Volatility and Returns Connectedness in Cryptocurrency Markets: Insights from Graph-based Methods

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Abstract

We employ graph-based methods to examine the connectedness between cryptocurrencies of different market caps over time. By applying denoising and detrending techniques inherited from Random Matrix Theory and the concept of the so-called *Market Component*, we are able to extract new insights from historical return and volatility time series. Notably, our analysis has revealed that changes in volatility-based network structure can be used to identify major events that have, in turn, impacted the cryptocurrency market. Additionally, we have found that these structures reflect investors' sentiments, including emotions like fear and greed. Using metrics such as *PageRank*, we have discovered that certain minor coins unexpectedly exert a disproportionate influence on the market, while the largest cryptocurrencies such as BTC and ETH seem less influential. We suggest that our findings have practical implications for investors in different ways. Firstly, helping them to avoid major market disruptions such as crashes, to safeguard their investments, and to capitalize on opportunities for high returns. Secondly, sharpening and optimizing the portfolios thanks to the understanding of cryptocurrencies' connectedness.

Keywords:
cryptocurrencies, volatility, correlation-based network, graph-based metrics, influential cryptocurrencies

1. Introduction

Cryptocurrencies are known for their sudden and unexpected price fluctuations [1]. While these price movements can be concerning for many investors - particularly inexperienced ones [2, 3], observing common patterns across different cryptocurrencies can provide valuable insights to all investors. Specifically, by understanding the correlation in the volatility of price between cryptocurrencies, investors can potentially gain high profits while avoiding significant losses [4].

Several methods exist to analyze the correlation between different cryptocurrencies and between cryptocurrencies and traditional assets (e.g. stocks, bonds, oil and fiat currencies). One of the first papers on this topic was conducted by Yermack [5], who tested the daily dependency between Bitcoin and national currencies (e.g., EUR, JPY, GBP) using *Pearson* correlation measurement. Since then, a variety of statistics-based correlation measures such as Wavelet Coherence, Vector Autoregressive (VAR), Granger causality and q-Dependent Detrended Correlation have been widely adopted on larger datasets, comprising different cryptocurrencies and asset classes. This diversification proposes a more comprehensive picture of the dependencies present in the financial markets [6–9]. Notably, with the fast growth of Deep Learning, several methods such as Multilayer Perceptron (MLP) and Long Short Term Memory (LSTM) have been

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successfully applied to cryptocurrency-related correlation studies [10, 11]. In summary, researchers found evidence of time-varying connectedness between cryptocurrencies themselves and between the cryptocurrency market and traditional markets. They discovered that these connections tend to fluctuate, either increasing or decreasing regularly. However, one consistent finding is that different asset classes become more closely related to each other during the Covid-19 pandemic and economic crises. Additionally, the cryptocurrency market is becoming more mature over time, and its correlation with other asset classes gradually increases.

Recently, graph-based methods have become widely applied to learn about co-movements and spillover effects in financial markets [12–14]. This is due to several factors: 1) their ability to observe the time-varying connectedness among multiple objects; 2) the diversity of metrics available in Graph Theory to analyze graph structures, such as *betweenness centrality*, *degree assortativity*, and *closeness centrality*. Such metrics can be used to learn and understand the underlying characteristics of a graph; 3) Their ease of implementation in comparison with statistical and Neural Networks methods. This method creates a network of various objects where the distance between them is determined by their similarity[1]. The closer the objects are, the more alike they are. In the realm of financial markets, the measurement of similarity between two assets relies on their co-movement as reflected in their corresponding financial time series, such as prices, returns, and volatility. When two assets are completely similar, any upward or downward movement in one asset is mirrored simultaneously in the other. By examining the structure of the network and analyzing its features, we can observe the interactions between the objects.

In [13], we adopted the method described above to construct time-varying network structures using cryptocurrencies' return time series over a 2-year period from 2019 to 2021. This period covers different market conditions, including normal times and downturn times (e.g., the market crash in March 2020 due to the Covid-19 pandemic). We found that the network structure reflects investors' investment decisions. During normal times, investors arguably make their own investment decisions based on their personal market analysis and experience. On the other hand, during turbulent times, investors appear to trade only cryptocurrencies with high market capitalization, while smaller cryptocurrencies are mainly used for other purposes such as transaction fees, smart contract tokens or simply to run a digital platform.

One possible gap recognized in our previous work as well as in the existing literature is the limited use of volatility time series as the main data in cryptocurrencies-related experiments since very few works have mentioned this indicator. However, as proved in [4], return values cannot explain all phenomena in the cryptocurrency market. Instead, volatility information might also add more insights to the return ones. From this point of view, we contribute to the existing literature by taking the volatility of cryptocurrencies into consideration. In particular, we will use cryptocurrencies' volatility and return time series to construct time-varying networks with a finer window size, allowing us to capture not only normal and downturn times but also times when bull market conditions pertain. Our research questions are described as follows:

- RQ1: Is there evidence of a difference between returns-based network structures and volatility-based network structures? In other words, do volatility-based networks provide different results from return ones?
- RQ2: If so, can we gain insights from these results in understanding the underlying structure (if any) in the cryptocurrency market? By this we mean, what can we learn from these results and where to use them?

For our research questions, we use a 30-minute dataset sourced from the HitBTC exchange[2], consisting

[1]Several methods for measuring the similarity between two time series such as *Pearson* [15], *Spearman* [16], Dynamic time warping [17], Cosine similarity [18], Euclidean distance [19]

[2]`https://hitbtc.com/`

of 34 closing price time series corresponding to the 34 most active cryptocurrencies. We rely on *Pearson* correlation and Minimum Spanning Tree (MST) to construct cryptocurrency networks. To observe the evolution of the network structure, we adopt 3 graph-based metrics, e.g. *betweenness centrality*, *degree assortativity* and *closeness centrality*. Additionally, we utilize the famous algorithm used by Google called *PageRank*[3] to examine the importance of each cryptocurrency in the network over time. Other features such as investors' sentiments and the number of transactions are also used to support and reinforce our findings.

Remarkably, we remove the noise and trend in cryptocurrencies using Random Matrix Theory (RMT) and the Market Component concept. This technique has been widely used in other areas such as education [20] and stock markets [21, 22] but is relatively new in the cryptocurrency market. We shall show later in this paper that the noise and trend removal scheme plays an important role in exploring the underlying characteristics of the cryptocurrency market, revealing several characteristics that become visible only after clearing the noise and trend.

The remainder of the article is organized as follows: Section 2 presents an overview of related works. Section 3 provides a description of the datasets. Section 4 discusses methodology, metrics and preprocessing procedures. Section 5 describes the experimental results followed by implications and hypothesis. Lastly, the conclusion of this study is given in Section 6.

2. Related Works

2.1. Analysis of Correlations in the Cryptocurrency Market and Graph-based Methods

The correlation between different financial assets has been the subject of extensive research over a considerable period of time, particularly in the realm of traditional markets (e.g. stocks, bonds, fiat currencies) [23–28]. This topic helps scholars and traders understand the underlying interactions among various assets, bringing in various advantages. For instance, knowing the correlations between different assets can empower investors to construct well-diversified portfolios by strategically allocating assets with low correlations, resulting in lower portfolio volatility and improving risk-adjusted returns [29, 30]. Moreover, knowledge of asset correlations can aid in identifying opportunities for hedging against potential losses. Specifically, by understanding the correlations between different financial assets, investors can identify assets that have negative or low correlation with the rest in their portfolio and use them as hedges potentially to reduce their overall portfolio risk [31, 32]. Additionally, by expanding correlation analysis to microeconomic variables such as interest rate, inflation rate and GDP growth rate, investors can be helped to anticipate changes in future asset prices [33].

Since the inception of the cryptocurrency market, several studies have also been conducted to support crypto investors in making trading decisions. Two main empirical findings are as follows: Firstly, the most renowned cryptocurrencies Bitcoin and Ethereum show the strongest correlation with other virtual currencies in this market and they are also seen to interact with each other. This correlation is primarily attributed to the impact of people's sentiment, widely recognized as a dominant factor influencing market dynamics [34]. Significantly, the correlation observed in the crypto market changes regularly with several consistent characteristics during a specific market condition. That is, different cryptocurrencies tend to show distinct behaviors during normal times, leading to a low correlation between them. However, they tend to display higher levels of correlation during downturn times, which is mirrored among conventional

[3] *PageRank* is an algorithm used by Google Search to rank web pages in their search engine results. It is named after both the term "web page" and co-founder Larry Page. The algorithm assigns a numerical weighting to each element of a hyperlinked set of documents, such as the World Wide Web, with the purpose of "measuring" its relative importance within the set

stocks [26]. This phenomenon appears to stem from changes in the investment decisions of cryptocurrency investors in response to varying market conditions [13].

Numerous studies have examined the relationship between cryptocurrencies and traditional assets such as stocks, commodities, and bonds. A common finding is that the cryptocurrency market is gradually aligning itself with traditional markets. For example, Drozdz et al. conducted an experiment to observe the statistical features of 70 cryptocurrencies that are actively traded nowadays, they cover different aspects of cryptocurrency time series such as returns, volatility and temporal multifractal correlations [14]. Their study revealed that the highest-capitalization cryptocurrencies (more matured) BTC and ETH share common statistical properties with the traditional financial markets. By contrast, smaller cryptocurrencies (less matured), e.g. DOGE, FUN, XLM and ONT, demonstrated some variations in this regard. Notably, a study conducted by Yosra et al. [32] examined the return characteristics of cryptocurrencies in relation to traditional asset classes and found that adding Bitcoin to the portfolio can reduce the risk and improve the Sharpe ratio, thereby playing a significant role in optimizing the portfolio and mitigating liquidity risk.

The adoption of graph-based methods for analyzing the correlation between different cryptocurrencies or between cryptocurrencies and conventional assets has steadily grown in recent years. Graph-based approaches offer unique capabilities such as ease of Visualization, Clustering, Centrality and Pathfinding [25], enabling comprehensive exploration of correlation-related issues within the cryptocurrency market, not only at a specific time but also in different periods [13, 35] thus potentially offering a way to observe the time-varying interactions within a system. Moreover, this method is relatively easy to implement and does not require a high amount of computation as is the case with existing statistical and regression methods [36–38].

Analyzing graph-based correlations adds more insights into the financial markets. In [35], the authors used Minimum Spanning Tree[4] to construct a graph of more than 100 cryptocurrencies. Based on the graph structure, they discovered the existence of different communities within the market, where each community consists of several cryptocurrencies that have similar return movements. Although these community structures do not persist over time, cross-correlation dynamics suggest a collective behavior exists among these communities. This result holds potential for portfolio diversification strategies, which has been explored and justified in [34]. Additionally, representing correlations between different assets through a graph can provide insights into the investment behavior of investors in different market conditions. This study has been conducted by An et al. who applied Minimum Spanning Tree and Community Detection algorithms to the graphs of cryptocurrencies in order to observe the changes in the community structures before, during and after the Covid-19 and market crash in 2020. The researchers discovered that these changes in community structures appeared to be influenced by the investment behavior of cryptocurrency traders. [13].

Given the widespread use of graph theory for analyzing the correlations between different cryptocurrencies, we notice that most studies tend to focus on basic financial time series such as return time series and price time series. However, another essential aspect that has received limited attention is volatility. Recognizing this research gap, we aim to contribute to the cryptocurrency literature by conducting a time-varying correlation analysis in the cryptocurrency market using volatility time series in this study.

2.2. The Cryptocurrency Market during Critical Events

In [39], the authors utilized more than 100 cryptocurrencies to investigate the cryptocurrency market between 2015 and 2020. Based on a regression model called cross-sectional absolute dispersion (CSAD),

[4] A technique to reduce the size of a graph (network) in order to identify the so-called *community structure* in the graph, in which each community comprises nodes that share similar characteristics and nodes in different communities have different characteristics.

they found herd effects during the intense period of the coronavirus outbreak. By contrast, crypto traders have not engaged in correlated investing since the end of March 2020, when the market started to recover. Instead, during the recovery time, they showed a more rational investment decision due to the restoration of the market and assets' prices. Moreover, from the experiments, the authors indicated that even though crypto traders tend to follow each other during both bull and bear market situations, their herds investing is stronger during the bullish regime while there are more rational investors during the bearish regime. On the same topic, Samuel in [40] examined the presence of herding for four different periods, e.g. pre and during Covid-19, bear and bull markets between April 2019 and January 2021. He provided the same results as in [39] since his experiment revealed that investors make similar trading decisions for positive market returns and during the COVID-19 pandemic period.

On the other hand, [41] observed the cryptocurrency market during the pandemic by using the price returns-based network approach. In particular, they investigated the structure of the Minimum Spanning Tree (MST) constructed from 128 cryptocurrencies before and during the pandemic to see whether this critical event causes the change of this structure. Indeed, the results showed that the network was distributed during the year 2019, which was before the onset of Covid-19. This network structure means that the cryptocurrencies had independent trends. Whereas, a centralized network appeared during the first half of 2020, in which cryptocurrencies formed a big community with a central node being USDT. In other words, the cryptocurrencies were closer to each other, sharing a common trend. This result is in line with the latter study conducted by An et al. [13].

The existing studies confirmed the significant changes in the cryptocurrency market during the pandemic. However, to our knowledge, there is a scarcity in terms of the analysis of cryptocurrencies during the bull market 2021. Our study aims to focus not only on the Covid-19 event but also the bull market in 2021, observed via the time-varying correlation between various cryptocurrencies derived from a graph-based approach.

3. Dataset

3.1. Dataset Description

For this study, we obtained tick-by-tick data of cryptocurrencies from the HitBTC exchange[5]. The dataset covers the period from 13/02/2019 until 06/04/2021. This timeframe encompasses two major events, which are the market crash triggered by the Covid-19 pandemic and the subsequent bull market starting in October 2020.

To ensure the availability of data and minimize the percentage of missing values, we narrowed down our analysis to a final list of 34 cryptocurrencies that were most frequently traded. These cryptocurrencies are shown in Table 1. Regarding granularity, our previous study indicated that high-frequency data is more appropriate for analysis tasks since it contains sufficient information and can capture unexpected movements, especially with highly volatile time series like cryptocurrencies [13]. Eventually, we chose a granularity of 30 minutes as it is the highest frequency we can use while keeping the percentage of missing values low.

For each time series, we use its average value to replace missing data points. We acknowledge that there are other interpolation methods (e.g. nearest, linear, splines) that are worth considering. However, the average method is chosen for the sake of the mathematics involved. In particular, since our first preprocessing step is normalization [42], those average values will become zero as a result of the normalization formula. Thus, they will be eliminated in further calculation steps. In other words, the average method marks missing values in the time series and these values will not be used to do experiments. Consequently,

[5]`https://hitbtc.com/`

Table 1: A list of 34 cryptocurrencies used in this study. Abbreviations are put in parentheses.

