest value. For the sake of visibility, only the top 10 cryptos are presented. We highlight in color those cryptocurrencies that took the first three places. As we assign an average for tied ranks, we sometimes obtain intermediate values. Thus we show the first place in red, rank 1.5 (joint first place) in blue, the second place in green, rank 2.5 in violet and the third place in orange.

Concerning the degree, Figure 5(a) shows that Bitcoin was the cryptocurrency with the highest value in 2015 and 2016, but then lost its leading position to other currencies such as LTC, ETH, QTUM, and WETH. After mid-2017, shifts in the ranking often occur daily, demonstrating that the market situation changes rapidly and that cryptocurrencies occupying central positions in the network frequently rotate.

Figure 5(b) shows that in the case of betweenness, the changes in the ranking are much less frequent. Crypto that reaches the highest measure of betweenness keeps it for a longer period of time. The characteristic feature, already observed for the previous centrality measure, is that Bitcoin was dominant in 2015 and 2016, but beginning in 2017, it started to lose its position. There was no single dominant player in terms of betweenness centrality measure in the cryptocurrency

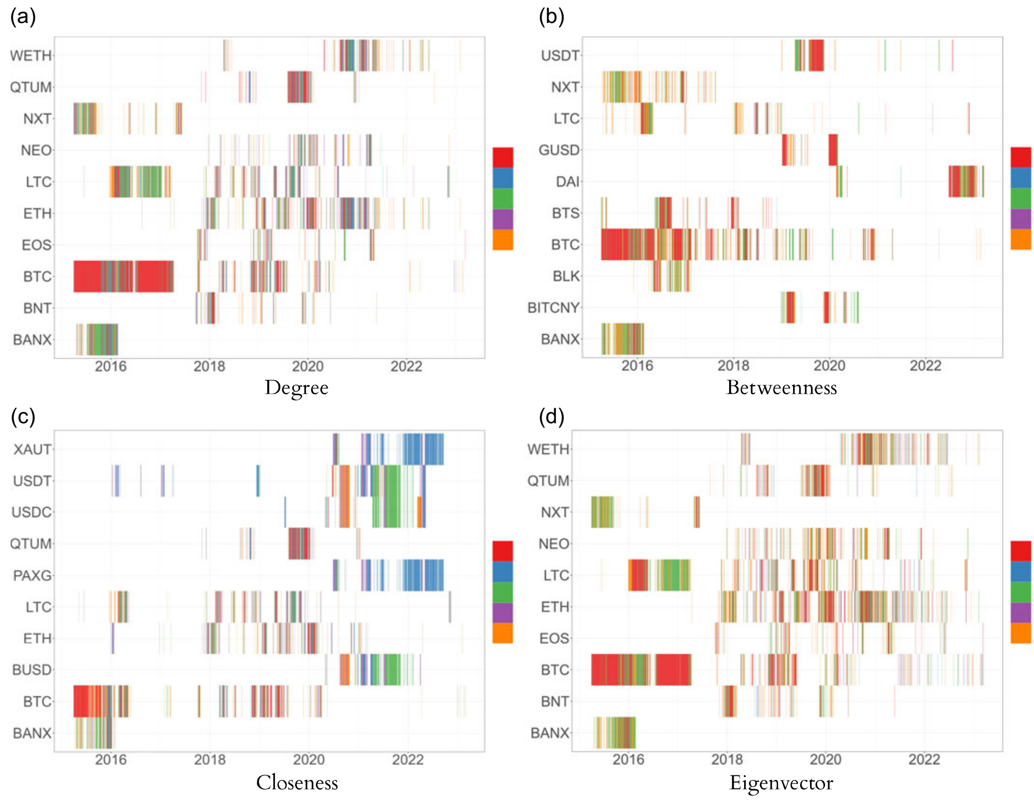

Figure 5. The ranking of cryptocurrencies based on a single centrality measure.
Note: The results for 10 cryptocurrencies with the highest centrality measure in the sample are shown. Bars represent positions in the ranking from the first (red) to the fifth (orange).

market during the crisis time in 2018. The second half of 2019 belonged to a stablecoin, USDT (Tether). At the beginning of the COVID-19 pandemic, BTC became again the most central in terms of betweenness, and at the end of the sample, DAI took the first position.

Figure 5(c) makes evidence of the ranking of cryptocurrency concerning the closeness measure. At the outset, BTC appears to have the highest closeness, but it loses position in the ranking around 2016. Later on, changes in the ranking are rapid. The second major cryptocurrency, ETH, was in the first position around 2020. Some patterns are visible—the stablecoins such as XAUT, PAXG, USDC, and USDT are together ranked in third (2021) or second (2022) place.

