The characteristics of International Financial Network

Masaki Yamaguchi

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Faculty of Humanities and Social Sciences
Yamagata University
Yamagata, Japan

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Masaki Yamaguchi, Yamagata University

Abstract

This study recognizes international capital flows as a complex network and analyzes their behavior as a whole. The study uses network analysis techniques to explore the characteristics and structure of international financial networks. The analysis of the shape of degree distributions and measurement of basic network measures indicate that international financial networks are scale-free, and hub countries link investment and procurement by countries. The exploration of network structure identifies an ordering of important countries based on centrality measures. It finds that there are three major communities in the network, and the network is highly concentrated and vulnerable to financial stress.

Keywords: International capital flow, Network analysis, Centrality, Community detection

1. Introduction

Although once stalled by the global financial crisis, international capital flows have since continues to expand. Total capital flows in the form of securities investments for 77 countries covered in this study increased from 42.6 trillion US dollars in 2015 to 70.4 trillion US dollars in 2023. The average annual growth rate from 2015 to 2023 was 7.4%, which exceeds the economic growth rate of the analyzed countries.

Recent international capital flows viewed on a gross basis far exceed those on a net basis (Forbes et al., 2012; Broner et al., 2013)[1]. Furthermore, money flows are concentrated in countries with international financial markets. The developed countries have attracted money from all over the world by monetary tightening to control the post-pandemic inflationary surge. For example, the United States' share of capital inflows in the form of securities investments increased from 22.3% in 2015 to 29.9% in 2023. The unipolar concentration of the US is being reinforced.

Amid the expansion and concentration of international capital flows, the international financial system has been frequently exposed to instability. Aside from the European debt crisis, financial shocks continued to occur in the 2010s, such as the China shock in 2016, VIX

[1] Net-based capital flows correspond to the current account balance.

shock in 2018, and COVID-19 shock in 2020. Each time, stock prices plunge, exchange rates fall, and capital outflows are repeated not only in developed countries but also in emerging markets and developing countries. Thus, the international financial system is still prone to instability.

This study analyzes vulnerable international capital flows from a different perspective. We overview the entire international financial network to show the said perspective. Figure 1 presents the situation in 2023 from investment and procurement on an aggregate basis among countries in international securities investment. The code diagram represents the flow among countries and provides a bird's eye view of the overall situation. In this graph, the size of the arc indicates the ratio of each country's total outward investment and procurement to the total. Apart from countries with major international financial markets such as the U S, the United Kingdom, and Japan, offshore financial markets such as Ireland, Luxembourg, and the Cayman Islands account for a relatively high percentage.

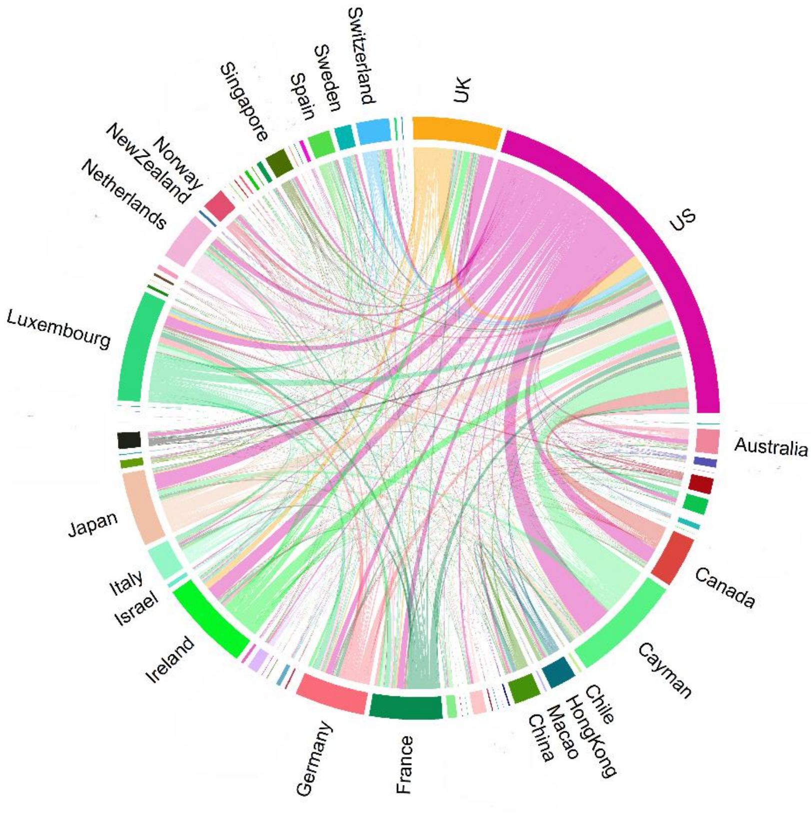

Figure 1. Overall picture of the international financial network (2023)

The bands and stripes within the circle represent the links among countries in terms of foreign claims and foreign debts. For example, the US and the Cayman Islands have strong financial ties, so their foreign claims and debts are banded. On the other hand, there are also numerous connections represented by thin stripes. An overview of the graph shows that the international financial network[2] is extremely complex.

Studies such as Agosin and Huaita, 2012; Fratzscher, 2012; Ahmed and Zlate, 2014 have used financial account data to examine the factors affecting capital flows. However, conventional analysis methods use financial account data and cannot analyze the linkages among countries. In addition, studies using the IMF's Coordinated Portfolio Investment Survey (CPIS) can analyze the linkages among countries, but it often only observes changes in securities investment. In other words, previous studies have not focused on the complexity of the network.