Cryptocurrencies					
Argur (REP)	Bitcoin SV (BSV)	Ethereum Classic (ETC)	MaidSafeCoin (MAID)	Ontology (ONT)	Tron (TRX)
Bancor (BNT)	Cardano (ADA)	FunToken (FUN)	Maker (MKR)	Ox (ZRX)	Verge (XVG)
Basic Attention Token (BAT)	Decentraland (MANA)	ICON (ICX)	Monero (XMR)	QTUM	Zcash (ZEC)
Bitcoin (BTC)	Dogecoin (DOGE)	IOST	Nem (XEM)	Ripple (XRP)	Zilliqa (ZIL)
Bitcoin Cash (BCH)	EOS	Lisk (LSK)	NEO	Stellar (XLM)	
Bitcoin Gold (BTG)	Ethereum (ETH)	Litecoin (LTC)	OMG Network (OMG)	Tezos (XTZ)	

Table 2: Average rankings of cryptocurrencies during the period between February 2019 and April 2021

BTC	ETH	XRP	BCH	LTC	ADA	BSV	EOS	XLM
1	2	4	6	7	10	11	11	12

TRX	XMR	XTZ	NEO	XEM	ETC	MKR	DOGE	ZEC
15	15	18	22	25	28	30	32	32

ONT	BAT	OMG	QTUM	ZRX	BTG	ICX	LSK	REP
37	40	51	51	51	59	60	64	66

ZIL	IOST	XVG	MANA	MAID	BNT	FUN
70	90	91	110	117	144	202

our experimental results are derived solely from the available data. On the contrary, if other interpolation methods were used, they would result in non-zero interpolated values, which would be used in further calculation steps, potentially affecting the experimental results.

3.1.1. Ranking Survey

We use the ranking[6] of each cryptocurrency to support our experiments. To do this, we collect monthly rankings from the Historical Snapshots page on Coinmarketcap.com from February 2019 to April 2021 and average them to obtain an overall ranking for each coin. This practice enables us to have a general assessment in terms of the size of a cryptocurrency during the considered period. A major coin tends to catch more attention of the general public and is utilized more often in cryptocurrency-related activities. This feature is displayed in Table 2

4. Methodology

4.1. Returns and Volatility Calculation

Given a price time series $x_i = \left(x_1^i, x_2^i, x_3^i, \ldots, x_T^i\right)$ of cryptocurrency i with a length of T, the log-return time series r_i is obtained using the formula $r_t^i = log(x_t^i/x_{t-1}^i)$, where r_t^i represents the return value at time t.

[6]The ranking of a cryptocurrency is determined by its market capitalization (current price × number of tokens in circulation). The higher the market capitalization, the higher the corresponding rank assigned to the cryptocurrency.

The volatility v_t at time t is calculated using the window of the last 48 data points from the return time series. The choice of this window size is explained by two reasons: Firstly, we use a 30-minute dataset, which results in 48 data points within a day (24 hours). In other words, we capture the intraday movements of a cryptocurrency by employing a sliding window of size 48 with a sliding stride of 30 minutes. Secondly, we tested the market efficiency[7] at each time window of 48 data points for each cryptocurrency, using two metrics: *permutation entropy*[8] and *statistical complexity*[9]. This testing procedure is proposed by [45]. Specifically, given an empirical time series in a corresponding time window, they first calculated permutation entropy and statistical complexity for the time series, then estimated the 95% random confidence interval for each measure by shuffling the time series randomly and calculating permutation entropy and statistical complexity for 30 independent realizations. The idea is that if two measures (e.g. permutation entropy and statistical complexity) derived from the empirical time series are within the 95 % confidence intervals of randomly shuffled time series, then the empirical time series share common characteristics with random time series and thus no dependence patterns exist in the empirical time series since the values are just randomly distributed. In other words, the future value is independent of the previous values. Thus, the market efficiency presents in this time series. We found that the majority of cryptocurrencies in our study retain their efficiency for roughly 70 percent of the observed period. This percentage is relatively high for digital currencies, which suggests the equivalence between a coin's market value and the relevant news of that coin on the internet at that time, according to [45]. Therefore, the window size of 48 data points can capture and explain the movements of a cryptocurrency. The results of this experiment are shown in Table 3. We calculate the volatility in 2 ways to ensure the stability and transparency of experimental results.

i. Using the standard deviation of log-returns:

$$v_t^i = \sqrt{\frac{\sum_{k=0}^{47}(r_{t-k}^i - \mu)^2}{48}}$$

where μ is the mean of these log-returns.

ii. Using the moving average of squared log-returns, as suggested by Fernando et al [46]:

$$v_t^i = \sqrt{\frac{\sum_{k=0}^{47} r_{t-k}^2}{48}}$$

[7]The efficient market hypothesis states that the current prices of an asset reflect all available public market information relevant to that asset, making them fairly valued as they are present. Thus, no level of analysis or market timing strategy will yield opportunities for gaining excess returns. In other words, past price movements are not useful for predicting future prices, i.e. the future value does not depend on the historical values.

[8]Permutation entropy is an ordinal-based non-parametric complexity measure for studying the temporal dependence structure in a linear or non-linear time series. A low permutation entropy (close to 0) means that a future value can be predictable from the historical values. Whereas, a high permutation entropy (» 0) indicates that all values in the time series are independent and uniformly distributed. This measure is calculated based on the frequency of different ordinal patterns (permutations) in the data. Details of this complexity measure are described in [43].

[9]Statistical Complexity quantifies the structural complexity of dependence patterns in a time series. A higher statistical complexity means that the dependence patterns occur in a more complex fashion. In other words, the time series is more fluctuated and the future value is complicatedly relevant to historical values. This measure combines permutation entropy with a measure of disequilibrium, as described in [44].

Table 3: Testing the market efficiency for each cryptocurrency using 48 data points

Crypto	Percentage	Crypto	Percentage
ADA	70,00%	MANA	54,32%
BAT	55,00%	MKR	58,09%
BCH	70,37%	NEO	70,10%
BNT	63,80%	OMG	69,17%
BSV	70,32%	ONT	69,34%
BTC	69,37%	QTUM	69,77%
BTG	71,17%	REP	68,38%
DOGE	70,00%	TRX	70,21%
EOS	69,53%	XEM	70,80%
ETC	68,72%	XLM	70,63%
ETH	70,08%	XMR	69,34%
FUN	43,44%	XRP	70,89%
ICX	70,90%	XTZ	69,81%
IOST	67,61%	XVG	70,08%
LSK	70,08%	ZEC	71,43%
LTC	70,70%	ZIL	69,64%
MAID	69,81%	ZRX	69,47%

4.2. Correlation Matrix Formation

Given a set of return or volatility time series z_i, $i = 1, 2, \ldots, 34$, corresponding to 34 cryptocurrencies mentioned in Section 3. We first calculate the similarity between each pair of cryptocurrencies C_{ij} as follows: $C_{ij} = \langle \hat{z}_i, \hat{z}_j \rangle$, with $\hat{z}_i = (z_i - \mu_i)/\sigma_i$, where i and j are cryptocurrencies, $\langle \cdot, \cdot \rangle$ represents the dot product, $\hat{z}_i$ is the normalized time series of z_i, μ_i is the mean value of z_i and σ_i is the standard deviation of z_i. Such a similarity measure is called *Pearson* correlation coefficient [15].

We acknowledge that this correlation calculation method has its limitations, such as being sensitive to outliers and not being able to capture non-linear relationships [47]. However, we have chosen to use it in our study for the following reasons:

i. We use returns and volatility to maintain the statistical nature of the time series. Other correlation metrics that address non-linear problem such as *Spearman* and *Kendall* show their own drawbacks. For instance, converting rational numbers into integer rankings can result in the loss of important information from financial time series [48]. In addition, it has been demonstrated that rank correlation metrics (e.g. *Spearman* and *Kendall*) can also experience issues with non-linearity in certain situations [47].

ii. *Pearson* correlation is a widely accepted method in the literature for both cryptocurrency [41, 49, 50] and traditional asset markets [51–53]. This strongly reinforces our belief in the applicability of this method of correlation calculation for our problem.

iii. *Pearson* correlation is suitable for time series with repeated observations, as is the case in financial time series, unlike other methods that require independent observations [48].

The correlation matrix C is formed from similarity coefficients obtained above such that

$$C = (C_{ij})_{1 \leq i \leq 34, 1 \leq j \leq 34}$$

A concern with this type of matrix is the reliability of the correlations, specifically whether the matrix accurately reflects true relationships between the time series being considered. To address this concern, the Random Matrix Theory provides a means of examination [13, 35, 54]. We have used RMT to test our correlation matrices and found that they all contain valuable information and are not random.

4.3. Denoise and Detrend

4.3.1. Denoise

The noise effect was shown to appear in the stock market several decades ago [55]. This phenomenon is even more apparent in the cryptocurrency market. According to Thomas and Franziska [56], the average daily signal-to-noise ratio for the cryptocurrency market is only 36%, which is significantly lower than the 90% average daily signal-to-noise ratio for established US stock exchanges like NYSE and NASDAQ during the period from March 2017 to November 2017.

There are several factors contributing to the noise in the cryptocurrency market. Firstly, this market is vulnerable to *Pump and Dump* schemes, which have become a typical characteristic that distinguishes digital assets from traditional ones [57]. Secondly, although the purpose for inventing cryptocurrencies is to reduce the complexity of regulatory and trading operation that exists in traditional markets [58], a large number of transactions have been found to be linked to illegal purposes [58]. Eventually, more and more regulations have been enacted to control this young market [59]. Thirdly, transaction-related actions, in that investors can split their budget for one transaction into multiple transactions with smaller worth net to reduce transaction fees, which may result in unexpected price movements [60]. Additionally, other causes such as noise traders and arbitrageurs have been found to deliberately manipulate the movement of assets [55].

We use Random Matrix Theory [54] to distinguish the noise in cryptocurrencies. This theory states that the random correlation matrix C_R obtained from N randomly generated time series with zero mean, unit variance and length T (matching the size of the empirical correlation matrix C described earlier) has eigenvalues γ that asymptotically converge ($N \to +\infty$ and $T \to +\infty$ with $\frac{T}{N} > 1$) to the Marcenko-Pastur probability density function f

$$f(\gamma) = \begin{cases} \frac{T}{N}\frac{\sqrt{(\lambda_{+}-\gamma)(\gamma-\lambda_{-})}}{2\pi\gamma} & \text{if } \gamma \in [\lambda_{-}, \lambda_{+}] \\ 0 & \text{if } \gamma \notin [\lambda_{-}, \lambda_{+}] \end{cases}$$

Where $\lambda_{-} = (1 - \sqrt{\frac{N}{T}})^2$ is the minimum expected eigenvalue and $\lambda_{+} = (1 + \sqrt{\frac{N}{T}})^2$ is the maximum expected eigenvalue of the Marcenko-Pastur distribution f.

Eventually, given eigenvalues λ obtained from the empirical correlation matrix C, $\lambda \in [\lambda_{-}, \lambda_{+}]$ are considered to exhibit random behavior as they belong to the random regime. Conversely, eigenvalues that fall outside of $[\lambda_{-}, \lambda_{+}]$ are expected to be informative signals. In practice, we only use informative eigenvalues that are greater than λ_{+} since those that are less than λ_{-} carry negligible information [21]. Thus, we associate eigenvalues $\lambda \in [0, \lambda_{+}]$ with noise. Our objective in the denoising task is to eliminate these noisy eigenvalues from the empirical matrix C. Consequently, the correlation between cryptocurrencies is calculated without the noise effect.

Figure 1 illustrates an example of the density distribution of eigenvalues (shown in blue) obtained from our empirical correlation matrix (from 2019-07-02 00:00:00 to 2019-07-24 23:30:00) and the corresponding Marcenko-Pastur distribution (shown in red). In this case, the majority of eigenvalues fall below λ_{+} (green vertical line), which are considered noise. Whereas, there are a few eigenvalues that are greater than λ_{+}, which carry important information. We would like to keep these informative eigenvalues while processing the noisy ones to eliminate their impact from the correlation matrix. The sub-figure in the top right corner is obtained by removing the largest eigenvalue in order to help readers compare the Marcenko-Pastur distribution with empirical eigenvalues more easily.

For this, we employ the Eigenvector Clipping method. One advantage of this approach is that it does not require any training parameters, making its outcome robust and more reliable [22]. On the other hand, other denoising methods such as Linear shrinkage [61], Non-linear shrinkage [62] and Rotationally invariant, optimal shrinkage [63] require users to specify several parameters, causing an obstacle: how do we

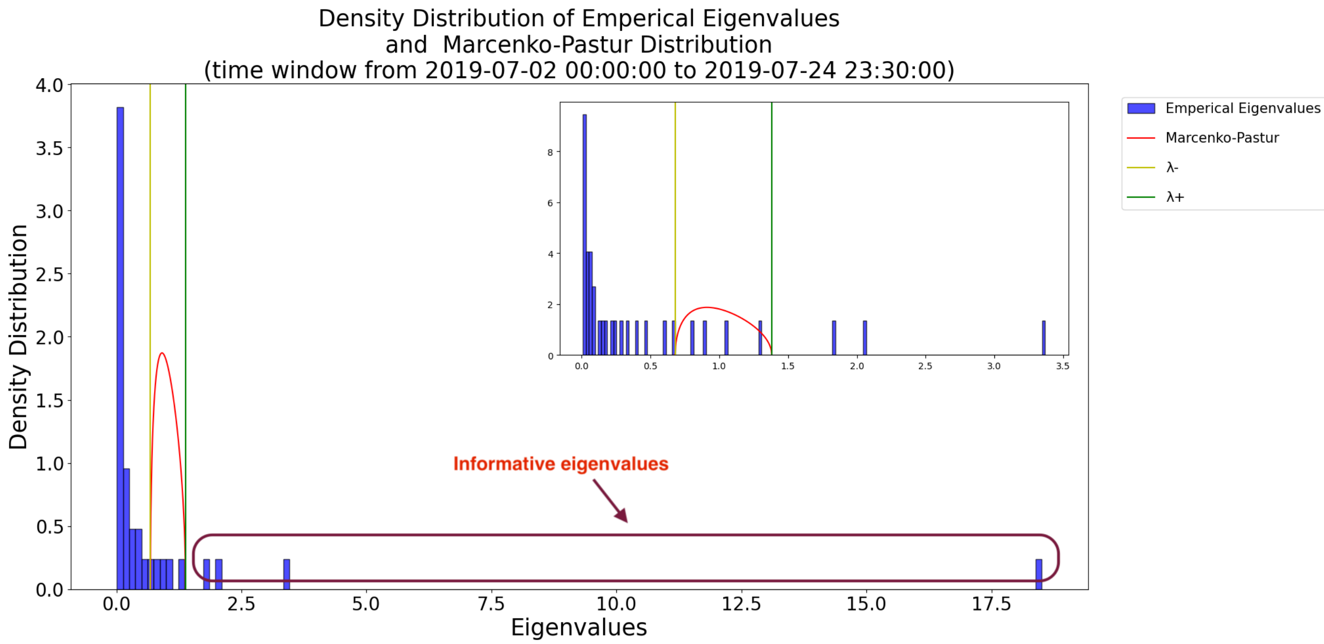


Figure 1: Density distribution of eigenvalues (blue) obtained from our empirical correlation matrix (from 2019-07-02 00:00:00 to 2019-07-24 23:30:00) and the corresponding Marcenko-Pastur distribution (red). The yellow vertical line represents the minimum expected eigenvalue λ_- while the green vertical line represents the maximum expected eigenvalue λ_+ of the Marcenko-Pastur distribution. The top right sub-figure is obtained by removing the largest eigenvalue.

choose parameters? Furthermore, Eigenvector Clipping is straightforward to implement, with guaranteed efficiency as it keeps the information part, i.e., after the cleaning process, the trace of the correlation matrix remains unchanged [64]. This method has shown good performance in different studies and has been applied widely to different topics such as education, portfolio optimization and signal processing [20, 65, 66].

