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Research on Dynamic Topological of Network of Exchange Rates of Major Global Currencies under the Background of the COVID-19 Epidemic

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Abstract: The COVID-19 has had a huge impact on the global economy, by constructing the global major currency correlation network, analyzing the network topology changes of the global foreign exchange market during the epidemic, the risk transmission channels between different currencies are discussed. It is found that during the epidemic, the average distance of the international currency market network first increased and then decreased, and remained at a high level in the middle of the epidemic. The global currency market has different systemically important nodes at different times, and the US Dollar is the largest network association node; Before and after the pandemic, the Chinese Yuan was always at the edge of the network.

1. Introduction

Sudden public events often bring great challenges to economic and financial stability. At the beginning of 2020, the COVID-19 epidemic ravaged the world, affecting the economies of all countries, the global economy has been greatly impacted in the past three years, and the fiscal policies of countries have also brought great uncertainty. Global economic integration provides a channel for the dissemination and diffusion of financial risks, which can easily lead to systemic risks. In order to prevent the spread of international financial risks and reduce the secondary disasters of the financial crisis, it is of great practical significance to analyze in detail the changes of market network structure and risk transmission path in the international monetary market under the impact of the COVID-19.

2. Literature Review

Complex networks are a widely used tool for studying the spread and diffusion of risks. Tse build a yield network between U.S. stocks, use changes in topology to prove the importance of different industries[1]. Qiao used real exchange rates to establish network models and found that there was a linkage effect between monetary networks, which was closer during the financial crisis[2]. Mandigma explored the relationship between stock markets in China, the United States and ASEAN, the relationship has declined significantly after the financial crisis[3]. Nobi have found that financial crises change the topologies of global networks[4].

Sudden public events often have a significant impact on the economy. The Worthington found that in addition to causing direct damage to the affected areas, public emergencies can also lead to a global transfer of risks[5]. During crisis, the distance between network nodes was generally shortened. Samitas built a network of correlation between world stock volatility in the COVID-19 period, pointing out that during the crisis, central indicators such as national centrality and intermediary centrality in each continent were increasing, and the distance between markets was shortened[6]. Demirer studied the correlation between global bank stocks and found that the correlation between bank stocks among countries increased in times of crisis[7].

The published research has yielded fruitful results on the linkage of the global foreign exchange market. However, there is still a lack of discussion on how the COVID-19 epidemic affects financial markets in various countries and how it affects them. Based on the exchange rate volatility data of 12 representative currencies in the world from 2019 to 2022, this paper establishes a complex network model, investigates the changes in the network topology of the global foreign exchange market, and analyzes the similarities and differences in the epidemic structure in different periods.

3. Modeling Strategy

3.1. Empirical Approach

In the international currency markets, the exchange rate fluctuations of various currencies not only reflect the economic situation of own countries, but also are affected by the fluctuation of the value of other currencies. According to the closing price of exchange rate, the correlation level between currencies is analyzed, and the correlation characteristics and dynamic stability of major global currencies are studied. If r_i and r_j are the rate of return for two currencies, the Pearson Correlation Coefficient between them is:

$$\rho_{ij} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{(\langle r_i^2 \rangle - \langle r_i \rangle^2)(\langle r_i^2 \rangle - \langle r_j \rangle^2)}} \tag{1}$$

The distance between two points in any n-dimensional space is called the Euclidean distance and can be expressed using the correlation coefficient:

$$d(i,j) = \sqrt{2(1-\rho(i,j))} \tag{2}$$

3.2. Definition of Characteristic Indicators

In a graph, G=(v, e), the Average Distance (Characteristic Path Length) is the average of the side lengths of all networks, which describes the degree of separation between nodes in the network.

