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RESEARCH ARTICLE

Exploring Key Properties and Predicting Price Movements of Cryptocurrency Market Using Social Network Analysis

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ABSTRACT The emerging cryptocurrency market is one of the largest financial markets in the world, with a market capitalization that is already surpassing the gross domestic product of many developed economies. Cryptocurrencies are increasingly being adopted as a means of transaction and ownership in the digital domain, particularly in areas like decentralized finance and non-fungible tokens. Known for its high volatility, this market offers investors the potential for higher returns than traditional financial markets like stocks, foreign exchange, and commodities. However, it remains underexplored in academic research. In this paper, we propose the use of social network analysis to effectively model and analyze the cryptocurrency market and conduct a comprehensive numerical study to explore its key properties, including correlation structure, topological characteristics, stability, and influence. Furthermore, we propose the use of centrality measures as novel indicators to improve the accuracy of cryptocurrency price movement predictions. Our research introduces a novel method for understanding and navigating the cryptocurrency market, enabling investors to integrate advanced analytical tools into their decision-making processes.

INDEX TERMS Centrality measures, cryptocurrency, price movement prediction, social network analysis.

I. INTRODUCTION

Over the past decades, an extensive amount of work has focused on applying social network analysis to model and analyze conventional financial markets, such as stock, foreign exchange, and commodity markets [1], [2]. More precisely, networks can be used to model the interactions among financial assets in these markets. A well-known technique involves the use of correlation-based networks to analyze the correlation dynamics among financial assets with the aim to build optimal investment strategies. In such a network, the nodes and edges represent financial assets and their correlations, respectively. All financial asset nodes are initially and fully connected in the network. However, the network may contain redundant information with no useful values, e.g., edges with zero correlation. Graph algorithms, such as the minimum spanning tree (MST), can be used to simplify the network by incorporating important nodes and edges only, e.g., those having strong connections and correlations with other nodes, as they usually convey valuable information. Centrality measures can then be used in this simplified network to pinpoint the most crucial or influential assets, those that hold key positions in the financial markets.

Since the emergence of Bitcoin, the cryptocurrency market has become one of the largest financial markets in the world, with trillions of dollars in market capitalization that exceeds the annual gross domestic product (GDP) of many developed economies. In recent years, many large global institutions

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have gradually ventured into cryptocurrency assets, from Facebook's release of Libra tokens to the huge transactions of metaverse virtual lands with non-fungible tokens, and more. Furthermore, the current number of cryptocurrencies has exceeded 20,000, and the market value of Bitcoin and Ethereum in 2023 has reached 378 and 189 billion U.S. dollars, respectively. From these indications, more and more attention has been paid to cryptocurrency investment, and their transaction volume continues to grow.

A tremendous amount of research on developing methods and tools has been dedicated to analyzing conventional financial markets [1]. However, the emerging yet volatile cryptocurrency market has not been extensively studied. A sound understanding of the market could help investors make informed investment and risk management decisions to earn profits or avoid losses through data-driven analysis and predictions. Therefore, the first research objective of this paper is to apply social network analysis to model the cryptocurrency market using MST networks and explore several key properties of the market, including (1) its correlation structure, (2) topological characteristics, (3) stability, and (4) influence of cryptocurrencies using centrality measures, at different time periods across the entire dynamic evolution of the market, and how these change over time.

Additionally, in the case of cryptocurrency market forecasting, one may be interested in the prediction of cryptocurrency prices. Nowadays, many investors are attracted to fundamental and technical analyses to make their investment decisions. Given the high volatility of the emerging cryptocurrency market, one needs to identify new and effective predictors to improve the accuracy of the predictions. Since centrality measures can be used to evaluate the influence of cryptocurrencies within a network, we propose to combine it with deep learning to predict the movement of cryptocurrency prices (i.e., upward or downward).

II. OUR CONTRIBUTIONS

Using historical daily closing prices of the top 145 cryptocurrencies from 2013 to 2022, we obtain the following findings about the cryptocurrency market:

- Cryptocurrencies are positively and moderately correlated with one another most of the time in recent years;
- Cryptocurrencies are becoming increasingly and tightly correlated during undesirable critical events;
- The distribution of the cross-return correlation coefficients in the recent cryptocurrency market exhibits lighter tails compared to the past;
- The structure of cryptocurrency networks changes as major corrections occur. It becomes more compact when corrections occur and becomes sparser after the corrections;
- The return correlations of cryptocurrencies are relatively stable in the short run but become less stable in the long run;
- The impact of corrections on the cryptocurrency market tends to be short-lived;
- Scale-free (or power-law) behavior is exhibited by cryptocurrency networks most of the time;
- Centrality measures are useful predictors for short-term trends of movement in the price of cryptocurrencies.

In summary our main research contributions are (1) the use of social network analysis as an effective modeling method to explore key properties of the cryptocurrency market, and (2) proposing novel centrality-based indicators to improve the accuracy of cryptocurrency price movement prediction. This comprehensive research is useful and informative as it could help investors choose the right cryptocurrencies to build a portfolio that can generate higher returns or lower risks even in a crisis.

Table 1 provides a description of the acronyms used in this paper. The remainder of this paper is organized as follows. Section III provides a literature review highlighting pertinent research, and elucidating the distinctive manner in which our study addresses an identified gap in this scholarly landscape. The methodology of this study is presented in Section IV. Sections V and VI present the experimental design and results for the cryptocurrency market analysis and the price movement prediction, respectively. Section VII summarizes our findings and presents future work. Finally, Section VIII presents the conclusion of this paper.

TABLE 1. List of acronyms commonly used in this paper.

Acronym	Meaning	Acronym	Meaning
ADA	Cardano	APL	Average Path Length
BC	Betweenness Centrality	BNB	Binance
BNT	Bancor Network Token	BTC	Bitcoin
CC	Closeness Centrality	DApp	Decentralized Application
DASH	Dash	DC	Degree Centrality
DeFi	Decentralized Finance	DOGE	Dogecoin
EC	Eigenvector Centrality	ERC	Ethereum Request for Comment
ETH	Ethereum	FCT	Factom
FTT	FTX Token	LINK	Chainlink
LSTM	Long Short-term Memory	LTC	Litecoin
MAID	MaidSafeCoin	MKR	Maker
MOL	Mean Occupation Layer	MSR	Multi-step Survival Ratio
MST	Minimum Spanning Tree	NEO	NEO
NFT	Non-fungible Token	NS	Node Strength
NTL	Normalized Tree Length	OMG	OmiseGo
SNA	Social Network Analysis	SSR	Single-step Survival Ratio
TUSD	TrueUSD	USDT	United States Dollar Tether
XLM	Stellar Lumens	XRP	Ripple
XTZ	Tezos	ZEC	Zcash

III. LITERATURE REVIEW

Social network analysis has been used to model, analyze, and understand different conventional financial markets, such as the stock, foreign exchange, and commodity markets, as well as to identify the most important or influential assets in these markets. A detailed survey of the use of social network analysis in these financial markets can be found in [1]. The approach of integrating social and economic aspects into financial decision-making is further enhanced by generalized optimal game theory, a branch of game theory that extends traditional concepts and models to incorporate more complex scenarios and decision-making processes. Its aim is to find optimal strategies and outcomes in situations where multiple players (or investors in this case) have different goals and uncertainties [3].

Regarding the use of social network analysis for the emerging cryptocurrency market, the work in [4] conducted a correlation analysis and found that cryptocurrencies with similar codebases were positively correlated with each other. The work in [5] analyzed 16 cryptocurrencies using MST and found that ETH has taken over BTC as the benchmark cryptocurrency in the market. Similarly, the work in [6] revealed that the importance and rankings of cryptocurrencies have been rising since 2014 and were not negatively affected by the price crash in 2018. The work in [7] investigated the systemic risk of the cryptocurrency market and found that the market was volatile. The work in [8] reported an increasing price synchronization in the market, and the work in [9] studied transitions in the cryptocurrency market during the COVID-19 pandemic and found that the pandemic significantly affected the market for a short period of time. The work in [10] studied the correlation dynamics of the cryptocurrency market and found that it was affected by some critical events that caused market fluctuation. The work in [11] discovered that collective behaviours are present in the cryptocurrency market. To the best of our knowledge, the key properties of the cryptocurrency market have not been fully explored. Our study marks the *first contribution* towards addressing the gaps in the state of the art by applying social network analysis for an extensive and dynamic numerical analysis of the cryptocurrency market. This encompasses aspects such as the markets's correlation structure, topological characteristics, stability, and influence, with the goal of providing in-depth insights into the market. These insights are intended to assist investors in making more informed and effective investment decisions.

Moreover, an increasing number of recent studies have also begun examining ways of predicting the price of financial assets. Some of the latest applications of deep learning in stock market prediction are presented in [12]. Specifically for the cryptocurrency market, a detailed survey of prediction methods using time series and machine learning techniques can be found in [13] and [14]. Some studies have found that machine learning has better prediction accuracy than time series [15], [16]. Specifically, LSTM performs better in predicting BTC prices compared to other deep learning models such as CNN, RNN, and GRU. On the other hand, few studies have attempted to find valuable predictors for predicting cryptocurrency prices or their movements. Some of the predictors that have been proposed include technical and market-based indicators [17], news and social media sentiment, and blockchain trading [18]. Specifically, technical indicators have proven useful for predicting BTC prices. Public attention (e.g., Google Trends and Twitter data) [19], social media remarks (e.g., statements from influencers like E. Musk and D. Trump) [20], Bitcoin blockchain data, including users, miners, and exchanges [21] and economic variables such as stock market indexes, crude oil prices and exchange rates [22] were found to be effective in forecasting. Since centrality measures examine the influence of a node in a network, they have been effectively used for prediction in different domains, such as justice [23] and social reputation [24]. Our study makes a *second contribution* by leveraging centrality measures as predictors, aiming to improve the accuracy of cryptocurrency price movement forecasts based on their network significance. This approach is unprecedented for price-related analysis in any financial market.

To effectively address the objectives outlined, this study enhances our previous research efforts [25], [26] by incorporating an updated and more comprehensive dataset. This strategic update allows us to delve deeper into the subject matter, yielding a range of new and significant findings and insights that contribute to the current state of the art in the field:

Objective #1 (Social network analysis in cryptocurrency market dynamics related):

- We investigate the proportional distribution of cross-return correlation coefficients and their strong connection to unfavorable critical events, particularly major Bitcoin corrections. This reveals an important insight: cryptocurrencies tend to respond more collectively during adverse market events;
- Our analysis shows that the recent cryptocurrency market's cross-return correlation distribution has become more pronounced and features lighter tails with fewer extreme values compared to the past. This insight indicates a growing interconnectedness among cryptocurrencies and a trend towards more stabilized returns;
- We demonstrate the effectiveness of MST in accurately modeling cryptocurrency networks, thereby confirming the practicality of social network analysis in this sector;
- We analyze the impact of several major market corrections on the cryptocurrency network's structure. Our findings indicate that the network becomes more interconnected following these corrections but tends to revert to its original state or a relatively stable condition shortly afterward, suggesting that the market's response to corrections is typically transient or short-lived.