Given eigenvalues $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots \geq \lambda_n$ and corresponding eigenvectors $v_1, v_2, \ldots, v_n$ of our empirical correlation matrix $\mathbf{C}$, we can identify $k \leq n$ such that $\lambda_k > \lambda_+$ and $\lambda_{k+1} \leq \lambda_+$. As a result, $\lambda_i, \forall i \leq k$ are noisy eigenvalues, according to the Random Matrix Theory. The Eigenvector Clipping replaces these noisy eigenvectors with their average value in which the trace of the correlation matrix $\mathbf{C}$ after denoising is similar to its origin. The denoised correlation matrix $\mathbf{C}_{denoised}$ is defined by [67]:

$$\mathbf{C}_{denoised} = \sum_{i=1}^{n} \lambda_i^* v_i v_i^\intercal, \lambda_i^* = \begin{cases} \frac{\lambda_{k+1}+\lambda_{k+2}+\ldots+\lambda_n}{n-k}, \forall i \geq k+1 \\ \lambda_i, \forall i \leq k \end{cases} \tag{1}$$

4.3.2. Detrend

As of 2023, there are nearly 23,000 cryptocurrencies in circulation in the market, as reported by one of the biggest websites for tracking digital coins Coinmarketcap.com. By contrast, only around 10 blockchain protocols are used to govern cryptocurrencies [68]. As a result, the same blockchain protocol is used by many cryptocurrencies [69]. Moreover, the cryptocurrency market is heavily manipulated by social media and breaking news, leading to herding behavior among investors [70]. These factors contribute to the co-movement in prices across different cryptocurrencies, which is referred to as the *trend* effect in the market.

Since the underlying characteristics of each cryptocurrency are masked by the existence of trend, we should eliminate this effect from the cryptocurrencies in order to observe each individual cryptocurrency's movements. In other words, we examine the interaction among different cryptocurrencies without considering external factors such as shared protocols and mass media-driven price manipulation.

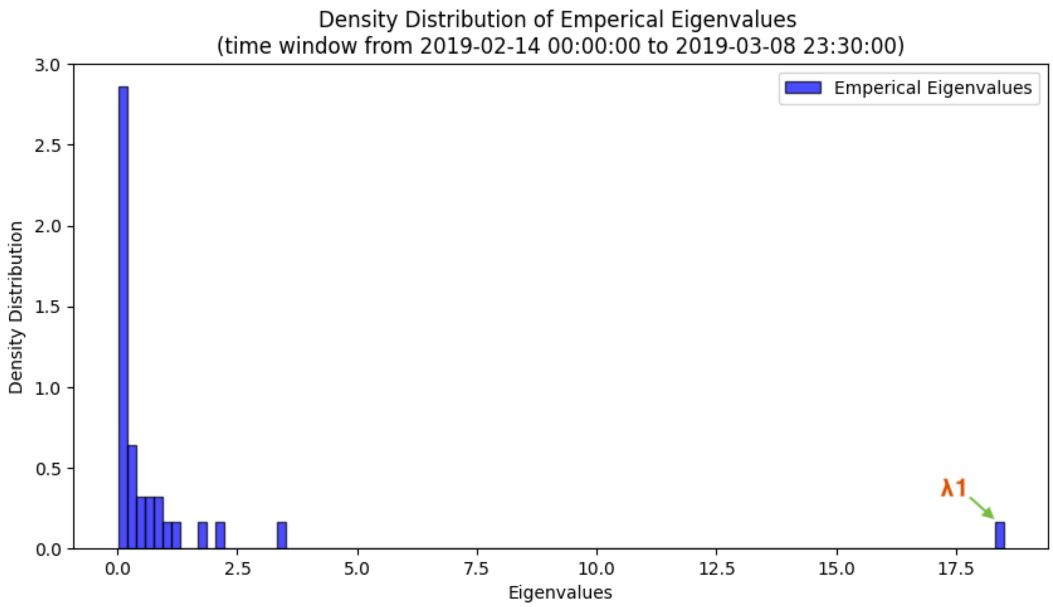


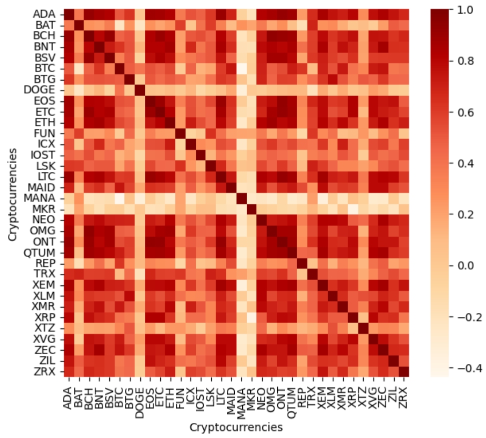
Figure 2: Market component (λ_1) in an empirical correlation matrix

We adopt the concept of "market component" which is described in [21] to remove the trend effect. Such a component refers to the first eigenvalue (i.e. the largest eigenvalue) and corresponding eigenvector of the correlation matrix. It represents the common systematic risk that impacts most assets in the market and provides insights into the overall relationship between individual assets and the market as a whole. By removing this component, the correlation matrix can highlight the unique relationships between individual assets, providing insights into their specific dependencies and individual movements. More intuitively, according to [21], it is similar to removing a loud tone that prevents us from hearing other sounds. We call $\mathbf{C}_{filtered}$ the denoised and detrended correlation, which is obtained by subtracting the first eigenvalue and eigenvector from the denoised matrix $\mathbf{C}_{denoised}$.

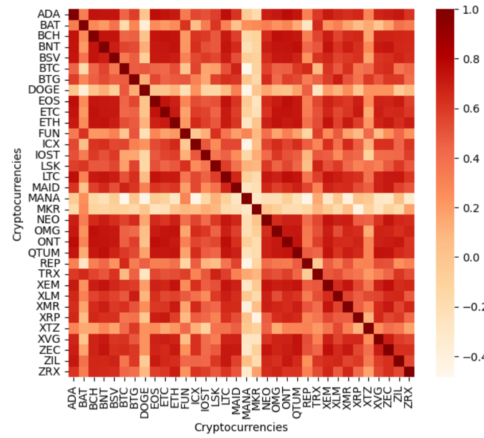
$$\mathbf{C}_{filtered} = \mathbf{C}_{denoised} - \lambda_1 v_1 v_1^{\intercal} \tag{2}$$

Figure 2 shows an example of the market component in our empirical correlation matrix (from 2019-07-02 00:00:00 to 2019-07-24 23:30:00). As can be seen, there is a blue bar that stands significantly apart from the other blue bars, which represents the market component. The market component is always the largest eigenvalue of a correlation matrix.

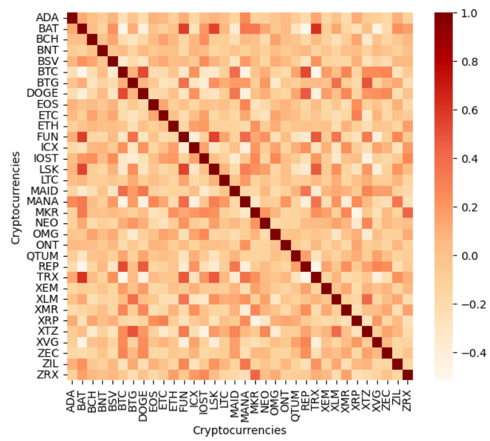
Figure 3 displays examples of the empirical correlation matrix before denoising and detrending (a), after denoising (b) and after denoising and detrending (c), respectively. The intensity of the red color (from white to dark red) represents the correlation between two cryptocurrencies, with darker red indicating higher correlation. The maximum value of the correlation is 1 which represents a complete similarity between two cryptocurrencies. By contrast, the minimum value of the correlation is -1 which represents a complete difference between two cryptocurrencies. Obviously, the correlation values in the diagonal line of each correlation matrix are all 1 because these values are derived from calculating the correlation between 2 identical cryptocurrencies. Figure 3a shows that most cryptocurrencies are strongly correlated with each other since the dark red color is distributed across the matrix. This means that the majority of cryptocurrencies share a common trend, i.e. the price/volatility movements of different cryptocurrencies are similar. Additionally, we can infer that the noise actually exists in the cryptocurrencies since the denoised correlation matrix in Figure 3b shows a brighter red color compared to the original correlation matrix. That is, the existence of noise results in the correlation between cryptocurrencies being higher



(a) Original correlation matrix



(b) Denoised correlation matrix



(c) Denoised-Detrended correlation matrix

Figure 3: Correlation matrix of 34 cryptocurrencies between 2019-07-02 00:00:00 and 2019-07-24 23:30:00. a) Correlation matrix before denoising and detrending, b) Correlation matrix after denoising, c) Correlation matrix after denoising and detrending.

than it should be. Regarding Figure 3c, this correlation matrix looks completely different from the first two cases since the low correlation is observed at a great number of cryptocurrency pairs. It is clear that the correlation between cryptocurrencies weakens significantly as a result of removing the trend effect. In general, the removal of noise and trend opens an opportunity to observe and explore underlying interactions between different cryptocurrencies. Hence, we can obtain novel findings that are hidden behind the noise and trend.

4.4. Cryptocurrency Network Construction and Metrics

4.4.1. Network Construction

Despite the usefulness of the correlation coefficient in understanding the relationships between cryptocurrencies, it fails to incorporate topological characteristics as it does not place connections in a metric space [71]. To overcome this limitation, the concept of *Distance Matrix* has been introduced as a substitute for the correlation matrix. Such a matrix, denoted as $\mathbf{D}$, is derived from the cleaned correlation matrix $\mathbf{C}$ such that each element d_{ij} of $\mathbf{D}$ is expressed as follows:

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

Where d_{ij} ranges from zero to two with zero indicates complete dissimilarity while two represents complete similarity between 2 objects. By utilizing this approach, the resulting distance matrix satisfies the essential properties of a metric [71]: $d_{ij} \geq 0$, $d_{ij} = 0$ if $i = j$, and $d_{ij} = d_{ji}$. Consequently, this distance matrix enables the construction of a network (graph) of cryptocurrencies, where the proximity of nodes reflects their similarity and nodes with distinct behaviors are positioned further apart. The distance values between pairs of cryptocurrencies serve as the links (edges) within the network.

Nevertheless, this approach tends to create a dense network. That is, each vertex is connected to every other vertices, thereby increasing complexity. To address this issue and focus on the most significant connections, the Minimum Spanning Tree (MST) [72] technique is employed. The MST is a specialized tree structure that connects all vertices with minimal total edge length. By selectively retaining only the $N-1$ most crucial edges, where N represents the number of nodes (cryptocurrencies), the MST effectively captures the underlying dynamics of network structures of a system [72]. This particular type of graph finds extensive applications across various domains [35, 73, 74], especially in studies of financial markets [14, 72, 75].

To derive the MST, the Kruskal algorithm is chosen due to its favorable performance and time complexity [76], which render it particularly suitable for relatively small networks like the one encompassing 34 cryptocurrencies in this study [77]. Furthermore, the Kruskal algorithm has demonstrated its applicability in numerous finance-related domains, thereby reinforcing its reliability and relevance [78, 79].

4.4.2. Metrics for Observing the Evolution of a Network

To track and evaluate the changes of cryptocurrency network structures over time, we use different graph-based metrics that can be categorized into 2 groups:

i. Category 1: Evaluation metrics for the entire network. These metrics allow us to observe the interactions among different cryptocurrencies over time and detect the changes in their interactions during different market conditions.

  - Average Degree Assortativity: *Degree assortativity* measures the correlation between node degrees in a network. An assortative network has high-degree nodes connecting to other high-degree nodes, while a disassortative network has high-degree nodes connecting to low-degree nodes. The assortativity coefficient ranges from -1 (disassortative) to 1 (assortative). A smaller coefficient indicates a well-connected network, while a larger coefficient suggests a more scattered network [80].
  - Average Betweenness Centrality: *Betweenness centrality* measures a node's importance in connecting others. It counts how many shortest paths pass through a node. A node with high betweenness centrality means that it lies on many shortest paths, indicating influence in information or resource flow. A high average betweenness centrality implies a scattered network with small communities, while a low average suggests a well-connected network forming a large community [7].
  - Average Closeness Centrality: This measures the average distance from a node to all other nodes in the graph. A node with a high closeness centrality is one that is close to many other nodes. Thus, it has a higher influence on the network. This metric is used to identify the central node (the node that directly connects to many other nodes) in the network. For the first category, we average the closeness centrality of all nodes. Eventually, a bigger value suggests a well-connected network, while a smaller value suggests a more scattered network [25].

ii. Category 2: Evaluation metrics for each entity, which is used to observe the influence of each cryptocurrency on the whole network over time to identify which cryptocurrencies have the strongest influence on the market and gain an understanding of how cryptocurrencies function within the network.

- PageRank: An algorithm used to measure the importance of nodes in a graph based on the number of links pointing to it. This is the same algorithm used by Google to rank web pages in search results [81].

5. Experimental Results and Discussion

In this section, we conduct an analysis of network structures derived from 2 primary types of financial time series, e.g. returns and volatility, through different graph-based metrics, e.g. *degree assortativity*, *betweenness centrality*, *closeness centrality* and *PageRank*. This experiment has two main objectives: Firstly, we aim to gain insights into underlying traits of interactions among cryptocurrencies. Secondly, we seek to identify distinctive features between returns-based crypto network and volatility-based crypto network. We then relate these analyzed findings to different external factors such as investors' sentiment and transaction patterns.

