An analysis of the transaction network in the Japanese OTC derivatives markets

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Abstract

From the reflection on the financial crisis in 2008, G20 Leaders, at the 2009 Pittsburgh Summit, agreed that over-the-counter (hereinafter referred to as OTC) derivatives trade (transactions) contracts should be reported to trade repositories (hereinafter referred to as TRs). Following this commitment, data reporting and aggregation requirements for OTC derivatives were implemented in most FSB member jurisdictions to reinforce monitoring and supervision systems in the usual period and ensure a prompt and optimal response to macro-prudential risks.

In Japan, JFSA implemented OTC derivatives trade (transactions) reporting requirements in 2013, mandating market participants, including financial instruments business operators and central counterparty clearing houses, to report their OTC derivatives transactions, whereby JFSA receives reports of trade repository data (TR data) pursuant to the Financial Instruments and Exchange Act (hereinafter referred to as FIEA).

This paper aims to clarify market features of the OTC derivatives in Japan by analyzing transaction networks based on reported data using metrics in graph theory. We found that the OTC derivatives markets in Japan have small-world feature and sparse network structure in common with all product markets. However, in the OTC derivatives market where foreign exchange is the underlying asset, the core players who act as the hub of market transactions have higher clustering coefficients than the average of the entire market, indicating that the core players' involvement in the market may differ relatively depending on the product category of the underlying asset.

Based on these analyses, we address the way to improve analysis and monitoring on OTC derivatives markets. Furthermore, in this paper, we also summarized issues for

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future research, such as the necessity of de-duplication processing for some transactions that are reported in duplicate due to reporting requirements of the OTC derivatives trading information.

1 OTC derivatives trade (transactions) reporting requirements in Japan

Trade (transactions) reporting is one of the main themes of G20's OTC derivatives reform program decided in the G20 Pittsburgh Summit.[1] Based on the principle that "OTC derivatives should be reported to trade repositories" in the agreement, the FSB discussed and worked on the trade reporting.

In a press release,[2] the FSB reported that "Authorities are using trade repository data for a wide range of tasks and incorporating it in their published work. Work continues internationally, including on data harmonisation." It also reported that "Trade reporting data provides important information for authorities as they seek to assess risks in OTC derivatives markets. However, where barriers to the full reporting of trade data and to authorities' access to this information exist, this reduces the usefulness of this data. This document[2] reports on actions FSB member jurisdictions have taken to address legal barriers to reporting and accessing trade data identified in a 2015 peer review." The Japanese government made amendments to FIEA in 2010 and enforced transaction reporting requirements consistent with the G20 and the FSB's initiatives to reduce systemic risks and improve the transparency of OTC derivatives markets. This paper analyzes the OTC derivatives market and transaction structures based on data from the report submitted by market participants.

1.1 OTC derivatives trade(transactions) reporting requirements in Japan

Article 156-63 and Article 156-64 of FIEA require financial instruments clearing organizations (central counterparty clearing houses [CCP])*1 and financial instruments business operators (FIBO)*2 to preserve and report OTC derivatives transactions records. The transactions records which CCPs are required to report are defined as "data on centrally cleared trades" (Article 156-63 of the FIEA), and the records FIBO are required to report are defined as "trade data (transaction information)" (Article 156-64 of the FIEA). *3

Article 156-63 of the FIEA delegates the details of "data on centrally cleared trades" to the Cabinet Office Order on the Regulation of Over-the-Counter Derivatives Transactions (hereinafter referred to as the "Cabinet Office Order"). *4 Article 156-64 of the FIEA also

*1 The name for financial instruments clearing organizations and foreign financial instruments clearing organizations in FIEA.

*2 The name for financial instruments business operators or registered financial institutions in FIEA.

*3 Article 3 of the Cabinet Office Order defined the transactions pointed out in Article 6 as "data on non-centrally cleared trades," which is required to be reported to the authorities

*4 Under Article 3 of the Cabinet Office Order, transactions set forth in each item of Article 6, paragraph (1) of the Cabinet Office Order (excluding transactions set forth in each item of Article 156-62 of the FIEA, and in case of the transactions set forth in Article 2, paragraph (22), items (ii), (iv), and (v) of the FIEA, excluding those pertaining to financial indicators set forth in Article 2, paragraph (25), delegates details of "trade data" to the "Cabinet Office Order." Article 6 of the "Cabinet Office Order" defines the following transactions [*5] as "trade data."

- transactions set forth in Article 2, paragraph (22), items (i) and (ii) of the FIEA [*6] :Forward transactions and index forward transactions
- transactions set forth in Article 2, paragraph (22), items (iii) and (iv) of the FIEA [*7] :Option transactions and index option transactions
- transactions set forth in item Article 2, paragraph (22), item (v) of the FIEA: Swap transactions
- transactions set forth in Article 2, paragraph (22), item (vi) of the FIEA[*8] :Credit derivatives transactions

In addition, Article 6 (2) of the Cabinet Office Order stipulates that transactions conducted by certain persons or entities are exempt from preserving (archiving) and reporting of trade data (transaction information) (meaning the "trade data [transaction information]" set forth in Article 156-64, paragraph (1) of the FIEA). Such persons and entities are the national government; local governments; the Bank of Japan; foreign governments or other specified persons equivalent to those set forth under the laws or regulations of foreign country; international organizations designated by the Commissioner of the Financial Services Agency (JFSA); parent companies, etc. of FBO, etc. conducting such transactions; those subsidiaries, etc.; or subsidiaries, etc. of parent companies, etc. (excluding those concerned FBO, etc.).

For the scope of entities subject to the reporting, Article 6 of the Cabinet Office Order designates "business operators, etc., that are subject to the creation of trade data (transaction information)" [*9] among financial instruments business operators (FBO), whereby the designated operators are required to preserve and report OTC derivatives transactions records.

The FIEA stipulates two reporting routes to JFSA: an "indirect reporting" route via trade repositories and a "direct reporting" route to JFSA. [*10]

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items (ii), (iii), or (iv) of the FIEA [limited to the portion pertaining to items (ii) and (iii) of the same paragraph]) are subject to reporting, specifically.

[*5] With the exception of transactions set forth in each item of Article 156-62 of the FIEA, in the case of transactions set forth in Article 2, Paragraph 22, item 2, item 4 and item 5 of the FIEA, Article 2, paragraph 25, item 2, item 3 or item 4 (limited to the portion pertaining to item 2 and item 3 of the same paragraph.

[*6] Excluding the cases where the period from the contract day to the date of delivery is two business days or less

[*7] Excluding the cases where the exercise period is two business days or less

[*8] Limited to transactions whose cause prescribed in that item is the cause set forth in (b) of that item

[*9] The term "financial instruments business operators" means a financial instruments business operator or a registered financial institution as a bank that conducts Type I Financial Instruments Business, The Shoko Chukin Bank, Ltd., Development Bank of Japan Inc., a federation of Shinkin banks (whose district is the entire nation), The Norinchukin Bank or an insurance company.

[*10] The amendments to the FIEA in 2010 established a regulatory framework for trade repository registration. Article 156-64(3) of the FIEA defines a designated domestic trade repository institution as "Trade Repository" and a foreign trade repository institution that is designated by JFSA via issuing a regulatory (enforcement) notification as "Designated Foreign Trade Repository." These trade repositories are required to preserve and report trade (transactions) data, whereby JFSA receives OTC derivatives transactions data via trade repositories. In this respect, FBO (financial business operators) that use the designated trade repository for statutory reporting are exempted from the trade reporting obligation.