It is difficult to infer the behavior of the international financial network as a whole. The connections seen in Figure 1 are a complex network and the linkages in international finance need to be analyzed as a complex network. This study observes the international financial network from a perspective that previous studies have missed.

The rest of this paper is organized as follows. Section 2 presents the research position of this study based on the review of previous studies. It also details the data used in the analysis and confirms the current state of international securities investment. Section 3 examines the scale-free characteristics of international financial networks and the presence of hubs. In addition, network filtering is performed as a preliminary step to the analysis. Section 4 examines the structure of the network from four perspectives: assortativity, network centrality, community detection, and centralization. At last, the concluding section summarizes the findings of this study and presents remaining issues and future research strategies.

2. Previous studies and data

2.1 Previous studies

Network analysis has been applied to research on systemic risk in the field of finance. Previous studies have analyzed the chain of defaults through interbank credit and debt networks and investigated the impact of network structure on systemic risk. Causal analysis related to a network structure is a central theme in complex network science. Watts (2002) analyzed the mechanism for small initial shocks causing large and rare cascades. The

[2] Previous studies have used terms such as international capital flows and global money flows. This study dares to use the term international financial network because it analyzes investment and financing balances and applies network analysis.

simulation adopted a setting in which each entity made decisions based on threshold rules depending on the status of neighboring entities. Simulation results found that the chain reaction depends on the network shape. In a densely connected network, the stability of the nodes suppresses the propagation of shocks. However, the scale of propagation is bimodal, making it difficult to predict the size of the spillover.

Subsequent studies have advanced the refinement of the setting. Lorenz et al. (2009) introduced heterogeneity in the threshold for default. The model states that if the vulnerability exceeds a certain threshold and the vulnerability of a neighboring node increases, the node in question will fail, increasing the likelihood of a cascade of defaults. A comparison of the three models shows different patterns of spillover depending on the network topology. Paynes et al. (2009) extended the threshold model by introducing degree correlations into the random network. Simulation results demonstrate that degree correlations increase in the class in which the chain occurs, and large-scale chains are strongly influenced by degree correlations. Early studies have used simulation to reveal the cascade mechanism, and model settings have introduced various elements into the mechanism and the network shape.

Recent studies have conducted empirical analyses using actual data as well as simulations. Rounkny et al. (2013) analyzed the impact of network structure on systemic risk by focusing on the propagation of defaults in banks' credit and debt networks. They introduced cascading dynamics to perform both simulation and empirical analysis. The analysis found that network structure is important only when markets are illiquid. Hence, policymakers should pay attention to network structure when deciding on liquidity injections. As we have seen, systemic risk analysis constitutes one category of application of network analysis.

On the other hand, several studies have focused on the network structure itself. Keller-Ressel and Nargang (2021) used the network among European banks to derive a well-fitting network structure. They concluded that the latent geometry of the observed financial networks is much better represented by negatively curved (hyperbolic) rather than flat (Euclidean) geometry. They also observed changes in network centrality over time and at the same time confirmed the existence of a center-periphery structure. Furthermore, they found communities formed by local banks.

Hattori and Suda (2007) also observed characteristics of financial networks. They explored the developments in the cross-border bank exposures using the BIS International Banking Statistics. They investigated the characteristics of the network topology using density, average path length, degree distribution, and cluster coefficients. They found that the network now has higher connectivity, a shorter average path length, a higher average degree, and a higher cluster coefficient than in the past. In particular, they observed that such tendency has never been hampered by any disturbances or crises in international financial markets

The current study shares research interests with Keller-Ressel and Nargang (2021), and Hattori (2009), and analyzes the structure of financial networks. However, unlike previous studies, which analyzed interbank networks, this study observes the network of securities investments among countries. Furthermore, this study proposes a systematic observation method for international financial networks by introducing measurements used in network science.

2.2 Data

The CPIS contains information on cross-border holdings of equities and long- and short-term bonds in various countries, broken down by the issuer's country of residence[3]. The CPIS has been conducted annually since 2001 and semi-annually since data collection at the end of June 2013. It is a unique tool for understanding the global aggregate and geographic distribution of portfolio investment assets, thereby contributing to a better understanding of financial interconnectedness. The CPIS data have implications for disclosing potential exposure to spillovers as well as cross-border financial linkages.

We must confirm the analytical nature of the CPIS data. There are three measurement methods for observing international financial linkages: net, gross, and aggregate. Net international capital flows are the difference between capital outflows and capital inflows in each country. In the balance of payments table, they correspond to the financial account balance, which is inextricably linked to the domestic savings-investment balance. The global imbalance theory that emerged in the 2000, suggests that the excess investment in advanced economies was financed by the excess savings in emerging market economies, which was a net international capital outflow from emerging market economies and a net capital inflow into advanced economies (Obstfeld and Rogoff, 2009; Borio and Disyatat, 2010). However, even though the financial account was in a state of near equilibrium, both investment and procurement dramatically increased in the period leading up to the global financial crisis. Therefore, it is necessary to observe gross investment and procurement amounts to grasp the actual status of international capital movement. The CPIS allows analysis on a gross basis.

As for another analytical nature of the CPIS, it is stock data unlike the financial account balance, which is flow data. The financial account records the inflow and outflow of capital over a period and helps in analyzing related to changes in financial variables such as exchange rates, interest rates, and stock prices. On the other hand, investment and financing balances published by the CPIS can be used to observe the strength of international financial linkages

[3] Using Japan as an example, we can see the outstanding investment from Japan to each country and the outstanding financing of Japan from each country.

among countries. For analysis in this paper, we will observe the linkages among countries based on the aggregate data of investment and procurement amounts.