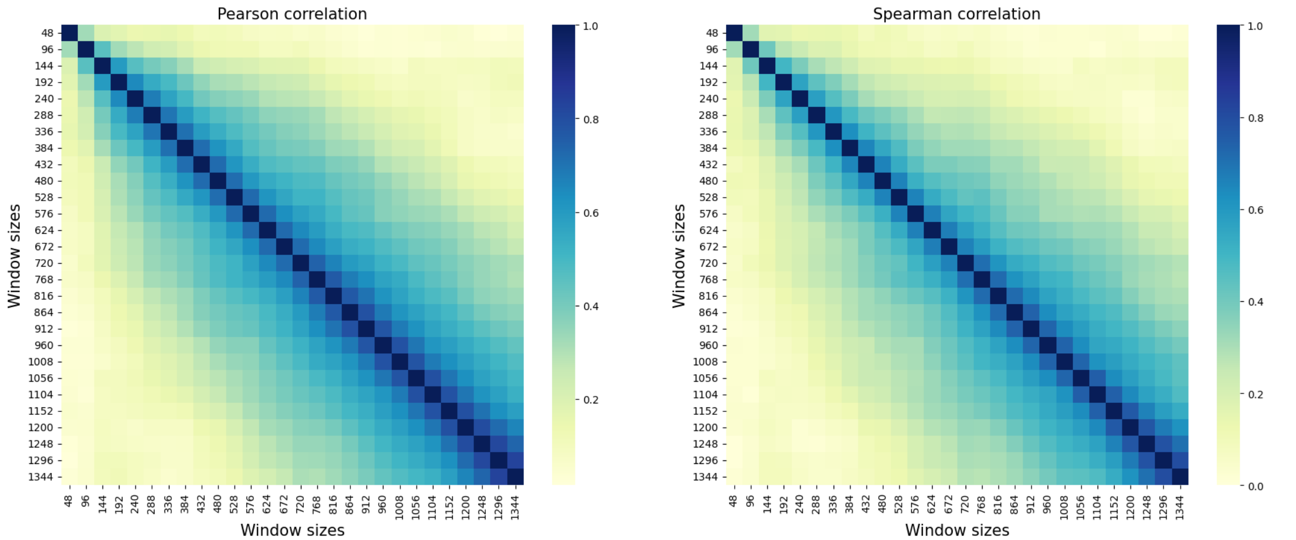
5.1. The Choice of Optimum Window Size for Network Construction

We have presented the process of constructing a network of cryptocurrencies in Section 4. However, it is necessary to determine the optimum window size (length) of time series for this construction. In this regard, we propose two criteria for choosing a suitable window size for network construction. Firstly, the chosen window size should minimize the change in network metrics built on different window sizes. In other words, we choose a window size such that the characteristics of the networks are constant for small changes of window sizes. Secondly, it is also expected to minimize the discrepancy in network metrics (e.g. *degree assortativity*, *betweenness centrality* and *closeness centrality*) obtained by two different volatility measures.

For this experiment, we have selected a range of potential window sizes, consisting of 28 cases spanning between 48 and 1344 data points, which correspond to 1 day to 28 days (4 weeks). The rationale behind this selection is that the cryptocurrency market varies very quickly, a longer duration might fail to capture significant events happening to the market [82]. We use the linear correlation metric *Pearson* and the non-linear correlation metric *Spearman* to calculate the similarity between network structures in different cases via *betweenness centrality*, *degree assortativity* and *closeness centrality*.

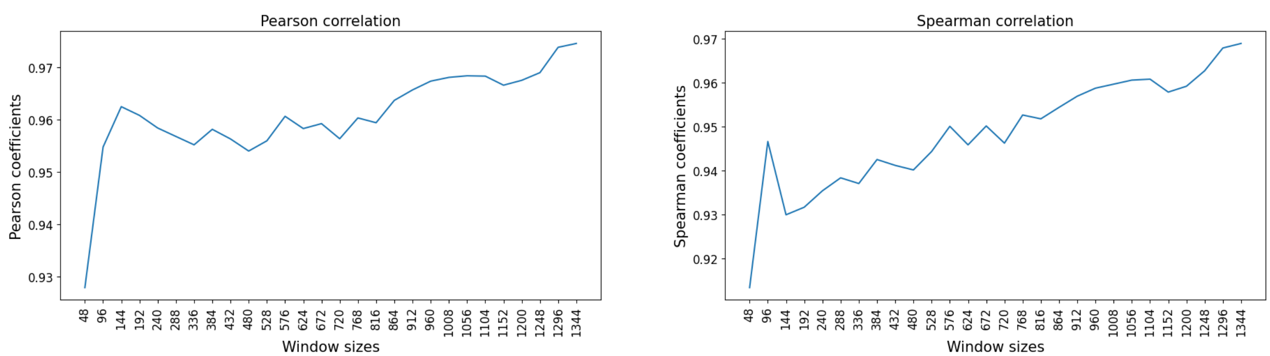
We gained valuable findings from our experiments that assist us in choosing a favorable network window size. In particular, by testing the first criterion, we found that the characteristics of the network structures do not change much when the window size is large. This suggests that the network structures can remain relatively stable if we use relatively large window sizes. Remarkably, we observed a plateau point starting at a window size of 816 (corresponding to 17 days) and the similarity slowly increases from here until the last case (corresponding to 28 days). Thus, based on the first criterion, we exclude window sizes that are less than 816. An example of this experimental result is shown in Figure 4, where we use *Pearson* and *Spearman* to calculate the similarity between *betweenness centrality* values of different network structures constructed using different window sizes.

Regarding the second criterion, we also found a rather similar result with the one obtained from the first criterion. Specifically, the network structures with the window size of 816 or more show negligible changes, indicating a high similarity between network structures with large window sizes. The only difference is that *Pearson* and *Spearman* values drop slightly after the window size of 1104 (corresponding to 23 days), before resuming a steady increase from the window size of 1248 (corresponding to 26 days). An example of this experiment is shown in Figure 5, where we use *betweenness centrality* as a feature to measure the similarity between 2 network structures derived from 2 different volatility formulas.



(a) *Pearson* correlation (b) *Spearman* correlation

Figure 4: The similarity of each pair of time-varying network structures using different window sizes, observed by *betweenness centrality*. a) Measured by *Pearson* algorithm, b) Measured by *Spearman* algorithm.



(a) *Pearson* correlation (b) *Spearman* correlation

Figure 5: The similarity between two time-varying network structures derived from 2 corresponding volatility formulas, observed by *betweenness centrality*. a) Measured by *Pearson* algorithm, b) Measured by *Spearman* algorithm.

In summary, we choose the window size of 1104 (23 days) to construct a network. This window size guarantees the consistency in results even if we use different volatility formulas, helps to minimize the change in a network structure when using a different window size and especially, large enough to satisfy the requirement of Random Matrix Theory (as described in Section 4.2) and minimize the time and space complexity.

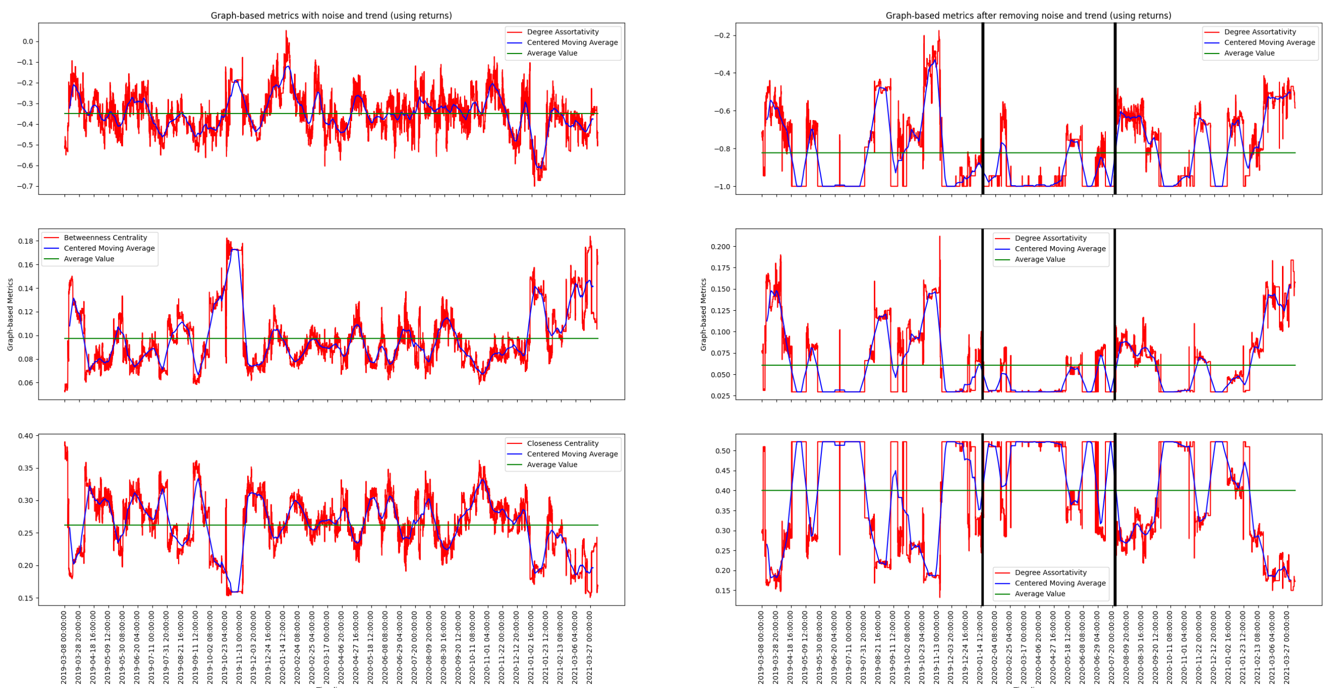
Additionally, we note that two volatility formulas show negligible differences in terms of graph-based experimental results when using this window size. Thus, without loss of generality, we only use the more commonly used standard deviation-based volatility to conduct the remaining experiments.

5.2. Analysis of Cross-interactions in Cryptocurrencies through Time-varying Networks

5.2.1. Returns-based Time-Varying Networks

We first observe the evolution of network structures obtained by return time series, which is the most frequently used financial feature in the existing literature. We implement this experiment in two cases, before and after the noise and trend removal, respectively.

Figure 6a and 6b depict the changes in network structure every 30 minutes, expressed by three different metrics before and after noise and trend removal, respectively. The red line indicates the original result, the blue line indicates the centered moving average over a 14-day period, the green line indicates the average value and the black line indicates the border of each period.



(a) Before denoising and detrending

(b) After denoising and detrending

Figure 6: Evolution of the returns-based network structure, measured by *degree assortativity*, *betweenness centrality* and *closeness centrality*, respectively. a) Before denoising and detrending, b) After denoising and detrending. The red line indicates the original result, the blue line indicates the centered moving average over the 14-day period, the green line indicates the mean of the time series, and the black line indicates the border of each period.

As expected, these graph-based metrics show significant fluctuations over the considered period, both before and after denoising and detrending. This means that the interactions between different cryptocur-

Table 4: The percentage of 3 SAX segments in each period. "a" stands for the first segment, corresponding to the first 50 percentiles of values of graph-based metrics, "b" stands for the second segment, ranging from the 51st percentile to the 80th percentile, "c" stands for the third segment, covering values that are greater than the 80th percentile.

	SAX type	Betweenness	Degree Assortativity	Closeness
08/03/2019 - 15/01/2020	a	47.6	47.7	47.6
	b	22.3	30.8	22.4
	c	30.1	21.5	30.0
16/01/2020 - 23/07/2020	a	75.3	76.8	75.3
	b	24.2	21.2	24.4
	c	0.50	2.00	0.30
24/07/2020 - 06/04/2021	a	34.3	33.4	33.9
	b	43.8	35.1	43.9
	c	21.9	31.5	22.2

rencies change over time, regardless of whether noise and trend are present or not. However, it can be seen that the changes in the network structure with the effect of noise and trend present seem to be rather random. By contrast, we see noticeable patterns in the cleaned network structure. Specifically, the values of graph-based metrics are relatively small during the period between January and July 2020, which means that the network tends to be compressed during this time, i.e. nodes are close to each other and form one large homogeneous group. On the other hand, large values are dominant during the first period from February 2019 until the end of the same year, implying a scattered network where nodes are more distant from each other, forming multiple smaller groups. The last period, after July 2020, reveals a mixture of characteristics observed in the first two periods.

For the purpose of verifying this phenomenon, we use the Symbolic Aggregate Approximation (SAX) [83] to compare the differences between the three mentioned periods relative to each other. This technique is designed to find similar patterns of behavior within a single time series even when the exact magnitudes of values differ due to factors like trend and seasonality [84]. In other words, SAX can potentially find patterns in what classic time series decomposition would consider noise, as these patterns do not occur regularly and are not part of the trend or seasonal behavior.

The SAX representation for the cleaned graph-based metrics is shown in Table 4. To implement SAX, we begin by splitting the time series' values into different segments based on the structure of the network. In particular, our experiments have revealed that graph-based metric values within the first 50 percentiles represent a compressed network (i.e. nodes are close to each other and form a big group). Values surpassing the 80th percentile represents a scattered network (i.e. node are far from each other and spread out). Whereas, values falling between the 51st and 80th percentile show a mixed network, displaying characteristics of both compression and scattering. Next, we partition the time series into three periods, including 08/03/2019 - 15/01/2020, 16/01/2020 - 23/07/2020 and 24/07/2020 - 06/04/2021. This division is based on the observation that the graph-based metric time series between 16/01/2020 and 23/07/2020 indicates a distinct pattern compared to the other periods. Lastly, we calculate the percentage of occurrence for each segment in each of the three periods.

Table 4 shows the percentage of each segment (e.g. a,b and c) in each period. Notably, the second period clearly displays a different behavior compared to the others. Specifically, the cryptocurrency network structure tends to be compressed during the second period (16/01/2020 - 23/07/2020) with more than 75 percent of the time displaying an "a" SAX type and nearly 100 percent of the time showing "a" and "b" SAX types. Conversely, the first and third periods are similar to some extent. The notable difference is that there is an increase of "b" SAX type and a decrease of "a" SAX type between the first and third periods. This result is in line with the findings in our previous study [13] and also other existing studies with different datasets and methodologies [85, 86], where significant changes in the network structure of cryptocurrencies during the Covid-19 pandemic from January to July 2020 were discovered. In the meanwhile, the post-pandemic period demonstrates a combination of network structure characteristics observed in both the pre-pandemic and peak pandemic seasons.

In summary, the return time series reveals a change between normal times and downturn times in terms of the correlation between cryptocurrencies. However, from the graph-based metrics, as shown in Figure 6, no other significant patterns can be discerned by this financial feature.

5.2.2. Volatility-based Time-varying Networks

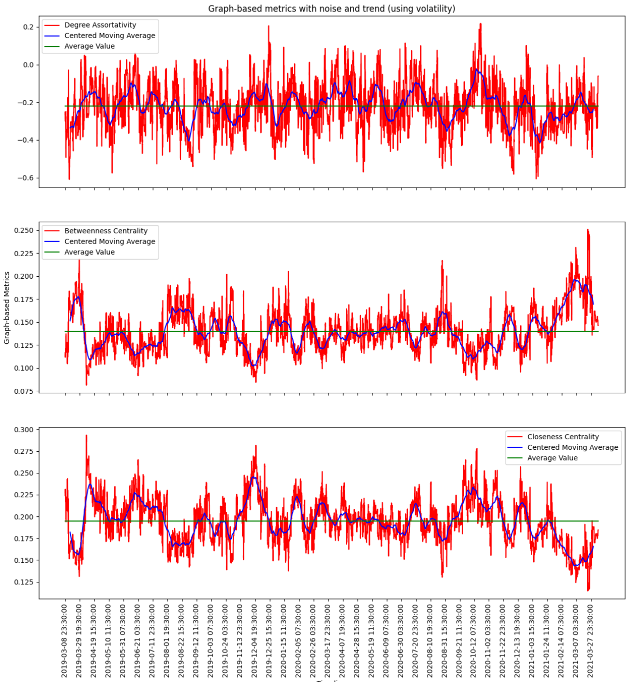
As mentioned earlier, volatility also plays an essential role in exploring and explaining the underlying characteristics of financial assets [4]. In this regard, we expect that the volatility information can add more insights into understanding the correlation among different cryptocurrencies. Thus, in this section, we analyze the time-varying network structures that are constructed by volatility time series.

