Application of Network Analysis to Cryptocurrency in the Global Financial Market

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ABSTRACT

Cryptocurrency based on blockchain technology has begun to transform the global financial system, evidenced by the increasing number and trading volume of cryptocurrencies. This study determines if the rankings of cryptocurrencies among international financial assets have continued to rise or if they have fallen after the 2018 cryptocurrency price crash. We use network analysis - specifically centrality analysis - to demonstrate the importance of cryptocurrencies. This study visualizes an international financial market including multiple cryptocurrencies. The results indicate that the rankings of cryptocurrencies have been rising since 2014. From the results of the centrality analysis, we demonstrate that the importance and rankings of cryptocurrencies were not negatively affected by the price crash in 2018.

Keywords: Blockchain, Cryptocurrency, Network analysis, Centrality.

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1. INTRODUCTION

Cryptocurrency is a digital currency unlike conventional currency, such as USD, EUR, and JPY. There are currently over a thousand cryptocurrencies, including Bitcoin, Ripple, and Ethereum. In fact, the number of cryptocurrencies has been increasing rapidly over the last few years.

Cryptocurrency has different characteristics — among them, the most unique one is its *decentralized system*. The value of a conventional currency is guaranteed by central banks; for example, in Japan, the value of Yen is guaranteed by the Central Bank of Japan. However, the values of most cryptocurrencies are not guaranteed. Their values are electronically and automatically guaranteed by their users, that is, via a "peer-to-peer network."

Cryptocurrency is based on blockchain technology, an innovative technology that enables cryptocurrency to be a secure system. Blockchain and Bitcoin, one of the first cryptocurrencies, were created by Satoshi Nakamoto in 2009. Due to its ability to handle private data safely, various institutions expect to apply this technology to a wide range of areas such as overseas remittance, copyright management, and healthcare. As Fisch (2019) and Chen (2018) demonstrated, entrepreneurs use cryptocurrency to fundraise by various means such as initial coin offering.

Cryptocurrency has the power to change not only the economy as it functions today,

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but also the foundations of capitalism, because its concept and system are completely different from conventional currencies. For these reasons, it is important to analyze cryptocurrency in many academic fields.

So far, the analysis of cryptocurrency has mainly prioritized mathematical or software engineering perspectives. However, with the widespread popularity of this alternative currency system, its role in other fields such as sociology, law, and economics has been examined too. Consequently, the number of studies analyzing cryptocurrencies has been increasing.

Dwyerab (2015), Davidson *et al.* (2016), El-Bahrawy *et al.* (2017), and Krafft *et al.* (2018) are examples of previous studies on cryptocurrency in the field of economics. According to Krafft *et al.* (2018), the marketplace of cryptocurrencies is growing in importance. Thus, analyzing how international global financial markets that include cryptocurrencies change over time is an important issue.

Network analysis is mainly based on mathematical graph theory developed in 1736 by the mathematician Leonhard Euler. Every graph (sometimes called a network) consists of nodes (sometimes called vertexes) and edges. Network analysis is often used in biology or sociology; for example, Albert (2005) applied this theory to understand cell behavior, whereas Scott (1988) applied this theory to study social relationships. Izuka (2015), Raddant *et al.* (2015), and Nagy *et al.* (2018) are rare cases of studies where the authors applied network analysis to economics. Especially, as Inuzuka (2015) shows, network analysis can be a powerful tool—like standard methods such as statistics, regression analysis, and the more recent machine learning—to analyze various kinds of data and to explain research hypotheses. However, these authors did not analyze cryptocurrencies.

Thus, our research aims to:

- Analyze the international financial market and cryptocurrencies using network analysis; and
- Clarify the ranking of cryptocurrencies in various years, including 2018, when the price crash occurred.

We thus analyze the international financial market including cryptocurrencies by using network analysis methods. The application of network analysis to economic data, including many assets and cryptocurrencies, is thus a novel endeavor.

The results of our research indicate that the rankings of cryptocurrencies have risen over time despite the price crash that occurred in early 2018. This trend may continue in the future.

2. DATA AND METHODOLOGY

2.1 Data

We classify the international financial market into five categories and gather weekly data on each asset from 2014 to 2018. We select major assets from each category following world gross domestic product (GDP) ranking and trading volumes. Data are obtained from *Investing.com*, a global financial portal site. We use data from the top 20 countries in terms of world GDP ranking: the top three countries account for around 45.93% of world GDP; the top 10, around 67.4%; and the top 20, around 81.2%. Detailed data are presented in Table 1.

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Table 1. Variables and nodes names (Stock Market Index, Currency, and Government Bond)

Country or Region	Stock Market Index	Currency	Government Bond
USA	Daw	USD	USA BOND
China	*	CNY	CHN BOND
Japan	NIKKEI	†	JPN BOND
Germany	DAX	EUR	GER BOND
United Kingdom	FTSE	GBP	GBR BOND
France	CAC	(EUR)	FRA BOND
India	NIFTY	IDR	IND BOND
Italy	FTMIB	(EUR)	ITA BOND
Brazil	BVSP	BRL	BRT BOND
Canada	GSPTSE	CAD	CAT BOND
Korea	KS11	KRW	KOT BOND
Russia	RTS	RUB	RUT BOND
Australia	AXJO	AUD	AUT BOND
Spain	IBEX	(EUR)	ESP BOND
Mexico	MXX	MXN	MEX BOND
Indonesia	JKSE	IDR	ITA BOND
Turkey	XU100	TRY	TUR BOND
The Netherlands	AEX	(EUR)	NED BOND
Switzerland	FTSE	CHF	SUI BOND
Saudi Arabia	TASI	SAR	‡
Hongkong	HIS	HKD	‡
European Union	STOXX	EUR	§

Notes:
* China's stock markets are not completely open to foreign investors. Thus, we select Hongkong as a representative market for China.
† JPY is the scale used to measure other currencies.
‡ No reliable data.
§ The EU is not a government.