The development of telecommunication technology has made OTC derivatives reporting more reliable in terms of preserving and reporting trade data (transaction information), which consequently led to the amendments to the FIEA in 2020 to integrate trade (transactions) reporting routes.[3] The purpose of the amendments mentioned above is to simplify reporting routes by adopting the indirect reporting in which trade data are reported to JFSA via trade repositories. The other aim of the amendments is to improve analysis and utilization of OTC derivative transactions, thereby enhancing investor protection thorough increasing OTC derivatives markets' transparency. In this regard, JFSA is working on drafting the relevant Cabinet Office Orders and subordinate orders to ensure the enforceability of the amendments to the FIEA in 2020.*11 In addition, JFSA began to share TR (trade repository) data with the Bank of Japan to effectively utilize OTC derivatives reporting.[5]

1.2 Initiatives toward utilization of OTC derivatives trade (transactions) reporting data in foreign countries

1.2.1 Hong Kong

Hong Kong Trade Repository (HKTR) receives trade reports as Hong Kong's central trade repository to implement the "OTC derivatives trade (transactions) reporting initiative." HKTR belongs to Hong Kong Monetary Authority (HKMA) and receives trade (transactions) reports based on the following regulatory regime for OTC derivatives markets (OTC Regulatory Regime), [6] whereby business operators responsible for reporting trade (transactions) data must become a member of HKTR. The Hong Kong Government, Securities & Futures Commission of Hong Kong, and Hong Kong Monetary Authority (HKMA) have established the Securities and Futures Ordinance (SFO) under the Hong Kong's OTC Trade (Transactions) Regulatory Regime. The Securities and Futures (Amendment) Ordinance 2014 has put the OTC Regulatory Regime into effect in two stages, thereby mandating the reporting to HKTR of the OTC derivatives trade (transaction) information for all key asset classes, including interest rates, foreign exchanges, equities, credit, and commodities.

Business operators responsible for reporting trade (transactions) data in Hong Kong are*12 as follows.

1. Authorized Institutions ("AIs")
2. Approved Money Brokers ("AMBs") licensed and regulated by the HKMA under the Banking Ordinance
3. Licensed Corporations ("LCs")、 recognised clearing houses ("RCHs")
4. Automated trading services - central counterparty ("ATS-CCP") licensed and regulated by the SFC under the SFO

This framework is a key element of indirect reporting mentioned above. At present, JFSA designates DTCC data repository Japan (DDRJ) as the designated "Trade Repository" and DDRJ is conducting trade repository business.

*11 Public consultation process started on Dec. 25, 2020 [4]

*12 There is a separate regulatory framework that exempts certain "AIs," "AMBs" and "LCs" from the reporting obligation provided that they meet certain conditions.

HKTR publishes two types of reports[7, 8] to increase market transparency. [*13]

1.2.2 The FSB' s discussion toward international sharing of OTC derivatives trade(transactions) data

The FSB has also been discussing the need to establish a framework for cross-border (cross-authority) sharing of OTC derivatives trade (transactions) data in order to grasp the actual status of OTC derivatives transactions on a global scale and enhance the effectiveness of supervision. Each jurisdiction is to cooperate building a cross-border sharing framework and address obstacles to sharing.

2 Purpose and target of analysis in this paper

To understand the actual situation of OTC derivatives markets and establish an optimal supervisory framework under international cooperation, JFSA should also try to refine the analysis technology for trade repository data (TR data) and pile up knowledge. Such initiative will contribute to the accurate understanding of OTC derivatives markets in Japan, practical use for monitoring and supervision, and increasing market transparency through publishing information that contributes to the development of markets. Furthermore, given the discussion about cross-border cooperation on sharing trade repository data (TR data) at the FSB and the initiatives by foreign authorities, it is crucial for JFSA to accumulate experience and knowledge on analytical methods for trade repository data (TR data) to promote international cooperation. For this purpose, this paper analyzes trade repository data (TR data) and addresses issues for a more accurate and in-depth analysis of the OTC derivatives market.

Besides the analysis of trade repository data (TR data), government agencies should take the initiative for data-driven analysis in society.[*14] Moreover, the experiences and knowledge accumulated from the trade repository data (TR data) analysis are applicable for analyzing other datasets for financial supervision. Therefore, we believe that the analysis in this paper is meaningful.

3 Data Set

The dataset analyzed in this paper is the flow data in OTC derivatives markets reported to JFSA between April 1, 2018, and March 31, 2020. The data includes detailed information about each transaction, including transaction parties, notional principal, the category of collateral, transaction type, contract date, and other related details.

We compare and analyze OTC derivatives transactions backed by products in the category of credit (CD), equity (EQ), foreign exchange (FX), and interest rate (IR) in this paper. A typical example of an OTC derivative for each underlying product is shown in Table 1.

[*13] Transactions included in the disclosed data in reports include interest rate swaps, forward foreign exchange transactions, foreign exchange futures, and other derivatives related to interest rates and currencies in general.

[*14] JFSA has been publishing annual flow and stock data of OTC derivatives transactions since 2014.[9]

Table 1 Examples of OTC derivatives trading for each underlying product

Product	Example
Credit（CD）	Credit Default Swap(CDS）
Equity（EQ）	Options trading backed by stocks and stock indices
Foreign Exchange（FX）	Currency options trading
Interest Rate（IR）	Swaption trading

Table2 shows the number of OTC derivatives transactions sorted by each collateral product.

Table 2 The number of reported OTC derivatives transactions for each product

	CD	EQ	FX	IR
Apr. 1, 2018 - June 30, 2018	11,513	11,497	206,877	291,509
Jury 1, 2018 - Sept. 30, 2018	9,968	12,323	281,263	271,073
Oct. 1, 2018 - Dec. 31, 2018	9,829	11,361	245,845	318,254
Jan. 1, 2019 - Mar. 31, 2019	12,600	9,368	245,949	356,890
Apr. 1, 2019 - June 30, 2019	16,473	6,863	206,049	278,419
July 1, 2019 - Sept. 30, 2019	12,881	29,556	218,397	758,452
Oct. 1, 2019 - Dec. 31, 2019	9,353	30,327	148,579	662,955
Jan. 1, 2020 - Mar. 31, 2020	12,820	26,484	283,081	558,387
Total	95,437	137,779	2,060,154	3,495,939

Table 2 shows the number of transactions in Japanese OTC derivatives market, where the interest-rate-backed products are the largest, followed by foreign exchange, equities, and credit. We discuss the practical use of trade repository data (TR data) for financial supervision and policymaking based on these data.

Here, we have to be careful about the double-counting problem. Since the reporting requirement is assigned for both parties in some transactions, multiple statutory reports can be submitted from them, thereby affecting the results in this paper. While it is desirable to solve this duplicity in reporting, due to technical difficulties in cross-referencing trade repository data (TR data) with the current analytical method, no adjustments are considered in this paper.

4 Visualizing OTC derivative transaction-network graph

This paper aims to clarify structures of the transaction network of the OTC derivatives market in Japan using trade repository data (TR data) based on graph theory. Therefore, in this section, we consider the visualization of a market network based on the information for each transaction.

First, we assign a weight for each transaction edge between business operators (contracting parties) in the OTC derivatives market to reflect the connectivity in the network visualizing process. Given that this paper aims to clarify structures of transaction networks in the markets, the weight should reflect the importance in the overall market. A typical metric of transactions with a significant impact is the large amount of the notional principal, which is recorded in trade repository data (TR data). Therefore, in this analysis, we set the weight for each transaction edge with the following equation:

$$w_{uv} \equiv \frac{\sum_\alpha v_{uv}^\alpha}{\sum_{u,v\in V}\sum_\alpha v_{uv}^\alpha} \tag{1}$$

where V and v_{uv}^α represent a set of market participants included in the transaction network and the amount of the notional principal of the α-th transaction executed by market participants u and v, respectively. In other words, the weight is set based on the percentage of notional amount that each combination of market participants holds in the total amount for each trading market. All the analyses in this paper are done with Python3.8 and numerical analysis modules such as NumPy, NetworkX, and Matplotlib.[10–12]

Fig.1 shows the cumulative distribution for each party's market share, listed in ascending order of the rank for the amount of notional principal and the number of transactions. We note that in this analysis, parties reported as "operating companies" are treated as a single entity, and the amount of notional principal and the number of transactions are aggregated.[*15]

Fig. 1 shows that the top 10% of participants hold most transactions and notional principals. Notably, the derivatives markets backed by foreign exchange and interest rates are highly oligopolistic, with a market share greater than 80%. Here, we note that the high concentration in the market backed by interest rates may come from regulatory requirements that these transactions be executed by centralized clearing organizations. Moreover, except for the credit-backed market, the cumulative distribution curve for the notional amount is above the one for the number of transactions, indicating that the degree of oligopoly for the notional amount is more significant than the number of transactions, which means that major players in each market tend to have larger notional principal per transaction. In such an oligopolistic market structure, a large number of trades are executed by major players, which can lead to economies of scale. However, on the other hand, information asymmetry regarding market transactions may cause a disincentive for market transactions. Although it is not discussed in this paper, it would be useful to quantify the merits and demerits of such an oligopolistic market structure and to examine whether the current structure is desirable for the OTC derivatives market from the perspective of market efficiency.