Objective #2 (Centrality measures as predictors related):

- Our study evaluates the utility of centrality measures as predictive tools, specifically identifying which centrality measures are most effective for forecasting the price movements of particular cryptocurrencies. This provides the insight that different centrality-based predictors are

suitable for different cryptocurrencies, depending on their unique attributes;
- We assess the robustness of predictions based on centrality measures in both static and dynamic environments (utilizing a rolling window technique). Our findings reveal that forecasts based on these centrality measure predictors are more effective than forecasts which rely on price and technical indicators only, suggesting that centrality-based indicators maintain their predictive strength over time.

IV. METHODOLOGY

Social network analysis (SNA) is a methodology for the in-depth study of relationships and interactions between individuals, groups, or organizations within a social system. Its main goal is to map and analyze complex patterns of connections, nodes, and interactions, providing valuable insights into the structure and dynamics of social networks. In particular, centrality measures are quantitative measures used in SNA to determine the importance or influence of individual nodes in a network. These measures evaluate the relative importance of a node based on its connections, location, and interactions with other nodes. Centrality measures help identify nodes that play a key role in maintaining connectivity, information flow, or control within a network. Nodes with high centrality scores are generally considered influential or central to network functionality.

Both SNA and centrality measures are very useful in cryptocurrency analysis for the following reasons:
- Understand the network structure: Cryptocurrencies run on a decentralized network and transactions occur between them. SNA helps analyze the relationships and connections between these cryptocurrencies, revealing the underlying network structure. This understanding is critical for identifying clusters, hubs, and communities within cryptocurrency networks, providing insights into how information, transactions, and influence flow through the system;
- Identifying influential actors: SNA, especially through centrality measures, helps identify the most influential or important nodes in a cryptocurrency network. These nodes can represent key cryptocurrencies that have a significant impact on network dynamics. By identifying influential players, analysts can gain insights into cryptocurrency market dynamics and the potential for market manipulation;
- Uncovering hidden connections: SNA can reveal hidden connections between cryptocurrencies that may not be immediately apparent. This information is valuable for understanding the interrelationships between different cryptocurrencies and identifying potential collaborations or dependencies involving multiple cryptocurrencies.

In summary, social network analysis and centrality measures are invaluable tools in cryptocurrency analysis as they provide insight into network structure, identify influential actors, and discover hidden connections. By leveraging these technologies, stakeholders can gain a deeper understanding of the complex dynamics within the cryptocurrency market, allowing for more informed decisions and improved risk management practices.

To begin, we transform the prices into log returns as:

$$r_i(t) = ln(\frac{p_i(t)}{p_i(t-\Delta t)}) = ln\, p_i(t) - ln\, p_i(t-\Delta t) \quad (1)$$

where $p_i(t)$ and $r_i(t)$ are the closing price and return of cryptocurrency i on day t, respectively. The return is computed on two consecutive days (i.e., $\Delta t = 1$). The reason for this price-to-return transformation is to make $r_i(t)$ stationary and independent of the price scale. For instance, a change in the BTC price from USD 10 to 11 has the same difference as a change from USD 500 to 550. This allows for meaningful comparisons of cryptocurrencies across different price ranges.

One additional challenge, however, is that as the cryptocurrencies enter the market at different times, the number of cryptocurrencies that appear on the market during any two time periods may differ. Therefore, normalizing our empirical results by the number of cryptocurrencies in each time period is necessary to enable meaningful comparisons between time periods.

A. CROSS-RETURN CORRELATION COEFFICIENT MATRIX

Social network analysis models each time period of cryptocurrency market evolution through a network. The input for constructing a cryptocurrency network for analysis is the correlation of returns between all the cryptocurrency pairs. We first create a cross-return correlation coefficient matrix using the Pearson product-moment correlation for each pair of cryptocurrencies i and j as follows:

$$c_{ij} = \frac{\sum_{k=1}^{T}(i_{r,k} - \bar{i_r})(j_{r,k} - \bar{j_r})}{\sqrt{\sum_{k=1}^{T}(i_{r,k} - \bar{i_r})^2 \sum_{k=1}^{T}(j_{r,k} - \bar{j_r})^2}} \quad (2)$$

where $i_{r,k}$ and $j_{r,k}$ are the returns of cryptocurrency i and j, respectively, on day k of time period T, while $\bar{i_r}$ and $\bar{j_r}$ are the average returns of cryptocurrencies i and j, respectively, during the same period. We chose $T = 182$ days (or six months) as the window length of each time period because the cryptocurrency market is so volatile that we want to trace its dynamics over a reasonable window size [27]. The value range of each cross-return correlation coefficient in the matrix is -1 to 1. When the value is close to 1, the returns of the two cryptocurrencies move similarly (i.e. when the returns of one cryptocurrency increase, the returns of the other also increase). Conversely, when the value approaches -1, one cryptocurrency's returns move in the opposite direction of another. When the value is 0, the two cryptocurrencies are completely independent, so their return moves vary arbitrarily. The output from (2) is an $N \times N$ cross-return correlation coefficient matrix, where N is the number of cryptocurrencies in the network at the given time period.

The diagonal of the matrix is always equal to 1, since any cryptocurrency has a perfect correlation with itself.

B. NETWORK CONSTRUCTION

In a cryptocurrency network, each node represents a cryptocurrency, whereas each edge connecting two nodes represents their return correlation coefficient. A cryptocurrency network that fully connects all the cryptocurrency nodes (i.e., clique) is thus formed. However, this network may contain a certain amount of redundant information that might not be useful (e.g., edges with zero correlation). One approach to streamline the cryptocurrency network is by utilizing graph-based algorithms such as the minimum spanning tree (MST), threshold network (TN), or plane maximum filter graph (PMFG). These algorithms help identify and retain nodes and edges with strong connections and correlations, which in turn provide valuable and informative insights [19]. MST is the subset of edges of the graph that connects all nodes without forming any cycles and has the smallest total cost among all possible spanning trees. TN is a graph that only retains edges between nodes that exceed a certain threshold. PMFG, on the other hand, is a planar graph that can be drawn on a flat surface without edge crossing, and it contains MST as a subgraph, thus retaining more information about the network than MST (Tumminello et al. [40], 2005). To effectively filter relevant information from large and complex cryptocurrency networks, we choose MST over TN and PMFG for the following reasons:

- Efficiency: The time complexity of MST is $O(ElogV)$, where E is the number of edges and V is the number of nodes. On the other hand, the time complexities of TN and PMFG are $O(V^2)$ and $O(V^3)$, respectively. This makes MST computationally efficient and scalable for large-scale cryptocurrency networks;
- Completeness: MST guarantees that all nodes in the network are connected, which helps maintain the integrity and efficiency of the network to facilitate more comprehensive cryptocurrency network analysis. On the other hand, TN and PMFG do not necessarily guarantee connectivity (e.g., TN is based on hard-to-determine thresholds), which may lead to cryptocurrency orphans or disconnections.

Overall, MST is simple, robust, and clear as it visualizes the linkages, and includes the entire set of the studied cryptocurrencies to facilitate a comprehensive analysis. Moreover, MST has the ability to provide economically meaningful information in many financial networks [28]. Nevertheless, there may be a trade-off between the efficiency and effectiveness of this information filtering.

Given a matrix of cross-return correlation coefficients, we construct undirected cryptocurrency networks using MST. Studying connectivity and correlation patterns in networks can help us better understand the inner structure of the cryptocurrency market. Constructing a cryptocurrency network requires a transformation from the cross-return correlation coefficients to distances that can be derived as in [28] using:

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

which satisfies the following axioms:

- positive definiteness: $d_{ij} \geq 0$ and $d_{ij} = 0$ if and only if $i = j$
- symmetry: $d_{ij} = d_{ji}$
- triangular inequality: $d_{ij} \leq d_{ik} + d_{kj}$

where d_{ij} denotes the distance between cryptocurrency nodes i and j, computed by their return correlation coefficients. The value of the distance lies between 0, for a complete correlation between the cryptocurrencies when $c_{ij} = 1$, and 2 for a complete anti-correlation when $c_{ij} = -1$. For uncorrelated cryptocurrencies when $c_{ij} = 0$, the distance is $\sqrt{2}$. The output of this transformation is an $N \times N$ distance matrix derived from the $N \times N$ cross-return correlation coefficient matrix. We use the MST algorithm outlined in [28] to construct the network, which connects N nodes using $N - 1$ edges without creating cycles such that the total distance of all the edges is minimal. Therefore, each cryptocurrency network filters and extracts the most valuable and useful information using the $N-1$ linkages. This enables us to identify and analyze the cryptocurrency market under different critical economic events, such as crises and crime.

C. CENTRALITY MEASURES

In the realm of SNA, the centrality of a node determines its influence or importance within a network. We use five well-established centrality measures to identify the most influential cryptocurrencies at different time periods across the entire dynamic evolution of the cryptocurrency market over time.

1) DEGREE CENTRALITY (DC)

The degree centrality of a node v is the total number of its directly connected neighbor nodes, defined as:

$$c_{DC}(v) = \frac{\sum_{u \in V}^{N} A_{vu}}{N - 1}, v \neq u \tag{4}$$

where V is the set of nodes in the network, A_{vu} is an element of the adjacency matrix, where the value is equal to 1 if nodes v and u are directly connected, and equal to 0 otherwise. DC values are normalized by the number of edges in the network (i.e. $N - 1$), where N is the number of nodes in the network (i.e. $N = |V|$). DC measures the importance of a cryptocurrency based on its number of adjacent connections, which can influence the behavior of other directly connected cryptocurrencies.

2) NODE STRENGTH (NS)

A large number of neighboring nodes may not necessarily indicate a strong correlation with these nodes in general. NS considers also the strength of node connections in addition to the DC. The node strength of a node v is the sum of the return correlation coefficients of all edges of v. It is further normalized by the number of edges in the network:

$$c_{NS}(v) = \frac{\sum_{u \in V}^{N} c_{vu} A_{vu}}{N-1}, v \neq u \tag{5}$$

NS measures how strongly a cryptocurrency is correlated with neighboring ones by considering both the node connections and the correlations between the relevant edges.

3) BETWEENNESS CENTRALITY (BC)

The normalized BC of node v is the sum of the fractions of the shortest paths (in terms of distance) of all pairs that pass through v. It is defined as:

$$c_{BC}(v) = \frac{2}{(N-1)(N-2)} \sum_{s,d \in V} \frac{\gamma(s,d|v)}{\gamma(s,d)} \tag{6}$$

where $\gamma(s, d)$ is the number of shortest paths between nodes s and d, and $\gamma(s, d|v)$ is the number of shortest paths passing through v between s and d. If $s = d$, then $\gamma(s, d) = 1$, and if $v \in (s, d)$ then $\gamma(s, d|v) = 0$. BC measures the intermediary control that cryptocurrency nodes have over the flow of information on a network. The larger the value of BC, the more likely the node is to act as an important intermediate node or broker, transmitting or coordinating information in the network, passing it from one node to another. With respect to regulation, cryptocurrencies with higher intermediary abilities can restrain the spread of abnormal price fluctuations in the market.

4) CLOSENESS CENTRALITY (CC)

The CC of node v is the reciprocal sum of the shortest paths originating from v to $N-1$ other nodes:

$$c_{CC}(v) = \frac{N-1}{\sum_{u \in V}^{N} d_{vu}}, v \neq u \tag{7}$$

where d_{vu} is the distance of the shortest path between nodes v and u. CC measures how close a cryptocurrency node is to the shortest path length of all other nodes. The larger the CC of a node, the faster the cryptocurrency can transmit information to all other nodes. Therefore, CC measures the efficiency of information dissemination in the network. If a cryptocurrency can reach other nodes quickly, it is usually at the center of the network.