Table 1 summarizes the total balance of external assets and liabilities in the form of securities for each country in 2015 and 2023. The countries are ranked based on their values as of 2023. We chose 2015 as the base year because the CPIS began publishing data for China in 2015, which is expected to have a growing presence in the international financial linkages. In 2023, the US interest rate reached its peak, with the FF rate guidance target range at 5.25%-5.50%. The 77 countries for which data were available in both 2015 and 2023 were used not only to create Table 1 but also for the analysis of international financial networks.

Table 1. International securities investments

(Unit: billion USD)

External investment					External borrowing				
Rank	Country	2015	2023	change(%)	Rank	Country	2015	2023	change(%)
1	US	8,969	14,367	60.2	1	US	9,514	21,045	121.2
2	Luxembourg	3,555	5,670	59.5	2	Cayman	2,709	4,934	82.2
3	Cayman	1,636	5,625	243.7	3	Luxembourg	2,973	4,872	63.9
4	Ireland	2,356	4,788	103.3	4	UK	3,710	4,669	25.8
5	Japan	3,409	4,280	25.6	5	Ireland	1,702	3,910	129.8
6	Germany	2,772	4,136	49.2	6	France	2,679	3,818	42.5
7	UK	3,438	3,825	11.3	7	Japan	1,822	2,771	52.1
8	France	2,476	3,115	25.8	8	Germany	2,326	2,583	11.0
9	Canada	1,182	2,498	111.3	9	Netherlands	1,851	2,551	37.8
10	Netherlands	1,583	2,143	35.4	10	Canada	1,174	2,371	101.9

Source: CPIS, IMF

The most striking trend in external investment is that the US holds an overwhelming amount, far ahead of the second place holder, Luxembourg. Luxembourg, the Cayman Islands, and Ireland, which are offshore financial markets, follow the US, the Cayman Islands, Ireland, and Canada stand out in terms of growth from 2015 to 2023, meanwhile the overall average increase was 65%.

Turning to external borrowing, the concentration in the US has become even stronger than that in overseas investment. The pace of capital inflows into the US is much faster than investments from the US Capital inflows to neighboring Canada and the Cayman Islands, which have strong financial linkages with the US, have also increased significantly; and the North American region is attracting money from around the world.

3. Characteristics of the international financial network

3.1 Relevance of scale-free networks

The international financial network constructed by this study consists of 77 nodes representing countries. The edges represent the creditor-debtor relationships between countries. Since the edges are not oriented, this network is classified as an undirected graph. Undirected graph is used because several analyses cannot be performed with a directed graph. Also, a directed graph can make it difficult to intuitively interpret the results of calculations. Careful consideration should be given to which graph to select for analysis.

Another network characteristic to be analyzed is the degree distribution of the nodes. The degree is the number of edges from one node to another. In this study, edges represent the sum of outward investment and outward procurement among nodes. If weights are added to edges, the degree is called strength. This study analyzes international financial networks as a weighted undirected graph.

The left-hand-side panel of Figure 2 shows the distribution of strength, with the vertical axis representing frequency and the horizontal axis the measure of strength. The shape of distribution shows that the international financial network is a scale-free network, one of the complex networks. In scale-free networks, the distribution has a long tail. In line with this study, a long tail is a state in which there are many countries with very low strength and some with large strength, although the frequency decreases rapidly as the strength increases. In such a network structure, nodes with small strengths are connected to each other by a small number of hubs with large strengths.

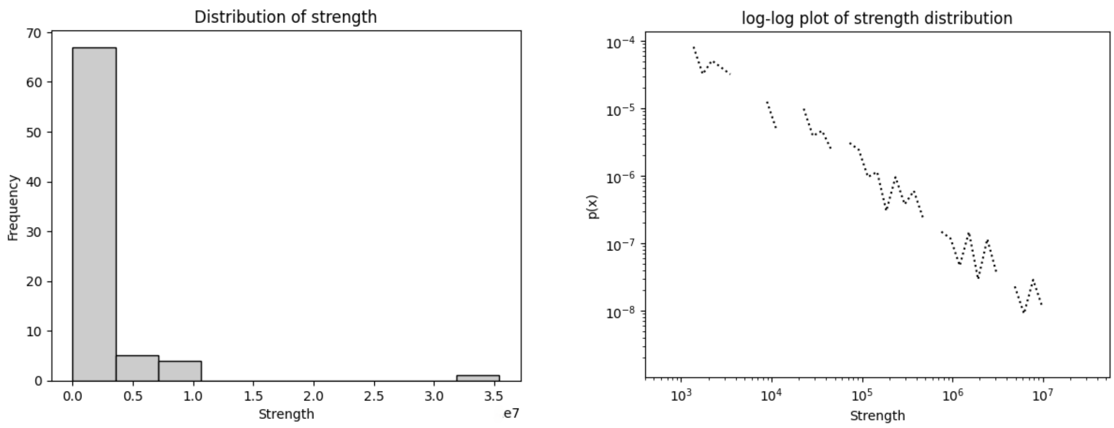

Figure 2. Strength distribution (2023)

A scale-free network can be defined as a network whose degree distribution is approximated by the power law, and whose shape is inversely proportional, as shown in the left-hand-side panel of Figure 2. The power-law distribution has a larger number of samples with extreme values than the normal distribution, so the curve has a long, gently sloping tail in the direction of the larger values. The tail fat, which is thicker than the normal distribution. In other words, the scale-free network contains a mix of nodes with completely different degree values and divergent second-order moments of degree. It is called a scale-free network because it is a distribution for which measures such as mean and variance are meaningless.