Here, in the trade repository data (TR data), transactions are categorized into new transactions (New), modifications to existing transactions (Modify), and cancellations of transactions (Cancel), and there are cases where transactions that are substantially equivalent to modifications to existing transactions are reported in installments. For example, a new transaction can be contracted to replace an existing transaction, which is practically the modification of the

[*15] Operating companies are counterparties of the Business Operator to Prepare Trade Data (financial institutions) but may be tagged individually or collectively with "operating companies" as tags.

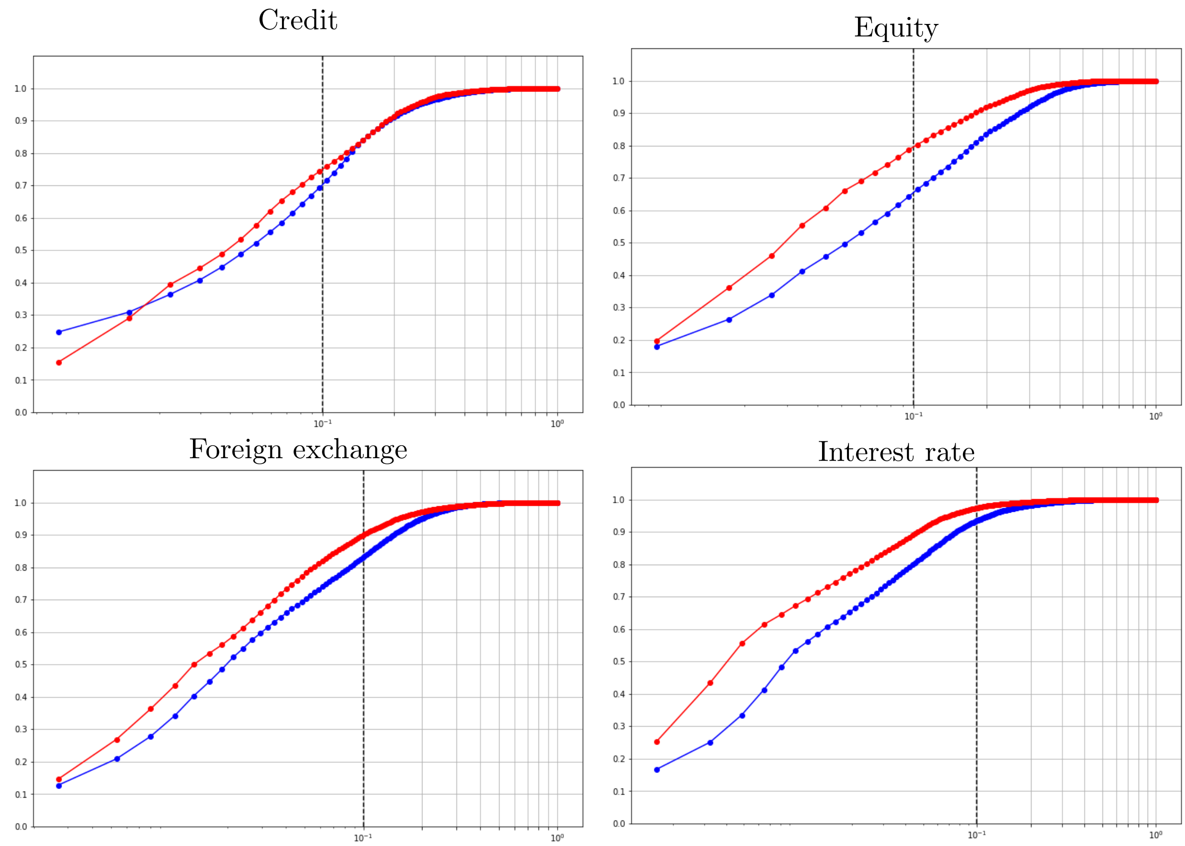

Fig. 1 Cumulative distribution of the number of trade and notional amounts for each market participant. The top-left panel shows the credit-backed market, the top-right panel shows the equity-backed market, the bottom-left panel shows the foreign-exchange-backed market, and the bottom-right panel shows the interest-rate-backed market. The blue line shows the cumulative distribution of the number of transactions, the red line shows the cumulative distribution of notional amount, and the black dotted line shows the top 10% of all market participants.

transaction. Since accurately cleansing the entire data in line with the correct category of each transaction is difficult, we aggregated data without considering the type of the transaction. We leave this point as a future task.

We exclude some transactions that deviate significantly from other transactions, such as transactions with excessive notional principal. The transactions with unclear parties based on the information in the TR data are also excluded when establishing the transaction (trading) network. The transaction (trading) network of the OTC derivatives market backed by each product is shown in Fig.2.*16

*16 Networks are drawn by Fruchterman-Reingold force-directed algorithm.[13]

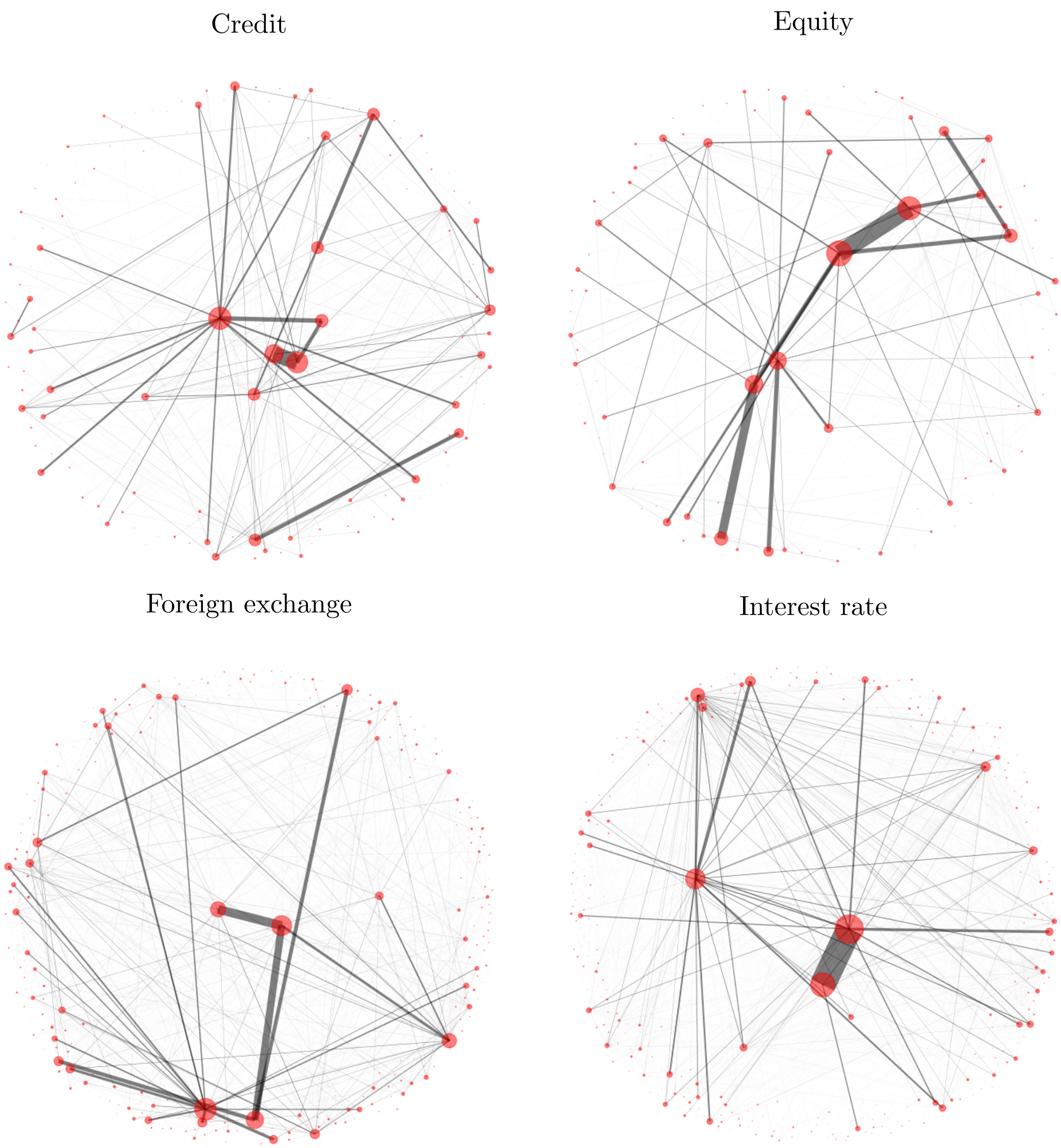

Fig. 2 The transaction network for each OTC derivatives market. The top-left figure shows the network for the credit-backed market. The top-right figure shows the network for the equity-backed market. The bottom-left figure shows the network for the foreign-exchange-backed market. The bottom-right figure shows the network for the interest-rate-backed market. The size of nodes and edges is proportional to the amount of notional principal of a participant and their combination, respectively.