5) EIGENVECTOR CENTRALITY (EC)

The DC or NS of a node may not be a sufficient representation of how influential it is as it does not consider the importance of the neighboring nodes, e.g., a node with a small DC may be connected to neighboring nodes with a large DC or NS. In this case, this node should be regarded as influential. This centrality, which takes into account the influence of neighboring nodes, is called eigenvector centrality. We first define an adjacency matrix, $\mathbf{A}$, whose element A_{ij} is 1 an immediate connection between nodes i and j exists, and is 0 otherwise. The EC of node v is defined as:

$$c_{EC}(v) = \frac{1}{\lambda} \sum_{u \in V}^{N} A_{vu} c_{EC}(v), v \neq u \tag{8}$$

Compared with DC and NS, EC considers not only the number of connections or the strengths of correlations to direct neighboring nodes, but also their importance. A node connected to a few influential nodes is likely to have a larger EC than one connected to many less influential nodes, thus revealing their importance in a network.

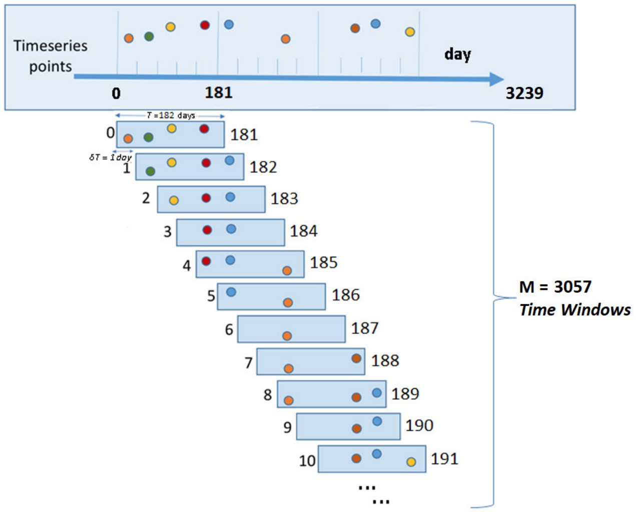

FIGURE 1. Parameters of the moving time window analysis.

V. EVALUATION OF THE CRYPTOCURRENCY MARKET USING SOCIAL NETWORK ANALYSIS

The dataset we used consists of the time series of daily closing prices of the top 145 cryptocurrencies by market capitalization as of March 11, 2022, covering the period from April 28, 2013 (i.e., the first day the dataset has a closing price of BTC) to March 11, 2022. It is collected from CoinMarketCap. Some decentralized finance (DeFi) and non-fungible token (NFT) cryptocurrencies are included in the dataset. This entire set of cryptocurrencies has been in the market for at least six months, which can be considered representative of the market since it covers over 95% of the total market capitalization as of the above date. There are at most 3,240 daily closing price observations for each of the cryptocurrencies as they enter the market at different times, and all the prices are quoted in USD. There are very few missing prices for certain cryptocurrencies in the dataset. The best way to deal with this is open to interpretation. We impute the missing prices by using the quoted prices on the last day of trading.

A. MOVING TIME WINDOW ANALYSIS

Since cryptocurrencies enter the market at different time periods, our work is not limited to dealing with only one set of cryptocurrencies within a specific time period. Instead,

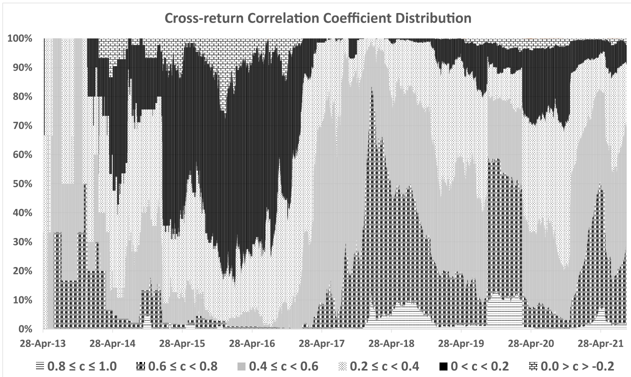

FIGURE 2. **Proportional distributions of cross-return correlation coefficients.**

we are more interested in the dynamics of the cryptocurrency market over time. Therefore, as shown in Fig. 1, the moving time window approach is adopted to study the dynamic evolution of the market over a nine-year time span. The entire study period is divided into M time windows $t = 1, 2, \ldots, M$, with a width of T, corresponding to the number of daily returns in each time window. Consecutive time windows can overlap each other, expressed by the window step length parameter δT (the unit is day), describing the displacement of the window. Given that the cryptocurrency market operates 365 trading days a year, our empirical results are calculated using a time window of $T = 182$ days (i.e., six months) [27] and $\delta T = 1$ day. Thus, each time window contains at most 182 daily returns for each cryptocurrency. With these parameters, the total number of time windows across the entire studied period is $M = 3059$. This procedure allows us to study the structural and evolutionary changes in cryptocurrency networks by using a relatively small interval between time windows for a large sample size of the data on cryptocurrency prices. Note that there are only a few cryptocurrencies in the dataset during the first few years. Over time, more and more cryptocurrencies are developed and enter the market. To help us draw meaningful conclusions, the correlation coefficients of returns between any pair of cryptocurrencies over a time window is calculated only if the number of daily returns of both cryptocurrencies is exactly $T = 182$. Otherwise, the correlation coefficient is not computed, and no edge is created between the corresponding cryptocurrency nodes in the network.

B. STATISTICAL PROPERTIES OF DISTRIBUTION OF CROSS-RETURN CORRELATION COEFFICIENT

We perform a dynamic analysis of the distribution of cross-return correlation coefficients over the studied period. Fig. 2 shows the proportional distribution of cross-return correlation coefficients throughout the evolution of the cryptocurrency market. Table 2 shows the return correlation coefficients c for different strength levels as defined in [29].

As is shown in Fig. 2, positive return correlation coefficients (i.e., $c > 0.0$) are far more common than

TABLE 2. **Levels of correlation strength.**

Correlation coefficient	Correlation Strength Level
$0.8 \leq c \leq 1.0$ or $-0.8 \geq c \geq -1.0$	Very strong
$0.6 \leq c < 0.8$ or $-0.6 \geq c > -0.8$	Strong
$0.4 \leq c < 0.6$ or $-0.4 \geq c > -0.6$	Moderately strong
$0.2 \leq c < 0.4$ or $-0.2 \geq c > -0.4$	Weak
$0.0 < c < 0.2$ or $0.0 > c > -0.2$	Very weak
$c = 0.0$	No correlation

anti-correlations (i.e., $c < 0.0$). Moreover, the overall proportional distribution is dominated by weak to moderately strong correlations, and the level of correlation tends to become stronger since 2016. This reveals that, overall, ***the cryptocurrencies are positively and moderately correlated with one another most of the time in recent years***. Hence, they are not totally independent or uncorrelated from one another, but their return movements tend to follow the same direction. In other words, any return or price fluctuations on some cryptocurrencies are likely to affect the prices or returns of the other cryptocurrencies.

Interestingly, we observe a remarkable change in the correlation distribution in Fig. 2 around September 12, 2019. On this day, the cryptocurrency Tether migrates millions of its coins in USDT from the Omin protocol on the Bitcoin blockchain network to the ERC-20 protocol on the Ethereum blockchain network. As a result, it produces negative return correlation coefficients not only between USDT and some other major cryptocurrencies, including BTC, but also between the TUSD, which is an Ethereum-based ERC-20 token, and other cryptocurrencies. This observation signals that the return correlations of the cryptocurrencies are sensitive to critical events in the market.

To verify this observation, we compute the first four moments (i.e., mean, variance, skewness and kurtosis) of cross-return correlation coefficients across the entire evolution of the cryptocurrency market in Fig. 3. The greater the mean correlation, the higher the interdependence among the cryptocurrencies. Fig. 3 shows that the mean correlation increases when undesirable critical events, particularly corrections, occur in the market. Correction is defined as a significant decline in the price (i.e., bear period) of a security, asset, or financial market (i.e., the cryptocurrency market in our work) primarily due to crises or crime (e.g., a large number of cryptocurrencies have been stolen from exchanges) in the market (see "Cryptocurrency bubble" and "Cryptocurrency and crime" at Wikipedia for crises and crime, respectively). Moreover, other corrections are caused by negative news in the market, e.g., Elon Musk tweeted that Tesla would stop accepting BTC payments in 2021, leading to a drop in BTC of 52%. As BTC is the most popular and valuable cryptocurrency, we create a list of major BTC corrections and their descriptions in Fig. 4 and Table 4, respectively. Many of them take place in mid 2013–mid 2014, mid 2016–early 2018, mid 2019–early 2020, and mid 2020–early 2022 (i.e., the correction periods)

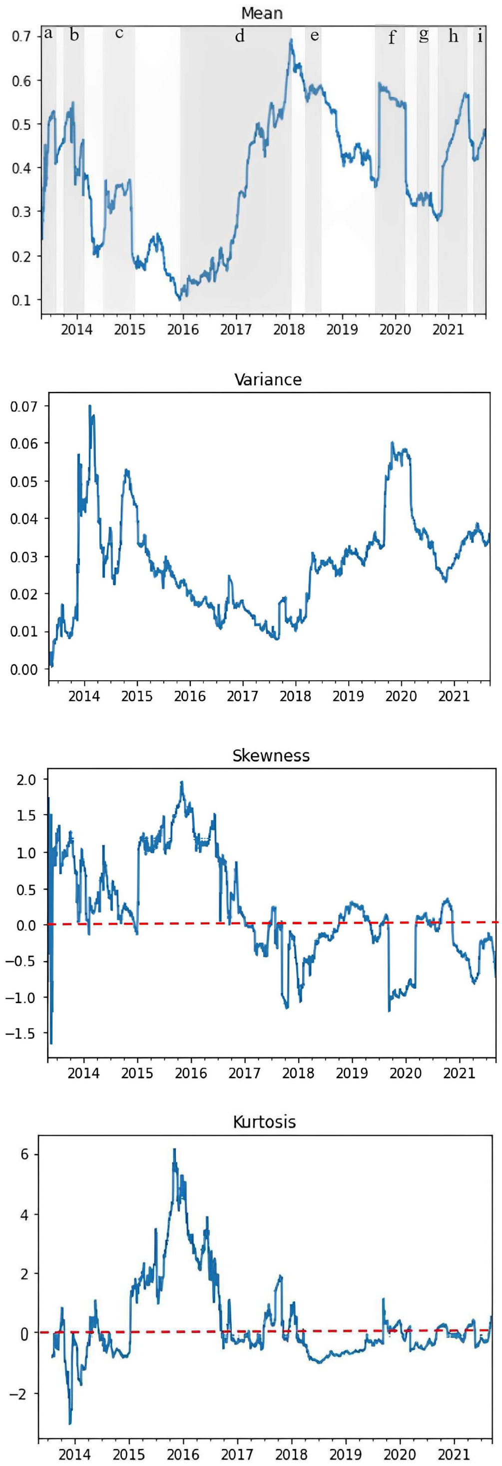

FIGURE 3. Mean, variance, skewness, and kurtosis of cryptocurrency cross-return correlation coefficients as a function of time.

due to various significant BTC crashes. Upon the occurrence of these corrections, the correlations of all cryptocurrencies seem to follow one another and move in the same direction, thus confirming the presence of increasing inter-correlations among them. These corrections are mapped by the corresponding grey shadows and alphabetical labels in Fig. 3 and Fig. 4.