Figure 5(d) illustrates the ranking of cryptocurrencies for the eigenvector centrality measure over the sample period. For this *measure of prestige*, changes in ranking occur most frequently. Leaving aside the initial period and prevalence of Bitcoin in 2015, followed by LTC and the return of BTC in the second half of 2016, it is apparent that no single cryptocurrency has maintained a central position for longer than a few weeks. Each cryptocurrency experiences brief periods of prominence, but these are typically short-lived.

The above-discussed centrality measures show slightly different results. In the early days of 2015 and the first half of 2016, Bitcoin seemed to be the undisputed major player. Its relevance disappeared early in 2016, depending on which measure of centrality we use. Several cryptos seem to be dominant in an era of accelerated growth in the cryptocurrency market after the 2018 crisis. In the COVID-19 pandemic, several cryptos appeared to be central in the network, such as Ethereum (degree, eigenvector) or Geminidollar (betweenness).

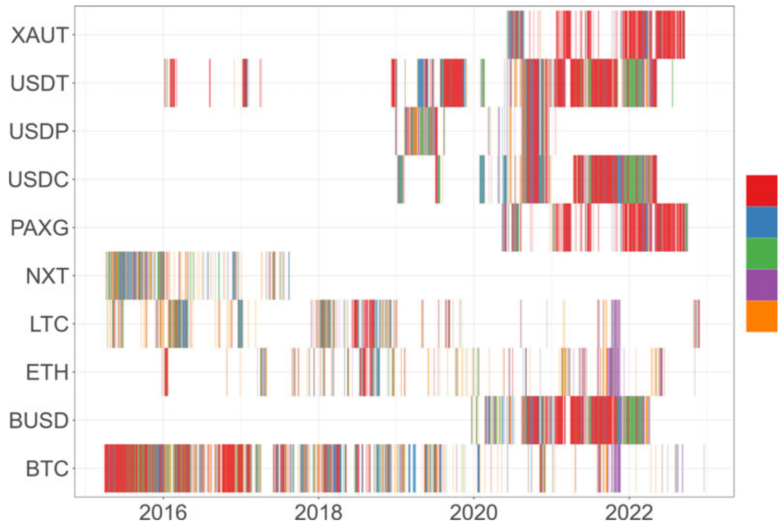

Figure 6. Entropy-weighted TOPSIS ranking of cryptocurrencies.
Note: The ranking is obtained by the entropy-weighted TOPSIS method considering the four centrality measures: degree, betweenness, closeness, and eigenvector centrality as decision criteria. The results for 10 cryptocurrencies with the highest ranking in the sample are shown. Bars represent positions in the ranking from the first (red color) to the fifth (orange).

To indicate a major cryptocurrency, we applied the ranks based on the entropy-weighted TOPSIS method described in Section 3.2. Figure 6 shows the first 10 cryptocurrencies, which are the most often ranked as the first five players. We find that Bitcoin is the most central cryptocurrency in 2015 and 2016. It also appears from time to time among the first five winners in subsequent periods. The next three positions on the list are taken by Tether, USD Coin, and Binance USD (all three are stablecoins). They are leading in the centrality measures' ranking from mid-2020 until the beginning of 2022. The other two commodity-backed stablecoins, PAX Gold and Tether Gold take over the lead in 2022. Both traditional cryptocurrencies like Ethereum and Lithium are occasionally leaders in the ranking over the whole period.

5. Discussion

In this article, we focus on the major players in the cryptocurrency market and examine which cryptos hold dominant positions and how stable these positions are. We use the tools of network science, which allows us to assess the relationships between multiple cryptocurrencies. The focus was on the connectedness of the cryptocurrency market from the point of view of time series properties with a correlation of returns as the main measure of dependence. We applied the RMT to "filter" correlation matrices from noise. We find out, that the correlations between crypto-asset returns are comparable to those observed on the stock markets.

We built static networks for the whole period, from 2015 to 2022, and four networks for two-year periods, from 2015–2016 to 2021–2022. Finally, we compared centrality measures obtained for networks built in a sequence of snapshots in the moving window.

The length of the analysis window determines the assessment of the results. In the long run, when only cryptocurrencies with a long history of listing are considered, we find communities built around several cryptocurrencies. The structure of this market is hierarchical. At the center of the network, we find XRP, which is directly linked to other highly capitalized cryptocurrencies such as Bitcoin, Ethereum, Stellar or Ethereum Classic. In the four snapshots, Bitcoin shares its privileged position with other cryptocurrencies. There are at least a few communities built around certain central cryptos. Some are not connected to the system and remain on the periphery. The other major players of connected communities are Litecoin and Ethereum. Apart from the main nodes and their clusters, there are some peripheral cryptocurrencies that are only connected to smaller systems that are not part of the overall structure.