Table 2. Variables and nodes names (Commodity Future Trading)

Commodity Future Trading	
Node Name	**Market Country**
GOLD	USA
SILVER	USA
COPPER	USA
PLATINA	USA
WTI CRUDE	USA
BRENT CRUDE	United Kingdom
HEATING OIL	USA
WHEAT	USA
CORN	USA
COTTON	USA
SHUGAR	United Kingdom

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Table 3. Variables and nodes names (Cryptocurrency)

Cryptocurrency*	
Node Name	**Official Name**
BTC	Bitcoin
BTCC	Bitcoin Cash
XRP	Ripple
ETH	Ethereum
LTC	Litecoin
XLM	Stellar
USDT	Tether
XMR	Monero
EOS	EOScoin

Note:
* The number of cryptocurrencies depends on the year.

2.3 Network construction

In many cases, economic data are value or volume data. Network analysis, however, requires relationships among data for the purpose of constructing a network because such networks consist of multiple nodes and (undirected or directed) edges. A "node" often refers to economic units such as a government, company, or region, whereas an "edge" refers to their mutual relationships. In our study, each node is an asset, and each edge is the relationship of each asset. The methods of applying economic data to construct a network and to perform network analysis are as follows:

1. Calculate Pearson product-moment correlation coefficient in every combination of nodes.
2. If the Pearson product-moment correlation coefficient between two nodes surpasses the threshold we set, we connect them. If it does not surpass this threshold, we do not connect them.
3. Perform this operation for every combination of nodes. In terms of threshold, we perform a statistical test for no correlation. The null and alternative hypotheses are as follows:

   Null hypothesis: *There is no relationship.*
   Alternative hypothesis: *There is statistically significance relationship.*

To perform this test, we first use Fisher's Z-transformation, which is defined as

$$Z_r = \frac{1}{2}\log\left(\frac{1+r}{1-r}\right),$$

where r is sample correlation coefficient. It is well known that Z_r has the approximately normal distribution $\mathrm{N}(\mu_Z, \sigma_Z^2)$ if the sample size is large enough. Then, μ_Z and σ_Z^2 are defined as follows:

$$\mu_Z = \frac{1}{2}\log\frac{1+\rho}{1-\rho}\ \sigma_Z^2 = \frac{1}{n-3},$$

where ρ is the population correlation coefficient. In this way, we obtain critical confidence values of the population group. The critical values are as follows:

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Case 1: 99% confidence interval is $\pm$ 0.3508
Case 2: 97.5% confidence interval is $\pm$ 0.3187
Case 3: 95% confidence interval is $\pm$ 0.2706
Case 4: 90% confidence interval is $\pm$ 0.2283

We adopt these critical values as thresholds. We create four versions of a network for each year to check for robustness because the central node depends on how many edges the network has on each threshold. Therefore, we set four threshold cases and construct 20 networks. Table 4 shows the number of nodes and edges in each network.

Table 4. Number of nodes and edges

Year	Significance Level	Number of Nodes	Number of Edges
2018	10%	79	2147
2018	5%	79	1986
2018	2.50%	79	1823
2018	1%	79	1703
2017	10%	77	1992
2017	5%	77	1803
2017	2.50%	77	1631
2017	1%	77	1523
2016	10%	75	2141
2016	5%	75	2026
2016	2.50%	75	1876
2016	1%	75	1777
2015	10%	73	1831
2015	5%	73	1694
2015	2.50%	73	1517
2015	1%	73	1438
2014	10%	71	2002
2014	5%	71	1914
2014	2.50%	71	1816
2014	1%	71	1745

3. CENTRALITY ANALYSIS AND RESULTS

3.1 Overview of networks

We display one network in each year in Figures 1 to 5, using the 5% significance level (equivalent to Case 3 from section 2.2) to save space. However, we construct 20 networks, as mentioned in section 2.2. As the figures indicate, the networks appear complex and the form of each network depends on each year and threshold.

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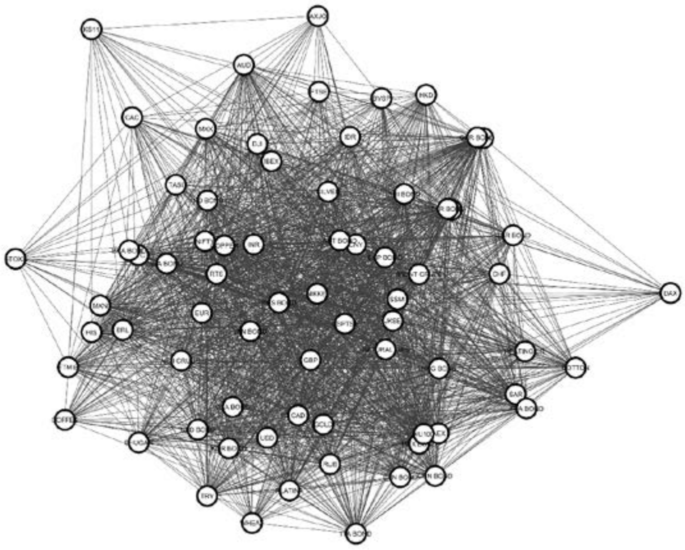

