Correlation-based Dynamics and Systemic Risk Measures in the Cryptocurrency Market

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***Abstract*—Cryptocurrency is a rapid developing financial technology innovation which has attracted a large number of people around the world. The high-speed evolution, radical price fluctuations of cryptocurrency, and the inconsistent attitudes of monetary authorities in different countries have triggered panic and chain reactions towards the application and adoption of cryptocurrency and have caused public security related events. So far, a lot of researches and analyses have focused on just one or only a few number of cryptocurrencies, a comprehensive analysis of the whole cryptocurrency market and its systemic risk is still lacking. In this paper, we analyze the dynamics and systemic risk of the cryptocurrency market based on the public available price history. We first validated that the correlation matrix and asset tree are good tools to analyze the risk and stability of the cryptocurrency market. Furthermore, consistent with public perception, our quantitative analysis reveals that the cryptocurrency market is relatively fragile and unstable. Our work is the first to investigate the systemic risk of the whole cryptocurrency market and may shed some light on cryptocurrency related investment decision, regulation, and legislation.**

***Index Terms*—cryptocurrency, blockchain, financial market, correlation matrix, asset tree, systemic risk**

I. Introduction

Cryptocurrency is a special digital currency which uses blockchain to build a decentralized public ledger without the central authority to secure transactions and control the creation of new units of currency. Since the first cryptocurrency Bitcoin emerged in 2009 [1], cryptocurrencies have now formed a complex system implemented through exchanges, wallets, payments, and coin mining [2]. According to the website Cryptocurrency Market Capitalizations [1], in April 2018, there are over 1600 active currencies in the cryptocurrency market with a total market cap of more than $268 billion, indicating that the cryptocurrency market has already become an important part of the international financial market.

Nonetheless, the cryptocurrency market is still under rapidly developing and transforming, experiencing dramatic price fluctuations, and facing inconsistent regulation rules announced by monetary authorities of different countries [3]. All of these pose a great challenge towards a comprehensive understanding of the cryptocurrency market and its systemic risk. Besides financial related security issues, investment loss caused by misleading information, unfamiliar with the nature of cryptocurrency, and governmental regulation also causes public security related events. So far, most of the current researches focus on the following two directions, one is the basic blockchain and other relevant technologies [4], [5], and the other is the analysis that focused on a single or several cryptocurrencies, including descriptive statistics [6], [7], network evolution [8]–[10], price bubbles and determinants [11]–[13].

It should be noted that very little work has been carried out on the whole cryptocurrency market. Gandal and Halaburda [14] analyzed the competition of seven cryptocurrencies by examining their exchange rates over time and interpreted their findings with the help of network effects. ElBahrawy et al. [15] investigated the evolutionary dynamics of cryptocurrency market using statistical methods. In contrast, there exists a large number of literatures that analyze traditional financial assets, such as stock [16]–[20] and foreign exchange [21]–[25]. Among which, correlation matrix and asset tree are widely adopted as they provide a unified framework to systematically investigate the dynamics of various financial markets and provide key information for a series of financial activities.

In this paper, based on price data from January 1, 2015 to April 20, 2018, we use the framework of the correlation matrix and the asset tree to analyze the dynamics of the cryptocurrency market. In addition, based on the global minimum variance (GMV) portfolio, we adopt the overall portfolio risk to measure the systemic risk. We find that the correlation matrix and the asset tree are good tools to investigate the cryptocurrency market. We also show that the cryptocurrency market is relatively fragile through quantitative analysis, which is consistent with the public perception on the cryptocurrency market. Our work may shed some light on the nature of price fluctuations in the cryptocurrency market and provides guidance for investing, regulation, and legislation.