Some real-world networks are approximated by scale-free networks, and many may immediately think of the World Wide Web[4]. A few well-known sites on WWW attract a huge number of links and few links to other sites. It is not difficult to predict that the degree distribution in such networks follows a power-law distribution. When analyzing a scale-free network, we check to see if the degree is indeed approximated by a power law distribution. Let k be the degree and $p(k)$ the ratio of nodes whose degree is k. The power law is expressed as

$$p(k){\sim}k^{-\gamma}$$

Here, ~ denotes proportionality and γ denotes power exponent. An intuitive way to check whether the degree distribution follows the power law is to use a logarithmic graph of both the degree k and ratio $p(k)$, and determine that the distribution follows the power law if the relationship is linear. Taking the logarithm of the above proportionality, we obtain

$$\ln p(k) \sim -\gamma \ln k$$

Here, $\ln p(k)$ is proportional to $\ln k$ and the power exponent is the slope of the line. The distribution is plotted on a double-logarithmic graph for node strength in the right-hand-side panel of Figure 2. It would be possible to approximate the distribution by a straight line with a negative slope, although it is uneven due to the small number of nodes.

We carefully decide about whether to follow the power law. Clauset et al. (2009) proposed a way to test whether a distribution follows a power law. However, perfect power laws are rarely observed in real networks. For example, in some scattered cases, the probability $p(k)$ is flat due to the small number of low-degree nodes in real networks compared to a pure power-law distribution. This phenomenon is called saturation of low degree. Meanwhile, the power exponent of this study drops sharply at high strength. In many cases, the probability declines rapidly for strengths greater than the cutoff level. This phenomenon is called cutoff at higher

[4] Another typical example of a scale-free network is an airline network that includes hub airports with many routes.

degrees[5].

In some cases, it is possible to accurately and statistically evaluate the degree distribution. However, simply determining whether the degree distribution is exponentially restricted or fat-tailed is sufficient for analysis. Before concluding that the power law is an adequate description of the data, one should evaluate the goodness-of-fit of these distributions. The goodness-of-fit of a distribution can be examined by comparing it to that of other distributions. Specifically, the bootstrap and Kolmogorov-Smirnov tests are used to generate p-values for individual goodness-of-fit and the log likelihood ratio is used to identify which of the two goodness-of-fit is better.

In practice, bootstrapping is computationally expensive, and the log-likelihood ratio test is faster. Philosophically, it is often unnecessary to answer if a distribution really follows a power law. The question is whether the power law is the best description available. In such cases, knowledge that the bootstrap test has passed is insufficient. While bootstrapping can find that a power distribution produces a given data set with a sufficient likelihood, a comparison test can find that a lognormal fit could produce it with an even greater likelihood.

The procedure for the test by Clauset et al. (2009) is as follows:

1. Estimate the parameter $k_{\min}$ and the parameters of the power law model.
2. Calculate the goodness-of-fit between the data and power law. If the p-value obtained is greater than 0.1, the power law is a plausible hypothesis for the data. Otherwise, it is rejected.
3. Compare the power law with the alternative hypotheses using a likelihood ratio test. For each alternative, if the computed likelihood ratio is significantly different from zero, its sign indicates whether the alternative is more or less favorable than the power-law model.

k_{min} is the minimum value of the range over which the distribution obeys the power law.

Using *powarlaw*, a Python package developed by Alstott et al. (2014), we tested whether the power-law distribution or the exponential distribution was more appropriate. This test presents a positive sign if the data are better fitted in the first distribution. The test result shows that the log likelihood ratio between the two candidate distributions is 2.088, with a significance level of 0.012, suggesting that the power-law distribution is more suitable. The strength of the nodes in the international financial network follows a power law, confirming

[5] In real networks, there is some level of restraint against excessive degree growth. For example, there is a physical limit to the number of routes at a hub airport with respect to airline routes.

that it is a scale-free network.

3.2 Network filtering

Traditionally, the characteristics of complex networks are measured by density, mean distance, and cluster coefficients as well as degree distribution. Weighted graphs such as the international financial network are not suitable for such measurements because the computation of these measurements is impossible with weighted graphs, and the interpretation of the computed results is more difficult than with unweighted graphs. Using unweighted graphs is suitable for checking network characteristics. However, there are problems with simply converting a weighted graph to an unweighted one. There are significant differences in weights at the edges of the international financial network. A simple transformation to an unweighted graph would treat edges of very large strength and edges of small strength as edges of similar importance. Simple conversions significantly impact the importance of nodes.

An edge filtering can avoid these problems while converting to an unweighted graph. For networks with many edges with small weights, such as scale-free networks, previous studies (Eguíluz et al., 2005; Allesina et al., 2006) have performed filtering to narrow down to fewer meaningful edges as a preparation for analysis. The extracted edges are commonly referred to as the backbone. A plausible method for extracting only important edges is to set a threshold for edge weights and select edges with weights above the threshold as important. However, this method has the problem of arbitrariness, as there are no firm criteria for setting the threshold. This approach systematically overlooks low-degree nodes, resulting in a network that focuses only on higher-degree nodes and ignores lower-degree nodes.