5 Analysis of Network Characteristics in Over-the-Counter Derivatives Transaction Networks

This section considers (1) the analysis of the transaction network constructed from the flow data in the entire data collection period and (2) the analysis for every six business days, based on graph theory.*17

5.1 Analysis of the transaction network constructed from the flow data for the entire two-year period

Fig.2 shows that each market has some participants who have a connection with many participants and function as core players. Therefore, in order to focus on the contribution of these participants, we define market participants who play an essential role (hereinafter referred to as core players) as market participants whose total amount of notional principal in which they are involved accounts for 5% or more in the entire market. The number of core players in each market is summarized in Table 3.

Table 3 The number of core players in each OTC derivatives market

	Credit	Equity	Foreign exchange	Interest rate
Number of core players	4	6	5	4

Next, we consider community detection based on a modularity maximization algorithm,*18 where modularity is a metric of the closeness of the nodes in a subset (cluster). Fig.3 shows the transaction network of each market divided into communities.[14, 15]

From the figure, we can see that participants with many counterparties are categorized as core players, and many of them belong to different communities. This result indicates that each core player in the OTC market has a tightly connected sub-network centered on itself and that the sub-networks often form core/marginal structures. This result indicates that each core player contributes to liquidity by participating in market as hubs of market transactions, but it also suggests that the market structure is such that information on trading trends of each market participant is easily concentrated in the core players. Therefore, it is desirable to further enhance studies on market structure, including quantitative analysis.

*17 We note that this analysis is intended only as a test case and that more detailed and sophisticated data cleansing methods will be required in the future.

*18 A method to divide a graph into clusters to maximize the modularity of the entire graph by evaluating the number of edges in a subset of vertices (clusters) with reference to a random graph. In general, when a graph is partitioned to maximize modularity, each cluster consists of vertices that are tightly connected to each other. See [14] for the definition.

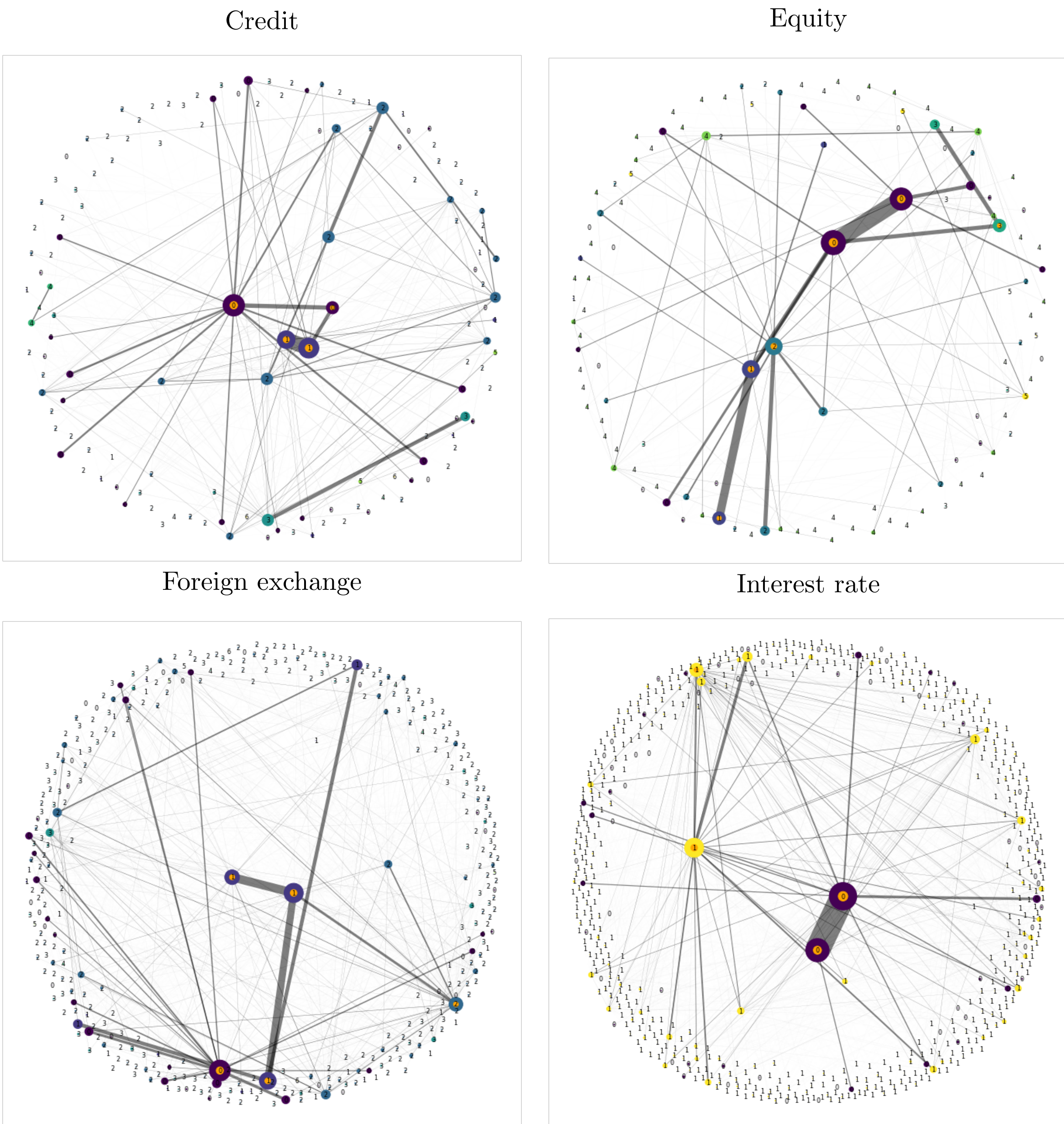

Fig. 3 Trading networks in each market. The top-left panel shows the credit-backed market (CD). The top-right panel shows the equity-backed market. The bottom-left panel shows the foreign-exchange-backed market, and the bottom-right panel shows the interest-rate-backed market. The size of each node is proportional to the sum of the notional principal occupied by trading participants. The size of nodes and edges is proportional to the amount of notional principal of a participant and their combinations, respectively. Vertices with orange circles inside indicate that they are core players. The color of each vertex (the outer color per core player) indicates the community to which each vertex belongs.

We summarize basic metrics[*19][*20] for each transaction network graph in Table4.

Table 4 Basic metrics for each OTC derivatives market

	Credit	Equity	FX	Interest rate
Number of participants	135	116	374	619
Number of edge	377	276	1,252	2,380
Mean order	5.581	4.759	6.695	7.690
Average path length	2.662	2.727	2.761	2.669
Network density	4.168%	4.138%	1.795%	1.244%

From the table, we can see that the average path length for each market is very close to each other, although the number of market participants and edges are significantly different for each product category. This result indicates that the small-world features[16] may also apply to the OTC derivatives market.

As to network density, we can see that the market for credit (CD) and equity (EQ) are dense compared with other product categories,[*21] but these are also very small, indicating that the transaction network in the OTC derivatives market is sparse. This result indicates that each market participant tends to trade intensively with a particular counterparty, but that each market participant is close to each other in the network, in line with the hub/edge structure seen in the network figure above.