TABLE 3. Pearson correlation coefficients on returns among the first four moments.

	Mean	Variance	Skewness	Kurtosis
Mean	1.0	0.33	-0.77	-0.64
Variance		1.0	-0.32	-0.32
Skewness			1.0	0.63
Kurtosis				1.0

	No	Correction start date	Correction end date	# Days in correction	Bitcoin high price $	Bitcoin low price $	Decline %	Decline $
a	1	11 Apr 2013	12 Jun 2013	60	266.34	70.00	-74%	196.34
b	2	19 Nov 2013	19 Dec 2013	30	1,242.00	600.00	-52%	642.00
	3	5 Jan 2014	11 Apr 2014	95	1,000.00	440.00	-56%	560.00
c	4	16 Sep 2014	29 Mar 2015	200	465.86	252.74	-46%	213.12
d	5	17 Jun 2016	2 Sep 2016	78	770.50	570.95	-26%	199.55
	6	10 Mar 2017	25 Mar 2017	16	1,350.00	891.33	-34%	458.67
	7	25 May 2017	27 May 2017	3	2,760.10	1,850.00	-33%	910.10
	8	12 Jun 2017	16 Jul 2017	35	2,980.00	1,830.00	-39%	1,150.00
	9	2 Sep 2017	15 Sep 2017	14	4,979.90	2,972.01	-40%	2,007.89
	10	8 Nov 2017	12 Nov 2017	5	7,888.00	5,555.55	-30%	2,332.45
	11	17 Dec 2017	22 Dec 2017	5	19,783.06	13,800.00	-31%	5,983.06
	12	22 Dec 2017	5 Feb 2018	14	13,800.00	6,200.50	-55%	7,599.50
e	13	5 Sep 2018	16 Dec 2018	100	7,361.46	3,236.27	-56%	4,125.19
f	14	27 Jun 2019	15 Dec 2019	195	13,017.12	7,116.28	-45%	5,900.84
	15	13 Feb 2020	19 Mar 2020	36	10,361.76	5,295.36	-49%	5,066.40
g	16	21 Aug 2020	11 Sep 2020	22	12,486.61	9,813.01	-21%	2,673.60
h	17	8 Jan 2021	22 Jan 2021	15	41,986.37	28,732.01	-31%	13,254.36
	18	14 Apr 2021	22 Jun 2021	69	64,706.86	29,031.74	-55%	35,675.12
i	19	10 Nov 2021	22 Jan 2022	73	68,991.76	35,030.27	-49%	33,961.49

FIGURE 4. Major BTC corrections between 2013 and 2022 [Last accessed: http://www.cnn.com/bitcoin-crash-the-history-of-bubble-bursts].

On the contrary, the mean correlation decreases during relatively calm periods, such as mid 2015–mid 2016, mid 2018–mid 2019, and mid 2020–early 2021. These results support our aforementioned finding that cryptocurrencies are sensitive (i.e., more likely to be correlated) to critical events (e.g., corrections) in the market. Although the work in [7] has conducted a dynamic correlation analysis, they have not uncovered such a relationship between correlation and critical events. Hence, our finding adds to the literature by showing that ***undesirable critical events, such as major cryptocurrency corrections due to crises, crime, and negative news, usually lead to an overall increase in the return correlations in the cryptocurrency market***. This has also been observed in the conventional financial markets [30]. Thus, any undesirable critical event will likely influence how cryptocurrencies behave and react collectively.

With respect to the variance, its movement generally follows the mean correlation as the correlation between them is moderate, as shown in Table 3. Nevertheless, their movement patterns are getting more similar in recent years. This implies that when the mean correlation increases, usually after the occurrence of an undesirable critical event, the variance (or risk) increases, as does the dispersion of the resulting correlation coefficients. Like the mean correlation, during the correction periods, the return correlations among the cryptocurrencies vary slightly more than in the calm periods, when volatility is lower. By considering both the mean correlation and the variance, we can observe that the return correlations of the cryptocurrencies become stronger during volatile periods than during calm periods. Moreover, the increased variance since 2017 indicates that

TABLE 4. Key Bitcoin correction events.

Label	Some key correction events
a	• Mt. Gox exchange suffered a sustained attack by hackers.
b, c	• Mt. Gox exchange went bankrupt. • Some banks were banned from handling Bitcoin trade.
d, e	• Coincheck exchange suffered a massive hack resulting in a loss of cryptocurrencies worth USD 530 million. • Tech giants (e.g., Facebook and Google) prohibited advertising initial coin offerings and token sales on their platforms. • The U.S. Securities and Exchange Commission (SEC) rejected Bitcoin ETF application.
f, g	• COVID-19 outbreak.
h	• Growing media reported that Bitcoin mining has caused problems related to environmental, social, and corporate governance. • Tesla stopped accepting Bitcoin for car payments. • Crackdowns were launched on some Bitcoin mining farms.
i	• A major algorithmic stablecoin, USTC, lost its 1:1 peg with the U.S. dollar, which triggered panic in the cryptocurrency market.

the return correlations tend to vary more than in the past, primarily owing to the more frequent occurrence of major cryptocurrency corrections.

Additionally, Fig. 3 shows the skewness of time-varying return correlation coefficients. Skewness is the inverse of the mean correlation, as is confirmed by their anti-correlation in Table 3. Interestingly, the return correlation coefficients before 2017 are positively skewed. This reveals that the market exhibits weaker return correlations than the average among the cryptocurrencies. By contrast, beyond 2017, the continuous negative skewness indicates that the market exhibits stronger correlations than the average. This again confirms that the return correlations among cryptocurrencies in recent years have become stronger than in the past.

Finally, as shown in Fig. 3, a high degree of positive excess kurtosis (i.e., leptokurtic, for which kurtosis is greater than kurtosis 0 of normal distribution) indicates that the market has a higher probability of experiencing extreme return correlations. It can be observed by the spikes around 2016 and 2018 in the figure that a few cryptocurrency pairs have extreme return correlations, which results in more outliers than in the normal distribution (e.g., a very strong correlation coefficient of 0.83 between BTC and LTC around 2016, while a majority of the other cryptocurrency pairs have weak return correlations of between 0.0 and 0.2). One may also find that the return correlation coefficients in recent years are negatively skewed while the kurtosis is mostly close to 0 (i.e., it is mesokurtic, and the return correlation tends to follow a normal distribution). Hence, the return correlations in recent years are becoming less extreme compared to the past. This finding concludes that ***the distribution of the cross-return correlation coefficients in the recent cryptocurrency exhibited lighter tails***.

The findings above lead us to conclude that the return correlations among cryptocurrencies in recent years have become stronger and have fewer extreme values than in the past. Investors should pay attention not only to the cryptocurrencies they have an interest in (e.g., to look beyond the basic characteristics of these cryptocurrencies in order to understand how their values will evolve as suggested in [4]), but also investigate other cryptocurrencies correlated with it when making investment decisions.

C. DYNAMIC STRUCTURE OF CRYPTOCURRENCY MST NETWORKS

As MST networks can model the cryptocurrency market, it is useful to understand their dynamic structure, particularly the topological characteristics and stability of the networks.

We use three evaluation criteria to analyze the topological characteristics of cryptocurrency networks. The first is the normalized tree length (NTL), which is used to analyze the effects of linkages among cryptocurrencies by measuring the average distance in the network in a time window [31]:

$$NTL(t) = \frac{1}{(N-1)} \sum_{d_{i,j}^t \in E_t} d_{i,j}^t \tag{9}$$

where $d_{i,j}^t$ is the distance between nodes i and j in time window t, E_t denotes the set of edges in the network in time window t, and $N-1$ is the number of edges in the network. The larger the NTL is, the longer is the average distance and, thus, the smaller are the mean return correlations, and vice versa.

Second, we use the average path length (APL) to analyze network density [32], which is defined as:

$$APL(t) = \frac{2}{N(N-1)} \sum_{i<j} l_{i,j}^t \tag{10}$$

where $l_{i,j}^t$ is the number of links (or hops) in the shortest path between nodes i and j in the network in time window t, N is the number of nodes and N-1 the number of edges in the network. The smaller the APL, the closer the nodes are in the network.

Third, the mean occupation layer (MOL) proposed by [31] is used to evaluate the change in density or spread of nodes in a MST network, which is defined as:

$$MOL(t, v_c^t) = \frac{1}{N} \sum_{i=1}^{N} Lev(v_i^t) \tag{11}$$

where v_c^t and v_i^t are the central node c and node i, respectively, in time window t, and $Lev(v_i^t)$ is the difference in level between nodes i and c in time window t when the level of the central node c is set to zero. The smaller the MOL, the higher the density or compactness of the network (i.e., the nodes tended to crowd the area around the central nodes in the network). The central node can usually be the node with the highest DC or NS. In such case, we choose the node with the highest DC as the central node, then if two nodes have the same DC, use NS as the tiebreaker. Furthermore, the central node can be static (i.e. fixed in all time windows) or dynamic (i.e. continuously updated in each time window). Since the

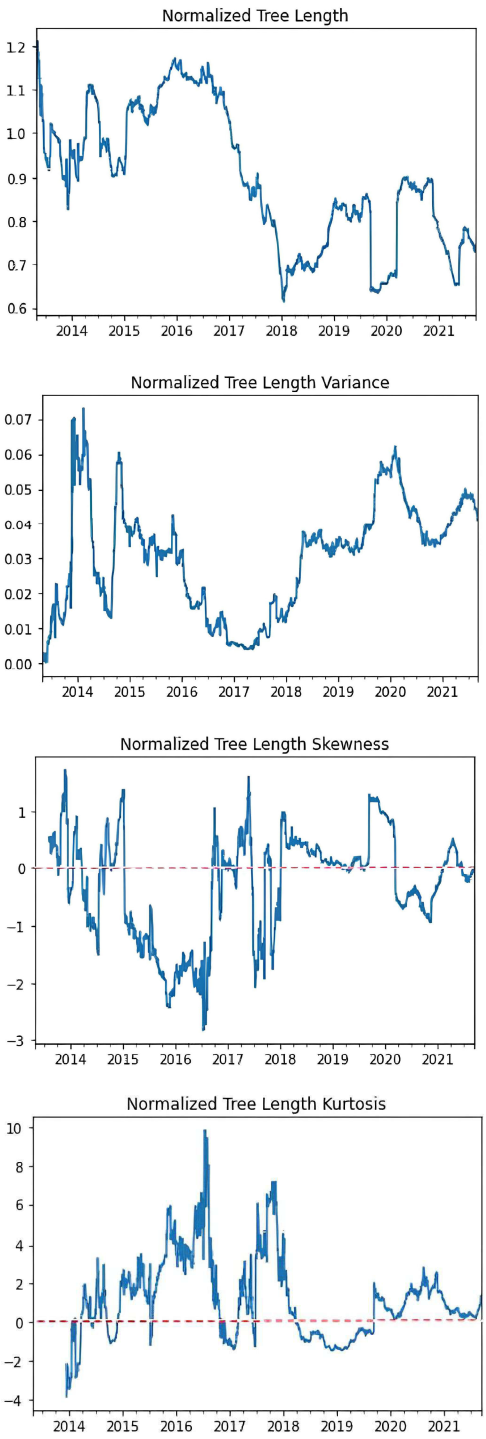

FIGURE 5. Mean, variance, skewness, and kurtosis of normalized tree lengths for cryptocurrency networks as a function of time.

cryptocurrency market may not always be dominated by one cryptocurrency, we adopt the dynamic approach.

