FSA Analytical Notes

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An Empirical Examination toward a Multi-faceted Understanding of the OTC Derivatives Market

(Summary)

This paper uses data on over-the-counter (OTC) derivatives transactions to advance the methodology for understanding the actual status of the OTC derivatives market by conducting analyses focusing on derivative product types and attributes of trading counterparties. The analysis confirms that, during episodes of sharp movements in foreign exchange rates within the observation period, the number of currency option transactions with non-financial corporate participants surged. In addition, a multi-layer network analysis suggests that financial institutions participating in the OTC derivatives market may be playing different roles by institution type. Going forward, the FSA will continue to deepen its understanding of the OTC derivatives market by further refining analytical methods and related approaches.

Ⅰ. Introduction

According to the Bank of Japan's Regular Derivatives Market Statistics in Japan,[1] as of end-June 2025, the outstanding notional amount of exchange-traded derivatives via domestic exchanges was USD 3.8 trillion, whereas that of OTC derivatives reached USD 85.6 trillion. Given this scale, OTC derivatives could have a material impact on the Japanese financial system. Therefore, from the perspective of maintaining the stability of the financial system, it is important to grasp and analyze the behavior of market participants and changes in trading structures in the OTC derivatives market.

[1] BIS semi-annual OTC derivatives statistics compiled jointly by the BIS and the central banks of the major reporting jurisdictions (12 countries as of end-June 2025). These statistics cover major financial institutions headquartered in the jurisdictions and present outstanding positions by instrument and by counterparty, among other breakdowns. They are on a consolidated basis including domestic and overseas branches and local subsidiaries of major Japanese financial institutions; therefore, transactions traded overseas by such institutions are included, and the figures do not represent those of the Tokyo market. Note also that the coverage and other compilation aspects differ from the trade repository (TR) data used in this paper.

With respect to data on OTC derivatives transactions (hereinafter, 'TR data' [2]), in light of the agreement at the 2009 G20 Pittsburgh Summit, among other developments, the Financial Services Agency (FSA) has, since 2013, received reports pursuant to the Financial Instruments and Exchange Act (FIEA) from central counterparties (CCPs)[3] and financial instruments business operators, etc.[4] (hereinafter, collectively 'reporting entities') for the purposes of reducing systemic risk and enhancing transparency in the OTC derivatives market.[5]

To further advance methods for understanding actual market conditions in the OTC derivatives market, this paper conducts multi-faceted analyses using TR data. Specifically, we (a) examine daily transaction conditions to capture market developments during foreign exchange movements and (b) analyze the tendencies of trading entities with high centrality across the entire OTC derivatives market by applying a multi-layer network analysis.

II. Data Set

The analysis uses TR data on transactions traded between April 1, 2024 and September 30, 2025 that were reported to the FSA.[6] OTC derivatives reference movements in the value of underlying assets, such as interest rate (IR), credit (CD), foreign exchange (FX), and equity (EQ). Representative examples are shown in Figure 1.

Figure Representative examples

Assets	Representative examples
Interest rate (IR)	Interest rate swap
Credit (CD)	Credit default swap (CDS)
Foreign exchange (FX)	Currency option
Equity (EQ)	Options trading on equities and equity indexes

Because both counterparties must submit reports when they are reporting entities (so-called

[2] An abbreviation for 'Trade Repository Data'.

[3] Refers to a central counterparty (CCP) or a foreign central counterparty (foreign CCP).

[4] Refers to financial instruments business operators or registered financial institutions.

[5] Under the Financial Instruments and Exchange Act (FIEA), CCPs, etc. and financial instruments business operators, etc. are required to provide transaction information to trade repositories, etc. (i.e., a (domestic) trade repository or a designated foreign trade repository). In addition, trade repositories are required to report to the Prime Minister the transaction information they have received from CCPs, etc. and financial instruments business operators, etc.

[6] TR data are reported for each transaction category of an OTC derivatives contract, such as new transactions, modifications to existing transactions, and cancellations. This analysis covers data reported as new transactions and modifications to existing transactions.

'dual-sided reporting'), we identify individual non-centrally cleared transactions using Unique Transaction Identifiers (UTIs)[7] and remove duplicates. By contrast, for certain OTC derivatives referencing interest rates (IR) or credit (CD), central clearing is mandatory. Although there is, in substance, a single contract, they are reported as two different contracts with the CCP as a counterparty. In such cases, two different UTIs are assigned to a single contract, and the original transaction cannot be identified solely from the UTI pair.[8] To address this issue, we estimate original centrally cleared transactions by classifying pairs with multiple reporting fields coinciding between them and perform a cleansing procedure to eliminate dual-sided reporting. Unless otherwise noted, the word 'TR data' hereafter refers to data after this cleansing.[9]

III. Recent Developments in OTC Derivatives Transactions

This section analyzes the trend of TR data for the type of derivatives and counterparties in the observation period.

1. Basic data

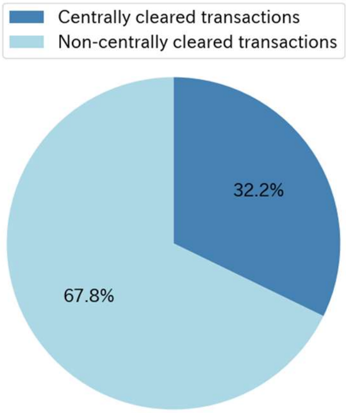
Figure 2 shows, on a trade-count basis, the share of centrally cleared versus non-centrally cleared transactions over the observation period, while Figure 3 shows the same shares on a notional amount basis. Comparing the two figures indicates that the centrally cleared share is higher on a notional basis than on a trade-count basis, confirming that the average notional amount per transaction tends to be larger for centrally cleared trades.