The cumulative distribution curve of the notional amount and the number of transactions is drawn in Fig.4, focusing on core players.

Fig.4 shows some core players have fewer transactions than other market participants, indicating that the oligopoly of notional amount does not necessarily directly linked to the number of transactions.

Next, we consider the centrality and clustering coefficients to understand the network structure in more detail. We calculate the betweenness centrality,[17–20] closeness centrality,[21,22] degree centrality, eigenvector centrality[23,24] and clustering coefficient[25–27] for the weighted graphs. Betweenness centrality is a metric for a node that indicates the extent of function as

[*19] The average path length L represents the minimum number of market participants that must be brokered to connect two randomly selected firms in a transaction (trading) network.

$$L = \sum_{u,v} \frac{d(u,v)}{n(n-1)} . \tag{2}$$

In this equation, $d(u,v)$ the distance of the shortest path between u and v, and n represents the number of nodes.

[*20] The network density D describes the degree to which market participants are connected to each other in the transaction (trading) network, i.e., the density of the trading network.

$$D = \frac{E}{{}_nC_2} \tag{3}$$

n and E represent the number of nodes and edges, respectively.

[*21] For the network of interest rates (IR), we note that the size is not shown in the Figure, but since all products have a certain size of the network, the density appears high.

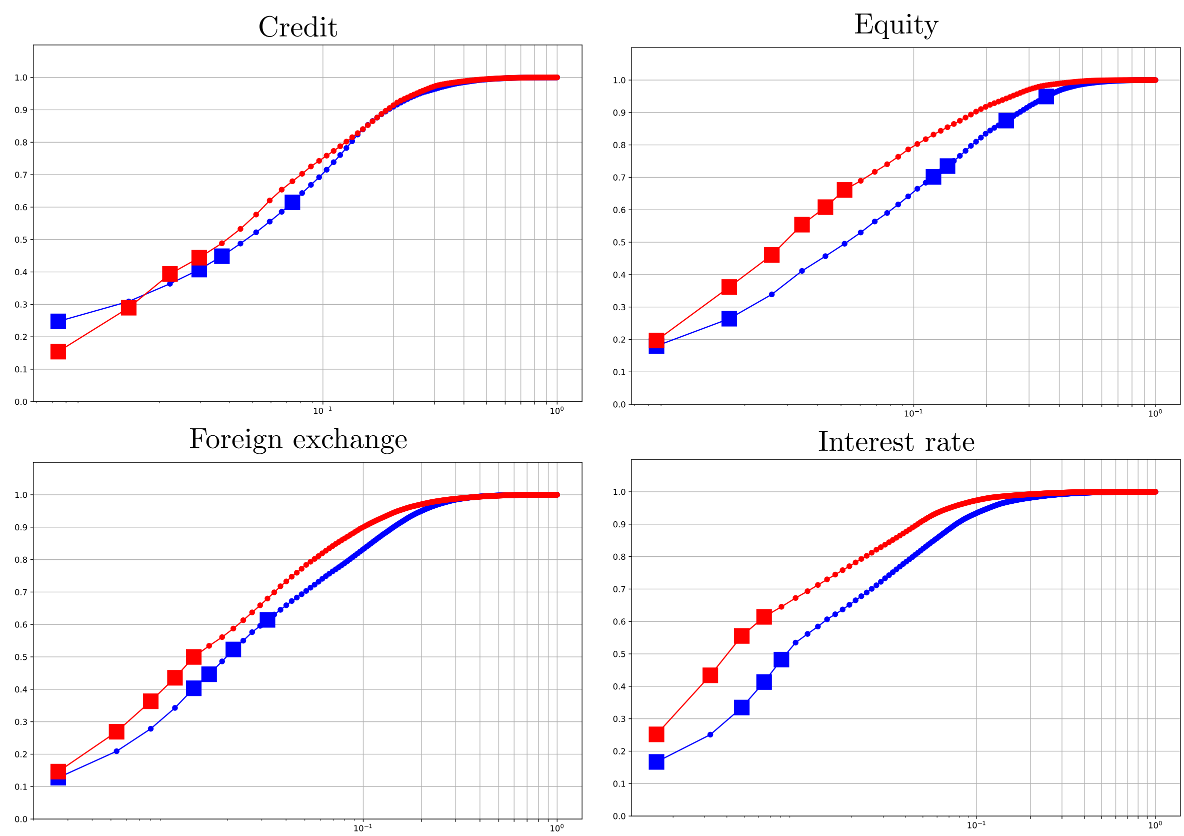

Fig. 4 Cumulative distribution of the number of transactions and notional amounts for each market participant. The top-left panel shows the credit-backed market (CD), the top-right panel shows the equity-backed market (EQ), the bottom-left panel shows the foreign-exchange-backed market (FX), and the bottom-right panel shows the interest rate collateral market (IR). The blue line shows the cumulative distribution of the number of transactions, and the red line shows the cumulative distribution of the amounts of notional principal. For each market, the square symbol ■ indicates a core player.

a bridge. It can be calculated from the number of shortest paths including the target node. Closeness centrality is a metric proportional to the reciprocal of the sum of the length of shortest paths between the target participants and other market participants in the network and indicates how close they are to each other. Degree centrality is defined by the number of edges that each market participant has, normalized by the number of market participants, and indicates how many trading partners it has. The eigenvector centrality is given by the eigenvector for the maximum eigenvalue of the adjacency matrix. The value for a participant with many counterparties, especially those who greatly influence the market, will be significant, indicating the participant's importance in the market. Finally, the clustering coefficient measures how tightly and locally the network is connected to others. It is significant when many derivatives transactions are settled within a group.

The participants with a large value for each metric are listed in descending order in Table 5. It shows that the core players are significant in centrality metrics and occupy a core position in the market. In particular, the core players have a higher value in the betweenness centrality,

Table 5 Attributes(core/non-core) of the top five companies in each centrality index and clustering coefficient.

	Betweenness centrality				Closeness centrality			
	Credit	Equity	FX	IR	Credit	Equity	FX	IR
1	non-core	core	core	core	non-core	core	core	core
2	core	core	core	core	non-core	non-core	core	core
3	non-core	non-core	non-core	non-core	core	core	core	non-core
4	non-core	non-core	core	non-core	non-core	core	core	core
5	non-core	core	core	core	non-core	non-core	non-core	core

	Degree centrality			
	Credit	Equity	FX	IR
1	non-core	non-core	core	non-core
2	non-core	non-core	core	non-core
3	non-core	non-core	non-core	non-core
4	core	non-core	core	core
5	non-core	core	non-core	non-core

	The eigenvector centrality				the clustering factor			
	Credit	Equity	FX	IR	Credit	Equity	FX	IR
1	core	core	core	core	non-core	non-core	non-core	non-core
2	non-core	core	core	core	non-core	non-core	non-core	non-core
3	core	core	core	non-core	non-core	non-core	non-core	non-core
4	core	core	non-core	non-core	non-core	non-core	non-core	non-core
5	non-core	non-core	non-core	non-core	non-core	core	non-core	non-core

closeness centrality, and eigenvector centrality. This result suggests that they are positioned at the center of each market, functioning as a hub though moderately connected with each other. Furthermore, the low clustering coefficient of core players indicates that they function as hubs in the market rather than concentrate on trading within a particular group.

Fig.5 shows betweenness centrality and the clustering coefficients for participants in each market. From the figure, we can see that core players have larger betweenness centrality than other market participants. This result indicates that core players play crucial roles as intermediaries in markets. On the other hand, some market participants other than the core players have very high clustering coefficients. This result indicates that some market participants are trading intensively in some closely correlated groups.