Previous studies have used two main categories of filtering methods: structural and statistical methods. Structural methods focus on the topological characteristics of the network and extract backbones with specific topological features. Statistical methods used to evaluate the importance of edges and nodes based on hypothesis tests or empirical distributions and remove noise in the network.

This study uses basic structural and statistical methods to filter and selects the backbone that retains the characteristics of the original network. The h-backbone is used as the structural method, which is intuitively easy to understand. According to Zhang (2018), It is inspired by the h-index and edge betweenness. First, using the edge weights, it extracts the h-strength network: h is the largest natural number such that there are h links, each with a weight at least equal to h. Then it extracts the h-bridge network similarly. A bridge of an edge is the edge betweenness divided by the number of all nodes. Finally, the h-backbone merges the two networks.

As a statistical method, we employ the disparity filter proposed by Serrano et al. (2009). This filter extracts the backbone from a large network that has the multiscale property of degree distribution over many orders of magnitude. Specifically, it identifies which edges should be preserved by calculating the probability α_{ij} that fits the null hypothesis for each edge of a given node. By imposing a significance level α, edges with weights that are considered to not fit the distribution can be filtered out by statistical significance. For filtering by this method, we used the package *backbone* of the statistical software *R* created by Serrano et al. (2009)[6].

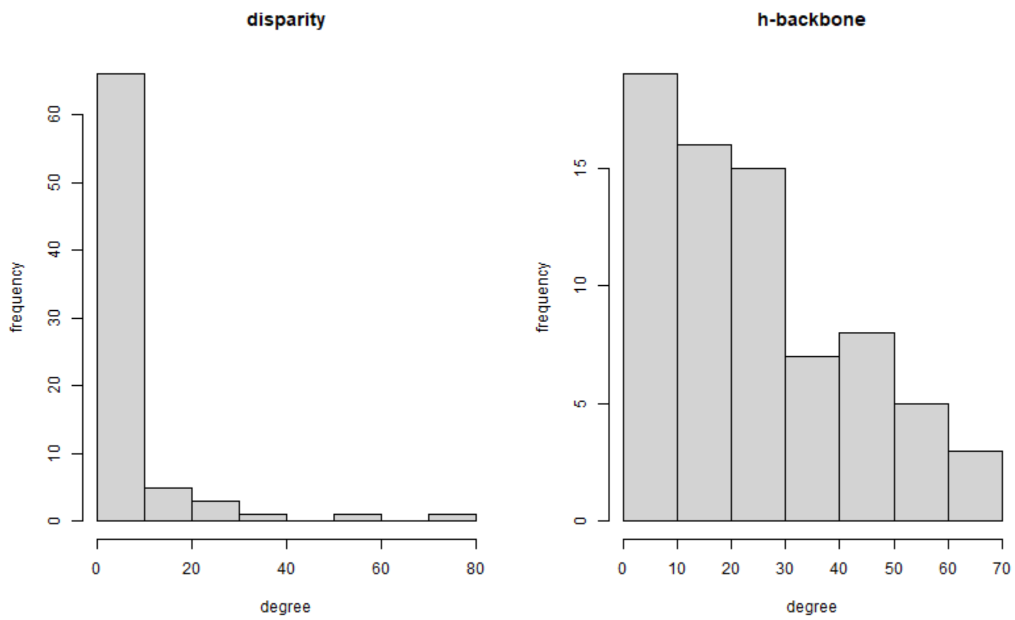

Figure 3. Comparison of backbones (2023)

Between the disparity[7] and the h-backbone, we must determine which backbone is more suitable for analysis. We compare their shapes for the distribution of strengths and choose the suitable one depending on which backbone is more similar to the original network. Figure 3 shows the strength distribution lined up for the network after filtering. Since the backbone after filtering by the disparity retains the shape of the original strength distribution, we use this backbone to examine the characteristics of the international financial network.

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[6] Serrano et al. (2009) confirmed that the backbone extracted by the disparity filter retains most of its nodes and weights, the cluster coefficients are the same as in the original network, and the degree distribution is stationary.

[7] Serrano et al. (2009) concluded that a significance level of [0.01, 0.5] is optimal. For this calculation, the significance level was set at 0.05.

3.3 Network characteristics

All 77 nodes remain after filtering, because the filtering targets edges and not nodes. Filtering reduced the number of edges on the backbone to about 15%. The shape of the distribution retains its characteristics even after significant trimming, as confirmed in Figure 3.

Since the international financial network is scale-free, it is meaningless to check the mean or variance of the degree. The maximum, minimum, and median values are presented for reference. For 2015, the maximum, minimum, and median values were 72, 1, and 5, respectively; for 2023, 72, 1, and 6, respectively. The extremely large degree of the nodes that serve as hubs is a characteristic of scale-free networks.

Density needs to be checked. Density indicates how dense the edges are in a network. It is calculated as the ratio of the actual number of edges to the number of all possible edges. The maximum number of edges E_{max} that a network of n nodes can stretch is obtained as

$$E_{max} = \frac{n(n-1)}{2}$$

Setting m as the actual number of edges in the network, the density can be defined as

$$density = \frac{2m}{n(n-1)}$$

In a complete graph with edges among all nodes, the density takes the maximum value of 1; and in an empty graph with no edges, it takes the minimum value of 0. The density of the international financial network was 0.111 in 2015 and 0.112 in 2023. In real networks, in many cases, the number of edges is much smaller and sparser than E_{max}. This low density indicates the scale-free network's characteristic of having hubs intervening nodes of small degree.