[7] A Unique Transaction Identifier (UTI) is a unique code assigned to each individual transaction subject to reporting.

[8] For centrally cleared transactions, approximately 30 percent of the data were difficult to infer (i.e., to estimate the original contracts). These data are excluded from the analysis.

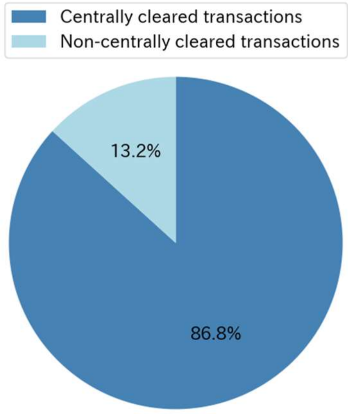
[9] In addition, adjustments are made for transactions whose notional amounts are evidently large compared with other transactions (outliers). We exclude them from aggregation transactions.

Figure 2 The share of centrally cleared and non-centrally cleared transactions (trade-count basis)



(N=763,109)

Figure 3 The share of centrally cleared and non-centrally cleared transactions (notional amount basis)



(Approximately 5.1 trillion yen)

2. Trends in OTC derivatives transactions

Figure 4 shows the temporal evolution of total notional amounts and the number of transactions; Figures 5 and 6 show the number of transactions and notional amounts over time, for derivative types, respectively. Taken together, Figures 4 and 5 make clear that, during episodes of pronounced fluctuations in the total number of derivatives transactions, ones in currency options surged. By contrast, as shown in Figure 6, interest-rate swaps (excluding cross-currency swaps) accounted for the bulk of notional amounts, and this tendency did not change even during episodes of large fluctuations in the total number of transactions.

Based on this finding, we focus on USD/JPY currency options, which are central to currency-options trading. Figures 7 and 8 plot the USD/JPY exchange rate and the number of currency-option transactions, and the USD/JPY implied-volatility [10] and the number of currency-option transactions, respectively. The results indicate a tendency for the number of transactions to increase around episodes of sharp yen appreciation and around upticks in volatility.

[10] Implied volatility refers to the future volatility inferred by inverting an option pricing formula using observed option prices. In this paper, we use the one-week USD/JPY option implied volatility, which indicates the market's expectation for how much USD/JPY will move over the next week.

