Bank of Japan Working Paper Series

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No.21-E-14
December 2021

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December 2021

Abstract

In this paper, we attempt to understand the characteristics of the Japanese government bond (JGB) repo market by applying network analysis methods to highly granular data on JGB repo transactions. We especially use a measure of "network centrality" which quantitatively identifies financial institutions that play an important role in the transaction network and a "community detection" method which identifies groups of financial institutions that have close transactional relationships with each other. From the results, it was observed that some highly important financial institutions functioned as intermediaries for transactions and that continuous transaction relationships within groups were built around them. These characteristics may contribute to the efficient matching of cash borrowing and lending needs, and to the smooth execution of large-lot transactions. We also conducted some analysis of the behavior of the network structure of the JGB repo market under market stress using the data from March 2020, when the repo rate fluctuated significantly due to the spread of the COVID-19 pandemic. The results of the analysis in this paper indicate the importance of continuously monitoring the functioning of the JGB repo market, and also provide clues for maintaining and improving the functioning and robustness of the market.

JEL Classification: D85, G14, G20, L14

Keywords: Network analysis, Financial markets, Repo transactions, PageRank,
Bow-tie decomposition, Community detection

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* This paper is a revised version of a paper presented at the 34th Annual Conference of the Japanese Society for Artificial Intelligence, 2020, and Japanese Joint Statistical Meeting 2020. The authors are grateful to the conference participants as well as staff members of the Japanese Financial Services Agency and the Bank of Japan for their helpful comments. Any remaining errors are our own. The views expressed in the paper are those of the authors and do not necessarily reflect the official views of the Bank of Japan.

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1. Introduction

A repo transaction is a financial transaction in which cash and securities are exchanged for a certain period of time set in a contract. There are two types of repo transactions: general collateral (GC) repo transactions, which do not specify the securities to be traded, and special collateral (SC) repo transactions, which specify the securities to be traded. The former, in general, are used for borrowing or lending cash with securities collateral,[1] while the latter are used for borrowing or lending specific securities.[2] As this description indicates, repo transactions are used for a wide range of purposes, including borrowing or lending short-term funds and securities, and these transactions play an important role in the functioning of financial markets.

During the Global Financial Crisis (GFC) in the 2000s, the functioning of repo markets was greatly degraded, which amplified the instability of the financial system. So after the GFC, the G20 and the Financial Stability Board have vigorously pursued efforts to enhance the stability and transparency of repo markets.[3] As part of these efforts, the Financial Services Agency in Japan (JFSA) and the Bank of Japan (BOJ) jointly started collecting detailed data on individual transaction units for repo markets in Japan from December 2018.[4] The data are highly granular, namely, include the names of both parties involved in any repo transactions conducted by Japanese financial institutions, those of both the cash borrowing (securities lending) side and the cash lending (securities borrowing) side, as well as such information as the transaction rate and amount of the transaction. This granularity makes it possible to grasp trends in the repo market from a variety of angles.

This paper identifies the network structure of the Japanese government bond (JGB) repo

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[1] "Do not specify the securities to be traded" in GC repo transactions means that the recipient of the securities will accept any securities as long as they are of a somewhat similar quality. Therefore, this is a transaction in which the securities to be delivered are chosen by the security lender.

[2] SC repo transactions are used, for example, to borrow specific securities with a short position due to short selling to be delivered to the counterparty, or to borrow specific securities to be delivered in bond futures transactions.

[3] It has been pointed out that repo transactions for some financial products such as securitized products in the U.S. functioned as credit intermediation conducted outside the normal banking system (so-called "shadow banking"), which may have led to the expansion of leverage and excessive risk-taking that were the background factors for the GFC. Against this backdrop, discussions were held on the stability and transparency of the repo market as part of efforts to reduce financial stability risks arising from shadow banking. See Ono *et al.* (2015) for details on the history of the international debate over repo transactions.

[4] Based on a report by the Financial Stability Board (Financial Stability Board, 2015), efforts are underway to collect similar repo transaction data in each country. See Sasamoto *et al.* (2020) for details on the background of this data collection.

transactions in Japan by taking advantage of these data that include the names of the parties involved in transactions, and then summarizes the characteristics of the network by applying methods of network analysis. Network analysis of financial markets uses a series of analytical methods to understand the structure of networks defined based on the transaction relationships among market participants by visualizing or measuring its characteristics, and to evaluate the robustness and functioning of the entire market. Network analysis of financial markets is widely used, and is especially suitable for research on interbank markets.