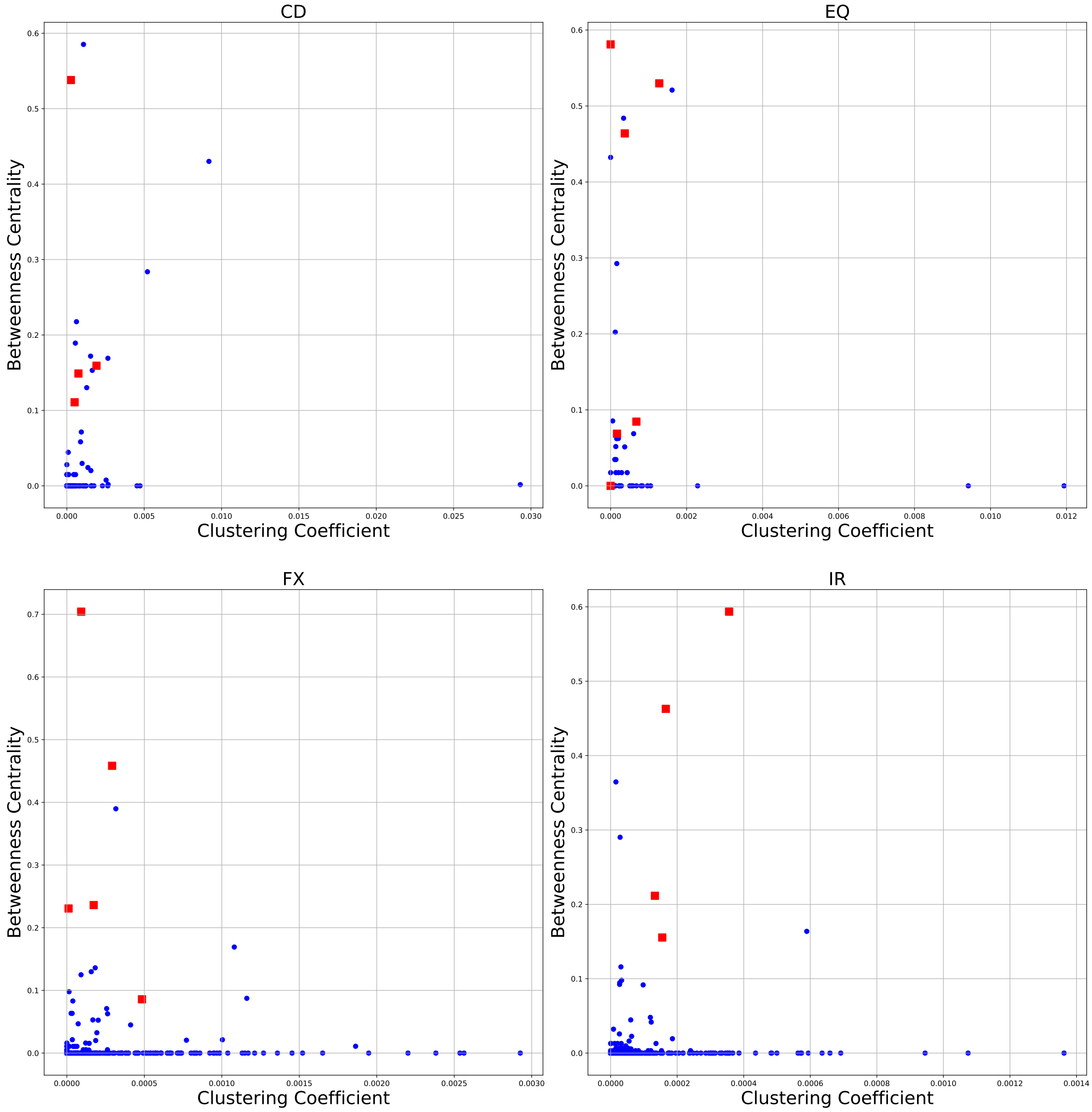

Fig. 5 Betweenness centrality and the clustering coefficient for each market. The top-left panel shows the credit-backed market, the top-right panel shows the equity-backed market, the bottom-left panel shows the foreign-exchange-backed market, and the bottom-right panel shows the interest-rate-backed market. The X-axis and Y-axis show the clustering coefficient and the betweenness centrality, respectively. The core players are represented by red squares, while the rest of the market participants are represented by blue circles.

5.2 Analysis of the market network structure based on transactions conducted over six business days

In the analysis for the previous section, we considered transaction networks created with all the flow data in the collection period. The analysis suggests that while activities in transaction (trading) networks of derivatives markets for all product types are sparse, the average distances between market participants are short, indicating a possibility of small-world features.

This section will focus on details of market structures from a short time viewpoint by dividing the data into small blocks in temporal dimension based on reporting reference dates included in the report. We construct networks based on transaction data every six business days, sliding the start day one by one to the end of the collection period.[*22]

Fig.6 shows networks of transactions in a six-day duration. In the figure, we define the weight $w_{uv}^{w_i}$ of each edge by the following equation:

$$w_{uv}^{\alpha,i} \equiv \frac{\sum_{\alpha} v_{uv}^{\alpha,i}}{\sum_{u,v\in V}\sum_{\alpha} v_{uv}^{\alpha,i}} \tag{4}$$

where $v_{uv}^{\alpha,i}$ is the notional amounts of α-th transaction included in six business days from the reporting base date i.

It shows that while core players are involved in many transactions, some other market participants also account for a large portion of the notional principal amount in transactions in a week (six business days), indicating that they make a certain contribution to market transactions.

To see this point quantitatively, we consider betweenness centrality and clustering coefficients for the transaction networks. They are drawn in Fig.7. It shows that core players have relatively high betweenness centrality compared with the average in every OTC derivatives market. This result indicates that the core players, defined solely by the notional principal, play a crucial role as core market participants. On the other hand, as to the clustering coefficients, there is no significant difference between the core players and the overall average for the trading of credit (CD), equity (EQ), and interest rate (IR). However, the clustering coefficient in foreign exchange (FX) shows a larger value than the overall average throughout the period. This suggests that core players have been forming clusters over a shorter period and making many transactions therein.

The comparison of this section and the previous section, regarding the difference in the period networks are based on, also suggests that, in the long term, core players are engaged in transactions with many market participants, resulting in an absence of a cluster structure, but there seem to be cluster structures when we consider the network structure in a period closer to the actual business day.

[*22] Since there are no reports with Sunday as the reporting reference date, we build a network structure based on the transactions included in each one-week period by summing every six business days.

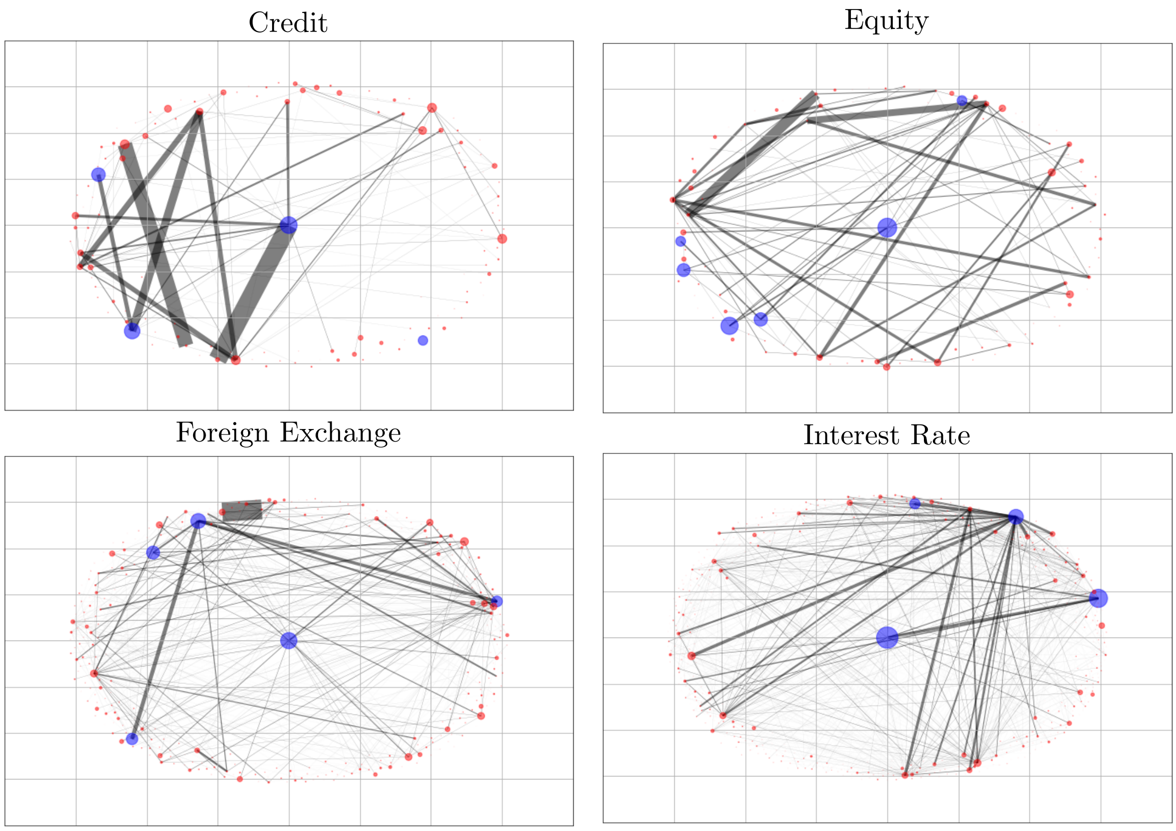

Fig. 6 Betweenness centrality and clustering coefficients for markets. The top-left panel shows the credit-backed market (CD). The top-right panel shows the equity-backed market (EQ). The bottom-left panel shows the foreign-exchange-backed market (FX). The bottom-right panel shows the interest-rate-backed market (IR). The X-axis and Y-axis represent the clustering coefficient and betweenness centrality, respectively. The core players are represented by blue circle, while the rest of the market participants are represented by red circles.