Figure 4 Notional amount and the number of transactions over time

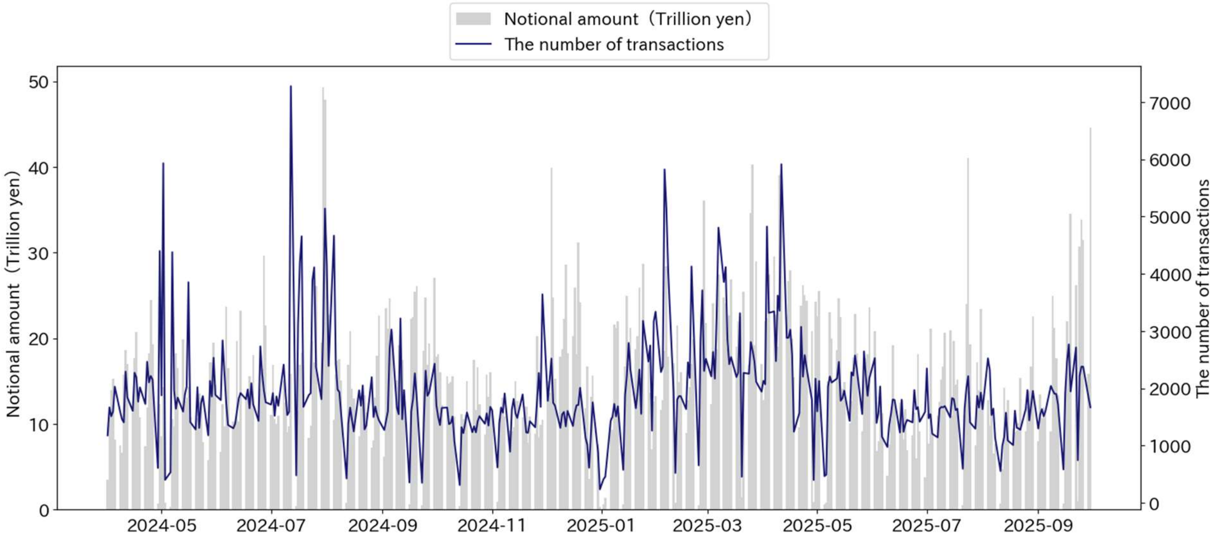


Figure 5 Number of transactions by derivative type

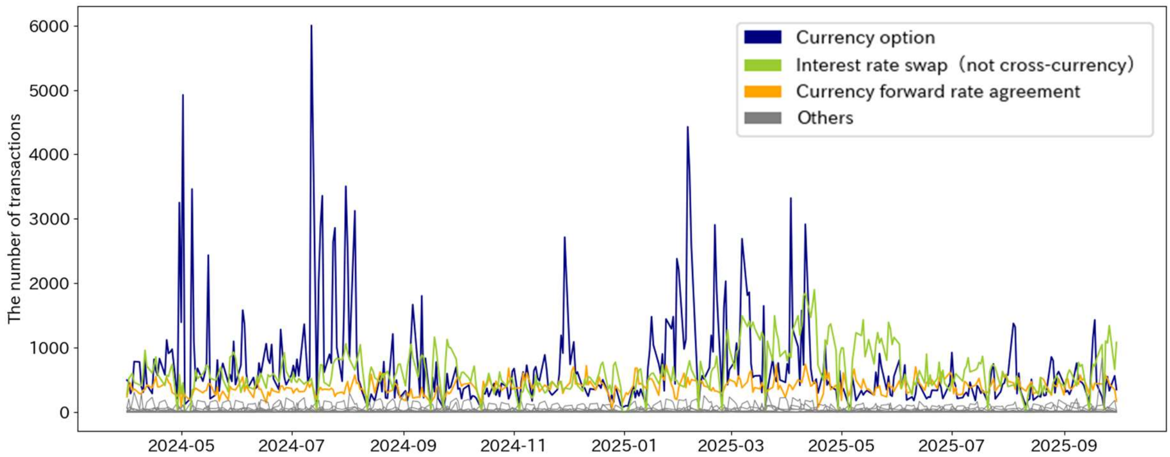


Figure 6 Notional amount by derivatives type

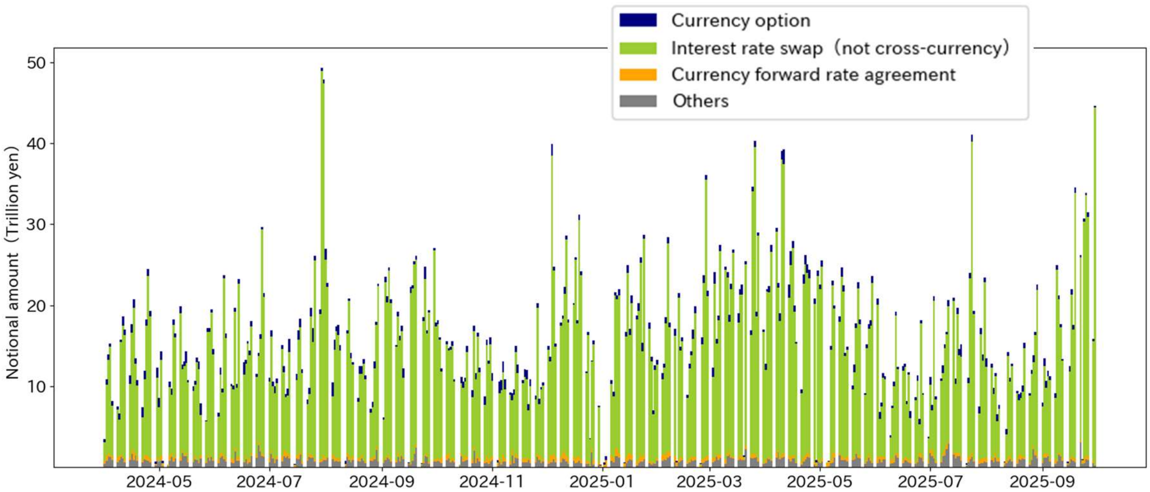
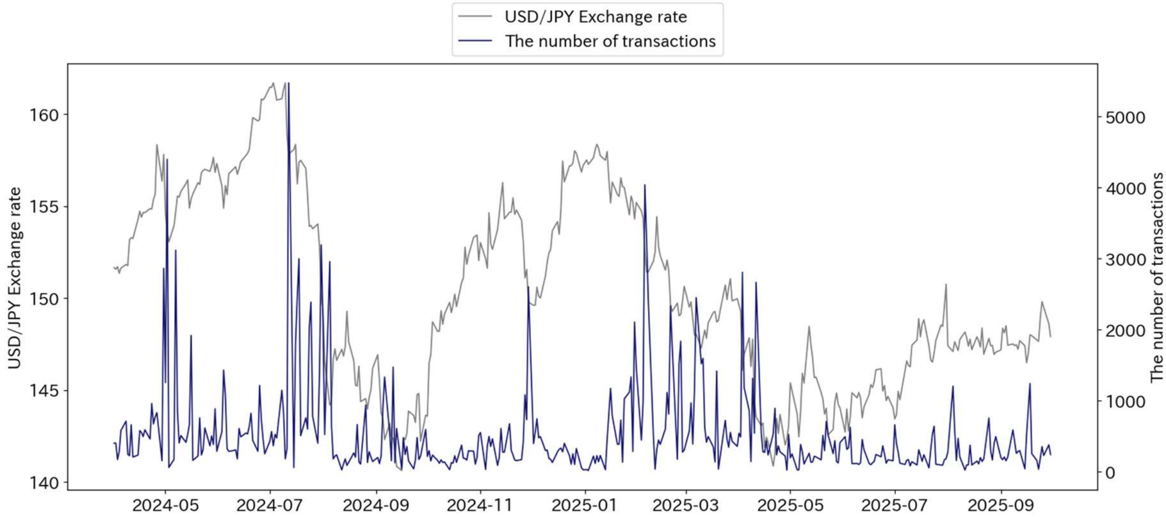
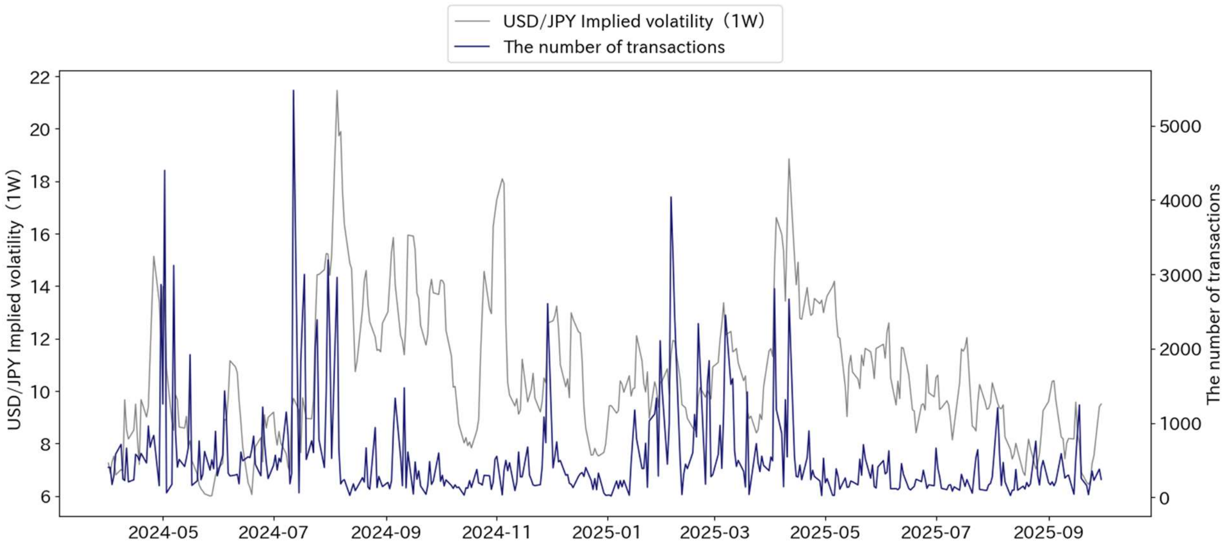