The contributions of this paper are as follows. First, for the JGB repo market, we attempted to understand the characteristics of the JGB repo market network by using the "network centrality," which qualitatively identifies the importance of financial institutions in the transaction network and the "community detection" method, which identifies groups of financial institutions that have close transactional relationships with each other. The results show that (i) some highly important financial institutions function as intermediaries for transactions in the market, and (ii) continuous transaction relationships are built around these financial institutions. These characteristics suggest that the JGB repo market is efficient in terms of matching needs of cash borrowing and lending, but may also suggest the need for caution about robustness in the sense that shocks to a few financial institutions that serve as the nexus for many transactions can easily spread throughout the entire repo market.

Second, we conducted some analysis of trends of the network structure of the JGB repo market during market stress. Specifically, we examined whether there were any significant changes in the network structure in the period after March 2020, when repo rates fluctuated significantly in response to the spread of the COVID-19 pandemic. As a result, we found from the data that the number of security lenders significantly decreased during the stress period due to certain factors, such as the increased demand for collateral, and that market functioning had deteriorated. On the other hand, the data also suggest that financial institutions were trying to develop new transaction partners during the period.

The analysis in this paper is based on observations of the network structure of the JGB repo market. We did not analyze the factors that contribute to the formation of the network structure, nor did we analyze how the structure of the repo market changes when market stress occurs in detail. However, the results of the analysis in this paper provide some perspectives for monitoring the functioning of the repo market. That is, the results in this paper provide perspectives that should be paid attention to when continuously checking the functioning of the repo market, as well as clues for maintaining and improving the functioning and robustness of the repo market.

The structure of this paper is as follows: Section 2 provides an overview of the data being analyzed and the definition of the network; Section 3 summarizes the characteristics of the network structure of the JGB repo market using network analysis methods; Section 4 provides some analysis of the network structure under market stress. Finally, Section 5 concludes.

2. Data and transaction network

The data used for the analysis in this paper are the transaction information for each repo transaction, which is collected jointly by the JFSA and the BOJ starting as of December 2018.[5] For each individual transaction with an outstanding balance as of the end of each month, information such as the type of GC/SC repo, the parties to the transaction (both the cash borrowing side and cash lending side), the transaction amount, the transaction rate (interest rate), the type of securities involved in the transaction, and the transaction period is recorded. The top 50 financial institutions in terms of transaction volume report the transactions in which they are either the cash borrowing side or the cash lending side; these constitute more than 90% of the total amount of repo transactions in the market. Although repo transactions relating to equities and other securities are also reported, we analyzed only transactions of JGBs in this paper.[6] Including the transactions in which only one party is among the reporting institutions whereas the counterparty is not, the data capture repo transactions conducted by about 170 financial institutions as either the cash borrowing side or cash lending side of the transaction.[7,8]

[5] There are two types of repo transactions: repurchase agreements (transactions in which parties sell securities with a special agreement to buy them back in the future) and securities lending transactions (transactions in which securities are loaned in exchange for cash or other securities collateral). The data reported jointly by the JFSA and the BOJ cover both. In this paper, we do not distinguish between the two, referring to both as repo transactions.

[6] The analysis covers reported transactions in which the type of securities to be traded is "government-issued bonds," the type of currency is "yen-denominated," and the rating is "investment grade." Although these definitions may include bonds other than JGBs, the majority of transactions are considered to be for JGBs, so we refer to all the transactions under analysis as JGB repo transactions.

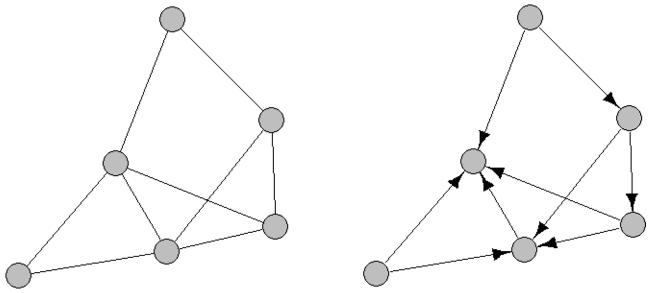
[7] Non-reporting institutions are lumped together by type of business and region of residence and treated as a single transaction party because the individual company name of non-reporting institutions cannot be identified in the data. Therefore, the actual number of financial institutions is larger than this figure. The number of non-reporting institutions includes some business corporations (non-financial institutions), but since these make up only a small number of the nodes in the repo market network, all nodes are referred to as "financial institutions" in this paper.