5.3 Analysis of scaling rules for market network structures by transactions executed within six business days

In this section, we consider the cumulative distribution function of market participants with respect to the number of the trading counterparty (orders) to see the distribution of transactions:

$$S(x) = \mathrm{Avg}_i \int_x^{\infty} I_i(x')dx' \tag{5}$$

From the definition, $I_i(x)$ represents the number of market participants whose number of trading counterparty equals x on the reporting base date i, where Avg_i is the average over the reporting period.

It is known that some networks in the real world have a scale-free property[28, 29] in which the degree distribution is described in a power function $f(x) = ax^{-b}\,(a, b \in \mathbb{R})$. Furthermore, it has also been reported in previous studies[30, 31] that the degree distribution of inter-bank

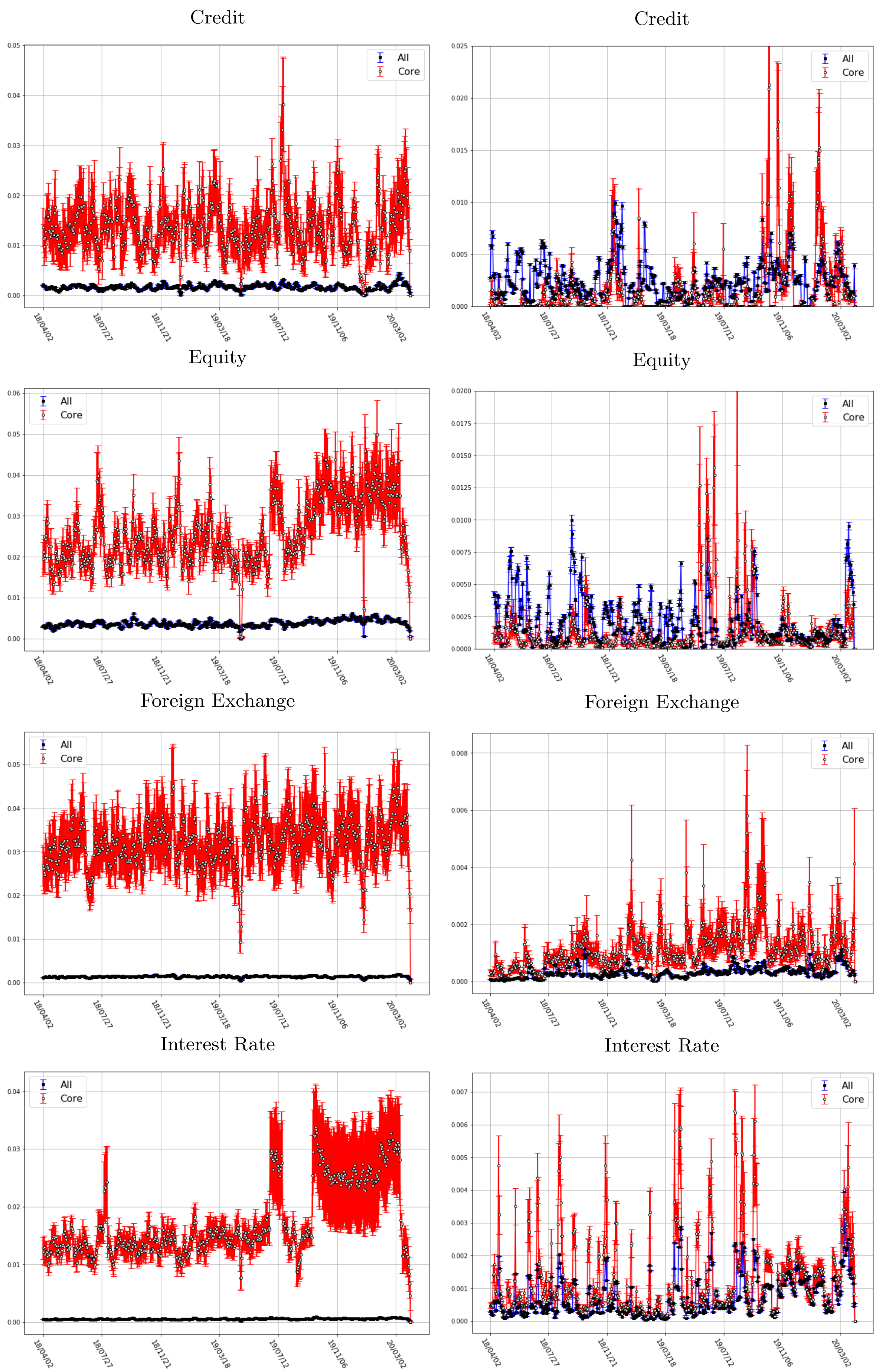

Fig. 7 Betweenness centrality (left Figures for each product category) and clustering coefficients for each market (right Figures for product category) for the transaction network on each reporting base date. The red line represents the average for the core players, whereas the blue line represents the average for all market participants.

transaction networks is written by a transient function between the power function type and the exponential type $f(x) = ae^{-bx}$. In this paper, we separately approximate $S(x)$ for the low-order region ($x \approx 0 \sim 10^2$) and the high-order region ($x \approx 10^4 \sim 10^5$) by a power function $f(x) = ax^{-b}$. $S(x)$ and the approximate curve are shown in Fig.8. From the Figure, we can