Figure 7 USD/JPY exchange rate and the number of transactions for currency option



(Source) Bloomberg、 (prior close)

Figure 8 USD/JOY implied volatility and the number of transactions for currency option



(Source) Bloomberg

We then examine the temporal evolution of the number of transactions by type of counterparty (industry classification of one side of the trade). This classification uses Legal Entity Identifiers (LEIs)[11] reported in the TR data. However, due to limitations of the TR data, when an asset management company executes OTC derivatives transactions on behalf of investment trusts or pension funds, it generally uses a trust account at a trust bank, and the transaction is reported under the LEI assigned to the trust account. Accordingly, neither the beneficial owner nor the asset management company can be identified. For this reason, the classification by counterparty type does not necessarily coincide with the beneficial owner or the asset manager.

[11] A Legal Entity Identifier (LEI) is a number used to identify a party to a transaction.

Figure 9 shows transactions where 'major banks, etc.' [12] participate as a counterparty. While the number of transactions between major banks and bank holding companies, etc. has remained stable, the number of transactions between major banks and non-financial corporations, etc. has exhibited irregular, large fluctuations. Furthermore, fluctuations in the number of transactions in currency options shown in Figure 5 broadly coincide with fluctuations in transactions between major banks and non-financial corporations. Taken together, this result demonstrates that the overall fluctuations in the number of transactions during the observation period were primarily driven by currency-option transactions between major banks and non-financial corporations.

Figure 9 Number of transactions where major banks etc. participate

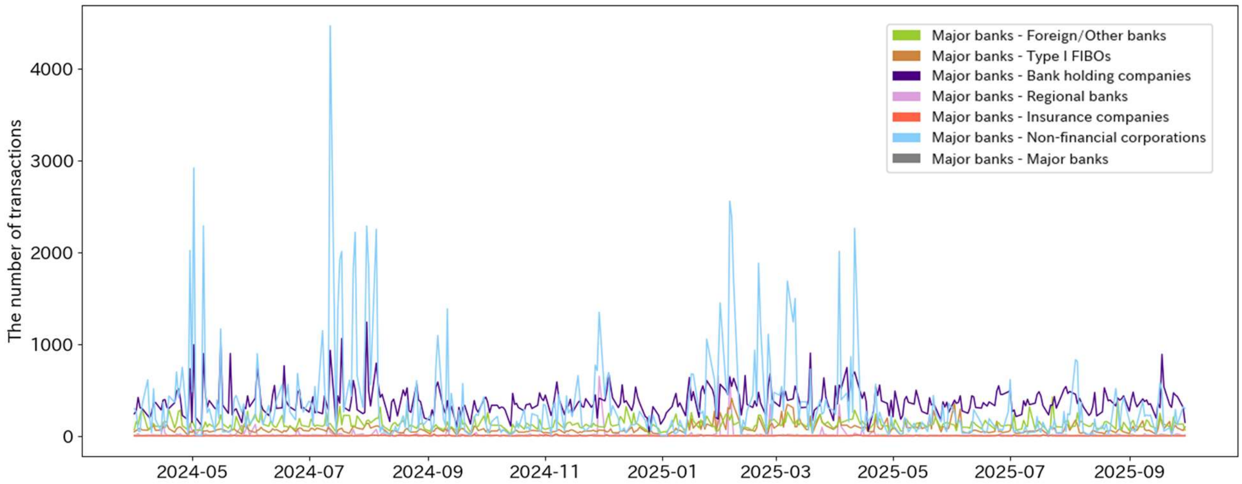


Figure 10 shows transactions where regional banks[13] participate as a counterparty. Although the overall number of transactions is lower than in Figure 9, which shows cases where major banks participate, irregular large fluctuations are observed in the number of transactions between regional banks and foreign/other banks, regional banks and major banks, and regional banks and non-financial corporations.