Fig. 5 shows the time-varying results of NTL. It shows that NTL decreases when the mean correlation in Fig. 3 increases, and vice versa. In other words, the networks shrink during undesirable critical events, which increases the interdependence among the cryptocurrencies, and this shrinkage is most significant around the frequent correction periods.

TABLE 5. Pearson correlation coefficients on network distance among the first four moments.

	Mean	Variance	Skewness	Kurtosis
Mean	1.0	-0.39	-0.68	0.38
Variance		1.0	0.28	-0.40
Skewness			1.0	-0.63
Kurtosis				1.0

TABLE 6. Pearson correlation coefficients between return and network distance among the first four moments.

	Mean	Variance	Skewness	Kurtosis
Mean	-0.92			
Variance		0.92		
Skewness			-0.72	
Kurtosis				0.68

Table 5 shows that the mean and the variance of the NTL are anti-correlated, and the skewness and the mean continue to be anti-correlated. This implies that after the impact of undesirable critical events has been absorbed by the market, the network shrink and the mean NTL decreases, while the variance and the skewness increases. The skewness is almost always negative (positive) before (after) mid-2017, showing that the network contains more edges with longer (shorter) distances than the average, which is opposite to the skewness of the mean return correlation in Fig. 3.

Examining the cross-corrections of the first four moments between the return correlation coefficients and the network distances can help us assess the effectiveness of using MST networks to model the cryptocurrency market. When comparing their first four moments in Fig. 3 and Fig. 5, the elements of the distribution of network distance have strong correlations or anti-correlations with those of the return correlation coefficients, as shown in Table 6: The Pearson's linear correlation between the skewness (kurtosis) of the return correlation coefficients and the skewness (kurtosis) of the network distance is -0.72 (0.68). On the contrary, the mean and the variance of the network distance are also strongly correlated with those of the return correlation coefficients. These striking correlations imply that MST networks are a good representation of the cryptocurrency market and can capture important correlation information well.

Fig. 6 shows the results of APL and MOL. The grey shadows in the figure correspond to the major BTC corrections in Fig. 4. APL decreases during the corrections and thus shortening the network distances among the cryptocurrencies. This reveals that the cryptocurrencies are getting closer to one another and are more strongly and directly correlated during the corrections. Nevertheless, the overall uptrend of the APL reveals that the networks are expanding with deeper branches. Hence, more intermediary cryptocurrencies are required to deliver pricing information from one cryptocurrency to another.

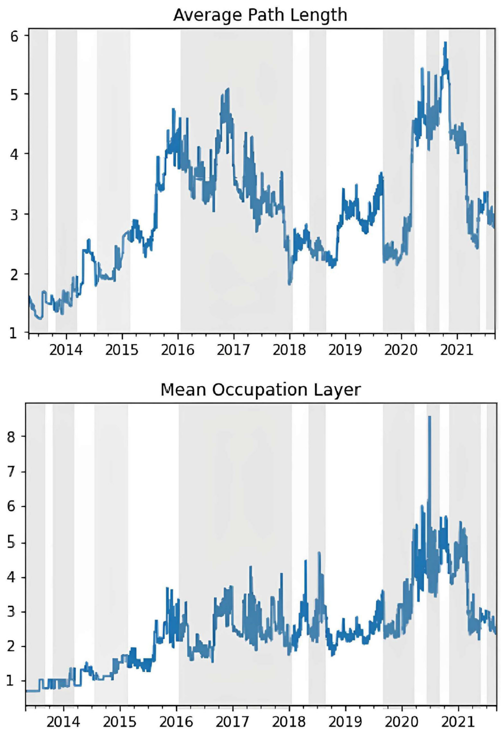

FIGURE 6. Time-varying APL and MOL of cryptocurrency networks.

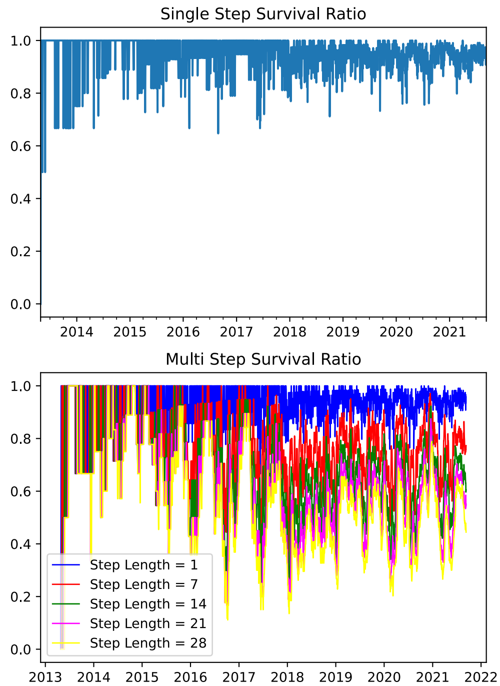

FIGURE 7. Time-varying SSR and MSR of cryptocurrency networks.

Similar to APL, MOL also decreases during the corrections. A low MOL reveals that the networks shrink and become denser and more compact, i.e., the nodes are more concentrated around the central node. An economic interpretation of this observation is that common factors should drive returns during a market crisis, and a denser network reveals the increasing importance of these factors [31]. As a result, a denser and more compact network is expected because crises, crimes, and negative news are common causes of cryptocurrency corrections. Nevertheless, an overall uptrend in the MOL indicates that the networks over time are becoming less compact when major cryptocurrency corrections occur less frequently. The overall results of the APL and MOL reveal that cryptocurrencies are agglomerating around some key cryptocurrencies and starting to form blocks (e.g., like blocks in stock markets) that consist of cryptocurrencies possessing common characteristics, such as a codebase, underlying technologies, and similar application. Clustering cryptocurrencies into blocks is a popular subject of research in finance. Instead of studying each of thousands of cryptocurrencies, investors may save time and effort by analyzing the characteristics of blocks for portfolio selection and optimization.

In summary, our analysis reveals that ***cryptocurrency networks tend to become more compact during significant market corrections, while conversely, when such corrections occur less frequently, the networks become increasingly sparse.*** Notably, these major corrections are associated with a decrease in the values of key topological characteristics, such as the Average Path Length (APL) and the Mean Occupied Layer (MOL). Consequently, the networks are evolving to be denser and more compact, with internal correlations strengthening and becoming more direct. However, with a declining mean correlation, alongside an increase in mean distance and mean occupied layer, these dynamic indicators point to a gradual decompression of MST. This suggests a weakening in the degree of interaction or integration among cryptocurrencies over time, indicating enhanced diversification benefits throughout the period under study.

D. STABILITY OF CRYPTOCURRENCY NETWORKS

In addition to topological characteristics, we studied the stability of cryptocurrency networks using the single-step survival ratio (SSR) [31] to measure the evolution and survivability of edges across networks:

$$SSR(t) = \frac{1}{N-1}|E(t) \cap E(t-1)| \tag{12}$$

where $E(t)$ is the set of edges in the network at time t. The larger the SSR is, the more stable networks are in the short run as edges survive from one network to the next (i.e., from time window t to $t+1$). Fig. 7 shows that the overall trend of the SSR is stable as its average value is 0.9523, which indicates that, on average, 95.23% of the edges in the network in time window t survived in the network in time window $t+1$. Hence, the structure of dependence on the cryptocurrency market in the short run (e.g., one day) is relatively stable. This reveals that short-lived and strong correlations among some cryptocurrencies have been formed.

To study the evolution and survivability of edges in the long run, we use the multi-step survival ratio (MSR) in time window t with different step lengths:

$$MSR(t,k) = \frac{1}{N-1}|E(t) \cap E(t-1) \cap \dots E(t-k+1) \cap E(t-k)| \quad (13)$$

where k is the step length. MSR computes the ratio of edges that survive in all the networks across the time window k steps from the given initial one. A small value of k measures the short-term network stability, whereas a large value evaluates the long-term stability. For small and large values of k, $MSR(t,k)$ quantifies short-term and long-term network stability, respectively. $SSR(t)$ is a special case of $MSR(t,1)$. We measure edge survivability by computing MSR with different step lengths. We use step lengths of 7, 14, 21, and 28 days, corresponding to 1, 2, 3, and 4 weeks, respectively. We also include step length of 1 for reference.

Fig. 7 shows that the downtrend across increasing step lengths reflects changes in the network structure after a longer period. This implies the stability of cryptocurrency networks in the long run decreased. Specifically, the average MSR drops rapidly (from 0.9523 to 0.7985) after only seven days. When the step length is increased to 14 days, the average MSR is 0.6910. When it is further increased to 28 days, the average MSR drops significantly to 0.5589, suggesting that only 55.89% of the edges in the network have survived over the previous 28 days. Thus, the survivability of the edges decreases rapidly as the step length increases. Nevertheless, a set of edges constantly survive in the networks for a very long period of time, thus creating persistently stable and strong correlations on some pairs of cryptocurrencies. To understand this long-term stability, we set the step length to a large value, e.g., 365 days.

Some edges survive across the networks over a year, such as BTC–LTC in 2014–2015, ETH–BNT in 2017–2018, ETH–MKR in 2018–2019, ZEC–DASH in 2019–2020, LINK–XTZ in 2020–2021. Such enduring stability can be explained by their commercial and technological relationships. For example, LTC is a "lite" version of BTC, designed to facilitate faster and cheaper transactions. ZEC and DASH are privacy coins designed to prioritize user privacy and anonymity. LINK and XTZ, on the other hand, have a partnership that helps smart contract developers working on XTZ access a decentralized oracle network managed by LINK.

These results are important for portfolio selection as the return correlations of many cryptocurrencies start to diminish gradually, whereas some structures of the cryptocurrency networks are always preserved and stabilized. This indicates that ***the structure of the return correlation of the cryptocurrency market is stable in the short run but becomes less stable over time, whereas the return correlations between some pairs of cryptocurrencies remain persistently stable in the long run***. Drastic changes in the cryptocurrency network structure are also highlighted in [10] through the Jaccard distance. However, such network stability is not analyzed dynamically on both a short-term and long-term basis. Thus, investors can manage investment risks by making timely and diverse adjustments to their portfolios, e.g., selecting a well-diversified portfolio with "uncorrelated" cryptocurrencies.