The tree that passes through all the points and has the smallest sum of its lengths is called the Minimum Spanning Tree(MST). The MST reflects the most likely path of risk propagation between markets, removes redundant information from the graph, and reflects the core, most concise relationship between variables. Define $L(t)$ as the length of the MST:

$$L(t) = \frac{1}{n-1} \sum_{v \epsilon MST} e_{i,j} \tag{3}$$

The nature of nodes in the network reflects the importance of different markets, and analyzing the topological properties of different nodes in the network can reflect the changes in market characteristics. The average degree of the network refers to the average degree of all points in the network, which is denoted as following:

$$\langle D \rangle = \frac{1}{N} \sum D_i \tag{4}$$

In an undirected weighted graph, the degree of a vertex is the weight of the edge pointed or emitted. The larger the degree value of a vertex, the more important it is in the graph, the Degree Centrality(DC) is denoted as D_i:

$$D_i = \sum_{j=1, j \neq i}^{n} a_{ij} \tag{5}$$

The Betweenness Centrality(BC) of node i is denoted as BC_i:

$$BC_i = \sum_{s<t} \frac{g_{st,i}}{n_{st}} \tag{6}$$

The Closeness Centrality(CC) of a node is used to indicate its centrality, and the closer it is to the center, the greater the value. Proximity centrality is defined as the reciprocal of the sum of the shortest distances from that point to all other points:

$$CC_i = \frac{1}{\sum_{j \epsilon V} d(i,j)} \tag{7}$$

According to the statistics of the Bank for International Settlements (BIS) trading data, the top 12 currencies in the international market by foreign exchange trading volume in 2019 are selected, and these currencies account for more than 95% of the total global foreign exchange transaction volume, which can fully reflect the currency trading status in the international market; The global market foreign exchange trading volume is counted every 3 years, and 2019 is the statistical year, which can reflect the trading situation of the global foreign exchange market before the epidemic. The 12 currencies are ranked by volume: USD, EUR, GBP, AUD, JPY, CAD, SEK, NZD, CNY, NOK, KRW, CHF. Table 1 shows the codes for different currencies.

Table 1: Currency indicator code.

Currency	U.S. dollar	Euro	British pound	Australian dollar	Japanese yen	Canadian dollar
Code	DXY	EUR	GBP	AUD	JPY	CAD
Currency	Swedish krona	New Zealand dollar	Chinese yuan	Norwegian krone	Korean won	Swiss franc
Code	SEK	NZD	CNY	NOK	KRW	CHF

Note: Index data from Wind, BIS.

This article uses the data from 2019/01/01 to 2022/12/31, uses the following equation to convert the closing price into a logarithmic return:

$$r_t = lnp_t - lnp_{t-1} \tag{8}$$

4. Empirical Analysis

4.1. Data

The COVID-19 occurred in 2020. On February 11, 2020, the World Health Organization named the pneumonia infected by the new coronavirus "COVID-19", and the selected sample period covered the time period of the epidemic. The descriptive statistics of the log return data of each indicator are shown in the Table 2, and the mean and standard deviation of all log yields are small, close to 0; During the sample period, the standard deviation of NOK is the largest and has large volatility. The volatility of all currencies is positively skewed, and the kurtosis are greater than 3, showing a sharp kurtosis, indicating that the sample distribution is concentrated. The J-B test showed that all samples significant at 1%, indicating that all samples did not obey the normal distribution. The ADF test showed that all samples were stationary sequences.

Table 2: Statistical description of samples.

	Mean	S.D.	Skewness	Kurtosis	J-B Test	ADF Test
USD	-5.29E-06	2.88E-03	0.44	9.25	1299.81***	-25.45***
EUR	4.66E-05	6.06E-03	-0.57	7.34	655.38***	-26.34***
GBP	-7.89E-05	4.21E-03	0.31	6.34	375.12***	-27.67***
AUD	-4.39E-06	3.67E-03	-0.24	5.68	241.79***	-25.08***
JPY	3.23E-05	6.26E-03	-0.56	6.10	354.27***	-28.28***
CAD	8.83E-05	5.45E-03	0.10	6.65	435.19***	-26.66***
SEK	-9.41E-05	2.43E-03	0.58	9.58	1457.29***	-30.25***
NZD	6.77E-05	3.99E-03	-0.41	9.03	1207.79***	-26.07***
CNY	7.69E-05	4.47E-03	-0.40	5.22	181.73***	-30.59***
NOK	1.61E-05	7.80E-03	1.04	14.00	4084.75***	-26.16***
KRW	8.03E-06	5.40E-03	0.55	7.10	589.25***	-26.63***
CHF	-9.91E-05	3.90E-03	0.27	5.69	245.15***	-26.20***

4.2. Analysis of the International Foreign Exchange Market Network

Firstly, we calculate the correlation coefficient of yield series between different currency to analyze the correlation between different financial sub markets. Figure 1 is the thermal diagram of the correlation coefficient of 12 currency exchange rates. In order to analyze the changes in the correlation of different currencies, according to the factual situation, four time points were selected to analyze the correlation: before the epidemic, March in 2020, at the end of 2020 and at the end of 2021.