[12] In this paper, 'major banks, etc.' follows the definitions in reporting for the TR data and refers to the following institutions: Mizuho Bank; MUFG Bank; Sumitomo Mitsui Banking Corporation; Sumitomo Mitsui Trust Bank; SBI Shinsei Bank; Aozora Bank; Mitsubishi UFJ Trust and Banking Corporation; Resona Bank; Development Bank of Japan; The Norinchukin Bank; Shinkin Central Bank; and The Shoko Chukin Bank. This definition follows the classification in TR data.

[13] In this paper, 'regional banks' refers to Saitama Resona Bank, members of the Regional Banks Association of Japan, and members of the Second Association of Regional Banks.

Figure 10 Number of transactions where regional banks participate

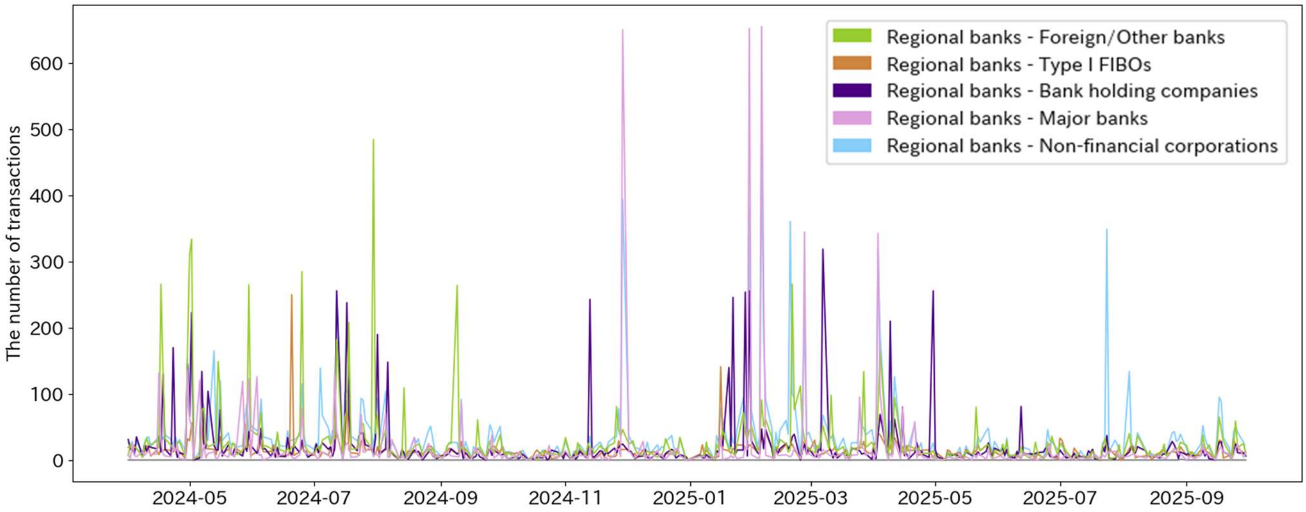


Figure 11 shows transactions where foreign banks or other banks ('foreign/other banks') participate as a counterparty. Unlike the cases of major or regional banks, irregular large fluctuations in transaction counts are not observed; at the same time, the number of transactions with non-financial corporations is consistently small.

Figure 11 Number of transactions where foreign banks or other banks participate

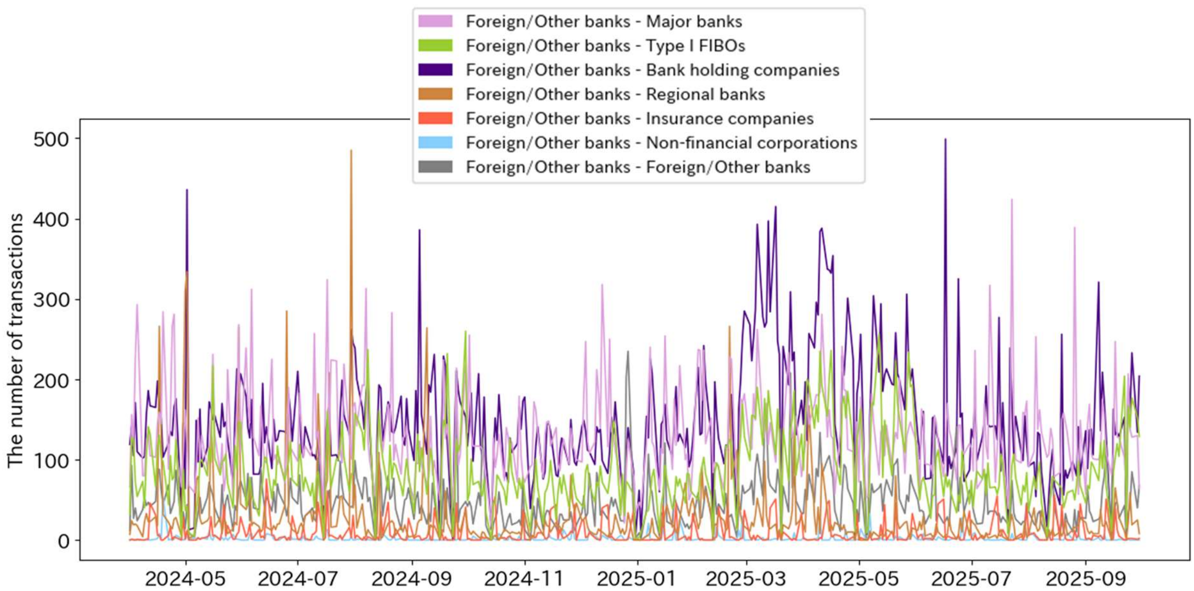
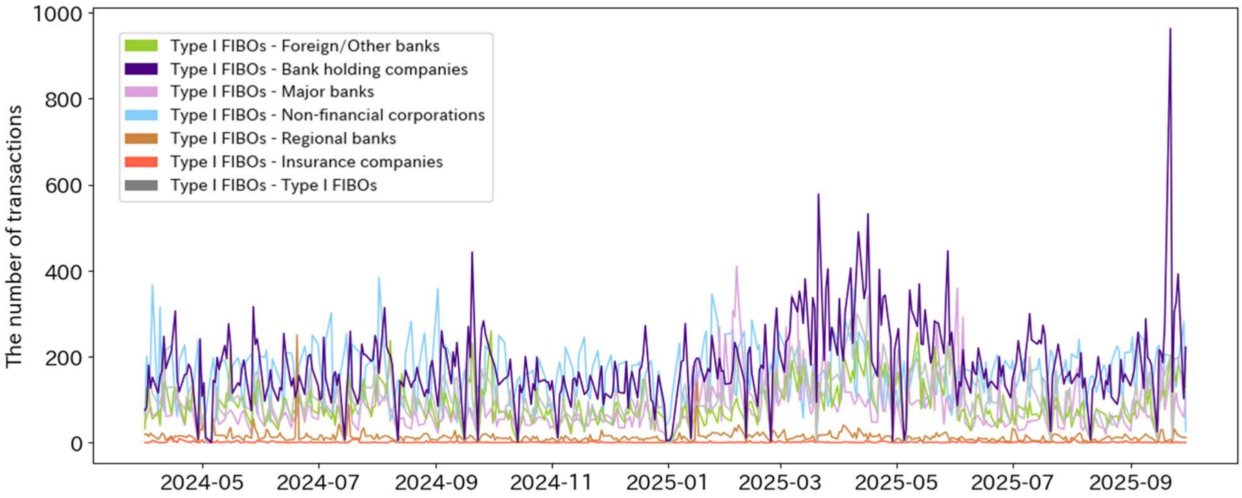