Figure 1. Visualized network for 2014

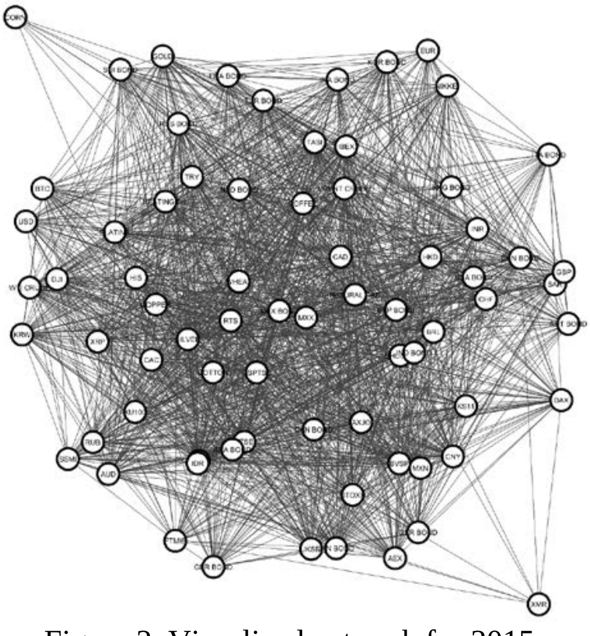

Figure 2. Visualized network for 2015

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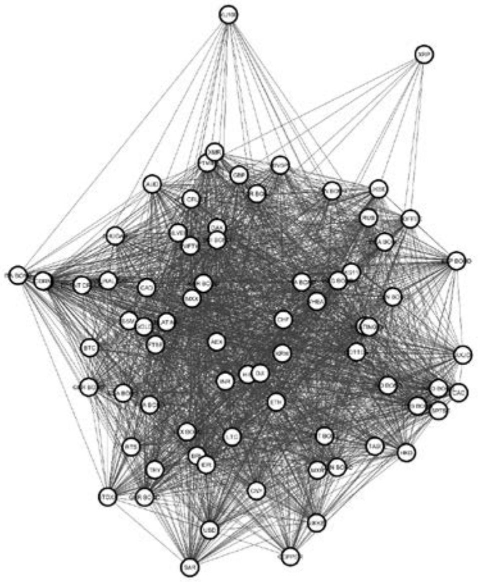

Figure 3. Visualized network for 2016

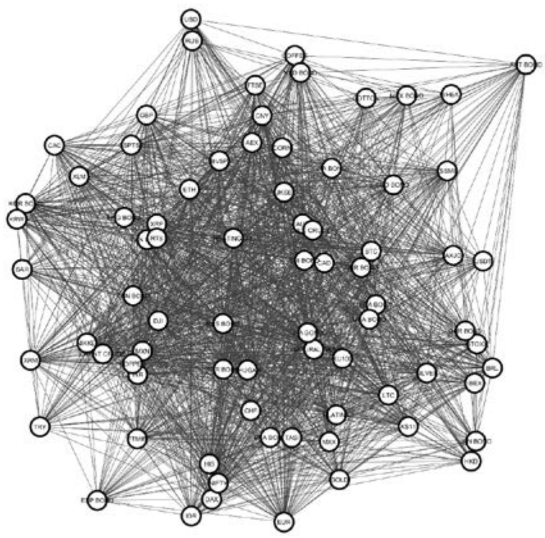

Figure 4. Visualized network for 2017

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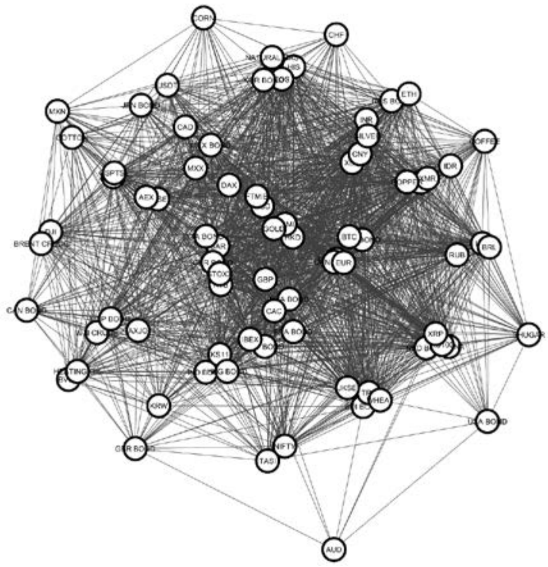

Figure 5. Visualized network for 2018

3.2 Centrality Analysis

3.2.1 Definition of centrality analysis

Because it may not be easy to find meaningful information by merely looking at the figures in section 3.1, we use centrality analysis because it can shed new light on the structure of a network. Centrality provides information regarding "which node is important in the network." This index is often used in network analysis because it is useful to elicit hidden information that the network contains. There are many methods to calculate centrality; we selected the following five representative methods:

Closeness centrality

Closeness centrality, which considers a node that is closer to all other nodes as the most important and central node in the network, was introduced in Bavelas (1950). Following Bavelas (1950), closeness centrality is defined as follows:

$$C_c(i) = \frac{1}{\sum_{j=1}^{n} d_{ij}},$$

where $C_c(i)$ is closeness centrality of node i and $\sum_{j=1}^{n} d_{ij}$ is the sum of the shortest distance from node i to other nodes.