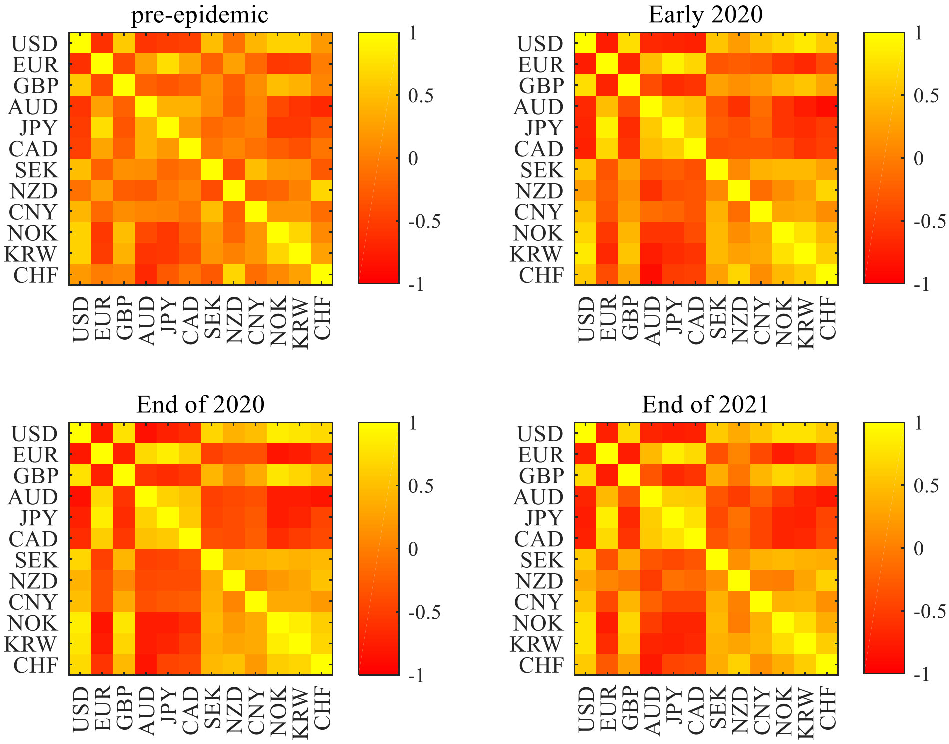

Figure 1: Heat maps of currency correlation coefficients at different times.

As shown in Figure 1, the overall correlation between different markets before the epidemic is not significant, and there is no obvious correlation structure. By March 2020, the COVID-19 pandemic began, and the volatility correlation of currencies began to rise; The correlation of some currencies has increased significantly, especially the USD, with an average correlation coefficient of about 0.8. By the end of 2020, the correlation level of currency volatility series remained at a high level, with a certain decrease but not obvious, and the average correlation coefficient decreased from 0.556 to 0.524. By the end of 2021, the correlation of currencies in various countries began to decrease and tended to return to the state before the epidemic, but it still needs some time to recover.

Using the rolling window method, the rolling step size is t=3 and the window length is T=110, a total of 225 complete windows are obtained, and the variation trend of the average path length of the network during the sample period is calculated. In order to better analyze the development of the new crown, this article calculates and graphs the number of infected people in all currency countries.

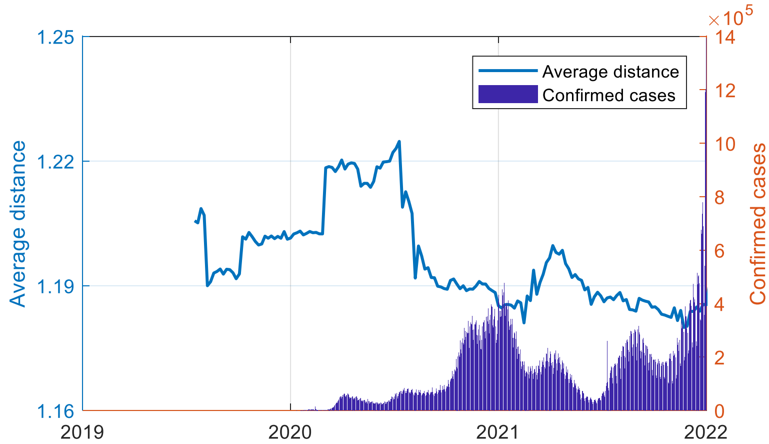

Figure 2: Dynamic changes in average network distance and the number of COVID-19 infections.