II. DATASETS

Among the complete list of cryptocurrencies, we investigate the daily close price data of $N = 50$ currencies. We choose them for the following two reasons. First, in April 2018, they accounted for more than 90% of the total capitalization and

[1] http://coinmarketcap.com/currencies/views/all/

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TABLE I
THE SET OF CRYPTOCURRENCIES

Currency	Symbol	Currency	Symbol	Currency	Symbol
Bitcoin	BTC	OmiseGO	OMG	Populous	PPT
Ethereum	ETH	Qtum	QTUM	Waves	WAVES
XRP	XRP	Zcash	ZEC	Status	SNT
EOS	EOS	ICON	ICX	RChain	RHOC
Litecoin	LTC	Lisk	LSK	Hshare	HSR
Stellar	XLM	Bytecoin	BCN	Stratis	STRAT
Cardano	ADA	0x	ZRX	Ardor	ARDR
IOTA	MIOTA	Aeternity	AE	Komodo	KMD
NEO	NEO	Decred	DCR	Ark	ARK
TRON	TRX	BitShares	BTS	Gas	GAS
Monero	XMR	Augur	REP	PIVX	PIVX
Dash	DASH	Steem	STEEM	Nano	NANO
NEM	XEM	Siacoin	SC	Verge	XVG
Dogecoin	DOGE	Vechain	VEN	Basic Attention Token	BAT
Bitcoin Cash	BCH	Bitcoin Gold	BTG		
Ethereum Classic	ETC	KingN Coin	KNC	Veritaseum	VERI
Binance Coin	BNB	Kucoin Shares	KCS	Waltonchain	WTC

each market share is fairly stable during the analysis period, this indicates that these currencies are more important than others. Second, the cryptocurrency market is changing over time, new currencies are released and some old currencies no longer have a trading volume on the exchange markets. To ensure the reliability of the analysis, we thus discard the currencies whose data period is less than six months.

We obtained the historical close daily price from the website Cryptocurrency Market Capitalizations. In particular, the dataset consists of cryptocurrencies from January 1, 2015 to April 20, 2018. Here each price is calculated by taking the volume weighted average of all prices reported at each market, and we should mention that these markets contain the majority of the markets, but not all of them. The currencies and the respective symbols are listed in Table I.

III. METHODOLOGY

In this section, we first construct the correlation matrix and asset tree using synchronized time series of different cryptocurrencies, which provide a basis for the subsequent analysis. Then we introduce the indicators that measure the cryptocurrency market from three aspects: volatility, centrality structure, and systemic risk.

A. Correlation Matrix and Asset Tree

The price of an asset is often affected by many factors, including inflation, economic growth or economic recession, and fluctuations in the global financial market [26]. We use the logarithmic return, which is by far the most widely used variable in econophysics, to investigate the price changes. Let $P_i\left(t\right)$ be the close price of cryptocurrency i on day t, the daily logarithmic return r_i is then

$$r_i\left(t\right) = \ln\frac{P_i(t)}{P_i(t-1)} = \ln P_i(t) - \ln P_i(t-1). \qquad (1)$$

A sequence of logarithmic returns for consecutive trading days over a window with width T constitutes a return vector $\boldsymbol{r}_i$. For example, if T is set to 3 months, then the return vector includes 90 elements, each corresponding to the return of that day.

In order to quantify the correlation of price changes between cryptocurrencies over the same period, we use the correlation coefficient. Specifically, the correlation coefficient between cryptocurrency i and j is calculated by the cross-correlation function

$$C_{ij} = \frac{E(\boldsymbol{r}_i\boldsymbol{r}_j) - E(\boldsymbol{r}_i)E(\boldsymbol{r}_j)}{\sigma_i\sigma_j}, \qquad (2)$$

where $E(\cdot)$ denotes the expectation operator and σ_i is the standard deviation of currency i's return vector $\boldsymbol{r}_i$. By definition (2), C_{ij} is symmetric and varies from -1 (completely linear anti-correlated) to 1 (completely linear correlated). For a set of N cryptocurrencies, we can then form a symmetric correlation matrix C with $N(N-1)/2$ different coefficients.