Degree centrality

Degree centrality is simple but useful. A "degree" refers to how many neighbors the node has in the network. Following Borgatti (2013), degree centrality is defined as follows:

$$C_d(i) = \sum_{j=1}^{n} a_{ij},$$

where $C_d(i)$ is degree centrality and a_{ij} is the (i, j) entry of the adjacency matrix.

Eigenvector centrality

Eigenvector centrality was introduced in Gould (1967). It reflects linked nodes' centrality and is an extension of degree centrality. In this way, a node that has a high value for

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degree centrality has a high value for eigenvector centrality. Following Gould (1967), Eigenvector centrality is defined as follows:

$$C_e(i) = \frac{1}{\lambda}\sum_{j=1}^{n} a_{ij} C_e\,(j),$$

where $C_e(i)$ is eigenvector centrality, a_{ij} is adjacency matrix of an undirected graph, and A$\left(A = a_{ij}\right)$ λ is the maximum eigenvalue of A.

Betweenness centrality

Betweenness centrality was introduced in Freeman (1977). It measures the frequency with which a node exists on the shortest paths of the other two node pairs. Therefore, a node that has a high value for betweenness centrality can be said to be an important node in the network. Following Freeman (1977), betweenness centrality is defined as follows:

$$C_b(i) = \sum_{i \neq j \neq k} \frac{g_{jk}(i)}{g_{jk}},$$

where $C_b(i)$ is the betweenness centrality, g_{jk} is the total number of short paths between *j*, and *k*, $g_{jk}(i)$ is the number of short paths that pass through *i* between *j* and *k*.

PageRank

PageRank was introduced Brin and Page (1998), the cofounders of Google. This method is a variation of eigenvector centrality. Thus, it is applied to the central method of the Google search engine and is defined as follows:

$$C_{pr}(P_i) = (1-d) + d\sum_{j=1}^{n} \frac{C_{pr}(P_j)}{C(P_j)},$$

where $C_{pr}(P_i)$ is the value of PageRank and the parameter *d* is a damping factor, which can be set between 0 and 1 and is usually set to 0.85. $P_1, P_2, \dots, P_n$ is the number of pages that Pi has and C(P_j) is defined as the number of links going out of page P_i.

3.3 Results of centrality analysis

We rank each node based on the results of the centrality analysis. It should be noted that different centrality analyses lead to different results. Thus, we cannot simply rank each node based on the results of centrality analysis. To address this issue, we use the following procedure.

Step 1: Rank each node simply based on each of the five aforementioned methods.[1]
Step 2: Sum each node's ranking value.
Step 3: Re-rank each node based on the result of step 2.

We thus obtain the relative and total rankings of each node. The main results are presented in Tables 6 to 9. These tables show the rankings of each node in each year. As shown in Table 5, each colored block shows each cryptocurrency's ranking. For example, the red block represents Bitcoin, the yellow block represents Litecoin, and the purple block represents Ripple. In 2014, the international financial market only managed Bitcoin and its ranking was low. In 2015, the market started to manage other cryptocurrencies

[1] Closeness centrality, Degree centrality, Eigenvector centrality, Betweenness centrality, and Page Rank

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like Ripple. However, their rankings were still low.

Although the rankings of cryptocurrencies were low at the time they entered the market, cryptocurrencies *have* moved up the ranking in many cases. Specifically, in 2017, the number of cryptocurrencies increased, and their rankings rose sharply. In terms of Bitcoin, a representative cryptocurrency, its price rose from approximately $100 to $2000 over the course of 2017. In 2018, most cryptocurrencies ranked high despite the price crash. For example, in Case 1, LTC is ranked third, XMR thirteenth, and ETH seventeenth. In Case 2, LTC is ranked seventh and XRP sixteenth. In Case 3, XMR is ranked sixteenth. In Case 4, ETH is ranked fifteenth, and XLM is ranked sixteenth. Bitcoin's ranking is twenty-fourth in Case 1, twelfth in Case 2, third in Case 3, and fifth in Case 4. In addition, BTCC's (Bitcoin Cash) ranking moved from twenty-seventh (Case 3) to eighteenth (Case 1) in the 17 months since it entered the market.

Table 5. Legend of cryptocurrencies' color

(Red)	**Bitcoin**	**(Sky Blue)**	**EOScoin**
(Vermilion)	**Monero**	**(Blue)**	**Stellar**
(Orange)	**Bitcoin Cash**	**(Indigo)**	**Tether**
(Yellow)	**Litecoin**	**(Purple)**	**Ripple**
(Green)	**Ethereum**		

Table 6. Ranking of cryptocurrencies (Case 1)

Rank	**2018**	**2017**	**2016**	**2015**	**2014**
1	CHN BOND	EUR	BRA BOND	FTSE	CAN BOND
2	KS11	HIS	ESP BOND	INR	FRA BOND
3	LTC	NIFTY	SILVER	CAD	ITA BOND
4	RUS BOND	SSMI	MXX	AXJO	NIFTY
5	MEX BOND	DJI	RUS BOND	CNY	SUI BOND
6	STOXX	INA BOND	NIFTY	TASI	KOR BOND
7	FTMIB	CHN BOND	EUR	PLATINA	ESP BOND
8	EUR	JKSE	INA BOND	HIS	NED BOND
9	SILVER	XU100	SHUGAR	BRENT CRUDE	GER BOND
10	AUT BOND	CNY	CNY	KRW	AUT BOND
11	GOLD	SHUGAR	GBR BOND	GSPTSE	AEX
12	KOR BOND	KS11	GER BOND	INA BOND	AUD
13	XMR	ETH	CHF	SILVER	JKSE
14	IBEX	COPPER	NED BOND	JPN BOND	XU100
15	DAX	BTC	SAR	WTI CRUDE	SSMI
16	GBP	NIKKEI	INR	JKSE	TUR BOND
17	ETH	FTMIB	GBP	NIFTY	COTTON
18	BTCC	XMR	HKG BOND	BVSP	KRW
19	XRP	LTC	HKD	IBEX	DJI
20	INA BOND	GBP	USD	AUD	GBR BOND
21	RUB	HEATING OIL	ETH	TUR BOND	JPN BOND
22	HIS	KOR BOND	JKSE	COPPER	HKG BOND
23	TUR BOND	TUR BOND	CAD	GOLD	PLATINA
24	BTC	AEX	MXN	RUB	TRY
25	ITA BOND	KRW	RTS	HEATING OIL	CHN BOND