As can be seen from Figure 2, from 2009 to 2022, the average distance of the entire foreign exchange market network fluctuates between 1.2~1.3. During the COVID-19 epidemic, the average distance between nodes increased significantly, the first time occurred around March 11, 2020 (since our rolling step is 5 days, the event occurred from the first 5 trading days to the same day, the same below), and the second occurred around February 26, 2021.

Table 3: The average distance between different currencies (2019-2022).

	USD	**EUR**	**GBP**	**AUD**	**JPY**	**CAD**	**SEK**	**NZD**	**CNY**	**NOK**	**KRW**	**CHF**	**AVE**
USD	0.000	1.877	0.696	1.860	1.861	1.833	0.923	1.212	0.979	0.682	0.678	0.932	1.230
EUR	1.877	0.000	1.853	0.942	0.497	0.868	1.668	1.546	1.685	1.840	1.828	1.674	1.480
GBP	0.696	1.853	0.000	1.707	1.820	1.757	1.131	1.385	1.123	0.840	0.928	1.165	1.310
AUD	1.860	0.942	1.707	0.000	0.908	0.963	1.642	1.695	1.594	1.806	1.878	1.902	1.536
JPY	1.861	0.497	1.820	0.908	0.000	0.894	1.660	1.590	1.652	1.830	1.823	1.706	1.476
CAD	1.833	0.868	1.757	0.963	0.894	0.000	1.636	1.589	1.626	1.752	1.757	1.681	1.487
SEK	0.923	1.668	1.131	1.642	1.660	1.636	0.000	1.364	1.097	1.084	1.091	1.221	1.320
NZD	1.212	1.546	1.385	1.695	1.590	1.589	1.364	0.000	1.430	1.318	1.225	0.925	1.389
CNY	0.979	1.685	1.123	1.594	1.652	1.626	1.097	1.430	0.000	1.127	1.126	1.278	1.338
NOK	0.682	1.840	0.840	1.806	1.830	1.752	1.084	1.318	1.127	0.000	0.679	1.057	1.274
KRW	0.678	1.828	0.928	1.878	1.823	1.757	1.091	1.225	1.126	0.679	0.000	0.901	1.265
CHF	0.932	1.674	1.165	1.902	1.706	1.681	1.221	0.925	1.278	1.057	0.901	0.000	1.313

Before March 2020, the early days of the epidemic, there was uncertainty and general optimism, and currency markets did not respond accurately. On March 11, the World Health Organization announced that the current coronavirus outbreak to be called ‘a global pandemic’, and the number of infections began to increase rapidly. There were significant fluctuations in global financial markets, and the average distance of the foreign exchange market network rose rapidly, reaching 1.22, and fluctuated at this level for a long time. It was not until August 2020, when the new variant was also well controlled, that the average distance of the network began to decrease and rapidly decline to pre-pandemic levels. However, the emergence of the Delta variant in the UK in March 2021 has caused the number of new infections to rise again, and the outbreak has recurred, which has hit the already low confidence in financial markets and made the average distance of the global money market network rise again. After this shock, the average distance of the network between the markets decreased, and there was no sharp increase.

This paper calculates the average distance between different currencies during the sample period, and the results are shown in Table 3. For any two currencies, the distance between the AUD and the CHF in the sample period is the largest, at 1.902, the lowest degree of mutual influence between the two, from the perspective of trade data analysis, Switzerland’s exports to Australia accounted for less than 1%, the main trading partners are Eurozone countries and China, the United States, India and other countries. The EUR and the JPY have the smallest distance, at 0.497, which indicates the greatest correlation between the two, the Euro area is one of Japan’s main trading partners, changes in the European economy directly affect Japan’s exports, during the epidemic period, taking 2022 as an example, Japan exported 9.369 trillion yen to the Euro; in the same period, imported 11.375 trillion yen from the Euro. From the perspective of average distance, the average distance of USD with others is the smallest, indicating that the correlation between the USD and other currencies is obvious, and the USD, as the most important international currency, is closely related to the risk of other currencies.