Based on the relationship between price changes among cryptocurrencies, we can introduce a metric to visually represent the relative distance between cryptocurrencies by converting the correlation coefficient C_{ij} to a distance coefficient [17] D_{ij} by transformation

$$D_{ij} = \sqrt{2\left(1 - C_{ij}\right)}, \qquad (3)$$

where $0 \leq D_{ij} \leq 2$, since $-1 \leq C_{ij} \leq 1$. After applying this transformation, the distance coefficient meets the axiom: $D_{ij} = 0$ if and only if $i = j$; $D_{ij} = D_{ji}$; $D_{ij} \leq D_{ik} + D_{kj}$.

Using the distance matrix D obtained from the distance coefficient D_{ij}, a fully connected undirected graph $G = (V, E)$ with N nodes and $N(N-1)/2$ edges can be constructed, where the node represents the cryptocurrency and the weight of the edge between cryptocurrencies i and j represents the distance between them.

Based on the fully connected graph G, we use the classic Kruskal's algorithm [27] to construct the asset tree $\hat{G} = \left(V, \hat{E}\right)$, which is a loop-free connected graph, where all the N nodes are connected with $N-1$ edges and satisfy that the sum of all edge weights is minimum. The Kruskal's algorithm consists of the following steps: 1) Construct a new graph $\hat{G}$ with the same nodes as G but no edges; 2) Sort the edges in G by weight to find the minimum weighted edge in a constant time; 3) Add the edge with minimum weight to the graph $\hat{G}$ provided that $\hat{G}$ after the edge intersection is still a forest or a tree; 4) Repeat the Step 3 until all the nodes are connected in the graph $\hat{G}$. Using the asset tree, the number of valid edges is reduced from $N(N-1)/2$ to $N-1$.

To capture the dynamics of the cryptocurrency market, we further employ the method of rolling windows [28] as follows. Suppose we have a daily return series of length n, we use the first $T(T < n)$ observations to form the first correlation matrix and asset tree. Subsequently, we get an overlapping moving window of length T from the second to $(T+1)$-th observation, and form the second correlation matrix and asset tree. Slide the window until the last observation is included. We then obtain a series of correlation matrices and corresponding asset trees, which serve as the basis of the evolutionary dynamics to be discussed later. We explore a large number of values for window width T, and find the optimal value is T = 90 days (3 months) when noise and smoothing factors are taken into consideration [17]. By setting $T = 90$, a total of 1116 windows are applied.

B. Analysis indicators

In this part, we analyze the cryptocurrency market from three aspects: temporal volatility, centrality structure, and systemic risk.

1) Temporal Volatility

First, we use four elementary statistics to investigate the distribution of all correlation coefficients and the length of the asset tree, and we use the changes of these indicators to characterize the temporal volatility of the cryptocurrency market.

The first measure is the *mean* defined as

$$\overline{C(t)} = \frac{2}{N\,(N-1)} \sum\nolimits_{C_{ij}^t \in C^t} C_{ij}^t. \tag{4}$$

Because of the symmetry of the correlation matrix, we only consider the non-diagonal elements $C_{ij}^t (i \neq j)$ in the upper or lower triangular matrix. In the context of financial market [17], this measure is called the *mean correlation coefficient* when the correlation matrix is used or the *normalized tree length* if otherwise the asset tree is employed.

The second measure is the *variance*, which measures how far the correlation coefficients are spread out from the mean and is defined as

$$V(t) = \frac{2}{N(N-1)} \sum\nolimits_{C_{ij}^t \in C^t} \left(C_{ij}^t - \overline{C(t)} \right)^2. \tag{5}$$

The third measure is the *skewness*, which quantifies the asymmetry of the correlation matrix with respect to the mean, i.e., the peak of the distribution, defined by

$$S(t) = \frac{2V(t)^{3/2}}{N(N-1)} \sum\nolimits_{C_{ij}^t \in C^t} \left(C_{ij}^t - \overline{C(t)} \right)^3. \tag{6}$$

In general, a negative value of skewness indicates that most of the correlation coefficients are concentrated on the right side of the distribution, while a positive value means concentrating on the left. For symmetrical distributions, such as the normal distribution, the value of skewness is zero.