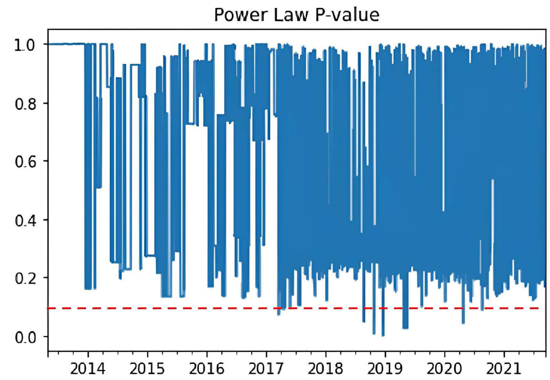

FIGURE 8. Time-varying power-law distribution of cryptocurrency networks.

E. SCALE-FREE STRUCTURE OF CRYPTOCURRENCY NETWORKS

It is beneficial to explore whether cryptocurrency networks exhibit characteristics of scale-free (or power-law) networks. In such networks, a small subset of nodes have numerous connections, while the majority of other nodes have only a limited number of edges, exhibiting a star-like structure. Many empirical networks, e.g., the Internet, have a scale-free structure. We denote $p(k)$ as the probability that a node has k edges (i.e., node degree). If $p(k)$ of a network follows the power law, i.e.,

$$p(k) \sim k^{-\alpha} \quad (14)$$

the network is scale-free. A small value of α indicates that a node may have a high edge density and vice versa. We adopt the analytical methodology in [33] to evaluate if the cryptocurrency networks are scale-free. It combines the maximum likelihood estimation (MLE) with goodness-of-fit and the Kolmogorov–Smirnov (KS) tests to derive [33]:

$$p(k) = \frac{\alpha-1}{k_{\min}}(\frac{k}{k_{\min}})^{-\alpha} \quad (15)$$

and MLE can be used to estimate the exponent α [33], i.e.,

$$\hat{\alpha} = 1 + N\left[\sum_{1}^{N} ln\frac{k_i}{k_{\min}}\right]^{-1} \quad (16)$$

where k_i is the observed node degree of $k \geq k_{\min}$ for $i = 1, 2, \dots, N$, and $k_{\min}$ is the lower bound for power-law behavior estimated by choosing the value of k_i that minimizes the standard KS statistic [32]:

$$dist = max_{k \geq k_{\min}}|y(k) - \hat{y}(k)| \quad (17)$$

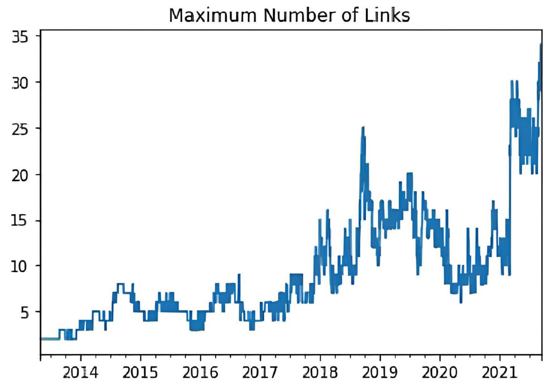

FIGURE 9. Maximum node degree of cryptocurrency networks.

where $y(k)$ is the cumulative distribution function (CDF) of node degree data with a value of at least $k_{\min}$, and $\hat{y}(k)$ is the power-law model that best fits the data in the region $k \geq k_{\min}$. Therefore, *dist* is the maximum distance between the CDF of the data and the fitted model.

The p-value of the KS test can be used to reject or accept the power-law distribution hypothesis. Following the work in [33], the power-law hypothesis holds when the p-value exceeds 0.1. The closer the value is to 1, the more likely the node degree is from a power-law distribution.

Fig. 8 shows the p-value of the cryptocurrency networks. Like many other real networks that usually have $2 < \alpha < 3$, the mean α over all cryptocurrency networks is 2.3427, and their p-values are larger than 0.1 most of the time ($>$ 99%). However, a few p-values are smaller than 0.1, which reveals that the node degree distribution of the networks in these time windows does not follow a power-law behavior. This demonstrates that ***cryptocurrency networks typically exhibit a scale-free nature and predominantly adhere to the power-law distribution.*** As a result, some cryptocurrencies always play a dominant role as they have the vast majority of connections to other cryptocurrencies. Investors can keep a close eye on the movements of these key cryptocurrencies when making investment decisions.

Fig. 9 also shows that this power-law characteristic is supported by the increasingly maximum number of links of the most connected nodes (i.e., maximal node degree) in the networks. With the increase of the maximal node degree, certain nodes become more prone to assuming central roles — those directly linked to numerous other nodes within a network. In contrast, the remaining nodes have fewer connections, giving rise to the formation of power-law networks. This observation supports our previous finding that when major cryptocurrency corrections occur, the networks shrink and become denser and more compact. This is accompanied by an increase in their node degree, leading to a smaller value of α to form power-law networks. This confirms our previous finding that cryptocurrencies are agglomerating into different blocks around key cryptocurrencies (to be identified by centrality measures in the next section). Fig. 10 shows the cryptocurrency network for the six most recent months of the studied period in the cryptocurrency market. It exhibits power-law characteristics (e.g., a star-like structure around a few key cryptocurrencies such as BNT) as well as increasing the APL and MOL (e.g., branches extending from the key cryptocurrencies as well as a high network density and a large number of layers).

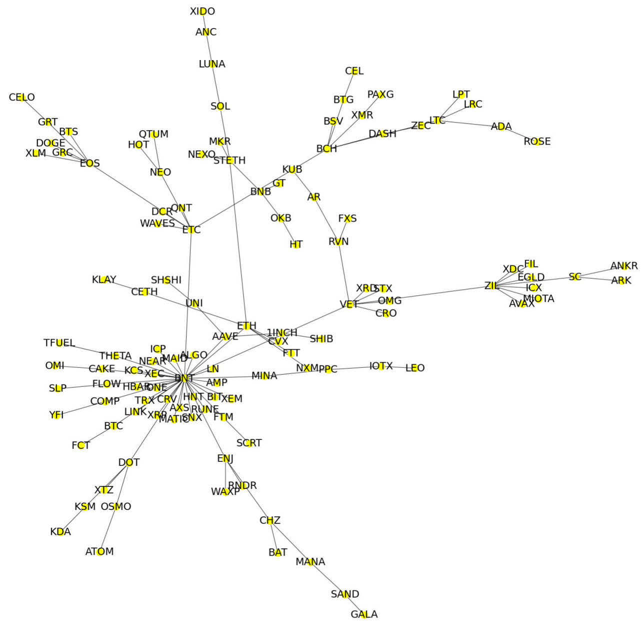

FIGURE 10. The power-law cryptocurrency network for the six most recent months of the studied period.

TABLE 7. Four phases across dynamic evolution of the cryptocurrency market.

Phase	Period	Cryptocurrencies with relatively high centrality measures	Main feature
1	Early 2013 - Mid 2016	BTC, DOGE, XRP, XLM, LTC	Payment transactions
2	Mid 2016 - Mid 2017	MAID, FCT	Security-driven blockchains
3	Mid 2017 - Early 2020	ETH, OMG, NEO, ADA	Smart contracts
4	Since early 2020	BNB, XTZ, BNT	Emerging services

F. CENTRALITY MEASURE EVALUATION

Nodes with high centrality are typically located in the core part of a network (i.e., central nodes) and thus can be regarded as influential. Cryptocurrencies that obtain the highest and second-highest values for each of the centrality measures are plotted in Fig. 11. The cryptocurrencies that have never been in one of the two with the highest centrality are not included in the figures. Typically, a cryptocurrency that ranks highest in one centrality is likely to also attain a high rank in some other centrality measure as well. Therefore, these figures show a similar pattern, and we can identify four phases of the entire evolution of the cryptocurrency market, as shown in the Table 7.

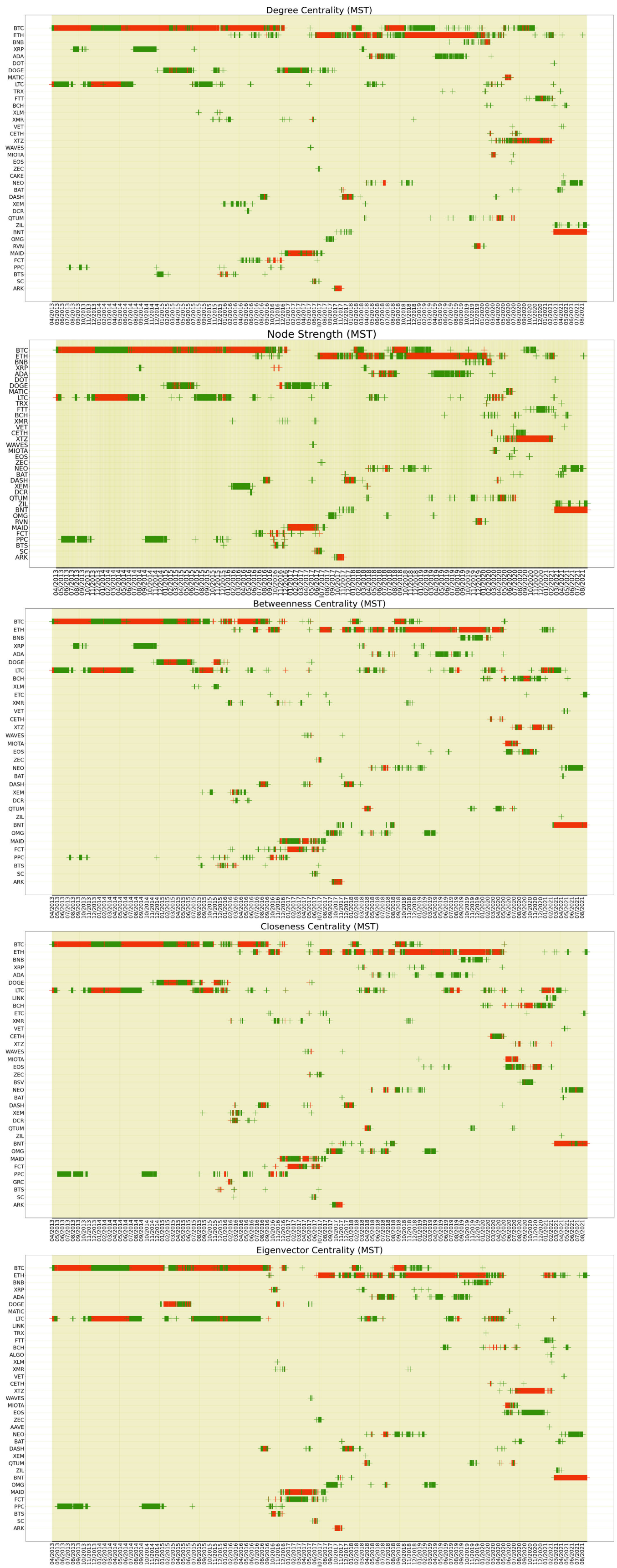

FIGURE 11. Cryptocurrencies with the highest (in red color) and the second-highest (in green color) centrality measures as a function of time.

The first phase, from early 2013 to mid 2016, is dominated by cryptocurrencies developed for financial services. As expected, the most influential cryptocurrency is BTC, which is mainly used for transaction payments and currency mining. Other influential cryptocurrencies, such as LTC, XRP, XLM, and DOGE, serve a similar purpose and use similar underlying blockchain technologies as BTC does. This confirms the findings in [34] and [35] that there is a close relationship between these cryptocurrencies at this phase, with BTC and LTC being close to each other, and XLM, XRP, and DOGE belonging to the same community within the network.