[8] Transactions in which both parties to the transaction are reporting institutions are double reported.

By using these data, which include the names of both parties, it is possible to identify the transaction network structure of the JGB repo market. The network structure is represented as a data structure consisting of points or "nodes" and lines or "links" connecting two nodes, as shown in Figure 1.[9] Representations that do not distinguish the direction of links are called "undirected networks" and those that do are called "directed networks."

Figure 1: Network structure

(a) Undirected network (b) Directed network



In this paper, we consider a network structure in which financial institutions are nodes and bilateral transaction relationships are directed links: the case where financial institution A's amount of cash lending to financial institution B exceeds its amount of cash borrowing (i.e., A is "net cash lending" to B) is represented by the directed link "A→B."[10,11] We consider GC repos and SC repos separately because they have different transaction purposes, i.e., whether they are used for the purpose of borrowing/lending cash or for the purpose of borrowing/lending specific securities. For example, Figure 2 shows the network structure of the GC repo market and the SC repo market as of the end of September 2019. This shows that transactions between financial institutions intersect in complex ways, making it difficult to capture the characteristics of the network at first glance. Network analysis can reveal the characteristics of such a complex network structure by visualizing and measuring the number

In this analysis, we adjust the data for such identical transactions to avoid double counting.

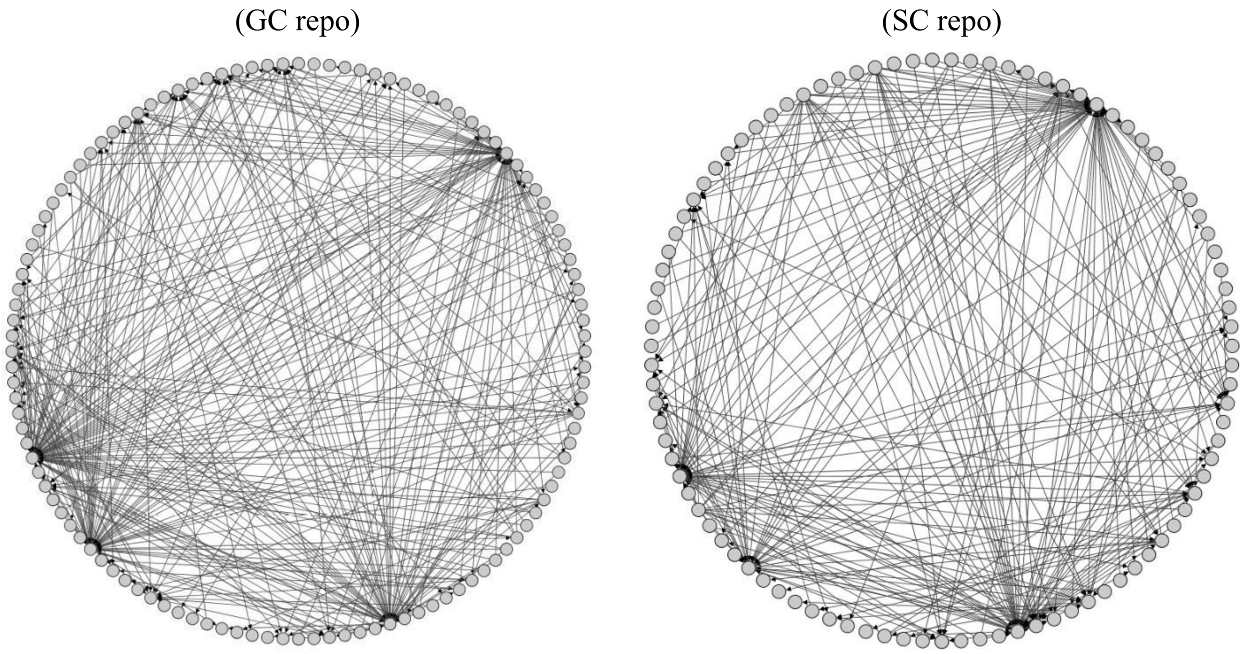
[9] This network structure is sometimes referred to as a "graph structure," the nodes as "vertexes," and the links as "edges."