An analysis of the networks created day by day shows a very different picture. There is no particular major player in the cryptocurrency market. As different centrality measures provide different rankings of crypto assets, we rely on the combined ranking. It shows a rapid change in leadership positions, with the two most capitalized Bitcoin and Ethereum far behind other assets. When we combine these three analyses, a snapshot and a sequence of snapshots, we find that cryptocurrencies form a rapidly evolving complex system in which there are multiple communities, each community has a major player, and the dominant currencies often change within these structures.

The question stated in the title of our paper, whether Bitcoin has been dethroned too quickly, has been already answered in the real world. In January 2024 financial regulators allowed introduce Bitcoin Exchange Traded Funds (ETFs). Thus, the markets and institutions seem to recognize the first-mover advantage and prefer the largest cryptocurrencies in terms of capitalization.

From the practical point of view, as the threshold used in the analysis was quite high (the correlation coefficient for a pair of cryptocurrencies was at least 0.4), the results indicate a high interdependence between some cryptocurrencies and thus a high systematic risk. The collapse of any of the cryptocurrencies at the top of the ranking poses a serious threat to the entire market. In the case of the portfolio, the risk increases together with the correlation between assets. Investors should avoid having highly correlated assets. Therefore, it will be reasonable to include only one cryptocurrency from a cluster or the ranking list in the portfolio. The best solution would be to include those cryptos that have the largest distances between them.

There are some limitations in our study. First, we focus on cryptocurrencies that ranked among the 100 highest capitalization cryptocurrencies at least once in the entire sample. In some cases, this means including temporary "stars" who have had a high capitalization in the short term but are not among the largest players in terms of capitalization over the whole period. At the same time, we might omit small cryptocurrencies in terms of capitalization. Second, within the graph construction, we chose to combine a MST with a particular threshold of WTA for the correlations between cryptocurrencies. The other methods of graph construction could produce different outcomes. However, the advantage of MST is crucial in our case as it leaves only a limited number of edges and allows us to obtain a sparse network. Further work would be focused on considering different thresholds for correlations and applying other methods of network construction.

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Competing interests. The authors declare no competing interests.

Data availability statement. Raw data are from the CoinMarketCap website (www.coinmarketcap.com). Derived data supporting the findings of this study are available from the corresponding author [BBS] on request.

Notes

1 The correlations are synchronous and symmetric so no causality claim is made based on them

2 https://corporatefinanceinstitute.com/resources/cryptocurrency/types-of-cryptocurrency/

3 A proper distance metric between two objects, i and j, d_{ij} should fulfil the following conditions (Onnela, Kaski and Kertész, 2004): (1) $d_{ij} = 0$ if and only if $i = j$, (2) $d_{ij} = d_{ji}$, and (3) $d_{ij} \leq d_{ik} + d_{kj}$. The correlation coefficient does not fulfil the third condition.

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A. Appendix

A list of nodes whose names appeared in the network plots and the centrality measure rankings

Table 2. A list of digital assets whose names appeared in the network plots and the centrality measure rankings

Ticker	Name	Centrality measures			
AXIOM	Axiom				
BANX	Banx	D	B	C	E
BCPT	Blockmason				
BITCNY	Bitcny		B		
BLK	Blackcoin		B		
BNT	Bancor	D			E
BTC	Bitcoin	D	B	C	E
BTS	Bitshares		B		
BUSD	Binance usd			C	
CRT	Cryptonits				
DAI	Multicolateral-dai		B		
DGB	Digibyte				
DGC	Digitalcoin				
DOGE	Dogecoin				

Table 2. Continued

Ticker	Name	Centrality measures			
EOS	Eos	D			
ETH	Ethereum	D		C	E
FCT	Factom	D			
FTC	Feathercoin				
FTT	Ftx token				E
GRS	Groestlcoin				
GUSD	Geminidollar		B		
LSK	Lisk				
LTC	Litecoin	D	B	C	E
LUN	Lunyr				
MIOTA	Iota	D			
NEO	Neo				E
NMC	Namecoin				
NXT	Nxt		B		E
OSDC	Usd coin			C	
PAXG	Paxgold			C	
PPC	Peercoin				
POWR	Power-ledger				
QTUM	Qtum	D		C	E
SC	Siacoin				
USDC	Usd-coin			C	
USDP	Paxos-standard				
USDT	Tether		B	C	
VIBE	Vibe				
WETH	Weth				E
XAUT	Tether-gold			C	
XLM	Stellar				
XPM	Primecoin	D			
XRP	Xrp				

Note: We show the degree for cryptos which are among the top five according to the ranking based on the degree at least two times in four two-year periods.

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