The fourth measure is the *kurtosis*, which measures the fatness of the distribution of the correlation coefficients, i.e., the tails of the distribution, defined by

$$K(t) = \frac{2V(t)^2}{N(N-1)} \sum\nolimits_{C_{ij}^t \in C^t} \left(C_{ij}^t - \overline{C(t)} \right)^4 - 3. \tag{7}$$

The kurtosis of a normal distribution is 0. If the value of kurtosis is larger than 0, then the distribution has a fatter tail than the normal distribution, meaning that the random variable attains very large positive and negative values more than if it were normal. Otherwise, the distribution will have a thin tail when the kurtosis is negative.

2) Centrality Structure

The *central node* is considered to be the central and reference node of the tree, and it is important in the sense that any change in its price can have a strong impact on the whole market. Here we select the node with the highest influence strength (the sum of correlation coefficients of edges) as the central node. For an arbitrary node (or cryptocurrency) i in the asset tree, let Γ_i be the set of all its neighbors, then its influence strength is

$$IS_i = \sum\nolimits_{j \in \Gamma_i} C_{ij} = \sum\nolimits_{j \in \Gamma_i} \left(1 - D_{ij}^2/2\right). \tag{8}$$

Further, we use the occupation layer to represent the relative location of a specific node in the tree, which gauges the distance between the node and the central node. The layers of the asset tree are characterized by natural numbers 0, 1, 2, 3, $\cdots$, where the occupation layer of the central node is 0, the layer of the child of the central node is 1, and so on. To measure the average location of all nodes other than the central node, we define the *mean occupation layer* [17] as

$$l(t, v_c) = \frac{1}{N} \sum\nolimits_{i=1}^{N} \mathcal{L}\left(v_i^t\right), \tag{9}$$

where $\mathcal{L}\left(v_i^t\right)$ denotes the occupation layer of the node v_i.

3) Systemic Risk

The systemic risk is useful in a range of financial activities, including portfolio optimization, risk management, and derivative pricing. In the cryptocurrency market, the systemic risk can be used to measure the influence of occurrence of an event on a certain number of cryptocurrencies [29]. Given a set of N cryptocurrencies with average returns $\bar{r}$ and the estimated covariance Σ_r of returns which were calculated from historical price data, we are interested in the global minimum variance (GMV) portfolio. The risk at the GMV portfolio is the minimal risk that can be obtained by adjusting the weights of all the cryptocurrencies. Formally, this can be stated as $\min_w w^T \Sigma_r w$, subject to $\sum_{i=1}^N w_i = 1$ (full investment) and $w_i \geq 0$ (no short selling), which is a constrained quadratic programming problem.

As the magnitude of returns in the different market is different, to enhance the reliability of the results, we replace the covariance matrix with the correlation matrix, whose (i, j) entry is changed from $\mathrm{Cov}(r_i, r_j)$ to $C_{ij} = \mathrm{Cov}(r_i, r_j)/\sigma_i \sigma_j$ as C_{ij} scales from -1 to 1. So the final optimization problem can be stated as

$$\begin{array}{ll} \min\limits_{w} & w^T C w \\ \text{s.t.} & \sum_{i=1}^N w_i = 1 \\ & w_i \geq 0 \end{array}. \tag{10}$$

In order to investigate how the cryptocurrencies in the optimal portfolio are located with respect to the central node, we use the *weighted portfolio layer* as

$$l(t, v_c) = \sum\nolimits_{i=1}^{N} w_i \mathcal{L}\left(v_i^t\right). \tag{11}$$

In the framework of the asset tree, we also compare the behavior of the mean occupation layer and the weighted portfolio layer.