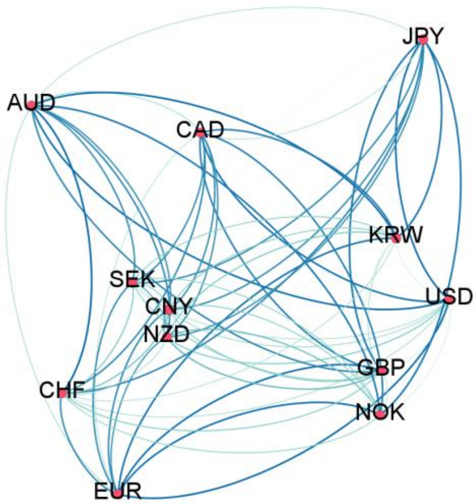

Figure 3: International foreign exchange market connection network.

Based on the network data, the association network of the international foreign exchange market was constructed and visualized using ‘Gephi’ software. As shown in Figure 3, the line between the nodes represents the distance between the two currencies. The darker the line color, the longer the distance. USD is less distant from other countries than currencies such as the JPY, EUR and CAD.

As shown in Figure 4, at the beginning of the epidemic, the length of the MST of the foreign exchange market network increased somewhat but not significantly, which may be caused by the fact that countries were faced with different economic risks in the early stage of the epidemic. At the same time, the market did not make a reliable judgment on the epidemic in the early stage of the epidemic, and it may be believed that it was only a problem faced by individual countries, so the correlation between different currencies decreased. In the middle of 2020, the long-term and global nature of the pandemic began to be accepted by countries around the world, resulting in increased currency correlation and reduced distance between countries.

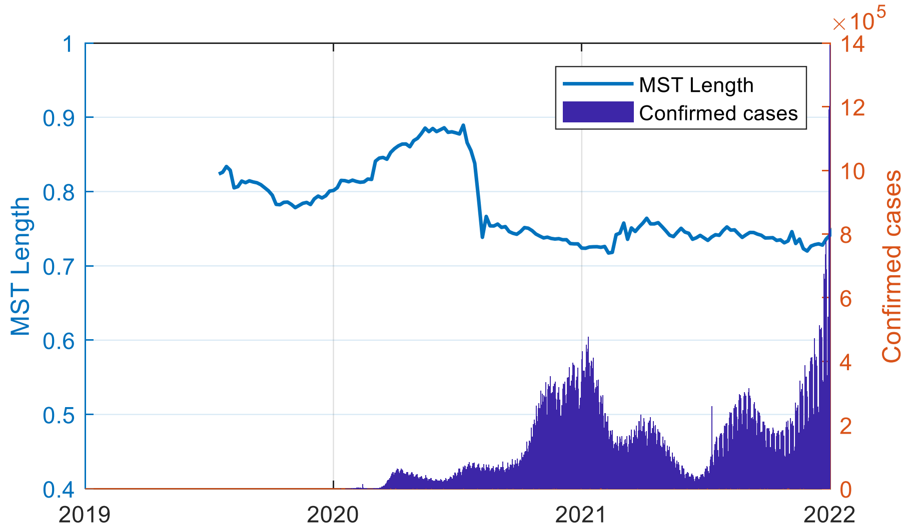

Figure 4: Dynamic changes in the length of MST and the number of COVID-19 infections.

Table 4 shows the frequency of centrality ranking in different markets during the sample period, and it can be found that the NZD has the highest intermediary centrality, reaching 44%, which indicates that the NZD is an important node in the network for risk transmission, and during the epidemic, New Zealand's tourism and transportation services have declined sharply, and economic uncertainty has increased, bringing risks to the world economy. The first frequency of the degree centrality of the USD is 84.44%, which is much greater than the second place, which shows that the USD and other currencies are more closely related, the importance is much greater than other currencies, according to the statistics of SWIFT and CIPSICON two systems, the proportion of international trade USD settlement in the world is 40%; At the same time, the USD is also an important reserve currency, the peak of the USD accounted for up to 71% of the global reserves, especially during the epidemic, as an important international reserve currency, it has an irreplaceable role.

Table 4: Systemically important first frequency in the MST of network.