The next feature is the mean distance. In a network, a route that can reach from one node to another along an edge is called a path. The physical distance between nodes is path length, which is the number of edges in the path. The path with the fewest number of edges between a node and another node is the shortest path, often referred to as distance. The mean distance is calculated by searching for the distance for all node combinations and calculating the average value.

The mean distance was 1.919 in 2015 and 1.928 in 2023. Table 2 shows the distance distribution. A distance of 1 indicates that the nodes are directly connected to each other. A distance of 2 indicates that nodes are connected through one node. At distance 3, there are two nodes in between for the nodes to connect. This network is connected because there is no combination of nodes with a distance of zero, so there are no disconnected nodes.

Table 2. Distance distribution

	Distance			
Year	0	1	2	3
2015	0	326	2510	90
2023	0	328	2482	113

The number of node combinations with a distance of 2 is outstandingly large, which is consistent with a mean distance value close to 2. This suggests that hubs act as intermediaries, linking nodes together. The mean distance is shortened because the hub bundles many smaller degree nodes and reduces the distance between them. This property in scale-free networks is referred to as an ultra-small world.

The third indicator is the average cluster coefficient. The degree to which nodes adjacent to a given node are connected to each other is called the cluster degree. It is measured by the local cluster coefficient. The local cluster coefficient C_i for node i is defined as

$$C_i = \frac{2L_i}{k_i(k_i - 1)}$$

where L_i is the number of edges between the k_i neighbors of node i. C_i takes values between 0 and 1. The cluster degree of the entire network can be measured from the local cluster coefficients. All local cluster coefficients should be averaged, giving the average cluster coefficient. The values for 2015 and 2023 were 0.797 and 0.743, respectively.

It is not prudent to determine the characteristics of the network solely from the average. We confirm the characteristics using Figure 4, which shows the relationship between degrees and local cluster coefficients. While cluster coefficients are high at nodes with low degree, connections are sparse at neighboring nodes of the hub. Hubs link with nodes of smaller degree and exhibit the pattern shown in Figure 4. This result is consistent with the degree correlation results in Section 4.

In summary, by measuring mean distance and average cluster coefficient as well as degree distribution, we can confirm that the international financial network is a scale-free network with hubs.

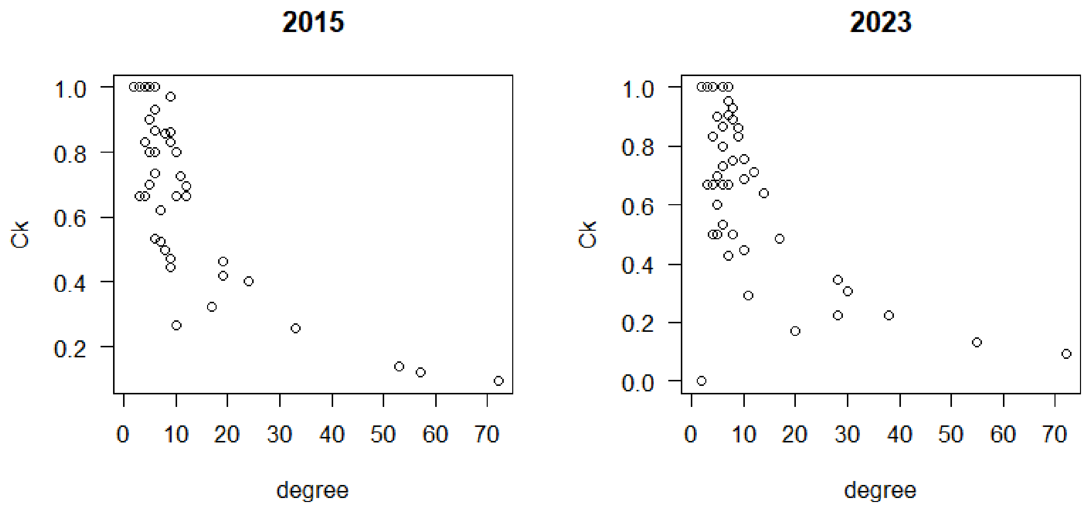

Figure 4. Degrees and local cluster coefficients

4. Network structures

4.1 Degree correlation

The next task is to determine what structure the international financial network holds. We address four questions to answer this. The first question is whether the international financial network is assortative or disassortative. When nodes of higher degree are associated with each other, it is called assortative, while when nodes of higher degree are associated with nodes of lower degree, it is disassortative. These patterns correspond to the property of degree correlation in the network. Degree correlations allow us to deal with quantitative patterns that explain ties between nodes that would not be revealed by degree distribution alone. To determine whether a network is assortative or disassortative, the Pearson correlation coefficient r for degrees is used:

$$r = \sum_{jk} \frac{jk(e_{jk} - q_j q_k)}{\sigma^2}$$

Here, the degree correlation matrix e_{jk} is the likelihood that a node of degree j and a node of degree k are at both ends of a randomly chosen edge. q_k is the probability that a randomly selected edge has a node of degree k. σ^2 denotes the standard deviation of q_k.

The calculation results were -0.490 for 2015 and -0.446 for 2023. Node degrees are negatively correlated. This shows that hubs with larger degrees are connected to nodes with smaller degrees. These values represent that the topology of the network is scale-free. Hubs with many edges are connected to nodes with few edges, thus suggesting the existence of hubs.

A possible network structure is a center-periphery structure, in which the central countries form a financial network among themselves, while smaller countries are excluded from the network and have few accesses to the financial markets of the central countries. However, the observations indicate that the central countries play the role of hubs and even small countries have access to financial markets.