Figure 12 shows transactions where type I financial instruments business operators (Type I FIBOs) are a trading entity. Type I FIBOs trade with a wide range of business categories, and the number of transactions between Type I FIBOs and non-financial corporations has remained stable. Separately, examining notional amounts by business category indicates that the average notional amount for Type I FIBOs is the highest among categories, implying that the average transaction size is large.

Figure 12 Number of transactions where Type I financial instruments business operators particiate



Ⅳ. Multi-layer Network Analysis

This section explores the type of trading entities with high centrality indices in the whole OTC derivatives market by using multi-layer network analysis. We construct a multi-layer network by concatenating networks built for each asset class.

1. Network Analysis

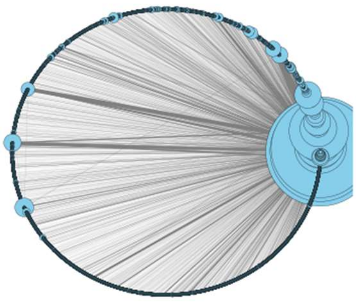
We construct, for each asset class, an undirected network in which trading entities are nodes and trading relationships are edges, without considering trade direction. Figure 13 visualizes the asset-class-specific networks.[14] Node size reflects the number of connected edges (the number of trading relationships), and edge thickness reflects the total notional amount aggregated over the observation period. From edge thickness, it is also evident that the scale of interest rate (IR)

[14] Where multiple transactions are traded between the same pair of nodes, they are aggregated into a single edge.

transactions is relatively large. From the number of nodes, it is observed that participation in OTC derivatives referencing equities (EQ) is relatively broad.[15]

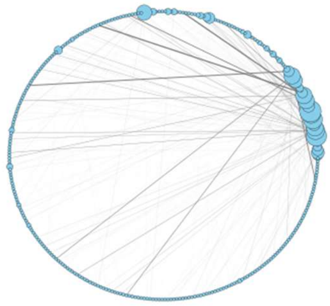
Figure 13 Transaction network[16]

Interest rate (IR)



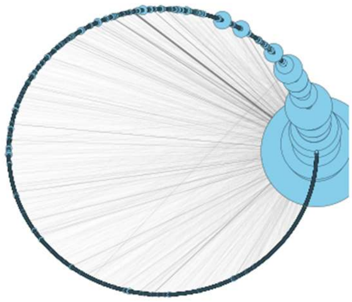
Total number of nodes	7,052
Total number of edges	9,121
Average degree	2.59
Network density	0.04%

Credit (CD)



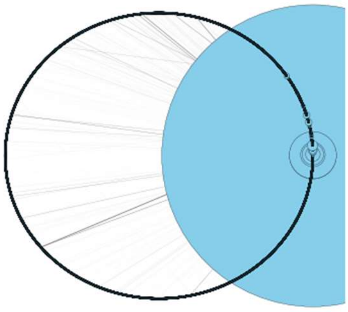
Total number of nodes	322
Total number of edges	421
Average degree	2.61
Network density	0.81%

Foreign exchange (FX)



Total number of nodes	5,778
Total number of edges	6,721
Average degree	2.33
Network density	0.04%

Equity (EQ)



Total number of nodes	25,489
Total number of edges	25,519
Average degree	2.00
Network density	0.01%

We use LEIs reported in the TR data to construct the networks. For trading entities without LEIs (mainly non-financial corporations), a temporary LEI is permitted in the TR data reporting. If different reporters assign different temporary LEIs to the same trading entity, the entity appears

[15] One reason for the large number of edges observed for equities (EQ) is that transactions include sales of derivatives to individuals and similar clients. For the same reason, entities with larger node sizes may include institutions that sell derivatives to individuals and similar clients.