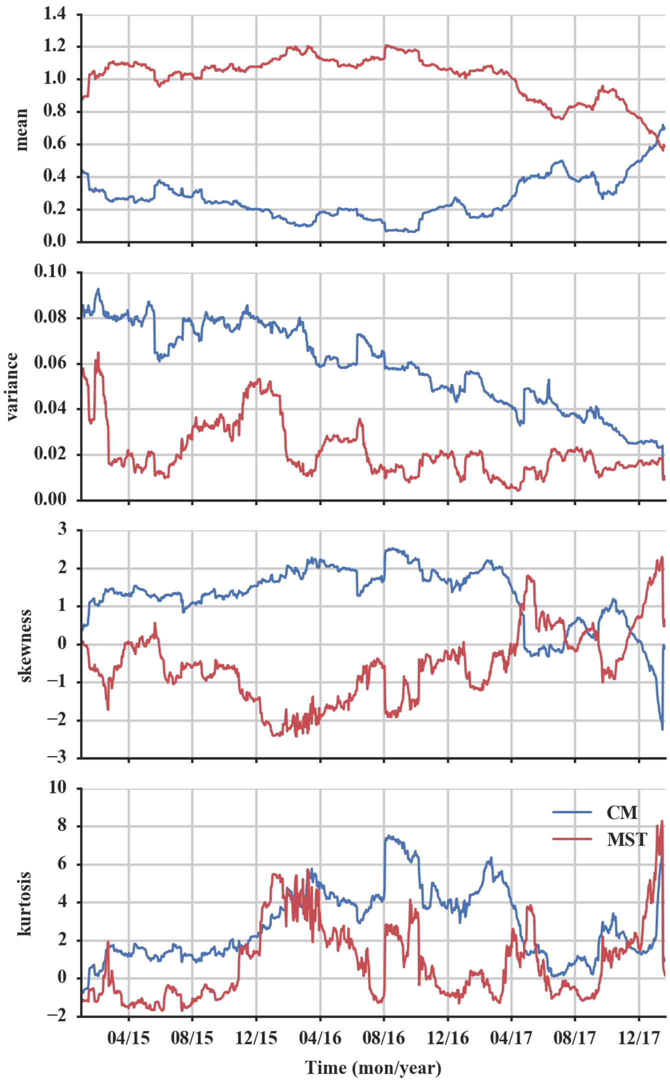

Fig. 1. The temporal volatility of the correlation coefficients matrix (blue) and asset tree (MST) path lengths (red).

IV. Results

A. Temporal Volatility

Here we use the four descriptive statistics defined in the above section to characterize the temporal volatility of the correlation coefficients and the asset tree path lengths.

First, financial events in the cryptocurrency market have a significant impact on the correlation coefficients as shown in Fig. 1. From July to October 2016, the cryptocurrency market has undergone the halving of Bitcoin production [30], the hard fork of Ethereum [31], and the stolen incident of the trading platform Bitfinex [32]. Correspondingly, we can see that in the course of this period, the value of the mean correlation coefficient reaches the lowest point, while the values of skewness and kurtosis respectively reach the highest points. Another evident period began in the second quarter of 2017, during which all four indicators have experienced dramatic fluctuations. A rising trend is observed in April 2017, roughly corresponding to the implementation of new legislation in Japan that accepts the using of digital currencies as a legal means of payment within the country [33]. When the US SEC issued the Investor Bulletin to announce that the requirement for regulation of Initial Coin Offerings (ICOs) and investors should be aware of potential risks of participating in ICOs [34], the mean correlation coefficient began to decline. Recovery is accompanied by an increase of the mean correlation coefficient. A second larger downward spike occurred when the People's Bank of China announced the illegality of ICOs and outlawed the use of cryptocurrencies for trading within the country [35]. In accordance with the release of bitcoin future contracts by CME and Cboe [36], the cryptocurrency market began to recover with an increase in the mean correlation coefficient. The above analysis illustrates that the correlation coefficient was changing dramatically during the uncertainty and turbulence of the cryptocurrency market. Further, we investigate whether these four indicators are correlated, as can be clearly seen in Fig. 1. For this, we determine the Pearson's correlation coefficient, and find that there exists a strong negative correlation between mean and variance, skewness, and kurtosis with -0.625, -0.930 and -0.669 respectively.