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26	PLATINA	BVSP	KOR BOND	MXN	INR
27	INR	FRA BOND	AXJO	RUS BOND	NATURAL GAS
28	CNY	XLM	FTMIB	BRA BOND	HEATING OIL
29	COPPER	RUS BOND	MEX BOND	IDR	MXN
30	SUI BOND	INR	IDR	COFFEE	GBP
31	XU100	CAN BOND	HIS	SUI BOND	CAD
32	MXX	COFFEE	COFFEE	BRL	CORN
33	XLM	GSPTSE	FTSE	CHN BOND	RTS
34	GER BOND	BRENT CRUDE	TRY	NATURAL GAS	WTI CRUDE
35	CAC	XRP	NIKKEI	KOR BOND	RUB
36	TRY	HKG BOND	JPN BOND	TRY	BRENT CRUDE
37	BRL	IND BOND	BVSP	MEX BOND	SILVER
38	JKSE	AXJO	KS11	CHF	IND BOND
39	NED BOND	DAX	GSPTSE	DAX	RUS BOND
40	RTS	MXN	COTTON	RTS	CNY
41	USD	CAD	SUI BOND	XU100	NIKKEI
42	SAR	ITA BOND	AEX	IND BOND	COPPER
43	FRA BOND	MXX	DJI	DJI	MXX
44	NIKKEI	USDT	XMR	SSMI	FTMIB
45	EOS	CAC	BTC	STOXX	IDR
46	AEX	BRL	USA BOND	GBP	SHUGAR
47	FTSE	MEX BOND	GOLD	USD	INA BOND
48	CAD	WTI CRUDE	LTC	NIKKEI	USD
49	HKD	GOLD	AUT BOND	FTMIB	HKD
50	BRA BOND	CORN	BRENT CRUDE	CAC	SAR
51	IDR	FTSE	HEATING OIL	KS11	GOLD
52	WHEAT	AUT BOND	XRP	EUR	USA BOND
53	HKG BOND	JPN BOND	AUD	HKD	HIS
54	COFFEE	IBEX	CAN BOND	SAR	BRL
55	DJI	ESP BOND	WHEAT	AEX	EUR
56	NATURAL GAS	USA BOND	PLATINA	MXX	MEX BOND
57	GSPTSE	IDR	WTI CRUDE	BTC	BRA BOND
58	SSMI	BRA BOND	TUR BOND	GBR BOND	BTC
59	IND BOND	STOXX	FRA BOND	XRP	GSPTSE
60	WTI CRUDE	GBR BOND	IND BOND	CAN BOND	CHF
61	TASI	SUI BOND	KRW	FRA BOND	IBEX
62	BRENT CRUDE	PLATINA	DAX	WHEAT	BVSP
63	SHUGAR	CHF	CHN BOND	AUT BOND	FTSE
64	ESP BOND	RTS	CAC	ESP BOND	TASI
65	JPN BOND	TRY	RUB	NED BOND	CAC
66	NIFTY	NED BOND	ITA BOND	SHUGAR	COFFEE
67	AXJO	NATURAL GAS	STOXX	GER BOND	AXJO
68	COTTON	SILVER	NATURAL GAS	COTTON	WHEAT
69	HEATING OIL	COTTON	COPPER	USA BOND	STOXX
70	USDT	GER BOND	CORN	HKG BOND	KS11
71	BVSP	HKD	BRL	ITA BOND	DAX
72	GBR BOND	AUD	IBEX	CORN	
73	CHF	WHEAT	TASI	XMR	
74	KRW	SAR	SSMI		
75	CAN BOND	USD	XU100		
76	CORN	TASI			
77	MXN	RUB			
78	USA BOND				
79	AUD				

Note: 99% confidence interval is ± 0.3508

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Table 7. Rankings of cryptocurrencies (Case 2)