Figure 7a and 7b illustrate the results of *degree assortativity*, *betweenness centrality* and *closeness centrality* of the volatility-based cryptocurrency network over time, before and after denoising and detrending, respectively. Similar to the returns-based results, we observe changes in the correlation between cryptocurrencies over time in both pre- and post-denoise and detrend scenarios. Additionally, the graph-based metrics, when affected by noise and trend, still fail to reveal any meaningful patterns as they appear to fluctuate randomly. This is particularly evident when looking at the *degree assortativity* in Figure 7a. However, after denoising and detrending, we observe abnormal spikes in the results, as shown in Figure 7b. Notably, two common spikes are present across all three metrics, including March 2020 and February 2021. These spikes indicate a compressed network, where its nodes are close to each other and form a big group. In other words, our examined cryptocurrencies share the same movement in terms of volatility.

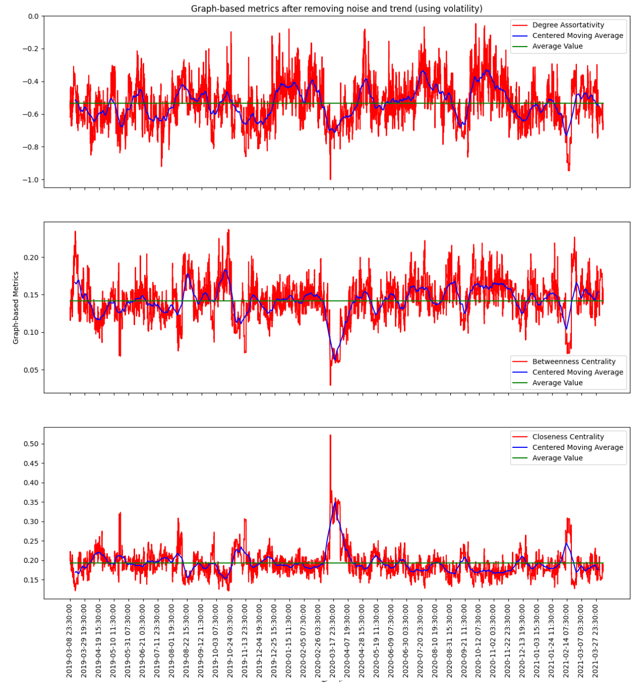
The first common spike was between 13/03/2020 and 27/03/2020, which was equivalent to the worst time in the first wave of the Covid-19 pandemic, i.e. when the global economy experienced a crash due to the regulations and health protection measures enacted by almost all countries across the globe to defend against the pandemic [87]. During this time, public attention towards the pandemic increased dramatically, which was revealed by the increased volume of searches for COVID-19-related terms, i.e. "covid 19" and "coronavirus disease 2019" (Figure 8a). Regarding the stock market, one of the largest stock market indices ($S\&P500$) experienced one of the biggest downturns ever seen with more than 30 percent loss (Figure 8b), while the stock volatility index VIX increased by more than 500% in a matter of 2 months (Figure 8c). The cryptocurrency market also reacted to this global crisis as the majority of digital coins started to lose their values in mid-February 2020 and reached the lowest values on 13/03/2020 (see `http://coinmarketcap.com/`), which was also the date graph-based metrics had the highest peak, i.e. the cryptocurrency network was compressed the most or cryptocurrencies were closest to each other. The financial markets quickly started to recover thereafter while graph-based metrics also gradually went back to their pre-pandemic values.

The second spike occurred between 12/02/2021 and 20/02/2021, coinciding with a bullish period in the cryptocurrency market (see `http://coinmarketcap.com/`). This was the first time the cryptocurrency market experienced a significant surge in prices, not only with major coins such as BTC and ETH but also with minor coins like BAT and MKR. However, the prices of most cryptocurrencies started to decline again after 19/02/2021. Interestingly, it can be seen that the network metrics fell back to their values prior to the spike period after 20/02/2021, as shown in Figure 7b.

These spikes in graph-based metrics can be attributed to herding behaviour [88], which is mainly driven by the trading decisions of naïve (irrational) traders [39, 40]. In particular, the cryptocurrency market is shown to be ruled by such investors (irrational investors), they tend to mimic other investment decisions and are strongly influenced by the market sentiment, especially during market crashes and bullish periods [88]. That is, they tend to sell off their shares when the market experiences a downturn or bad news circulates on the internet in order to avoid the loss. By contrast, they are more likely to purchase new shares during bullish phases or when positive news about cryptocurrencies spreads among

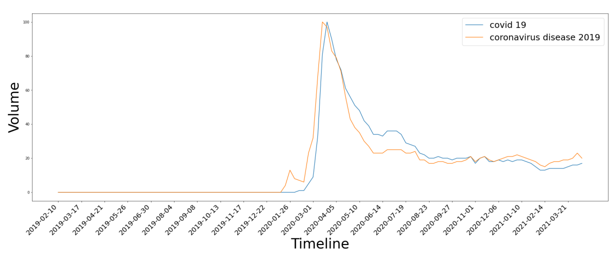


(a) Before denoising and detrending

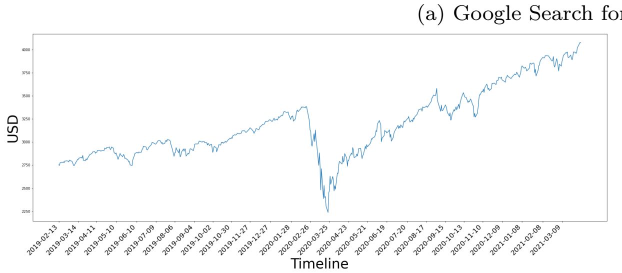


(b) After denoising and detrending

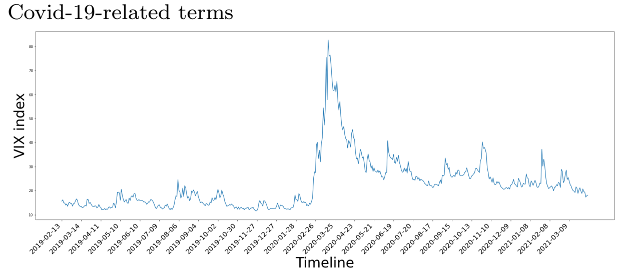
Figure 7: Evolution of the volatility-based network structure, measured by *degree assortativity*, *betweenness centrality* and *closeness centrality*. a) Before denoise and detrend, b) After denoise and detrend. The red line indicates the original result, the blue line indicates the centered moving average over the 14-day period, the green line indicates the mean of the time series.



(a) Google Search for Covid-19-related terms



(b) S&P500 prices



(c) VIX index

Figure 8: Public attention (a), stock volatility index (VIX) (b) and S&P500 index (c), from 13/02/2019 until 4/06/2021

the general public due to the fear of missing out on rising the cryptocurrency price. As a result, similar trading actions occur across different cryptocurrencies of all sizes, causing a consistent impact on the volatility of different coins, which in turn, leads to an increase in the correlation within the cryptocurrency market with respect to the volatility. This collective correlation has been discussed in a study by James and Menzies [4], where the authors calculated the proportional contribution of one cryptocurrency to the total volatility of 52 major cryptocurrencies throughout the period between April 2019 and June 2021. They found that the proportion of the market's total volatility is more evenly distributed among all the cryptocurrencies during the Covid-19 market crisis and the bull market of 2021. There was less deviation between different volatilities of individual cryptocurrencies in these two periods, i.e. everything was similarly volatile together.

To reinforce our interpretation of the aforementioned spikes in graph-based metrics, we examine the correlation between these two spikes and the Fear and Greed index[10] of investors in the cryptocurrency market. Without loss of generalization, we display the correlation between the *betweenness centrality* and the Fear and Greed index in Figure 9. In accordance with our expectations, the spike in March 2020 corresponds to the time people are extremely pessimistic about the market due to the significant decrease in prices. Regarding the spike in February 2021, it corresponds to the time people are most optimistic about cryptocurrencies, boosted by the continuous growth of this market. This result clearly points out the relationship between the volatility network structure and people's sentiments. That is, the cryptocurrency network constructed by volatility time series is strongly compressed (i.e. the correlation between different cryptocurrencies increases, and the network forms a big group) when investors overreact to the market, which is a consequence of a herding phenomenon, either buying (positive sentiment) or selling (negative sentiment) behavior.

We also notice that the magnitude of the first spike in March 2020 is much larger than that of the second spike in February 2021. This is not a trivial phenomenon but rather, it carries a significant implication regarding the influence of people's sentiment on the cryptocurrency market. Specifically, crypto investors, being naïve, tend to overreact and trade irrationally when confronted with negative news. They engage in herding activities by imitating others' actions in an attempt to avoid substantial losses. This causes an increase in volatility and influences a wide range of cryptocurrencies. On the other hand, the majority of investors demonstrate greater wisdom and make more rational investment decisions when the market sentiment is positive, thereby reducing herding behavior. These findings contradict several studies conducted before 2020 such as [89, 90], which argued that positive returns exerted a stronger influence on volatility than negative returns. The rise in volatility can be interpreted as being due to the dominance of uninformed traders, this time reacting to positive news. However, our result is in line with a recent study utilizing a dataset covering 3 continuous years from 2019 until 2021 [91]. More importantly, the stronger influence of negative news compared to positive news on investors has been well-established in traditional markets and has stood as an enduring fact [92]. This implies that the cryptocurrency market is becoming progressively more mature and that it is more similar to traditional ones. This is aligned with [14], where the authors showed that major and famous cryptocurrencies are becoming more and more similar to the stock market.

We acknowledge that there are other spikes spotted in graph-based metrics (Figure 7b). However, they are only consistent in one or two graph-based metrics and the duration for these spikes is much shorter, within one or two days. For instance, three spikes are in *betweenness centrality* and *closeness centrality* but not in *degree assortativity* including May, August and November 2019. We suspect that this might stem from illicit trading activities which we cannot track or collect information on, such as money laundering, terrorist financing and corruption [93]. In addition, another potential reason stems from social

[10] Assessing the emotions and sentiments of people towards the cryptocurrency market. The index ranges from 0 to 100, which is classified into 5 levels in total, including extreme fearful (0 - 25), fearful (26-46), neutral (47-54), greedy (55-75) and extreme greedy (76 - 100), website: `https://alternative.me/crypto/fear-and-greed-index/`

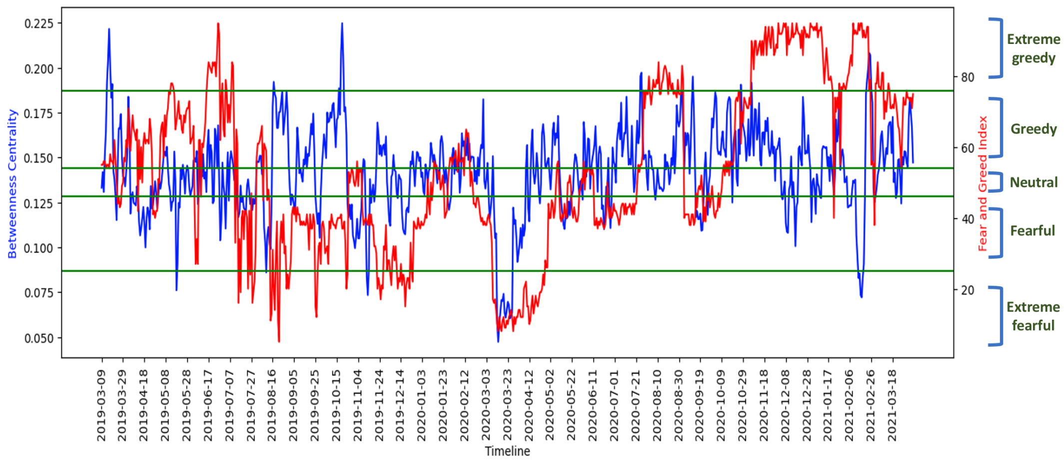


Figure 9: The movement of *betweenness centrality* and *Fear and Greed* index from 09/03/2019 until 06/04/2021. The red line refers to the *betweenness centrality*, the blue line refers to the sentiment index, and each green line corresponds to a boundary for a type of sentiment, including extreme fearful, fearful, neutral, greedy and extreme greedy.

media-related activities such as market manipulation or pump-and-dump schemes, where a portion of crypto traders try to create herding to take advantage of the price movement. This possibly explains the reason why people changed their sentiment regularly during the year 2019, as shown in Figure 9. This phenomenon will be the preserve of future work since it is outside the scope of this study.

5.3. Information Flow in the Cryptocurrency Network: Which Cryptocurrency Acts as the Information Transmission Center?

In this section, we aim to analyze the influence of each cryptocurrency on a network comprising 34 diverse cryptocurrencies. The influence of a cryptocurrency on this network is determined by the extent to which the other cryptocurrencies' values change when the value of that particular cryptocurrency fluctuates. Therefore, a cryptocurrency with a greater influence is associated with a larger number of interconnected cryptocurrencies. For this purpose, we use an algorithm launched by Google which is originally used to assess the importance of web pages based on their links, called *PageRank* [81]. It assigns a numerical score between 0 and 1 to each node, considering factors such as the number and quality of incoming links. Nodes with higher scores are considered more influential, and thus transfer their information to a wider range of coins in the network.