Sort	Between centrality		Closeness centrality		Degree centrality	
	Code	frequency	Code	frequency	Code	frequency
1	NZD	44.00%	CHF	58.22%	USD	84.44%
2	CAD	29.33%	USD	40.44%	KRW	8.89%
3	JPY	14.67%	CNY	0.89%	EUR	3.56%
4	EUR	7.56%	SEK	0.44%	JPY	2.22%
5	KRW	3.56%	NZD	0.00%	NOK	0.89%

In order to analyze the changes in the network structure of the foreign exchange market, this article calculates the centrality characteristics of nodes in the associated network at different periods, as shown in Table 5. After the 'pandemic', the centrality of the KRW, SEK and GBP sterling decreased significantly, and it did not recover until the end of 2022. During the epidemic, the centrality of the NZD increased, and it fell back to its original level after the epidemic.

Table 5: The central characteristics of each currency at different times.

	USD	KRW	EUR	JPY	NOK	CHF	CNY	SEK	NZD	CAD	AUD	GBP
Before												
Degree centrality	4	2	1	2	2	1	1	2	1	2	2	2
Between centrality	0	15	0	7	12	0	0	16	0	7	12	15
Closeness centrality	0.026	0.026	0.020	0.019	0.022	0.016	0.020	0.029	0.020	0.029	0.030	0.030
Early of 2020												
Degree centrality	4	2	1	2	2	1	1	1	2	1	3	2
Between centrality	0	4	0	6	6	0	0	0	4	0	3	2
Closeness centrality	0.040	0.022	0.029	0.032	0.027	0.018	0.029	0.021	0.037	0.026	0.034	0.027
End of 2020												
Degree centrality	4	2	1	2	2	1	1	1	2	1	3	2
Between centrality	0	4	0	6	6	0	0	0	4	0	3	2
Closeness centrality	0.040	0.022	0.029	0.032	0.027	0.018	0.029	0.021	0.037	0.026	0.034	0.027
End of 2021												
Degree centrality	5	3	1	1	2	1	1	2	1	1	2	2
Between centrality	0	12	0	0	5	0	0	12	0	0	6	10
Closeness centrality	0.033	0.029	0.025	0.019	0.024	0.023	0.025	0.033	0.025	0.025	0.036	0.036

5. Robustness Test

In order to further verify the robustness of the results, we can change the window length or rolling step size for testing. In this paper, we choose to change the window length to analyze the robustness of the results. The number of fixed rolling window steps is 3, the window length is changed to 90 and 150, and the change of the average distance of market network nodes during the sample period is calculated. The results are shown in Figure 5. From the two graphs, it can be found that the results obtained after changing the window length are basically consistent with the previous ones, which shows that the results of this paper are robust.

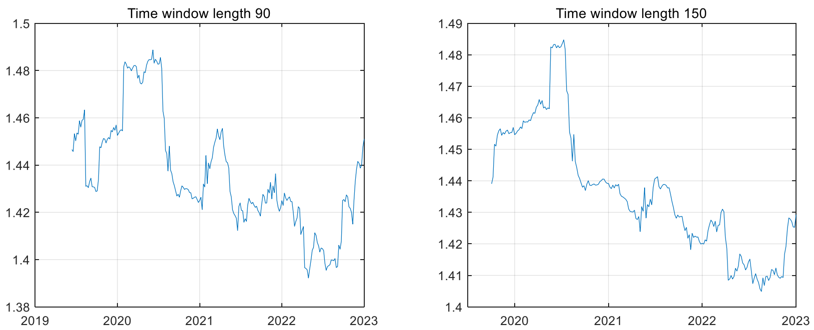

Figure 5: Robustness test results.

6. Conclusions and Discussion

The outbreak of COVID-19 has greatly affected the development of the world economy and caused a huge impact on the international financial market. Combined with the theory of complex network, this paper constructs the correlation network of global foreign exchange market during the epidemic period, and analyzes the changes in the structure of the world's major monetary networks during the COVID-19 epidemic period.

The results show that:

1) In the early stage of the COVID-19 epidemic, the average distance of the international foreign exchange market network increased and oscillated at a high level, and did not begin to decrease until August 2020.

2) As the world's main trading currency, the USD has the greatest correlation and the shortest distance with other currencies.

3) During the epidemic period, CNY was at the edge of the network, and its correlation with other countries was low, but it was not the lowest, and there was still much room for improvement in the level of CNY internationalization.

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