We now move on to the asset trees and its correlation relationship with the correlation matrix. As shown in Fig. 1, the asset tree maintains most of the characteristics of the correlation matrix, including the lowest/highest point from July to October in 2016, and the fluctuations starting from the second quarter of 2017. Further evidence is the correlation coefficient between the mean correlation coefficient and the normalized tree length, -0.957 fully demonstrates the strong negative correlation. In addition, we calculate the correlation of these four indicators between correlation matrix and asset tree. We find that the correlation between variance and kurtosis is positively correlated with 0.580 and 0.434, while the correlation of mean and skewness is negatively correlated with -0.957 and -0.828. Consequently, the asset tree can retain salient, but not all, of properties of the correlation matrix and is a good representation by reducing the information space from $N(N-1)/2$ correlation coefficient to $N-1$ edges of the asset tree.

The above analysis demonstrates that the correlation matrix and the asset tree can reflect the financial events in the cryptocurrency market as such in the traditional financial markets. The volatility of the four indicators of the correlation matrix and the asset tree all reveal that the cryptocurrency market is relatively unstable.

B. Centrality Structure

To establish a reference in the asset tree, we further analyze the central nodes using the criteria with the largest sum of correlation coefficients as defined in the last section. As shown in Fig. 2, the central node is varying: Bitcoin(BTC) dominates 47.7% of the time windows, followed by Ethereum (ETH) at 7.7%, then Stellar (XLM) at 6.5%, and Ark (ARK) at 5.7%.

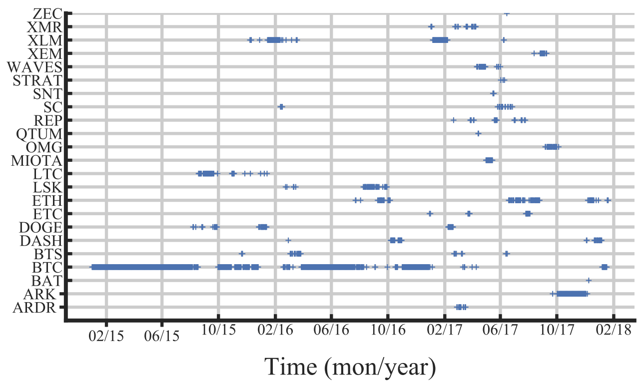

Fig. 2. The changes of central nodes over time.

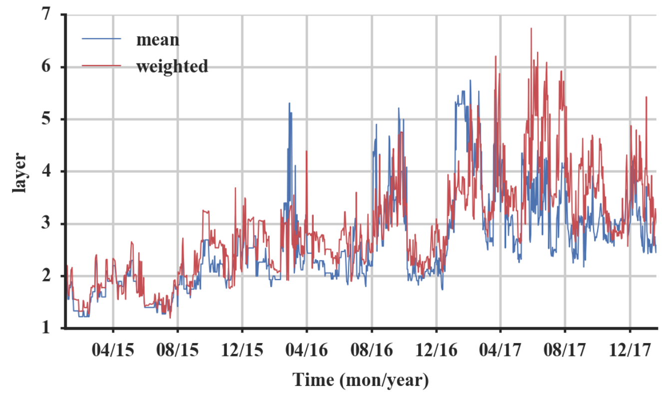

Fig. 3. Plots of the weighted portfolio layer (red) and the mean occupation layer (blue) with dynamic central nodes.