We calculate the *PageRank* value for each cryptocurrency at each timestamp based on the corresponding network structure, as observed via both returns and volatility. To assess the influence of each cryptocurrency in the network, we define two metrics inherited from *PageRank* that quantify the magnitude of influence for each cryptocurrency:

- *Total Accumulation* (TA): calculates the sum of *PageRank* values for each cryptocurrency across the period.

$$\textbf{Total Accumulation}_i = \sum_{k=1}^{T} pr_k^i \tag{4}$$

- *Dominance Score* (DS): counts the number of times that a cryptocurrency has the highest *PageRank* value.

$$\textbf{Dominance Score}_i = \sum_{k=1}^{T} hpr_k^i$$

Crypto	TA	Rank	Percentage
ETH	1.564	2	4,29
BCH	1.387	6	3,80
BTC	1.375	1	3,77
XLM	1.361	12	3,73
NEO	1.335	22	3,66
LTC	1.324	7	3,63
EOS	1.304	11	3,58
ADA	1.265	10	3,47
ONT	1.211	37	3,32
QTUM	1.137	51	3,12
TRX	1.070	15	2,93
ZEC	1.058	32	2,90
ETC	1.050	28	2,88
ZRX	1.044	51	2,86
XRP	1.037	4	2,84
LSK	1.032	64	2,83
ZIL	1.010	70	2,77
BAT	1.008	40	2,76
DOGE	998	32	2,74
OMG	996	51	2,73
XMR	991	15	2,72
BSV	982	11	2,69
ICX	976	60	2,68
BNT	971	144	2,66
XVG	965	91	2,64
XEM	964	25	2,64
XTZ	952	18	2,61
MANA	925	110	2,53
REP	908	66	2,49
BTG	901	59	2,47
MKR	894	30	2,45
FUN	860	202	2,36
MAID	823	117	2,26
IOST	803	90	2,20

(a) Volatility

Crypto	TA	Rank	Percentage
BTC	3.414	1	9,35
ETH	3.090	2	8,46
LTC	1.692	7	4,63
NEO	1.495	22	4,09
BCH	1.473	6	4,03
EOS	1.443	11	3,95
ONT	1.206	37	3,30
ADA	1.161	10	3,18
QTUM	1.095	51	3,00
TRX	1.054	15	2,89
XRP	1.010	4	2,77
XLM	985	12	2,70
BNT	912	144	2,50
ZRX	895	51	2,45
ETC	879	28	2,41
ICX	856	60	2,34
OMG	848	51	2,32
BAT	822	40	2,25
MKR	797	30	2,18
ZIL	791	70	2,17
REP	785	66	2,15
XTZ	783	18	2,14
XVG	783	91	2,14
MANA	780	110	2,13
ZEC	774	32	2,12
XMR	772	15	2,11
LSK	756	64	2,07
BSV	754	11	2,06
MAID	754	117	2,06
DOGE	753	32	2,06
BTG	747	59	2,05
XEM	733	25	2,01
FUN	732	202	2,00
IOST	703	90	1,93

(b) Returns

Table 5: Total Accumulation (TA) for each cryptocurrency with the effect of noise and trend, observed via volatility (a) and returns (b), respectively. Each table has 4 columns: Crypto represents cryptocurrency symbols; TA represents Total Accumulation values; Rank represents the ranking of cryptocurrencies; Percentage represents the ratio of one cryptocurrency's Total Accumulation value to the sum of all Total Accumulation values. The results are ordered from high to low.

With

$$hpr_k^i = \begin{cases} 1, & \text{if } pr_k^i \text{ is the highest value at time } k \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Where i represents the cryptocurrency i, T represents the length of the period and pr_k^i represents the *PageRank* value of the cryptocurrency i at time k.

Tables 5 to 8 display the results of this experiment before and after denoising and detrending. Although there are minor variations in results between the two *PageRank*-related metrics, these differences can be considered negligible and they are the same in general. Furthermore, our experiment demonstrates that returns and volatility yield similar outcomes. In particular, with the influence of noise and trend, the prominent cryptocurrencies such as BTC and ETH appear to have a greater influence on the market than the rest, as evidenced by their high *PageRank* values throughout the observed period. This is a common result obtained by various studies whose experiments are based on original data with the presence of noise and trend [70, 94, 95]. By constrast, this characteristic disappears after removing the noise and trend contributions. Specifically, smaller and less famous cryptocurrencies tend to have a larger impact on the market. In contrast, BTC and ETH show negligible impact on the market. We note that this phenomenon remains consistent across different window sizes of the network construction.

The significant influence of minor cryptocurrencies on the market can be attributed to 3 key factors: the prevalence of Pump & Dump schemes, the transaction activity of crypto investors and the treatment of investors on minor cryptocurrencies (e.g. how minor cryptocurrencies are used by investors).

In relation to Pump & Dump, it has become a familiar characteristic of the cryptocurrency market, which is organized regularly by a wide range of investors. A study [96] observed 355 such events on 2 major exchanges, Binance and Yobit. The researchers collected data from 2 different sources, namely Telegram and PumpAnalysis.com during a 4-year period from 2018 to 2021, to analyze the characteristics

Crypto	TA	Rank	Percentage
BAT	1.818	40	4,98
MKR	1.627	30	4,46
FUN	1.460	202	4,00
MANA	1.405	110	3,85
XTZ	1.309	18	3,59
ZIL	1.288	70	3,53
IOST	1.260	90	3,45
XVG	1.206	91	3,30
MAID	1.190	117	3,26
BNT	1.182	144	3,24
BTG	1.079	59	2,96
REP	1.077	66	2,95
DOGE	1.074	32	2,94
ZRX	1.073	51	2,94
XLM	1.069	12	2,93
LSK	1.046	64	2,87
ICX	1.042	60	2,86
BTC	981	1	2,69
BSV	975	11	2,67
OMG	952	51	2,61
ADA	940	10	2,58
XEM	937	25	2,57
ETC	931	28	2,55
ZEC	919	32	2,52
NEO	907	22	2,49
ETH	904	2	2,48
LTC	903	7	2,47
EOS	880	11	2,41
TRX	872	15	2,39
XMR	863	15	2,37
ONT	850	37	2,33
XRP	837	4	2,30
QTUM	813	51	2,23
BCH	811	6	2,22

(a) Volatility

Crypto	TA	Rank	Percentage
MKR	3.354	30	9,18
FUN	3.152	202	8,63
MANA	2.318	110	6,35
BAT	2.130	40	5,83
DOGE	1.550	32	4,24
ZRX	1.309	51	3,58
BNT	1.243	144	3,40
OMG	1.207	51	3,31
MAID	1.177	117	3,22
XTZ	1.054	18	2,89
NEO	923	22	2,53
IOST	896	90	2,45
ONT	877	37	2,40
LSK	864	64	2,36
BTG	856	59	2,34
XVG	798	91	2,19
EOS	794	11	2,17
BTC	787	1	2,15
BCH	771	6	2,11
ZIL	768	70	2,10
QTUM	766	51	2,10
REP	740	66	2,03
ICX	717	60	1,96
ADA	714	10	1,95
XRP	711	4	1,95
LTC	709	7	1,94
ETH	707	2	1,93
XEM	692	25	1,89
TRX	684	15	1,87
ETC	676	28	1,85
XLM	670	12	1,83
BSV	653	11	1,79
XMR	641	15	1,75
ZEC	619	32	1,70

(b) Returns

Table 6: Total Accumulation (TA) for each cryptocurrency after removing noise and trend, observed via volatility (a) and returns (b), respectively. Each table has 4 columns: Crypto represents cryptocurrency symbols; TA represents Total Accumulation values; Rank represents the ranking of cryptocurrencies; Percentage represents the ratio of one cryptocurrency's Total Accumulation value to the sum of all Total Accumulation values. The values are ordered from high to low.

of coins that are most likely to be targeted by manipulators for Pump & Dump. Their findings revealed that manipulators target relatively illiquid coins (low-ranking coins). This means that individuals will be more attracted to pumps of low-ranking coins. These schemes were found to impact not only the pumped cryptocurrency but also other cryptocurrencies. In particular, a study conducted by Balcilar and Ozdemir [97] investigated the risk spillover effect caused by the Pump & Dump among various cryptocurrencies, using the frequency connectedness approach. They found evidence of the risk spillover among different cryptocurrencies during pump events. Therefore, a Pump & Dump scheme often originates from a low-ranked cryptocurrency, resulting in synchronized fluctuations between that coin and other coins.

In order to investigate the connection between investor transaction activity and the significant influence of small cryptocurrencies, we calculate the correlation between our examined cryptocurrencies with respect to the number of transactions recorded every 30 minutes throughout the period, the result is illustrated in Figure 10. We collect the number of transactions within every 30 minutes for each cryptocurrency throughout our data period, between 13/02/2019 and 06/04/2021, we then use the non-linear correlation metric *Spearman* to calculate the similarity between each pair of cryptocurrencies. Additionally, we also include the ranking information in this figure to facilitate a comparison between high-ranking and low-ranking cryptocurrencies. Specifically, we classify cryptocurrencies ranked 21[11] or lower as low-ranking, which are colored green in the figure, while the rest are considered high-ranking, which are colored red in the figure.

Our analysis has revealed that low-ranking cryptocurrencies tend to have similar transaction activity

[11]Based on our analysis, the number of circulating cryptocurrencies exceeded 5000 as of April 2021. However, only 20 cryptocurrencies had an average market capitalization (throughout the duration of our dataset) of more than 1.5 billion USD. This is the reason for classifying the top 20 cryptocurrencies with the highest market capitalization as high-ranking cryptocurrencies.

Crypto	DS	Rank	Percentage
ETH	4244	2	11,63
LTC	3544	7	9,71
BCH	3347	6	9,17
NEO	3094	22	8,48
BTC	2913	1	7,98
XLM	2563	12	7,03
EOS	1588	11	4,35
QTUM	1499	51	4,11
ONT	1372	37	3,76
ZIL	1327	70	3,64
ADA	1326	10	3,63
ETC	977	28	2,68
TRX	963	15	2,64
XEM	947	25	2,60
XRP	916	4	2,51
ZEC	675	32	1,85
XVG	598	91	1,64
ZRX	579	51	1,59
DOGE	511	32	1,40
MAID	490	117	1,34
ICX	475	60	1,30
LSK	442	64	1,21
BAT	319	40	0,87
OMG	313	51	0,86
MANA	248	110	0,68
XTZ	238	18	0,65
XMR	208	15	0,57
BTG	190	59	0,52
BSV	190	11	0,52
BNT	177	144	0,49
REP	154	66	0,42
MKR	48	30	0,13
IOST	6	90	0,02
FUN	0	202	0,00

(a) Volatility

Crypto	DS	Rank	Percentage
BTC	14204	1	38,89
ETH	11481	2	31,43
LTC	3618	7	9,90
NEO	1697	22	4,65
EOS	1356	11	3,71
QTUM	601	51	1,65
TRX	600	15	1,64
ADA	521	10	1,43
XRP	517	4	1,42
ONT	474	37	1,30
ICX	434	60	1,19
ZRX	278	51	0,76
ETC	259	28	0,71
BCH	214	6	0,59
BAT	188	40	0,51
MANA	66	110	0,18
ZEC	9	32	0,02
XLM	5	12	0,01
BNT	4	144	0,01
MAID	2	117	0,01
BSV	0	11	0,00
BTG	0	59	0,00
DOGE	0	32	0,00
FUN	0	202	0,00
IOST	0	90	0,00
LSK	0	64	0,00
MKR	0	30	0,00
OMG	0	51	0,00
REP	0	66	0,00
XEM	0	25	0,00
XMR	0	15	0,00
XTZ	0	18	0,00
XVG	0	91	0,00
ZIL	0	70	0,00

(b) Returns

Table 7: Dominance Score (DS) for each cryptocurrency with the effect of noise and trend, observed via volatility(a) and returns (b), respectively. Each table has 4 columns: Crypto represents cryptocurrency symbols; DS represents Dominance Score values; Rank represents the ranking of cryptocurrencies; Percentage represents the ratio of one cryptocurrency's Dominance Score value to the sum of all Dominance Score values. The values are ordered from high to low.

Crypto	DS	Rank	Percentage
BAT	4842	40	13,27
MKR	3358	30	9,20
IOST	2026	90	5,55
ADA	1839	10	5,04
XTZ	1696	18	4,65
ZIL	1612	70	4,42
DOGE	1601	32	4,39
MANA	1573	110	4,31
XVG	1471	91	4,03
REP	1265	66	3,47
FUN	1231	202	3,37
MAID	1165	117	3,19
ETH	1080	2	2,96
BTG	1002	59	2,75
XLM	993	12	2,72
ZEC	879	32	2,41
ZRX	835	51	2,29
BNT	777	144	2,13
ETC	716	28	1,96
BTC	691	1	1,89
XEM	648	25	1,78
OMG	647	51	1,77
LSK	612	64	1,68
ONT	557	37	1,53
BCH	552	6	1,51
NEO	541	22	1,48
ICX	515	60	1,41
XMR	488	15	1,34
BSV	458	11	1,26
TRX	299	15	0,82
EOS	168	11	0,46
XRP	143	4	0,39
QTUM	111	51	0,30
LTC	90	7	0,25

(a) Volatility

Crypto	DS	Rank	Percentage
MKR	6328	30	17,32
FUN	5876	202	16,09
MANA	3782	110	10,35
BAT	3489	40	9,55
ZRX	2747	51	7,52
DOGE	2053	32	5,62
OMG	1924	51	5,27
MAID	1864	117	5,10
BTG	1479	59	4,05
NEO	1105	22	3,03
XTZ	993	18	2,72
EOS	683	11	1,87
QTUM	664	51	1,82
IOST	619	90	1,69
BNT	479	144	1,31
ONT	448	37	1,23
XVG	433	91	1,19
ETH	429	2	1,17
LSK	388	64	1,06
BTC	346	1	0,95
LTC	187	7	0,51
XEM	64	25	0,18
XLM	52	12	0,14
ICX	48	60	0,13
REP	23	66	0,06
TRX	13	15	0,04
ETC	4	28	0,01
ZIL	3	70	0,01
XRP	2	4	0,01
ZEC	2	32	0,01
BCH	1	6	0,00
ADA	0	10	0,00
BSV	0	11	0,00
XMR	0	15	0,00

(b) Returns

Table 8: Dominance Score (DS) for each cryptocurrency after removing noise and trend, observed via volatility (a) and returns (b), respectively. Each table has 4 columns: Crypto represents cryptocurrency symbols; DS represents Dominance Score values; Rank represents the ranking of cryptocurrencies; Percentage represents the ratio of one cryptocurrency's Dominance Score value to the sum of all Dominance Score values. The values are ordered from high to low.

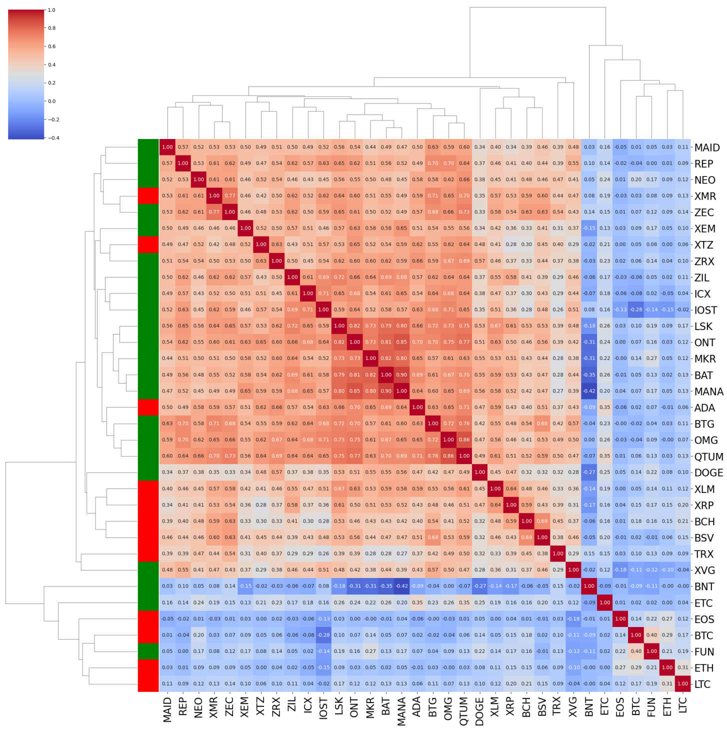


Figure 10: The correlation between 34 cryptocurrencies in terms of the number of transactions from 13/02/2019 until 06/04/2021 (on a 30-minute basis). Cryptocurrencies which are ranked 21 or lower are considered low-ranking (marked as green), while the rest are considered high-ranking (marked as red).

patterns. That is, an increase or decrease in the number of transactions of one coin is reflected in other coins, resulting in a similarity among their volatility movements. However, the biggest coins such as Bitcoin, Ethereum and Litecoin tend to behave independently from the rest since they show nearly zero correlation with other coins, showing that they have their unique trading patterns. In the cryptocurrency market, only a few assets are well-known and have a large market capitalization, while the majority of coins are unpopular and do not attract much public attention. Therefore, in the absence of noise and trend, we should see real connections between different cryptocurrencies. That is, when the volatility of a small coin changes, it tends to affect the majority of cryptocurrencies. Conversely, changes in the volatility of a major coin are usually isolated due to its distinct trading pattern.