4.2 Network centrality

The second question is which country is the central node in the network. Since the analyses have revealed the existence of hubs in the international financial network, this question implies identifying countries that play the role of hubs. Weighted graphs will be used in subsequent analyses because, unlike the measures used to observe the network characteristics, the measures used from now on are not particularly hindered even if it is a weighted graph.

This study uses eigenvector centrality to search for central nodes. In evaluating the centrality of a node, we need to reflect the centrality of neighboring nodes. We can appreciate ties to countries that are central as international financial markets are more important in terms of access to investment and procurement than ties to countries that are not so central. The centrality that can reflect these ideas is eigenvector centrality, and this study uses it to observe the importance of each country. The eigenvector centrality as a ratio with the maximum value as 1.

Let $\boldsymbol{A}$ be the adjacency matrix of the undirected graph, and $\boldsymbol{c}$ be the column vector whose components are the centrality of the nodes in $\boldsymbol{A}$. Eigenvector centrality is expressed as

$$\lambda c = Ac$$

Here, λ is the eigenvalue of the adjacency matrix $\boldsymbol{A}$. When the initial vector is set appropriately and the computation is iterated, the column vector $\boldsymbol{c}$ converges to the eigenvector corresponding to the largest eigenvalue of $\boldsymbol{A}$. The eigenvectors obtained are the eigenvector centrality of each node[8].

[8] Eigenvector centrality is the first eigenvector corresponding to the eigenvalue with the largest absolute value.

Table 3 shows the calculation results from countries with the highest centrality values, confirming the importance of developed countries and offshore financial markets. There are three noteworthy points. First, the US is by far the most centralized. Its importance in the network has increased as its centralities have risen. We can assert that the US is the most important hub in the international financial network. Second, Japan's ranking is third in both years and its unexpected importance is striking. The highly centralized figures can be explained by the fact that Japan has the strong linkage with the U.S. and the Cayman Islands. Third, the UK has declined in status, presumably due to Brexit. It has lost its status as a gateway to the right to do business throughout the EU. London maintains second place behind New York in the International Financial Centers Index published by Z/Yen, a British consultant. However, Table 3 confirms the UK's decline in international securities investment. Eigenvector centrality allows us to track the importance of each country and how it has changed given its ties to countries of higher importance.

Table 3. Network centrality

	2015		2023	
Rank	Country	Centrality	Country	Centrality
1	US	0.609	US	0.647
2	UK	0.354	Cayman	0.427
3	Japan	0.323	Japan	0.259
4	Cayman	0.303	UK	0.252
5	Luxembourg	0.24	Ireland	0.248
6	Ireland	0.212	Luxembourg	0.216
7	France	0.21	Canada	0.209
8	Germany	0.199	France	0.158
9	Canada	0.172	Germany	0.149
10	Netherlands	0.163	Netherlands	0.122

4.3 Community detection

The third question is whether there are more tightly connected groups in the international financial network. This question raises awareness regarding the problem of instability in international finance. International capital movements centered in the US have the following composition. The US has been running huge current account deficits, which have been financed by capital inflows from other countries. Japan, China, and emerging economies have supported current account deficits while shifting their importance in capital inflows to the US. Inflows to the US flowed back to emerging economies in the form of short-term funds and became a source of financial instability. Previous studies have pointed to the formation of this unstable network. This study does not focus on the US alone but observes international capital flows from a global perspective to see how groups with close linkages exist.

In network science, a community is a set in which nodes belonging to one set are more likely to be connected to each other than to nodes belonging to another set. From this point on, we use the term “community” instead of group. The network is divided into communities as follows. The algorithm compares the density of edges in one community to that in a randomized network between the same nodes. This comparison can determine whether the original community indeed corresponds to a dense subgraph, or whether the combination pattern arose by chance. The comparison employs a measure called modularity, which measures the quality of a division by its systematic deviation from a random shape.

The division that maximizes modularity represents the optimal community structure. We can examine the modularity for all possible divisions and find the division with the maximum modularity. However, the number of divisions is extremely large, making the brute force method of calculation impractical. Therefore, an algorithm that does not require examining all the divisions is needed. This study employs the Louvain method (Blondel et al., 2008). Barabási (2016) reported that the Louvain algorithm produced the most accurate results in an evaluation by the Lancichinetti-Fortunato-Radicchi (LFR) benchmark. The LFR measures the accuracy of community detection. It generates a network that follows the power-law distribution and measures the accuracy of the division by the mutual information. The algorithm for the Louvain method follows these steps.

Step 1: Select one node. Incorporate that node into the community to which its neighbors belong and calculate the change in modularity ΔM:

$$\Delta M = \left[\frac{\sum_{in} + 2k_{i,in}}{2W} - \left(\frac{\sum_{tot} + k_i}{2W}\right)^2\right] - \left[\frac{\sum_{in}}{2W} - \left(\frac{\sum_{tot}}{2W}\right)^2 - \left(\frac{k_i}{2W}\right)^2\right]$$

Here, Σ_{in} is the sum of the weights of the edges in community C, Σ_{tot} is the sum of the weights of the edges of all nodes in the community, k_i is the sum of the weights of the edges leaving node i, $k_{i,in}$ is the sum of the weights of the links from node i to the nodes in C and W is the sum of the weights of all edges in the network.

We search for the community with the greatest change and move the node. This operation is performed for all nodes.

Step 2: We group the communities in step 1 together as nodes and obtain a new network. Edges between nodes in a community that are grouped into a single node in this process become self-looping. Repeat steps 1 and 2 for this new network. This process is repeated until no increase in modularity occurs.