Rank	2018	2017	2016	2015	2014
1	CHN BOND	EUR	INA BOND	CNY	XU100
2	IBEX	XU100	MXX	FTSE	CAN BOND
3	KS11	JKSE	ESP BOND	AXJO	AUD
4	FTMIB	NIFTY	EUR	CAD	KOR BOND
5	DAX	CNY	NIFTY	TASI	FRA BOND
6	STOXX	HIS	BRA BOND	HIS	NED BOND
7	LTC	KS11	SILVER	JKSE	SSMI
8	XMR	INA BOND	CHF	BRENT CRUDE	AEX
9	AUT BOND	NIKKEI	RUS BOND	JPN BOND	ITA BOND
10	SILVER	CHN BOND	CNY	GSPTSE	ESP BOND
11	RUB	DJI	GBR BOND	INR	SUI BOND
12	BTC	SSMI	SHUGAR	WTI CRUDE	JPN BOND
13	EUR	SHUGAR	INR	KRW	NIFTY
14	MEX BOND	KRW	NED BOND	COPPER	GER BOND
15	HIS	COPPER	GBP	SILVER	AUT BOND
16	XRP	FTMIB	JKSE	INA BOND	CHN BOND
17	INR	HEATING OIL	USD	PLATINA	JKSE
18	GOLD	ETH	HKD	BVSP	TUR BOND
19	RUS BOND	XMR	SAR	NIFTY	COTTON
20	GER BOND	GBP	KS11	IBEX	HKG BOND
21	KOR BOND	RUS BOND	HIS	GOLD	PLATINA
22	BTCC	KOR BOND	MXN	HEATING OIL	TRY
23	CNY	LTC	IDR	TUR BOND	GBR BOND
24	GBP	AEX	CAD	RUB	KRW
25	ETH	BTC	GER BOND	CHN BOND	DJI
26	CAC	AXJO	AXJO	RUS BOND	NATURAL GAS
27	TUR BOND	TUR BOND	COFFEE	COFFEE	GBP
28	NED BOND	FRA BOND	FTMIB	TRY	HEATING OIL
29	EOS	CAC	FRA BOND	AUD	INR
30	MXX	GSPTSE	RTS	BRL	CNY
31	COPPER	CAD	NIKKEI	IDR	MXN
32	SUI BOND	INR	GSPTSE	SUI BOND	CAD
33	INA BOND	BRL	TRY	BRA BOND	SHUGAR
34	XU100	COFFEE	BVSP	MXN	BRENT CRUDE
35	ITA BOND	MXN	BRENT CRUDE	XU100	USD
36	TRY	CAN BOND	HKG BOND	MEX BOND	HKD
37	PLATINA	DAX	FTSE	KOR BOND	SAR
38	USD	BVSP	STOXX	IND BOND	IND BOND
39	SAR	BRENT CRUDE	MEX BOND	SSMI	GOLD
40	XLM	IND BOND	COTTON	NATURAL GAS	SILVER
41	JKSE	MXX	AEX	DJI	CORN
42	WHEAT	GOLD	GOLD	RTS	INA BOND
43	RTS	CORN	ETH	CHF	MXX
44	BRA BOND	WTI CRUDE	CAC	STOXX	RTS
45	NATURAL GAS	ITA BOND	DJI	NIKKEI	WTI CRUDE
46	NIKKEI	FTSE	HEATING OIL	KS11	RUB
47	CAD	XLM	WTI CRUDE	FTMIB	COPPER
48	BRL	HKG BOND	USA BOND	AEX	NIKKEI
49	HKD	SILVER	KOR BOND	DAX	FTMIB
50	FRA BOND	IBEX	AUD	XRP	BRL
51	IDR	XRP	KRW	MXX	MEX BOND
52	COFFEE	STOXX	JPN BOND	GBR BOND	HIS
53	FTSE	IDR	PLATINA	BTC	USA BOND
54	AEX	AUT BOND	BTC	CAC	CHF
55	HKG BOND	USA BOND	SUI BOND	ESP BOND	IDR
56	IND BOND	BRA BOND	RUB	FRA BOND	RUS BOND
57	SSMI	PLATINA	AUT BOND	SAR	BRA BOND
58	WTI CRUDE	CHF	WHEAT	NED BOND	BTC
59	GSPTSE	ESP BOND	CAN BOND	CAN BOND	EUR

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60	TASI	RTS	DAX	WHEAT	FTSE
61	DJI	MEX BOND	COPPER	GBP	GSPTSE
62	ESP BOND	NATURAL GAS	IND BOND	SHUGAR	BVSP
63	NIFTY	HKD	TASI	HKD	IBEX
64	JPN BOND	COTTON	BRL	GER BOND	WHEAT
65	SHUGAR	AUD	XMR	USD	CAC
66	AXJO	TRY	NATURAL GAS	COTTON	TASI
67	HEATING OIL	GBR BOND	IBEX	AUT BOND	COFFEE
68	BRENT CRUDE	USD	TUR BOND	USA BOND	AXJO
69	KRW	SAR	CHN BOND	EUR	STOXX
70	COTTON	USDT	ITA BOND	HKG BOND	KS11
71	USDT	JPN BOND	SSMI	ITA BOND	DAX
72	CHF	WHEAT	LTC	CORN	
73	CAN BOND	SUI BOND	CORN	XMR	
74	GBR BOND	NED BOND	XU100		
75	BVSP	GER BOND	XRP		
76	CORN	TASI			
77	MXN	RUB			
78	USA BOND				
79	AUD				

Note: 97.5% confidence interval is ± 0.3187

Table 8. Rankings of cryptocurrencies (Case 3)