In the second phase, from mid-2016 to mid-2017, MAID and FCT replace BTC as the most influential cryptocurrencies. This shows that BTC is starting to lose its dominance in the cryptocurrency market (e.g., BTC's dominance in market capitalization drops from 85% in 2010 to less than 50% in 2018). Therefore, cryptocurrencies with the highest market capitalization, like BTC, may not always be the most influential, which is also highlighted in [5] and [8]. This change in influential cryptocurrencies may have occurred owing to the frequent BTC corrections starting from mid 2016. In addition, reports of some crimes in Table 4, e.g., the Mt. Gox event between 2011 and 2014, and the Bitfinex theft in mid-2016, drive the market to pay increasing attention to security-driven cryptocurrencies like MAID and FCT. The work in [11] and [31] show that MAID and FCT have been among the top central cryptocurrencies since 2016, and that MAID is one of the largest communities in terms of the number of cryptocurrencies in it (including FCT). The results of this phase reveal that significant events may change influential cryptocurrencies in the market.

In the third phase, from mid 2017 to early 2020, ETH is the most influential cryptocurrency, primarily due to its promising feature of smart contracts that allows to encode pre-determined rules of any activity into unbreakable contracts. It then automatically executes these contracts when the agreed upon conditions are met. Other cryptocurrencies that run on Ethereum-based blockchain networks, such as ADA, NEO, and OMG, are therefore strongly correlated with ETH (0.8 – 0.87) and have been regarded as influential.

Finally, in the fourth phase since early 2020, we observe that some emerging cryptocurrencies intermittently replace ETH as the leading cryptocurrencies, such as BNB, XTZ, and BNT, which are well connected with two blockchain frontiers, DeFi and NFT. This reveals that the cryptocurrency market is no longer dominated by the most popular cryptocurrencies (e.g., BTC and ETH), but is also affected by other emerging and contemporary cryptocurrencies, as discussed below.

First, cryptocurrencies developed by exchanges (or so-called platform coins), notably BNB and FTT, have been receiving increasing attention, primarily due to the reduced transaction costs (or gas fees) charged by the exchanges.

Second, towards the end of the studied period, DeFi has caught the attention of the financial industry, which is a collective term for financial products and services that are accessible to anyone without any centralized authority blocking payments or denying access to anything. A cryptocurrency that supports DeFi is Tezos (its coin is XTZ). It is a fourth-generation blockchain network that incorporates the self-amending capability with a unique on-chain governance mechanism for managing protocol upgrades without requiring the networks to hard-fork (e.g., leading to the creation of Ethereum Classic from Ethereum, and Bitcoin Cash from Bitcoin). Tezos has completed its latest upgrade, "Delphi," which aims to reduce smart contract gas fees by 75% to motivate DeFi developers to build on top of its blockchain. Moreover, Tezos's smart contract capabilities allow it to support not only DeFi, but also a range of decentralized application (DApp) and NFT projects that are becoming popular nowadays. Because of its flexible governance, Tezos has become a leading competitor of Ethereum as the DApp, DeFi, and NFT projects continue to grow.

Another cryptocurrency that supports DeFi is BNT, the native currency of Bancor which is a DeFi network. It enables users to swap digital currency tokens automatically through the Bancor protocol within the network without any exchange platform or intermediary. Hence, it can efficiently process token trades across different blockchains.

Most of the centrality analyses in the literature [6], [8], [9], and [10] are static (i.e., for one specific time period). On the other hand, the dynamic (or time-varying) analysis in [7] also reveal that BTC and ETH are leading cryptocurrencies before 2018. Our study extends their finding to uncover additional contemporary cryptocurrencies that are closely related to the emerging DeFi and NFT era beyond 2020. Based on the results discussed above, we find that social network analysis and centrality measures can adequately capture critical trends in the evolution of the cryptocurrency market. For making investment decisions, the results of social network analysis and centrality measures can provide useful insights about cryptocurrencies at any given time.

Using social network analysis and centrality measures, we also evaluate the impact of corrections on the cryptocurrency market. Fig. 12 shows the NS (i.e., correlation strength) and CC (i.e., network tightness) of the cryptocurrency network during major corrections with the most significant price decline rates (e.g., event No. 12, 13, 15 an 18 in Fig. 4). The horizontal lines in the graph represent the corresponding average values. From all results, we observe a consistent finding that NS and CC increase significantly when corrections begin, which makes cryptocurrency networks tightly interconnected. After that, the market gradually and relatively quickly returns to its original state (i.e., before the correction begins) or relatively steady state. Therefore, it can be concluded that ***the impact of corrections on the cryptocurrency market is often short-lived (i.e., only last for a short period of time).*** Investors can still take a long-term perspective to whether the temporary downturn and

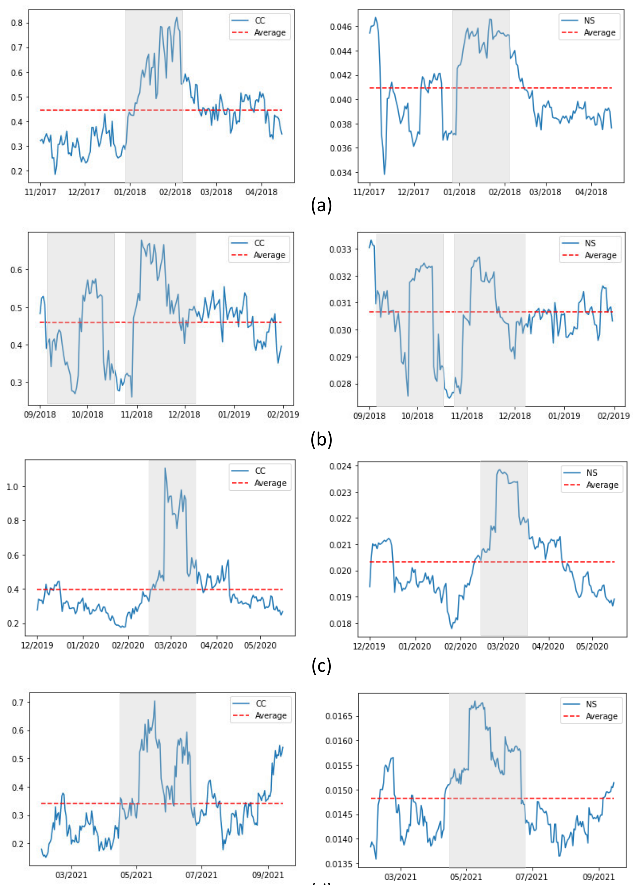

FIGURE 12. Network of the cryptocurrency market, in terms of closeness centrality and node strength, along with their average during four particular events in Fig. 4 highlighted by grey color: (a) No. 12, (b) No. 13, (c) No. 15 and (d) No. 18.

potentially benefit from future growth despite short-term and non-structural market volatility.

VI. PREDICTION OF THE MOVEMENT IN PRICE OF CRYPTOCURRENCY USING CENTRALITY MEASURES

As centrality measures aim to identify cryptocurrencies capable of influencing the prices of other cryptocurrencies in the market, we believe this influence can be a useful predictor of short-term cryptocurrency prices, which is of interest to investors looking for price increases or decreases in cryptocurrency markets. However, owing to the short history and high volatility of cryptocurrency prices, we consider a binary classification problem that predicts if prices will go up or down only with respect to historical prices.

The centrality measures of a cryptocurrency in different time windows may return different values. A centrality measure with identical values in two different networks may indicate different levels of influence. We, therefore, transform their raw values into normalized ranking scores between 0 and 1 to represent their relative position of influence in the network in each time window. For example, the normalized

TABLE 8. Predictors for cryptocurrency price movement.

Dataset	Predictors
ohlc	Open, High, Low, Close
ohlc_tech	Open, High, Low, Close, Volatility, Overlap, Momentum
ohlc_cent	Open, High, Low, Close, DC^{rs}, NS^{rs}, BC^{rs}, CC^{rs}, and EC^{rs}

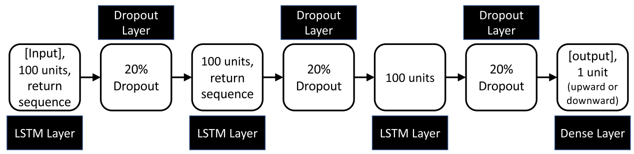

FIGURE 13. LSTM model for cryptocurrency price movement prediction.

ranking score of DC is defined as:

$$DC_{i,t}^{rs} = \frac{DC_{i,t}}{DC_{max,t}} \tag{18}$$

where $DC_{i,t}$ is the DC value of cryptocurrency i in time window t and $DC_{max,t}$ is the highest DC value among all cryptocurrencies in time window t. This transformation also applies to the other four centrality measures (i.e., $NS_{i,t}^{rs}$, $BC_{i,t}^{rs}$, $CC_{i,t}^{rs}$, and $EC_{i,t}^{rs}$.

To evaluate the power of centrality measures to predict the movement in the price of cryptocurrencies, we built a long short-term memory (LSTM) model as shown in Fig. 13. LSTM has been widely used for stock price prediction [36], [37] as they are able to learn the dependencies between data points on a long-term basis and, from which, to extract useful features automatically. Hence, it is suitable for modeling time series data over other conventional machine learning algorithms, such as logistic regression. In our LSTM model, one sequence is defined as a sequential collection of the daily features of any cryptocurrency in a time window. The model contains 3 LSTM layers, each followed by a 20% dropout layer to reduce overfitting for regularization purposes. The first layer is the input layer, which takes as input all the features that a sequence may contain. The final dense layer is the output layer, which generates the predicted price movement (i.e. upward or downward) of the cryptocurrency.

We used different predictors to forecast the short-term movement of prices of the top 4 cryptocurrencies in terms of the highest market capitalization, namely BTC, ETH, BNB, and XRP. These cryptocurrencies have covered 65% of the market capitalization, and hence, can be considered as representative. As shown in Table 8, the "ohlc" feature dataset uses only the fundamental pricing data (i.e., Open, High, Low, and Close) as predictors, whereas the "ohlc_tech" and "ohlc_cent" feature datasets additionally take into consideration the technical indicators and ranking scores of the five centrality measures (i.e., DC^{rs}, NS^{rs}, BC^{rs}, CC^{rs}, and EC^{rs}), respectively. Technical indicators are obtained from mathematical and statistical calculations, which are widely used by traders and investors to analyze market trends and make informed decisions about buying or selling assets. These indicators are typically based on historical price data and are used to identify patterns, trends, and potential reversals in the market. We have selected and implemented some commonly used technical indicators from the TA-Lib library, including volatility features (volatility and average true range), overlap features (SMA, EMA, DEMA and correlation) and momentum features (MACD, RSI, William's %R, ROC, ROCP, Aroon Oscillator and Commodity Channel Index).

A. STATIC PRICE MOVEMENT PREDICTION

We first perform the evaluation using a static approach that covers the entire studied period of pricing data for each of the cryptocurrencies. The dataset is divided into 80% for training and 20% for testing. The labels of the data (i.e., upward or downward) are determined by the return: If a return is smaller than 0, the label is set to 0 to represent a downward movement; otherwise, the label is set to 1 to represent an upward movement. We find that the number of data points with class labels 0 and 1 is balanced (e.g., 53% representing upward and 47% representing downward for BTC, 51% representing upward and 49% representing downward for ETH, 52% representing upward and 48% representing downward for BNB, and 47% representing upward and 53% representing downward for XRP). Therefore, no label-class imbalance is observed. Each sequence of predictors is normalized to a value between 0 and 1 by min-max normalization.