The best community structure is detected by finding the division that maximizes modularity through the above procedure. The community detection found four communities (Table 4). Community 3 consists of the UK and the tax havens of the British Crown Dependencies, with the core of the community being the UK and Ireland, an offshore financial center. Community 2 is formed by strong international financial network ties among European countries, and Luxembourg occupies a central position in this community as well. The result that the major offshore financial centers - Ireland, Luxembourg, and the Cayman Islands - belong to different communities is a characteristic of the international financial network.

Table 4. Results of community detection

No.1		No.2		No.3	No.4
Argentina	Israel	Albania	Latvia	Egypt	Bahrain
Aruba	Japan*	Austria	Lebanon	Gibraltar	Kuwait
Australia	Kazakhstan	Belarus	Lithuania	Guernsey	Turkiye
Bangladesh	South Korea	Belgium	Luxembourg*	Iceland	
Bermuda	Macao	Bulgaria	Mongolia	Ireland*	
Bolivia	Malaysia	Cyprus	Netherlands*	Jersey	
Brazil	Mauritius	Czech	Poland	Malta	
Canada*	Mexico	Denmark	Portugal	SouthAfrica	
Cayman*	New Zealand	Estonia	Romania	UK*	
Chile	Norway	Finland	Slovak		
China	Pakistan	France*	Slovenia		
Colombia	Panama	Germany*	Spain		
CostaRica	Philippines	Greece	Sweden		
Honduras	Saudi Arabia	Hungary	Switzerland		
Hong Kong	Singapore	Italy	Ukraine		
India	Thailand	Kosovo			
Indonesia	US*				

Note: Astarisks indicate countries in the top 10 in Table 1.

Community 1 is a community with the US at its center and incorporating the Cayman Islands and Japan. Asian countries, Oceania countries, and South American countries geographically close to the US are also included in this community. The community detection found that Asian countries that are forming intra-regional capital flows remain encompassed by the US-centered community.

4.4 Centralization

The fourth question is whether the centralization of the international financial network has increased. Here, we observe a shift in the bias of capital movement toward a particular country. We set this question because we are aware of excessive international capital movement. As an example, we review the situation in the US, which is considered the center of the international financial network. The current account deficit in 2023 was 905 billion US dollars. On the other hand, capital inflows in the form of portfolio investments amounted to 1,231 billion US dollars and capital inflows in the form of other investments[9] amounted to 307 billion US dollars, which significantly outweighed the current account deficit.

The concentration of capital inflows in certain countries can lead to massive capital reversals during severe stress in the financial markets. This has been repeated many times, not to mention the example of the global financial crisis. The degree of concentration risk in the international financial network is measured by centralization.

We employ the Gini coefficient. It is a well-known indicator for expressing the degree of inequality with respect to assets and income. However, it can be used to measure the degree of disparity, not only income inequality, and network analysis has measured disparity in terms of node centrality (Melamed et al., 2022). In this case, the case of perfectly even distribution of centrality is used as the standard, and its deviation from the perfectly even state is measured. The value of the Gini coefficient ranges from 0 to 1, with a maximum disparity of 1 and a value of 0 for perfect equality.

We measure the level and change in disparity for distributional states of eigenvector centrality. The Gini coefficient g can be calculated as the mean absolute difference using the disparities among countries:

$$g = \frac{1}{2n^2\bar{x}} \sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|$$

Here, x_i, x_j are the eigenvector centralities for country i and country j, $\bar{x}$ is the mean value of eigenvector centrality, and n is the number of countries.

The calculation resulted in a Gini coefficient of 0.780 for 2015 and 0.791 for 2023. The high value of the Gini coefficient indicates a large bias. This means that international securities investment is concentrated in the countries listed in Table 3. As for change, the bias is widening, albeit slightly, and concentration risk in the international financial network

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[9] Other investments consist primarily of bank lending and trade finance.

remains high.

5. Conclusion

This study aimed to characterize international financial networks from a network science perspective. Unlike previous studies, the introduction of network analysis allows us to observe the behavior of the network as a whole, since the analysis includes country-to-country links. First, we measured the characteristics of the international financial network as a scale-free network. We then set four tasks to identify the structure of the network. Those issues are whether central countries tend to be linked to each other, which countries occupy a central position in the network, which communities exist as closely connected, and whether the network is becoming more concentrated. International financial networks have rarely been analyzed from a complex network perspective. This study attempted to establish a systematic observation method through network analysis.

This study statistically confirmed that the strength of the node follows a power law. It also found that the network is sparse because the presence of the hub links countries of small degree, and it preserves a very small world with a short mean distance. These are the characteristics of the international financial network as a complex network.

The four issues regarding the structure of the network were answered as follows. First, the degree correlation coefficients reveal that the network is disassortative, indicating that small countries are not in a situation where they are excluded from access to finance. Second, the central position in the network is occupied not only by developed countries led by the US, but also by offshore financial centers such as Luxembourg and Ireland. Third, there are four communities in the international financial network. The major communities were centered in the US, the UK, and Luxembourg, respectively. Fourth, the measurement of eigenvector centrality resulted in a modest increase in network centralization. This result suggests that concentration risk may materialize when financial markets are stressed.

This study has scope for improvement, such as examining whether there is a more appropriate centrality measure for measuring the importance of each country and applying community extraction based on directed graphs. It is necessary not only to improve methods but also to continue observations. In addition, in the future, variables measured by network analysis can be incorporated into the model to explain international capital movements.

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