Rank	**2018**	**2017**	**2016**	**2015**	**2014**
1	CHN BOND	CNY	INA BOND	INR	AUD
2	IBEX	XU100	MXX	CNY	XU100
3	BTC	NIKKEI	EUR	COPPER	GER BOND
4	GER BOND	INA BOND	CNY	CAD	NED BOND
5	STOXX	HIS	NIFTY	TASI	AUT BOND
6	KS11	JKSE	ESP BOND	JKSE	KRW
7	FTMIB	EUR	NED BOND	GSPTSE	DJI
8	CNY	GBP	CHF	INA BOND	SUI BOND
9	GBP	SHUGAR	JKSE	AXJO	TUR BOND
10	GOLD	NIFTY	SILVER	WTI CRUDE	JKSE
11	MEX BOND	FTMIB	GBR BOND	TUR BOND	KOR BOND
12	INR	CHN BOND	RUS BOND	FTSE	AEX
13	RUB	KS11	USD	JPN BOND	NIFTY
14	AUT BOND	XMR	SAR	BRENT CRUDE	CAN BOND
15	HIS	ETH	COFFEE	NIFTY	FRA BOND
16	XMR	DJI	INR	PLATINA	HKG BOND
17	EUR	BTC	BRA BOND	COFFEE	NATURAL GAS
18	MXX	RUS BOND	GOLD	XU100	CHN BOND
19	INA BOND	DAX	HKD	HIS	SSMI
20	TUR BOND	BRENT CRUDE	HIS	MXN	ITA BOND
21	DAX	SSMI	KS11	GOLD	ESP BOND
22	RUS BOND	COPPER	FRA BOND	SILVER	JPN BOND
23	COPPER	HEATING OIL	BRENT CRUDE	CHN BOND	COTTON
24	NED BOND	KOR BOND	FTMIB	KOR BOND	GBR BOND
25	XRP	KRW	GBP	KRW	MXN
26	KOR BOND	AEX	SHUGAR	HEATING OIL	PLATINA
27	BTCC	FRA BOND	GER BOND	STOXX	CAD
28	EOS	ITA BOND	NIKKEI	BVSP	SILVER
29	CAC	MXN	IDR	TRY	TRY
30	LTC	CAD	COTTON	RUS BOND	IND BOND
31	XLM	BVSP	WTI CRUDE	AUD	CNY
32	SUI BOND	COFFEE	MXN	AEX	GBP

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33	SILVER	CAN BOND	BVSP	IBEX	HEATING OIL
34	ETH	TUR BOND	GSPTSE	BRL	RUS BOND
35	ITA BOND	CAC	FTSE	BRA BOND	GOLD
36	FRA BOND	AXJO	CAD	DAX	USD
37	BRL	LTC	AXJO	IND BOND	HKD
38	XU100	INR	TRY	SUI BOND	BRENT CRUDE
39	JKSE	GSPTSE	RTS	RUB	SAR
40	HKD	BRL	CAC	DJI	CORN
41	TRY	MXX	STOXX	IDR	INR
42	IDR	GOLD	KRW	MEX BOND	USA BOND
43	PLATINA	IND BOND	DJI	NATURAL GAS	HIS
44	NIKKEI	CHF	PLATINA	CHF	WTI CRUDE
45	USD	XLM	HEATING OIL	SSMI	NIKKEI
46	SAR	SILVER	RUB	XRP	INA BOND
47	WHEAT	FTSE	JPN BOND	NIKKEI	COPPER
48	BRA BOND	WTI CRUDE	HKG BOND	KS11	FTMIB
49	RTS	CORN	AEX	RTS	MXX
50	AEX	IDR	ETH	ESP BOND	RTS
51	CAD	XRP	WHEAT	NED BOND	RUB
52	SSMI	STOXX	MEX BOND	FRA BOND	SHUGAR
53	IND BOND	IBEX	CAN BOND	USD	BRL
54	NATURAL GAS	HKG BOND	BTC	HKD	CHF
55	FTSE	COTTON	AUD	SAR	BTC
56	COFFEE	BRA BOND	USA BOND	SHUGAR	MEX BOND
57	TASI	RTS	KOR BOND	CAN BOND	EUR
58	HKG BOND	USA BOND	AUT BOND	CAC	IDR
59	GSPTSE	PLATINA	DAX	BTC	GSPTSE
60	DJI	AUD	BRL	GBR BOND	BRA BOND
61	NIFTY	AUT BOND	IND BOND	WHEAT	FTSE
62	WTI CRUDE	NATURAL GAS	IBEX	GBP	CAC
63	SHUGAR	MEX BOND	SUI BOND	FTMIB	TASI
64	AXJO	GBR BOND	LTC	GER BOND	IBEX
65	ESP BOND	TRY	NATURAL GAS	MXX	BVSP
66	JPN BOND	USD	COPPER	COTTON	WHEAT
67	USDT	SAR	XMR	USA BOND	COFFEE
68	HEATING OIL	ESP BOND	CHN BOND	AUT BOND	AXJO
69	BRENT CRUDE	JPN BOND	ITA BOND	EUR	DAX
70	GBR BOND	HKD	TASI	HKG BOND	KS11
71	KRW	TETER	TUR BOND	ITA BOND	STOXX
72	COTTON	SUI BOND	CORN	CORN	
73	CAN BOND	NED BOND	XU100	XMR	
74	BVSP	WHEAT	SSMI		
75	MXN	TASI	XRP		
76	CHF	GER BOND			
77	CORN	RUB			
78	USA BOND				
79	AUD				

Note: 95% confidence interval is ± 0.2706

Table 9. Positions of cryptocurrencies (Case 4)

Rank	**2018**	**2017**	**2016**	**2015**	**2014**
1	GBP	XU100	INA BOND	JKSE	KRW
2	IBEX	NIFTY	NED BOND	COPPER	DJI
3	CHN BOND	CNY	SILVER	CNY	AUD
4	AUT BOND	INA BOND	CHF	KOR BOND	NIFTY
5	BTC	GBP	MXX	INR	XU100
6	DAX	SHUGAR	ESP BOND	AXJO	JKSE