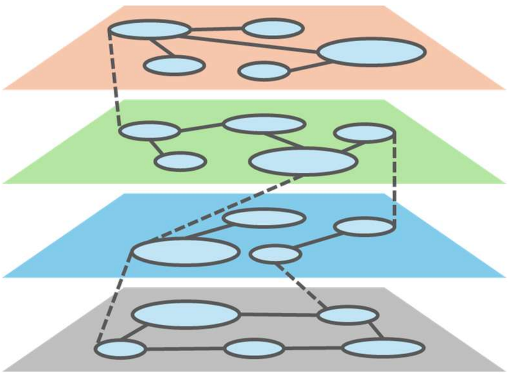
[16] Average degree: the degree is the number of edges connected to a node; the average degree is its average across nodes. Network density: an indicator of how tightly market participants are connected in the trading network.

as distinct entities and the same entity is represented as multiple nodes. In addition, because the data used to construct the network exclude CCPs in the cleansing procedure that estimates original trades reported as two trades with the CCP as a counterparty, CCPs are not included. For these reasons, the networks in this paper do not necessarily represent the relationships among entities in the real trading network.

2. Centrality measures in the multi-layer network

Next, we construct a multi-layer network by combining the asset-class-specific networks and compute several centrality measures.[17] The use of a multi-layer network is motivated by prior research indicating, among other points, that analyzing only a single layer in isolation may lead to misidentification of systemic risk.[18]

Figure 14 Multi-layer network



(Note) The solid lines represent edges within each layer, while the dashed lines indicate the connections of identical entities across different layers.

Figure 15 lists the top ten trading entities for each centrality measure in their business category. Entities at the top of betweenness centrality are dominated by Japanese securities firms and foreign-affiliated financial institutions. This suggests that these business categories lie along many shortest paths in the network across the OTC derivatives market as a whole and function as hubs in market trading relationships. Entities with high closeness centrality are mainly Japanese securities firms, suggesting that, being structurally close to many other trading entities in the network, they are likely to maintain trading relationships with many counterparties. Entities

[17] For an overview of the centrality measures, see the BOX presented later.

[18] For example, when centrality is evaluated by analyzing each asset class separately, it is possible that intermediation structures spanning multiple asset classes are abstracted away.

with high eigenvector centrality are mainly foreign-affiliated financial institutions, implying strong connections with trading entities that have high centrality across the OTC derivatives market and suggesting that they may be trading with participants that have a significant impact on the market.

These results suggest that financial institutions participating in the OTC derivatives market may play different roles across the market depending on their business category. As noted earlier, however, CCPs are not included in the networks used in this paper, and some care is needed in the interpretation of this result as the actual trading network may differ.

Figure 15 Top 10 trading entities for centrality measures

Betweenness centrality		Closeness centrality		Eigenvector centrality	
1	Major banks	1	Type I FIBOs	1	Type I FIBOs
2	Type I FIBOs	2	Type I FIBOs	2	Financial institutions
3	Foreign/Other banks	3	Type I FIBOs	3	Type I FIBOs
4	Type I FIBOs	4	Type I FIBOs	4	Foreign-affiliated type I FIBOs
5	Foreign-affiliated type I FIBOs	5	Type I FIBOs	5	Financial institutions
6	Type I FIBOs	6	Foreign/Other banks	6	Foreign-affiliated financial institutions
7	Foreign/Other banks	7	Foreign/Other banks	7	Foreign-affiliated type I FIBOs
8	Foreign/Other banks	8	Foreign-affiliated financial institutions	8	Foreign/Other banks
9	Type I FIBOs	9	Major banks	9	Foreign-affiliated financial institutions
10	Financial institutions	10	Major banks	10	Foreign-affiliated financial institutions

V. Conclusion

Using TR data, this paper examined (a) daily transaction to capture developments during episodes of foreign exchange movements, and (b) tendencies of trading entities with high centrality across the OTC derivatives market by applying a multi-layer network analysis. Regarding the first point, we confirmed that the number of transactions in currency options with non-financial corporations as counterparties increases sharply during episodes of exchange-rate fluctuations. For the latter point, we observed differing tendencies by centrality measure, suggesting that financial institutions participating in the OTC derivatives market may play different roles depending on business category.

It should be noted that the analyses in this paper were conducted after estimating original contracts and performing data cleansing. Results may differ depending on the estimation and cleansing methods used. The findings should therefore be interpreted with care.

The FSA will continue to accumulate TR data and enhance analytical sophistication to deepen understanding of the OTC derivatives market.

BOX: Centrality Measures

This Box briefly introduces the centrality measures used in this report. The explanations below are simplified sketches of each measure; readers are encouraged to consult relevant literature for details as appropriate.

Betweenness centrality: In the trading network constructed for the OTC derivatives market, betweenness centrality indicates the extent to which a trading entity functions as a hub within the market.

We compute betweenness centrality on undirected networks constructed separately for each asset class α as follows.

For asset class α, we define the weight (tie strength) of a trading pair $\{i, j\}$ as

$$w_{ij}^{(\alpha)} = \sum_{\tau \in T_{ij}^{(\alpha)}} Notional(\tau) \quad \ldots①,$$

where $T_{ij}^{(\alpha)}$ is the set of all transactions belonging to asset class α traded between nodes i and j, and $Notional(\tau)$ denotes the notional amount of transaction τ.