Overall, there is one main finding that has been uncovered from the results. In particular, the significant impact of the largest coins in the network when considering the noise and trend effect highlights the crucial role of people's sentiment in the cryptocurrency market. Individuals primarily focus on the most prominent coins like BTC, ETH, and LTC, using them as a basis to evaluate the entire market. Consequently, they react when the prices of these coins change and anticipate similar changes in other assets [98, 99]. This results in similar trading decisions, ultimately leading to parallel volatility movements between different cryptocurrencies. However, without the effects of noise and trend, the dominance of large cryptocurrencies tends to diminish, giving way to the rising influence of minor and less famous coins in the network referred to above. This observation highlights the true nature of the cryptocurrency market. That is, small cryptocurrencies are frequently targeted for a Pump & Dump, leading to an increase in its volatility and a spillover effect that impacts a broad spectrum of coins [96]. Additionally, the transaction activity appears to exhibit similarities among the majority of small cryptocurrencies, while major cryptocurrencies demonstrate their own distinctive trading patterns (see Figure 10). The similarity in transaction activity among small cryptocurrencies might arise from the lead-lag phenomenon[12] between different cryptocurrencies. That is, small cryptocurrencies often follow the price movements of major cryptocurrencies like Bitcoin (BTC) and Ethereum (ETH) with a slight delay, usually within a few minutes. As a result, it is feasible to generate a profit by purchasing small cryptocurrencies whenever the price of Bitcoin (or ETH) increases, waiting a few minutes until the price of the small coins increases as well, and then selling them [100]. Another possible reason for the similarity in transaction activity is that cryptocurrencies with a low market capitalization are often used as safe-heavens in a portfolio, especially during turbulent economic and market conditions [101].

Furthermore, we notice another common result from Tables 5 to 8. That is, cryptocurrencies with the highest influence are BAT, MKR and FUN. This seems to stem from their increasing popularity and use cases. Specifically, these cryptocurrencies gain higher and higher usage demand and are associated with various cryptocurrencies in the market. In particular:

- **BAT**[13]: Since the beginning, BAT has been shown to have a robust business model and real-world use cases [102]. This cryptocurrency has experienced a continuous surge in usage, partly thanks to the increase in usage of the Brave browser. To date, Brave has 55 million monthly active users, 16 million daily active users and millions of verified creators accepting BAT. Bat is considered one of the most successful alt-coins to date. Moreover, it is bridged across Ethereum and Solana blockchains and offers utility to both ecosystems [103, 104].

- **MKR**[14]: MKR is created to govern the MakerDAO platform. Specifically, MakerDAO offers its community of MKR holders the right to vote on risk management and business logic. Thus, this coin plays an important role in the development of the platform [105]. Moreover, MKR is also utilized for paying various fees associated with generating DAI- one of the most famous stablecoins at the time of writing [105]. Initially, DAI served primarily as a means of lending and borrowing crypto assets on MakerDAO. Over time, its utility expanded to a wide range of applications on the Ethereum blockchain such as the creation of smart contracts. Thanks to the success of the Ethereum blockchain, DAI maintains its popularity and is relevant to various cryptocurrencies [105, 106]. Consequently, MKR experiences increased usage and is associated with numerous cryptocurrencies, as a result of the DAI's flourishing.

- **FUN**[15]: FUN is the only token accepted for making as well as receiving payment from players and game creators, respectively, on FunFair. Thus, players have to exchange other cryptocurrencies or fiat currencies into FUN to be able to play on FunFair. This online gaming platform has experienced a significant increase in different aspects, including business scale, daily active users, and net worth [107]. Especially, since the outbreak of the pandemic, online gaming platforms have attracted a record amount of users as a result of their being forced to stay at home due to the lockdown policy [108]. Eventually, the demand for using FUN keeps increasing over time.

[12] A lead–lag effect describes the situation where one (leading) variable is cross-correlated with the values of another (lagging) variable at later times.

[13] A cryptocurrency invented for revolutionizing the advertising industry on the internet. This coin is used on the Brave web browser as a reward for Brave users when they read an ads. This browser has a unique mechanism to block ads and only recommends relevant ads based on users' preferences (`https://basicattentiontoken.org/`).

[14] A main token on a peer-to-peer decentralized protocol called MakerDAO. This platform serves as an online bank for cryptocurrencies, facilitating borrowing, lending and savings of various cryptocurrencies (`https://makerdao.com/en/`).

[15] A token on the decentralized, cryptocurrency-based casino gaming platform called FunFair (`https://funfair.games/`), which is the number one online gaming platform in the world.

6. Conclusions

In this study, we constructed a time-varying network of 34 cryptocurrencies with a mix of low and high rankings. Our main contributions to the existing literature arise from 2 aspects: Firstly, the use not only of the return time series but also the volatility time series to observe the time-varying correlations between different cryptocurrencies. Secondly, the use of noise and trend removal scheme, which is not widely considered in the cryptocurrency market at the moment. To our knowledge, this is one of the first studies using volatility time series to calculate the correlation coefficients between different cryptocurrencies. Our expectation is that volatility information can provide new insights compared to return information. Thus, this draws a more complete picture of cryptocurrency correlations. Besides this, removing noise and trend from cryptocurrencies is expected to help us find out underlying characteristics of the cryptocurrency market that are invisible with the existence of noise and trend.

We found that the use of volatility provides different signals compared to the return one. In particular, the returns-based correlation network reacts to the change in market condition between January and July 2020 (e.g. during the outbreak of the Covid-19 pandemic and the global economic crisis) by changing its structure and this change lasts until the market recovers to its previous condition. In the meantime, the volatility-based network can point out the most changing period within a critical event, such as the worst period of the market crash in March 2020 and the most bullish period in 2021. From these findings, investors can adjust their portfolios to benefit from a particular market condition. Moreover, they can anticipate the movements in the market, especially major events such as the economic crisis and health crisis by using the volatility-based network, thereby preparing and proposing a reasonable investment strategy to adapt to those movements.

We also used the *PageRank* method to analyze the influence of each cryptocurrency on the collection of 34 coins collected from the HitBTC exchange and found contradicting results between before and after the noise and trend removal. Specifically, low-ranking cryptocurrencies have the greater influence on the collection after denoising and detrending while the most influential coins in the pre-denoised and detrended collection are high-ranking cryptocurrencies (e.g. BTC, ETH and BCH). More interestingly, we found that the most influential cryptocurrencies after denoising and detrending are BAT, MKR and FUN. This is explained by their increasing popularity and use cases. From these results, investors should be aware of low-ranking cryptocurrencies and not underestimate them. Moreover, knowing the correlation between different cryptocurrencies helps investors adjust their portfolios to reduce the risk while maximizing future returns. For instance, they can avoid investing in cryptocurrencies with strong correlations and diversify their portfolios by choosing cryptocurrencies with low correlations.

This work can be expanded in the future in different ways. Firstly, one can take the correlation of different cryptocurrencies into consideration to create portfolio optimization models. For example, the models can avoid choosing strongly correlated cryptocurrencies while spending a portion of their budget on safe-haven cryptocurrencies. Secondly, researchers can expand on this study's concepts to other financial asset classes such as stocks, commodities as well as a combination of different asset classes.

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References

[1] G. Giudici, A. Milne, and D. Vinogradov, "Cryptocurrencies: market analysis and perspectives," *Journal of Industrial and Business Economics*, vol. 47, pp. 1–18, 2020.

[2] Y. Liu and A. Tsyvinski, "Risks and returns of cryptocurrency," *The Review of Financial Studies*, vol. 34, no. 6, pp. 2689–2727, 2021.

[3] D. Fantazzini and S. Zimin, "A multivariate approach for the simultaneous modeling of market risk and credit risk for cryptocurrencies," *Journal of Industrial and Business Economics*, vol. 47, pp. 19–69, 2020.

[4] N. James and M. Menzies, "Collective correlations, dynamics, and behavioural inconsistencies of the cryptocurrency market over time," *Nonlinear Dynamics*, vol. 107, no. 4, pp. 4001–4017, 2022.

[5] D. Yermack, "Is bitcoin a real currency? an economic appraisal," in *Handbook of digital currency*, pp. 31–43, Elsevier, 2015.

[6] A. Bejaoui, W. Frikha, A. Jeribi, and A. F. Bariviera, "Connectedness between emerging stock markets, gold, cryptocurrencies, defi and nft: Some new evidence from wavelet analysis," *Physica A: Statistical Mechanics and its Applications*, vol. 619, p. 128720, 2023.

[7] M. Balcilar, H. Ozdemir, and B. Agan, "Effects of covid-19 on cryptocurrency and emerging market connectedness: Empirical evidence from quantile, frequency, and lasso networks," *Physica A: Statistical Mechanics and its Applications*, vol. 604, p. 127885, 2022.

[8] I. Omri, "Directional predictability and volatility spillover effect from stock market indexes to bitcoin: evidence from developed and emerging markets," *The Journal of Risk Finance*, no. ahead-of-print, 2023.

[9] M. Wątorek, J. Kwapień, and S. Drożdż, "Cryptocurrencies are becoming part of the world global financial market," *Entropy*, vol. 25, no. 2, p. 377, 2023.

[10] S. Hyun, J. Lee, J.-M. Kim, and C. Jun, "What coins lead in the cryptocurrency market: using copula and neural networks models," *Journal of Risk and Financial Management*, vol. 12, no. 3, p. 132, 2019.

[11] M. Maiti, Y. Vyklyuk, and D. Vuković, "Cryptocurrencies chaotic co-movement forecasting with neural networks," *Internet Technology Letters*, vol. 3, no. 3, p. e157, 2020.

[12] P. Pagnottoni, "Superhighways and roads of multivariate time series shock transmission: Application to cryptocurrency, carbon emission and energy prices," *Physica A: Statistical Mechanics and its Applications*, vol. 615, p. 128581, 2023.

[13] A. P. N. Nguyen, T. T. Mai, M. Bezbradica, and M. Crane, "The cryptocurrency market in transition before and after covid-19: An opportunity for investors?," *Entropy*, vol. 24, no. 9, p. 1317, 2022.

[14] S. Drożdż, J. Kwapień, and M. Wątorek, "What is mature and what is still emerging in the cryptocurrency market?," *Entropy*, vol. 25, no. 5, p. 772, 2023.

[15] I. Cohen, Y. Huang, J. Chen, J. Benesty, J. Benesty, J. Chen, Y. Huang, and I. Cohen, "Pearson correlation coefficient," *Noise reduction in speech processing*, pp. 1–4, 2009.

[16] J. H. Zar, "Spearman rank correlation," *Encyclopedia of biostatistics*, vol. 7, 2005.

[17] E. Keogh and C. A. Ratanamahatana, "Exact indexing of dynamic time warping," *Knowledge and information systems*, vol. 7, pp. 358–386, 2005.

[18] V. Marella, B. Upreti, J. Merikivi, and V. K. Tuunainen, "Understanding the creation of trust in cryptocurrencies: the case of bitcoin," *Electronic Markets*, vol. 30, no. 2, pp. 259–271, 2020.

[19] S. A. Manavi, G. Jafari, S. Rouhani, and M. Ausloos, "Demythifying the belief in cryptocurrencies decentralized aspects. a study of cryptocurrencies time cross-correlations with common currencies, commodities and financial indices," *Physica A: Statistical Mechanics and its Applications*, vol. 556, p. 124759, 2020.

[20] T. T. Mai, M. Bezbradica, and M. Crane, "Learning behaviours data in programming education: Community analysis and outcome prediction with cleaned data," *Future Generation Computer Systems*, vol. 127, pp. 42–55, 2022.

[21] M. M. L. de Prado, *Machine learning for asset managers*. Cambridge University Press, 2020.

[22] J.-P. Bouchaud and M. Potters, "Financial applications of random matrix theory: a short review," *arXiv preprint arXiv:0910.1205*, 2009.

[23] T. C. Silva, P. V. B. Wilhelm, and B. M. Tabak, "The effect of interconnectivity on stock returns during the global financial crisis," *The North American Journal of Economics and Finance*, vol. 67, p. 101940, 2023.

[24] S. Shafiq, S. S. Qureshi, and M. Akbar, "Dynamic relationship of volatility of returns across different markets: evidence from selected next 11 countries," *Journal of Economic and Administrative Sciences*, no. ahead-of-print, 2023.

[25] T. Lan, L. Shao, H. Zhang, and C. Yuan, "The impact of pandemic on dynamic volatility spillover network of international stock markets," *Empirical Economics*, pp. 1–30, 2023.

[26] B. Korkusuz, D. G. McMillan, and D. Kambouroudis, "Complex network analysis of volatility spillovers between global financial indicators and g20 stock markets," *Empirical Economics*, vol. 64, no. 4, pp. 1517–1537, 2023.

[27] K.-H. Choi, R. P. McIver, S. Ferraro, L. Xu, and S. H. Kang, "Dynamic volatility spillover and network connectedness across asx sector markets," *Journal of Economics and Finance*, pp. 1–15, 2021.

[28] S. J. H. Shahzad, E. Bouri, L. Kristoufek, and T. Saeed, "Impact of the covid-19 outbreak on the us equity sectors: Evidence from quantile return spillovers," *Financial Innovation*, vol. 7, no. 1, pp. 1–23, 2021.