The model is trained using 100 epochs and a batch size of 32. Early stopping as a form of regularization is adopted to avoid overfitting. More specifically, training stops when the monitored loss has stopped decreasing. We iterate the evaluation for 100 independent trials and evaluate the accuracy of predicting the movement of prices, which is defined as:

$$Accuracy = \frac{tp + tn}{tp + fp + tn + fn} \tag{19}$$

where the accuracy accounts for correct predictions of true positive (tp) and true negative (tn), as well as for incorrect predictions of false positives (fp) and false negatives (fn).

Fig. 14 shows that the prediction accuracy, when the five centrality measures are also used as predictors (i.e., the "ohlc_cent" feature dataset), is higher than when only fundamental pricing data are used (i.e., the "ohlc" feature dataset). To determine if there is a statistically significant improvement in the predictive accuracy between these two scenarios using different predictors, we conduct the independent samples t-test on the results. For all four cryptocurrencies, the test produces p-values less than the specified significance level of 1%. This indicates a significant statistical difference between the predictive accuracy in these two scenarios. Therefore, centrality measures help to improve accuracy. Although the improvement in overall accuracy is not outstanding from a numerical point of view (e.g., around 3%), it should be considered a significant achievement in

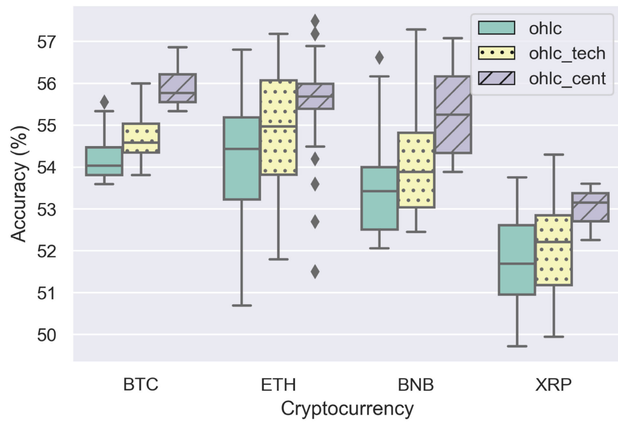

FIGURE 14. Accuracy of prediction when using different combinations of predictors on BTC, ETH, BNB, and XRP (static approach).

many domains where forecasting is considered challenging. On the other hand, the predictive power using the technical indicators (i.e. the "ohlc_tech" feature dataset) is only slightly better than the "ohlc" predictors, which is consistent with the findings in [38] and [39], but it is not as compelling as using computationally inexpensive centrality measures. Overall, our findings suggest that ***centrality measures serve as valuable indicators to enhance the precision of predicting short-term fluctuations in cryptocurrency prices***, which has not been studied in the literature.

Since the deep learning LSTM model is unexplainable (i.e., a black-box model), we are interested in determining which of the five centrality measures are significant predictors when using logistic regression, which is an interpretable model. The p-value of the model is < 0.05 for all these four cryptocurrencies, and therefore the models are significant.

As shown in Table 9, BC contributes to the prediction for BTC at 5% significance (i.e., $p \leq 0.05$). On the contrary, for ETH, DC and CC contribute to the prediction. It is not surprising that BC and CC are significant predictors for BTC and ETH, respectively, because both BC and CC measure the global metric of the entire network. More precisely, as BTC is the most popular and valuable cryptocurrency, it has a network-wide impact on the entire cryptocurrency market that can be measured by BC. By contrast, ETH establishes an increasing number of localized and close connections with many other cryptocurrencies running on the Ethereum-based blockchain networks, which can be measured by CC. On the other hand, since BNB can be traded directly with many other cryptocurrencies, DC and NS are significant predictors as they measure the local metric of node degree and the strength of the correlation with the connecting cryptocurrencies. Furthermore, XRP is found to be strongly and positively correlated with BTC, which is the leader in the cryptocurrency market. This may explain that EC is the significant predictor for XRP as it is highly correlated with other influential cryptocurrencies, such as BTC, which typically have high centrality measures.

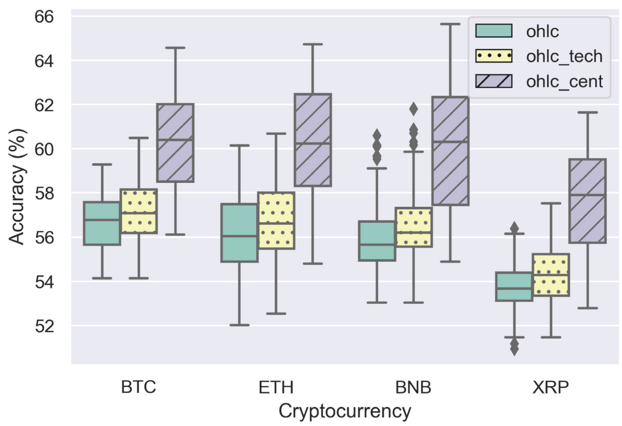

FIGURE 15. Accuracy of prediction when using different combinations of predictors on BTC, ETH, BNB, and XRP (dynamic rolling window approach).

We can observe from these results that leading cryptocurrencies (e.g., BTC) that may influence the price fluctuations of other cryptocurrencies in the market can be associated with BC. Moreover, cryptocurrencies that play leading roles in clusters, which connect many other cryptocurrencies with purpose, can be associated with DC, NS, and CC (e.g., ETH and BNB are being used as utility tokens on numerous trading applications for many other cryptocurrencies). Cryptocurrencies (e.g., XRP) that always maintain a strong correlation with leading cryptocurrencies can be associated with EC. These observations may serve as a guideline for determining the right predictors for cryptocurrencies with different characteristics. Overall, all the five centrality measures show good predictive abilities, with different cryptocurrencies using different centrality measures as their key predictors.

B. DYNAMIC PRICE MOVEMENT PREDICTION

In addition to the previous static evaluation using fixed-period one-shot forecasts, we employ a dynamic rolling window-based approach (similar to that in Fig. 1) to assess the robustness of the predictability of centrality measures. This dynamic approach uses a window width of 182 days to predict the price change for the next day outside the window, for example using days 1 to 182 to predict the price change for day 183, and so on. Figure 15 shows that the accuracy of the dynamic approach improves compared to the static method because it uses an updated window to predict near-term price movements rather than long-term price movements. Likewise, using centrality measures as predictors can improve prediction accuracy by 3-5%. Therefore, centrality predictors perform well under both static and dynamic time period conditions. In the evaluation we also find that the accuracy of predicting price decline (65%) is higher than the accuracy of predicting price increase (55%). This is because, during corrections, the structure of cryptocurrency networks change more frequently (such as APL and MOL), and machine learning algorithms are more adept at capturing and assimilating such fluctuations. On the other hand, similar to the static prediction results, the predictive power using the technical indicators (''ohlc_tech'') is better than the ''ohlc'' predictors, but not as significant as using the centrality measure indicators (''ohlc_cent'').

TABLE 9. Significant predictors of the movements in the price of BTC, ETH, BNB, and XRP. ***, ** and * represent significance at 1%, 5% and 10% respectively.

Cryptocurrency	Significant Predictors	p-value (p)
BTC	BC^{rs}	0.0208**
ETH	DC^{rs}	0.0056***
	CC^{rs}	0.0142**
BNB	DC^{rs}	0.0066***
	NS^{rs}	0.0127**
XRP	EC^{rs}	0.0368**

VII. SUMMARY OF FINDINGS, LIMITATIONS AND FUTURE WORK

All the findings in this study can be summarized as follows:

- In recent years, cryptocurrencies have typically shown a positive and moderate correlation with one another. This interdependence suggests that fluctuations in the price or return of a particular cryptocurrency are likely to impact the prices or returns of many others in the market;
- During undesirable critical events, such as significant cryptocurrency corrections caused by crises, crimes, or negative news, cryptocurrencies become increasingly and tightly correlated. Thus, any significant event in the market is likely to drive cryptocurrencies to behave and react collectively;
- The cross-return correlation coefficient distribution in the recent cryptocurrency market has lighter tails indicating that correlation among cryptocurrencies has become stronger and has fewer extreme values than in the past. Investment strategies should involve monitoring not only the targeted cryptocurrency for purchase but also other correlated cryptocurrencies;
- The structure of cryptocurrency networks evolves in response to major market corrections. When a correction takes place, these networks become denser and more compact. Conversely, they tend to grow sparser once the correction phase concludes;
- The return correlations of cryptocurrencies are relatively stable in the short run, but become less stable over time. Nevertheless, the correlations between some cryptocurrencies remain consistently strong and stable in the long run. To minimize risk, it is advisable to enhance investment strategies by promptly and diversely adjusting portfolio selection and optimization;
- The impact of corrections on the cryptocurrency market tends to be short-lived. Investors can take a long-term perspective to whether temporary downturns and potentially benefit from future growth amid short-term and non-structural market volatility;

- Scale-free (or power-law) behavior is observed in cryptocurrency networks, which reveals that some key cryptocurrencies always influence prices in the market;
- Centrality measures can adequately capture the key trends across the evolution of the cryptocurrency market. They can serve as useful indicators for short-term movement predictions in the price of cryptocurrencies.

A key limitation of our current study is the exclusion of emerging and yet-to-mature cryptocurrencies. As a result, our findings may not fully apply to these nascent cryptocurrencies. In future research, we aim to incorporate these emerging cryptocurrencies once the market reaches relative maturity, allowing us to compare their properties and behaviors with those of high market capitalization cryptocurrencies. Additionally, our use of the MST method to construct cryptocurrency networks is another limitation. Future analyses exploring alternative methods, such as TN and PMFG, would be valuable to ascertain if they yield results consistent with our MST-based study. Moreover, our focus was primarily on price, technical analysis, and centrality measures for predicting cryptocurrency price movements, potentially overlooking the influence of external blockchain-related factors, which might lead to reduced prediction accuracy. To address this, we plan to further incorporate a wider range of predictive factors, including on-chain and blockchain data, market sentiment, and other centrality measures such as Katz and PageRank centrality. This holistic approach is aimed at enriching our exploration of the cryptocurrency market and enhancing the accuracy of our predictions.

VIII. CONCLUSION

The emerging cryptocurrency market is one of the largest financial markets in the world. However, it has not been extensively studied yet. In this paper, we applied social network analysis to model and analyze different aspects of the cryptocurrency market, including correlation structure, topological characteristics, stability, influence, and price movement prediction. We believe that our comprehensive findings can assist in forecasting strategies by offering solid insights into the cryptocurrency market. This enables the construction of improved investment portfolios, potentially leading to higher expected returns and reduced risk, even in times of crisis.

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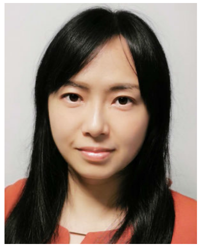

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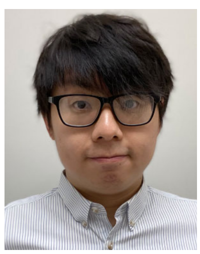

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