We then define the edge distance $d_{ij}^{(\alpha)}$ as the reciprocal of the total notional,

$$d_{ij}^{(\alpha)} = \frac{1}{w_{ij}^{(\alpha)}} \quad \ldots② \ .$$

This definition treats ties with larger notional amounts as shorter when computing shortest paths.

For node v in asset class α, we define its betweenness centrality $b_v^{(\alpha)}$ based on the fraction of shortest paths between unordered pairs of distinct nodes s and t $(s \neq t \neq v)$ that pass through v:

$$b_v^{(\alpha)} = \frac{2}{(N-1)(N-2)} \sum_{\substack{s,t \in V^{(\alpha)} \\ s \neq t, s \neq v, t \neq v, \sigma_{st}^{(\alpha)} > 0}} \frac{\sigma_{st}^{(\alpha)}(v)}{\sigma_{st}^{(\alpha)}} \quad \ldots③ \ ,$$

where $\sigma_{st}^{(\alpha)}$ is the number of shortest paths between s and t computed using ②, and $\sigma_{st}^{(\alpha)}(v)$ is the number of those paths that pass through v. Here, N denotes the total number of nodes across all asset classes, and the factor $2/(N-1)(N-2)$ normalizes the index by the number of unordered node pairs in an undirected graph.[19, 20]

Finally, the multi-layer betweenness centrality used in this paper is obtained as the sum, over asset classes, of the $b_v^{(\alpha)}$ computed above.

Closeness centrality: Closeness centrality is defined as the reciprocal of the average shortest-path length from a node to all other nodes, and represents how close a trading entity is, in network-structural terms, to others within the market.

In this paper, for each asset class α, the closeness centrality of node i is computed as

$$C^{(\alpha)}(i) = \frac{(N-1)}{\sum_{i \neq j} d(i,j)} \ ,$$

where $(N-1)$ is the number of nodes reachable from node i and $d(i,j)$ is the shortest-path distance from node i to node j, ignoring weights and defined as the minimal number of nodes traversed from origin to destination (i.e., the unweighted shortest path length).

The multi-layer closeness centrality used in this paper is the sum, over asset classes, of $C^{(\alpha)}(i)$.

Eigenvector centrality: Eigenvector centrality is the centrality measure given by the eigenvector associated with the largest eigenvalue of the adjacency matrix; it takes larger values for market participants connected to other important participants. We extend it to the multi-layer structure as follows.

Let P be the set of all transactions across all asset classes, V be the set of all trading entities that appear at least once across all asset classes, and $N = |V|$. We define the set of asset classes as ④ $A = \{\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_L\}$. Let the node index set be $\{1,2,3,\dots,N\}$, and denote by $i(v)$ the index corresponding to node $v \in V$.

[19] The factor 2 in $2/(N-1)(N-2)$ is introduced to reconcile the normalization based on the number of unordered node pairs in an undirected graph with the fact that the sum for betweenness centrality is calculated over ordered node pairs.

[20] A node that does not exist in a given asset class is assigned a betweenness centrality value of 0 for that asset class.

$$A = \{\alpha_t | t \in P\}, \quad L = |A| \quad \dots④$$

For each asset class $l \in \{1,2,3,\dots,L\}$, we define the symmetric $N \times N$ matrix $A^{(l)}$ as an undirected, weighted adjacency matrix whose $(p,\ q)$ entry equals the total notional amount across transactions between nodes p and q within asset class l (with u_t denoting the origin and v_t the destination of transaction t).

$$A_{ij}^{(l)} = \sum_{\substack{t \in P \\ \alpha_t = \alpha_l \\ i(u_t)=i, i(v_t)=j}} w_t + \sum_{\substack{t \in P \\ \alpha_t = \alpha_l \\ i(u_t)=j, i(v_t)=i}} w_t, \quad (i \neq j), \quad A_{ii}^{(l)} = 0 \quad \dots⑤$$

We set the inter-layer coupling strength to $\omega = 1.0$, and define the $(NL) \times (NL)$ $Supra-adjacency$ matrix S whose diagonal blocks are $A^{(l)}$ and whose off-diagonal blocks connect the same node across different layers with uniform coupling ω. Indices (l,i) and (m,j) denote node i in asset class l or node j in asset class m, respectively. Under this construction, the same node is uniformly coupled across all asset classes (we do not connect only adjacent asset classes; rather, all pairs of layers are coupled at the same ω).[21]

$$S_{(l,i),(m,j)} = \begin{cases} \omega, & l \neq m,\ i = j \\ 0, & l \neq m,\ i \neq j \\ A_{ij}^{(l)}, & l = m \end{cases} \quad \dots⑥$$

Based on the multi-layer network thus constructed, compute the principal eigenvector x corresponding to the largest eigenvalue λ_{max} of S.

$$S\boldsymbol{x} = \lambda_{max}\boldsymbol{x} \quad \dots⑦$$

The component $x_{(l,i)}$ is taken as the eigenvector centrality of node i in asset class l. The multi-layer eigenvector centrality used in this paper is the simple sum, for each node, of its eigenvector centralities across all asset classes.

[21] Only identical nodes across different asset classes are coupled with ω. For example, in layers A, B and C, if node X exists only in layers A and C, then node X is coupled between A and C with weight ω.

This analysis was mainly conducted by Yuto Sekiguchi, Section Chief; Daisuke Kawai, Deputy Director; Hiroki Kubo, Data Analysis Specialist; and Michiko Sato, Deputy Director of the Macro-financial Stability and Data Strategy Office, Risk Analysis Division, Strategy Development and Management Bureau.