[29] G. B. Koumou, "Diversification and portfolio theory: a review," *Financial Markets and Portfolio Management*, vol. 34, no. 3, pp. 267–312, 2020.
[30] D. K. Nguyen, N. Topaloglou, and T. Walther, "Asset classes and portfolio diversification: Evidence from a stochastic spanning approach," *Available at SSRN 3721907*, 2020.
[31] B. Abuzayed and N. Al-Fayoumi, "Diversification and hedging strategies of green bonds in financial asset portfolios during the covid-19 pandemic," *Applied Economics*, pp. 1–11, 2022.
[32] Y. Ghabri, K. Guesmi, and A. Zantour, "Bitcoin and liquidity risk diversification," *Finance Research Letters*, vol. 40, p. 101679, 2021.
[33] H. M. Reyad, M. A. Zariyawati, T. S. Ong, and H. Muhamad, "The impact of macroeconomic risk factors, the adoption of financial derivatives on working capital management, and firm performance," *Sustainability*, vol. 14, no. 21, p. 14447, 2022.
[34] J. Gavin and M. Crane, "Community detection in cryptocurrencies with potential applications to portfolio diversification," *arXiv preprint arXiv:2108.09763*, 2021.
[35] H. Chaudhari and M. Crane, "Cross-correlation dynamics and community structures of cryptocurrencies," *Journal of Computational Science*, vol. 44, p. 101130, 2020.
[36] C. Chen, L. Liu, and N. Zhao, "Fear sentiment, uncertainty, and bitcoin price dynamics: The case of covid-19," *Emerging Markets Finance and Trade*, vol. 56, no. 10, pp. 2298–2309, 2020.
[37] M. Jose, G. Silvio, R. Heather, S. Adel, and C. Martin, "Correlation of worldwide markets' entropies," *Centro*, 2006.
[38] M. Kumar, G. S. Priya, P. Gadipudi, I. Agarwal, and S. Sumalatha, "Exploring patterns and correlations between cryptocurrencies and forecasting crypto prices using influential tweets," in *Machine Learning, Image Processing, Network Security and Data Sciences: 4th International Conference, MIND 2022, Virtual Event, January 19–20, 2023, Proceedings, Part II*, pp. 308–321, Springer, 2023.
[39] G. Rubbaniy, S. Polyzos, S. K. A. Rizvi, and A. Tessema, "Covid-19, lockdowns and herding towards a cryptocurrency market-specific implied volatility index," *Economics Letters*, vol. 207, p. 110017, 2021.
[40] S. A. Gyamerah, "Covid-19 pandemic and herding behaviour in cryptocurrency market," *Applied Finance Letters*, vol. 10, pp. 58–66, 2021.
[41] S. Drożdż, J. Kwapień, P. Oświęcimka, T. Stanisz, and M. Wątorek, "Complexity in economic and social systems: Cryptocurrency market at around covid-19," *Entropy*, vol. 22, no. 9, p. 1043, 2020.
[42] S. Nayak, B. B. Misra, and H. S. Behera, "Impact of data normalization on stock index forecasting," *International Journal of Computer Information Systems and Industrial Management Applications*, vol. 6, no. 2014, pp. 257–269, 2014.
[43] C. Bandt and B. Pompe, "Permutation entropy: a natural complexity measure for time series," *Physical review letters*, vol. 88, no. 17, p. 174102, 2002.
[44] R. Lopez-Ruiz, H. L. Mancini, and X. Calbet, "A statistical measure of complexity," *Physics letters A*, vol. 209, no. 5-6, pp. 321–326, 1995.
[45] H. Y. Sigaki, M. Perc, and H. V. Ribeiro, "Clustering patterns in efficiency and the coming-of-age of the cryptocurrency market," *Scientific reports*, vol. 9, no. 1, p. 1440, 2019.
[46] F. Pérez-Cruz, J. A. Afonso-Rodriguez, and J. Giner, "Estimating garch models using support vector machines," *Quantitative Finance*, vol. 3, no. 3, p. 163, 2003.
[47] D. Tjøstheim, H. Otneim, and B. Støve, "Statistical dependence: Beyond pearson's ρ," *Statistical science*, vol. 37, no. 1, pp. 90–109, 2022.
[48] S. Lieberson, "Limitations in the application of non-parametric coefficients of correlation," *American Sociological Review*, vol. 29, no. 5, pp. 744–746, 1964.
[49] C.-X. Nie, "Analysis of critical events in the correlation dynamics of cryptocurrency market," *Physica A: Statistical Mechanics and its Applications*, vol. 586, p. 126462, 2022.
[50] H. R. Atiya and H. N. Nawaf, "Prediction of link weight of bitcoin network by leveraging the community structure," in *IOP Conference Series: Materials Science and Engineering*, vol. 928, p. 032080, IOP Publishing, 2020.
[51] C.-X. Nie, "A network-based method for detecting critical events of correlation dynamics in financial markets," *Europhysics Letters*, vol. 131, no. 5, p. 50001, 2020.
[52] J.-P. Onnela, A. Chakraborti, K. Kaski, and J. Kertesz, "Dynamic asset trees and black monday," *Physica A: Statistical Mechanics and its Applications*, vol. 324, no. 1-2, pp. 247–252, 2003.
[53] L. Zhao, W. Li, and X. Cai, "Structure and dynamics of stock market in times of crisis," *Physics Letters A*, vol. 380, no. 5-6, pp. 654–666, 2016.
[54] A. Edelman and N. R. Rao, "Random matrix theory," *Acta numerica*, vol. 14, pp. 233–297, 2005.
[55] J. B. De Long, A. Shleifer, L. H. Summers, and R. J. Waldmann, "Noise trader risk in financial markets," *Journal of political Economy*, vol. 98, no. 4, pp. 703–738, 1990.
[56] T. Dimpfl and F. J. Peter, "Nothing but noise? price discovery across cryptocurrency exchanges," *Journal of Financial Markets*, vol. 54, p. 100584, 2021.
[57] T. Li, D. Shin, and B. Wang, "Cryptocurrency pump-and-dump schemes," *Available at SSRN 3267041*, 2021.

[58] C. Katarzyna, "Cryptocurrencies: opportunities, risks and challenges for anti-corruption compliance systems," in *OECD Conference on Global Anti-corruption and Integrity Forum. Paris, March*, pp. 20–21, 2019.

[59] R. Auer and S. Claessens, "Regulating cryptocurrencies: assessing market reactions," *BIS Quarterly Review September*, 2018.

[60] A. Sarr and T. Lybek, "Measuring liquidity in financial markets," 2002.

[61] Z. Burda and A. Jarosz, "Cleaning large-dimensional covariance matrices for correlated samples," *Phys. Rev. E*, vol. 105, no. 3, p. 034136, 2022.

[62] O. Ledoit and M. Wolf, "Nonlinear shrinkage estimation of large-dimensional covariance matrices," *Ann. Stat.*, vol. 40, no. 2, pp. 1024–1060, 2012.

[63] J. Bun and A. Knowles, "An optimal rotational invariant estimator for general covariance matrices: The outliers," *Preprint*, 2018.

[64] R. Markowitz, "Cleaning correlation matrices," 2016.

[65] T. Conlon, H. J. Ruskin, and M. Crane, "Random matrix theory and fund of funds portfolio optimisation," *Physica A*, vol. 382, no. 2, pp. 565–576, 2007.

[66] L. Yang, M. R. McKay, and R. Couillet, "High-dimensional mvdr beamforming: Optimized solutions based on spiked random matrix models," *IEEE Trans. Signal Process*, vol. 66, no. 7, pp. 1933–1947, 2018.

[67] T. Heimo, K. Kaski, and J. Saramäki, "Maximal spanning trees, asset graphs and random matrix denoising in the analysis of dynamics of financial networks," *Physica A: Statistical Mechanics and its Applications*, vol. 388, no. 2-3, pp. 145–156, 2009.

[68] B. Council, "10 blockchain protocols to know in 2023." `https://www.blockchain-council.org/blockchain/10-blockchain-protocols/`, 2023.

[69] S. Zhang and J.-H. Lee, "Analysis of the main consensus protocols of blockchain," *ICT express*, vol. 6, no. 2, pp. 93–97, 2020.

[70] P. V. J. da Gama Silva, M. C. Klotzle, A. C. F. Pinto, and L. L. Gomes, "Herding behavior and contagion in the cryptocurrency market," *Journal of Behavioral and Experimental Finance*, vol. 22, pp. 41–50, 2019.

[71] M. O'Searcoid, *Metric spaces*. Springer Science & Business Media, 2006.

[72] C. Huang, X. Zhao, R. Su, X. Yang, and X. Yang, "Dynamic network topology and market performance: A case of the chinese stock market," *International Journal of Finance & Economics*, vol. 27, no. 2, pp. 1962–1978, 2022.

[73] B. Ghosh, M. Motagh, M. H. Haghighi, M. S. Vassileva, T. R. Walter, and S. Maghsudi, "Automatic detection of volcanic unrest using blind source separation with a minimum spanning tree based stability analysis," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7771–7787, 2021.

[74] A. Denkowska and S. Wanat, "Linkages and systemic risk in the european insurance sector. new evidence based on minimum spanning trees," *Risk Management*, vol. 24, no. 2, pp. 123–136, 2022.

[75] Q. Nguyen, N. Nguyen, and L. Nguyen, "Dynamic topology and allometric scaling behavior on the vietnamese stock market," *Physica A: Statistical Mechanics and its Applications*, vol. 514, pp. 235–243, 2019.

[76] J. B. Kruskal, "On the shortest spanning subtree of a graph and the traveling salesman problem," *Proceedings of the American Mathematical society*, vol. 7, no. 1, pp. 48–50, 1956.

[77] F. Huang, P. Gao, and Y. Wang, "Comparison of prim and kruskal on shanghai and shenzhen 300 index hierarchical structure tree," in *2009 International Conference on Web Information Systems and Mining*, pp. 237–241, IEEE, 2009.

[78] R. N. Mantegna, "Hierarchical structure in financial markets," *The European Physical Journal B-Condensed Matter and Complex Systems*, vol. 11, pp. 193–197, 1999.

[79] B. Zhao, W. Yang, J. Wen, and W. Zhang, "The financial market in china under the covid-19," *Emerging Markets Finance and Trade*, vol. 58, no. 13, pp. 3726–3738, 2022.

[80] R. Khanna and I. Guler, "Degree assortativity in collaboration networks and invention performance," *Strategic Management Journal*, vol. 43, no. 7, pp. 1402–1430, 2022.

[81] S. Ilbeigipour and B. Teimourpour, "A social network analysis approach to evaluate the relationship between the mobility network metrics and the covid-19 outbreak," *Health Services Insights*, vol. 16, p. 11786329231173816, 2023.

[82] R. Grinis, A. Kislitsyn, I. Drozdov, and K. Shulga, "Are cryptocurrency markets running behind the fed? a significant shift in crypto markets microstructure," *A Significant Shift in Crypto Markets Microstructure (October 20, 2021). Available at SSRN: https://ssrn.com/abstract=3951812*, 2021.

[83] V. Jha and P. Tripathi, "Semantic modelling of multivariate time-series data in cognitive iot," in *2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS)*, vol. 1, pp. 943–948, IEEE, 2023.

[84] W. Song, Z. Wang, Y. Ye, and M. Fan, "Empirical studies on symbolic aggregation approximation under statistical perspectives for knowledge discovery in time series," in *2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*, pp. 1040–1046, IEEE, 2015.

[85] P. Katsiampa, L. Yarovaya, and D. Zięba, "High-frequency connectedness between bitcoin and other top-traded crypto assets during the covid-19 crisis," *Journal of International Financial Markets, Institutions and Money*, vol. 79, p. 101578, 2022.

[86] A. Kumar, N. Iqbal, S. K. Mitra, L. Kristoufek, and E. Bouri, "Connectedness among major cryptocurrencies in

standard times and during the covid-19 outbreak," *Journal of International Financial Markets, Institutions and Money*, vol. 77, p. 101523, 2022.

[87] W. Huang, P. Molyneux, S. Ongena, and R. Xie, "The new challenges of global banking and finance," *The European Journal of Finance*, pp. 1–7, 2023.

[88] J. Almeida and T. C. Gonçalves, "A systematic literature review of investor behavior in the cryptocurrency markets," *Journal of Behavioral and Experimental Finance*, p. 100785, 2023.

[89] E. Bouri, G. Azzi, and A. H. Dyhrberg, "On the return-volatility relationship in the bitcoin market around the price crash of 2013," *Economics*, vol. 11, no. 1, 2017.

[90] N. B. Cheikh, Y. B. Zaied, and J. Chevallier, "Asymmetric volatility in cryptocurrency markets: New evidence from smooth transition garch models," *Finance Research Letters*, vol. 35, p. 101293, 2020.

[91] S. Kakinaka and K. Umeno, "Asymmetric volatility dynamics in cryptocurrency markets on multi-time scales," *Research in International Business and Finance*, vol. 62, p. 101754, 2022.

[92] D. Easley, N. M. Kiefer, M. O'hara, and J. B. Paperman, "Liquidity, information, and infrequently traded stocks," *The Journal of Finance*, vol. 51, no. 4, pp. 1405–1436, 1996.

[93] J. Collins, "Crypto, crime and control," 2022.

[94] J. Y. Song, W. Chang, and J. W. Song, "Cluster analysis on the structure of the cryptocurrency market via bitcoin–ethereum filtering," *Physica A: Statistical Mechanics and its Applications*, vol. 527, p. 121339, 2019.

[95] J. Kwapień, M. Wątorek, and S. Drożdż, "Cryptocurrency market consolidation in 2020–2021," *Entropy*, vol. 23, no. 12, p. 1674, 2021.

[96] A. Dhawan and T. J. Putniņš, "A new wolf in town? pump-and-dump manipulation in cryptocurrency markets," *Review of Finance*, vol. 27, no. 3, pp. 935–975, 2023.

[97] M. Balcilar and H. Ozdemir, "On the risk spillover from bitcoin to altcoins: The fear of missing out and pump-and-dump scheme effects," *Journal of Risk and Financial Management*, vol. 16, no. 1, p. 41, 2023.

[98] P. D. DeVries, "An analysis of cryptocurrency, bitcoin, and the future," *International Journal of Business Management and Commerce*, vol. 1, no. 2, pp. 1–9, 2016.

[99] H. Bukhary, K. Shibano, and G. Mogi, "High-frequency spillover analysis of cryptocurrency in the exchange listings," *Edited by Sergey Y. Yurish*, p. 61, 2022.

[100] B. Anderson, "A tick-by-tick level measurement of the lead-lag duration between cryptocurrencies: The case of bitcoin versus cardano," *Investment Management and Financial Innovations*, vol. 20, no. 1, pp. 174–183, 2023.

[101] N. Kyriazis, S. Papadamou, P. Tzeremes, and S. Corbet, "The differential influence of social media sentiment on cryptocurrency returns and volatility during covid-19," *The Quarterly Review of Economics and Finance*, vol. 89, pp. 307–317, 2023.

[102] A. Bylund, "3 cryptocurrencies to buy in any bear market." `https://www.fool.com/investing/2023/01/30/3-cryptocurrencies-to-buy-in-any-bear-market/`, 2023.

[103] J. Caroline, "Brave browser surpasses 25 million monthly active users." `https://zycrypto.com/brave-browser-surpasses-25-million-monthly-active-users/`, 2021.

[104] Y. Khatri, "Privacy-focused brave browser added 1m new users in march." `https://finance.yahoo.com/news/privacy-focused-brave-browser-added-190400408.html`, 2020.

[105] Kriptomat, "What is cryptocurrency maker (mkr) and how does it work?." `https://kriptomat.io/cryptocurrencies/maker/what-is-maker/`, 2023.

[106] M. Young, "How dai is dominating the world of nfts and digital art." `https://beincrypto.com/how-dai-is-dominating-the-world-of-nfts-and-digital-art/`, 2020.

[107] M. Pechman, "Funfair (fun) gains 183% as the blockchain-based gaming industry grows." `https://cointelegraph.com/news/funfair-fun-gains-183-as-the-blockchain-based-gaming-industry-grows`, 2021.

[108] E. Howcroft, "Virtual real estate plot sells for record $2.4 million." `https://www.reuters.com/markets/currencies/virtual-real-estate-plot-sells-record-24-million-2021-11-23/`, 2021.