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7	MXX	KS11	INR	TASI	AUT BOND
8	GER BOND	HIS	EUR	FTSE	SUI BOND
9	CNY	JKSE	CNY	TUR BOND	HKG BOND
10	STOXX	EUR	NIFTY	CAD	GER BOND
11	INA BOND	SSMI	COFFEE	GSPTSE	NED BOND
12	INR	NIKKEI	GOLD	JPN BOND	KOR BOND
13	RUB	CHN BOND	USD	PLATINA	CHN BOND
14	FRA BOND	FTMIB	HKD	WTI CRUDE	TUR BOND
15	ETH	BTC	SAR	INA BOND	MXN
16	XLM	KOR BOND	HIS	RUB	ITA BOND
17	RUS BOND	XMR	GBR BOND	NIFTY	FRA BOND
18	MEX BOND	COPPER	RTS	BRL	ESP BOND
19	BTCC	ITA BOND	FRA BOND	XU100	NATURAL GAS
20	EUR	AEX	FTMIB	IBEX	CAN BOND
21	LTC	MXN	GBP	MXN	JPN BOND
22	GOLD	LTC	GER BOND	SILVER	AEX
23	XMR	ETH	JKSE	COFFEE	SSMI
24	SILVER	DJI	GSPTSE	CHN BOND	TRY
25	EOS	TUR BOND	BRA BOND	HEATING OIL	CORN
26	KS11	KRW	KS11	IDR	GBR BOND
27	CAC	INR	RUS BOND	MEX BOND	COTTON
28	FTMIB	FRA BOND	BRENT CRUDE	BRENT CRUDE	USD
29	TUR BOND	HEATING OIL	BVSP	STOXX	SILVER
30	HIS	CAN BOND	SHUGAR	AEX	BRENT CRUDE
31	NED BOND	DAX	IDR	GOLD	HKD
32	ITA BOND	COFFEE	CAC	CHF	SAR
33	SUI BOND	BRENT CRUDE	WHEAT	HIS	WTI CRUDE
34	XRP	RUS BOND	AXJO	NIKKEI	INR
35	TRY	GSPTSE	WTI CRUDE	KRW	CAD
36	COPPER	GOLD	HEATING OIL	BVSP	INA BOND
37	KOR BOND	BRL	PLATINA	IND BOND	IND BOND
38	COFFEE	CAD	COTTON	BRA BOND	CHF
39	JKSE	MXX	FTSE	TRY	CNY
40	IDR	CAC	NIKKEI	RUS BOND	HIS
41	PLATINA	BVSP	MXN	DAX	GOLD
42	NIKKEI	AXJO	TRY	NATURAL GAS	HEATING OIL
43	AEX	XLM	RUB	DJI	PLATINA
44	HKD	IND BOND	MEX BOND	SSMI	USA BOND
45	IND BOND	CHF	STOXX	AUD	COPPER
46	XU100	FTSE	CAD	SUI BOND	BTC
47	USD	IDR	HKG BOND	SHUGAR	GBP
48	SAR	SILVER	JPN BOND	KS11	FTMIB
49	SSMI	HKG BOND	CAN BOND	GBR BOND	RUS BOND
50	WHEAT	STOXX	DJI	RTS	MXX
51	RTS	XRP	KRW	COTTON	RUB
52	BRA BOND	AUD	IBEX	XRP	NIKKEI
53	CAD	WTI CRUDE	AUD	CAC	SHUGAR
54	BRL	RTS	AEX	BTC	EUR
55	HKG BOND	CORN	NATURAL GAS	FRA BOND	BRL
56	NATURAL GAS	NATURAL GAS	BTC	WHEAT	IDR
57	GSPTSE	COTTON	LTC	ESP BOND	WHEAT
58	SHUGAR	IBEX	COPPER	NED BOND	MEX BOND
59	FTSE	USA BOND	ETH	SAR	GSPTSE
60	TASI	PLATINA	AUT BOND	GBP	FTSE
61	WTI CRUDE	MEX BOND	SUI BOND	CAN BOND	RTS
62	HEATING OIL	ESP BOND	CHN BOND	USD	BRA BOND
63	USDT	BRA BOND	TASI	HKD	CAC
64	KRW	USD	USA BOND	FTMIB	BVSP
65	AXJO	SAR	KOR BOND	MXX	COFFEE
66	GBR BOND	AUT BOND	DAX	GER BOND	IBEX
67	DJI	TRY	IND BOND	EUR	TASI
68	NIFTY	GBR BOND	BRL	USA BOND	AXJO

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69	BRENT CRUDE	NED BOND	XMR	AUT BOND	KS11
70	JPN BOND	JPN BOND	ITA BOND	ITA BOND	STOXX
71	ESP BOND	HKD	TUR BOND	HKG BOND	DAX
72	COTTON	TETER	CORN	XMR	
73	CAN BOND	SUI BOND	XU100	CORN	
74	BVSP	GER BOND	SSMI		
75	CHF	WHEAT	XRP		
76	MXN	TASI			
77	CORN	RUB			
78	USA BOND				
79	AUD				

Note: 90% confidence interval is ± 0.2283

4. CONCLUSION

We analyzed the importance of cryptocurrencies in the international financial market using network analysis. Specifically, we used centrality analysis methods, that is, betweenness, closeness, degree, eigenvector centrality, and PageRank. Our main results can be summarized as follows:

1. We visualized an international financial market including multiple cryptocurrencies by applying network analysis. The market was found to be a complex network.
2. In the global financial market, the importance and ranking of cryptocurrencies have risen over time.
3. From the results of the centrality analysis, we demonstrate that the importance and ranking of cryptocurrencies were not negatively affected by the price crash that occurred in early 2018.

Researchers can reveal hidden information by using network analysis. We expect the network analysis to become a standard tool for analyzing data, with researchers using this technique in the economic field to reveal further insights.

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