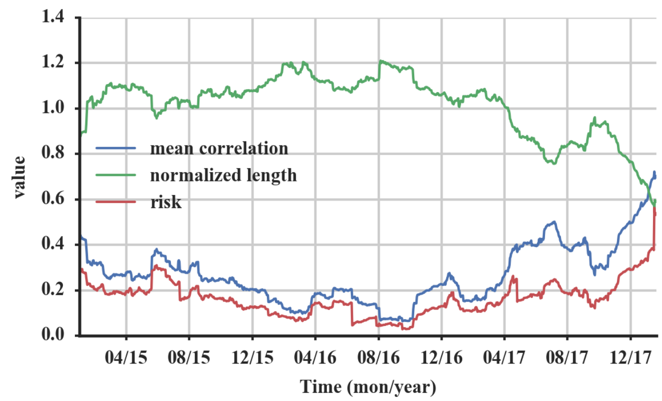

Fig. 4. Plots of the mean correlation coefficient (blue), the normalized tree length (green), and the systemic risk (red) as functions of time.

Overall, Bitcoin was the well-deserved dominant node in the early days, as Bitcoin is the oldest and the most popular cryptocurrency in the market. Almost all cryptocurrencies need to use Bitcoin as a medium if they want to trade with fiat currencies or other cryptocurrencies. But later, the central position of Bitcoin weakened, and the central node diversified, more than 20 out of 50 cryptocurrencies have taken the position of central node.

In addition, we characterize the topology of the asset tree by the mean occupation layer based on these central nodes. As shown in Fig. 3, the mean occupation layer fluctuates with the changes of the asset tree. Specifically, the two lowest values in July 2016 and October 2016, located symmetrically, correspond to the highest point of the normalized tree length. Roughly starting from 2017, the mean occupation layer tends to increase over time with fluctuations. The possible reason is that the stability of the cryptocurrency market has improved through the improvement of regulation and the enhancement of investor concerns. Therefore, high values of the mean occupation layer correspond to a stable market, while the extremely low values are associated with financial events, when the price changes of different cryptocurrencies are homogeneous, the distance between other nodes from the central node shortens.

Consequently, the diversity of the central node and the volatility of the mean occupation layer, both indicate the varying of the topology of the asset tree, thus the cryptocurrency market is relatively fragile with respect to traditional financial markets.

C. Systemic Risk

In this part, we adopt the minimum portfolio risk to measure the systemic risk, i.e., the influence of occurrence of an event on the cryptocurrency market.

First, we investigate how the cryptocurrencies included in the minimum portfolio risk are located with respect to the central node. From Fig. 3 we can see the behavior of the weighted portfolio layer and its comparison with the mean occupation layer. We find that the weighted portfolio layer is higher than the mean occupation layer practically at all times, specifically, the difference between the two layers is 0.31. Therefore, compared to the mean occupation layer, for the most time, the cryptocurrencies included in the minimum risk portfolio are consistently located further away from the central node, i.e., distributed on the outskirts of the tree, to eliminate risk.

Fig. 4 shows the curve of the minimum risk as the function of time, we find it has remarkable similarities to the curve of the mean correlation coefficient and the curve of the normalized tree length. Specifically, the correlation coefficient between the risk and the mean correlation coefficient is 0.906, while the coefficient between the risk and the normalized tree length is -0.788. Therefore, in the cryptocurrency market, though not as strong as the mean correlation coefficient, the normalized tree length can explain the diversification potential of the market.

In conclusion, the volatility of the weighted portfolio layer and the systemic risk further validate the relative instability of the cryptocurrency market, which is consistent with the public perception.

V. Conclusion

Based on the price history, this paper analyzed the cryptocurrency market from temporal volatility, centrality structure, and the systemic risk. We validated that the correlation matrix and the asset tree are good tools to investigate the dynamics and systemic risk of the cryptocurrency market by relating their dynamic changes to known financial events. As an emerging and rapidly developing financial market, our quantitative analysis reveals that the cryptocurrency market is relatively fragile and unstable with respect to traditional financial market which is consistent with public perception. However, this paper only investigated the cryptocurrency market, we will conduct a comparative analysis of cryptocurrency, foreign exchange, and stock to make further understandings on the nature of cryptocurrency in our future research.

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