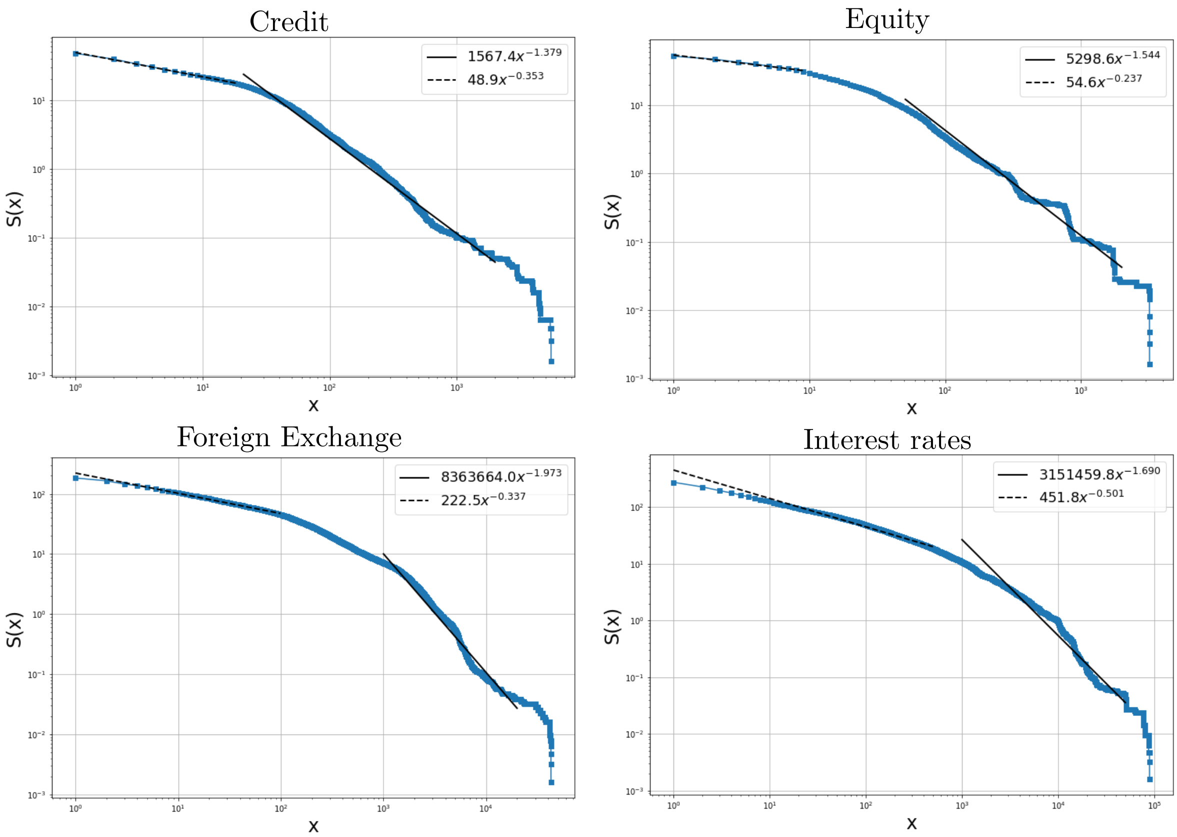

Fig. 8 Cumulative distribution function of market participants for each transaction volume. The top-left panel shows the credit-backed market (CD). The top-right panel shows the equity-backed market (EQ). The bottom-left panel shows the foreign-exchange-backed market (FX). The bottom-right panel shows the interest-rate-backed market (IR). The straight lines in the chart for each market show an approximation of cumulative distribution function by $f(x) = ax^{-b}$ (note that both the vertical and horizontal axes are on a log scale).

see that the order b is approximated by a small value of $0.35 \sim 0.50$ in the low degree region in four markets, whereas, in the higher-order region, the value is as large as $b \approx 1.3 \sim 2.0$, indicating that the number of trading partners (order) decreases more rapidly.

When $S(x)$ is given by a power function type of $S(x) = ax^{-b}$, the distribution function is written as $I_i(x) = abx^{-b-1}$ since it is given by the derivative of $S(x)$ with respect to x. Therefore, from the approximation result of the cumulative distribution function $S(x)$ described above, the exponent $b + 1$ of the distribution function is approximated as $1.3 \sim 1.5$ and $2.4 \sim 3.0$ in the low degree region and the high degree region, respectively. The large exponent of the distribution function in a high degree region probably comes from various factors, such as the restriction of resources necessary for executing transactions and how few market participants can trade on this scale per week.

6 Discussion

This paper analyzed trade repository data (TR data) reported to JFSA during the two years from April 1, 2018, to March 31, 2020. In the trading networks constructed from trade repository data (TR data), although the number of market participants is significantly different, the average path length between each market participant is less than 3, suggesting that small-world features exist in the OTC derivatives market. It is also indicated that the network density is small, and the trading network in the OTC derivatives market is sparse.

This paper defines core players based on the notional principal as a trial. The analysis on the players suggests that core players defined in that way execute transactions with many market participants. Furthermore, community detection based on the modularity maximization algorithm showed that they belong to different communities in most cases and suggested that they can have a partial network structure with closely related participants.

In addition, multiple network centrality metrics and clustering coefficients are calculated and compared between core players and others. The result indicates that core players tend to be higher in all centrality indices, which means they function as hubs of transaction networks.

The analysis of trading networks in six-day durations showed that the core players' betweenness centralities are larger than the overall average throughout the analysis period. This result suggests that the core players play an important role in trading intermediation on the time scale.

Finally, we considered the possibility that the degree distribution can be approximated by power functions. This result indicates that the network structure of the OTC derivatives market can be described by scenarios suggested in previous works.[32–40] Therefore, a detailed analysis on this point may be helpful for the understanding of the OTC derivatives market. Table 6 summarizes the trends in the network structure of each OTC derivatives market analyzed in this paper so far. Although this paper's analysis is just a test case, we hope that it will serve as a reference for future research.

However, data cleansing for transactions reported from both participants who are legally obliged is not considered in this analysis. Thus, the number of transactions and notional principal of core players and some equivalent participants might be overestimated as they have a significant influence on the market. The effect can cause the metrics we considered to change. We note that this point should be carefully considered when interpreting the results in this paper.

7 Future Works

In the analysis of this paper, we calculated the metrics related to the market structure of the OTC derivatives based on the OTC derivatives transaction data (TR data), and discussed the findings. However, the following points, which are important to further understand the market

Table 6 Characteristics of each OTC derivatives market in this paper

	Credit	Equity	Foreign Exchange	Interest Rate
Whole analysis period				
Network density	Sparse	Sparse	Sparse	Sparse
Small-world feature	Yes	Yes	Yes	Yes
Market oligopoly(Market share of top 10% companies)				
- By transactions	70%	65%	80%	90%
- By notional amount	75%	80%	90%	95%
Every 6 business days				
Comparison of core players to market average				
- Betweenness centrality	Higher	Higher	Higher	Higher
- Clustering Coefficient	Same	Same	Higher	Same
Exponent of the distribution function				
- Low-order region	1.35	1.24	1.33	1.50
- High-order region	2.38	2.54	2.97	2.69

structure and to make proposals for future policy on financial markets, were not studied in depth in this paper, thus we hope that further research will be conducted to deepen the understanding.

1. Trade repository data (TR data) cleaning
   Due to analytical difficulties, this paper does not correct the bilateral reporting of transactions between market participants that are required to be reported. Correcting for this point is expected to reduce the number of transactions and the notional amount of transactions executed by market participants with a large impact on the market. It would be desirable to examine the extent to which the results obtained in this paper would be affected by this correction.
2. Impact of oligopolistic market structure
   In Sections 4 and 5, we observed a structure in which the number of transactions and notional amount were unevenly distributed to major market participants, mainly core players. While such a market structure can be expected to provide economies of scale, the asymmetry of information may be a major disadvantage for market transactions. In this regard, it is desirable to enhance studies on OTC derivatives trading from various perspectives.
3. Impact on market trading of each market participant
   In the trading pattern for each of the six business days discussed in Section 5.2, we saw that market participants other than the core players also had a significant impact on market trading. This impact has not been analyzed in detail in this paper, thus a more detailed quantitative assessment of the impact of each market participant on market

trading is preferred.

4. On the dynamic changes in market structure
   In this paper, we have analyzed the static characteristics of the market structure during normal times based on the accumulation of trade repository data (TR data) for two years. However, it is also important to clarify how the market structure changes when events that have a large impact on the market occur so as to consider financial regulations. It is also desirable to focus on the period before and after a sudden and significant event, such as a change in the market structure caused by the spread of coronavirus since last year, and to study what kind of changes can be seen in the market within that time frame.

8 Conclusion

This paper analyzed trade repository data (TR data) reported to JFSA pursuant to the FIEA to consider the transaction network structure of the OTC derivatives market in Japan.

After the financial crisis in 2008, the system for preserving and reporting information on OTC derivatives transactions has been considered to accurately understand the OTC derivatives market and improve market transparency. Amid such a trend, in this paper, we tried to obtain preliminary results and knowledge of analysis for a deeper understanding of the market structure and improvement of market transparency. For instance, betweenness centrality, which is used many times in this paper, is a metric that shows how much each market participant functions as a hub in the trading network. Thus, it may be possible to obtain knowledge on the degree to which market participants will influence others if any trouble occurs in them.

In addition, it will be critical to accumulate knowledge on the way to utilize the viewpoints obtained by analyzing the network structure of each market for the supervision of the financial sector, including verification of the usefulness of metrics such as clustering coefficients and community detection techniques in the supervision.

Therefore, as mentioned above, it is crucial for JFSA to pile up knowledge and analytical methods on market networks by analyzing the transaction data to consider the application in the monitoring, supervision, and regulations planning of the financial sector in the future. In other words, it is important for JFSA to continue accumulating and analyzing information on OTC derivatives transactions and enhancing staff data analytics skills.

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