[10] There are two transaction schemes for GC repo transactions: the "Subsequent Collateral Allocation Repo Transactions" scheme, which was introduced at the same time that the JGB settlement period was shortened in May 2018, and the traditional "Standard Repo Transactions" scheme. See Fujimoto *et al.* (2019) for details on the differences between the transaction schemes. The former is excluded from the analysis in this paper because the market volume is currently limited compared to the latter, and the risk properties are different from those of the latter, since clearing houses always clear the claims and obligations related to transactions.

[11] In this paper, we use the amount of net cash lending on an aggregate basis, which does not distinguish between different transaction periods, collateral bond issues, and other transaction details. It is conceivable that the network structure may differ across transaction periods and collateral bond issues. Thus, examining the characteristics of these factors remains a matter for future study.

of transaction partners (the number of links to other nodes) of each financial institution and the relative importance of each financial institution in the network.[12]

Figure 2: Repo transaction network



(Note) Based on transaction relationships as of the end of September 2019.

There have been many previous studies on network analysis of financial markets in various countries. Since it is generally difficult to obtain information on individual financial transactions, most of these studies focused on interbank cash lending and borrowing transactions based on settlement data held by central banks. In recent years, however, with the accumulation of transaction data through electronic platforms and other means, there have been some studies covering transactions of corporate bonds and municipal bonds. Figure 3 shows the main empirical studies relating to the network structure of financial markets. In the next and following sections, we attempt to summarize the characteristics of the JGB repo market while referring to the discussions in the previous studies.

[12] In the analysis, functions of "igraph", a package for the statistical software R, were used as necessary.

Figure 3: Major empirical studies on transaction networks in financial markets

Market under analysis	Previous studies [country]
Interbank market	Inaoka *et al*. (2004), Imakubo and Soejima (2010) [Japan], Furfine (2003), Afonso *et al*. (2013), Soramäki *et al*. (2007) [US], Abbassi *et al*. (2013), Allen *et al*. (2020) [Euro area], Bargigli *et al*. (2015), Iazzetta and Manna (2009), Mistrulli (2011) [Italy], Martínez-Jaramillo *et al*. (2014) [Mexico].
Government bonds	Sakiyama and Yamada (2016) [Japan].
Corporate bonds	Di Maggio *et al*. (2017) [US].
Equities	Di Maggio *et al*. (2019) [US].
Municipal bonds	Li and Schürhoff (2019) [US].
Securitized products	Hollifield *et al*. (2017) [US].
OTC derivatives	Bardoscia *et al*. (2019) [UK].
CDS	Markose *et al*. (2012) [US].

3. Characteristics of the Network Structure of the JGB Repo Market

(1) Overview of JGB Repo Market by Network Statistics

Prior studies on network analysis of financial markets have proposed methods to understand the market structure using "network statistics" that measure the characteristics of the network structure. In this section, we summarize the characteristics of the JGB repo market network by focusing on two representative network statistics, "degree" and "shortest distance."

Degree

The "degree" statistic is a measure of the number of counterparties of each financial institution. There are two types of transactions for each financial institution in the repo market: those in which the financial institution borrows cash and those in which it lends cash. Therefore, we distinguish the number of counterparties for cash borrowing transactions as "in-degree" and the number of counterparties for cash lending transactions as "out-degree" (see Figure 4 for examples).

Figure 4: In-degree and out-degree

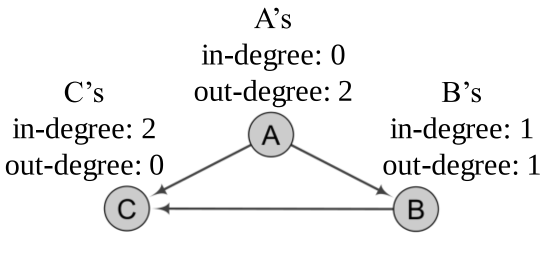
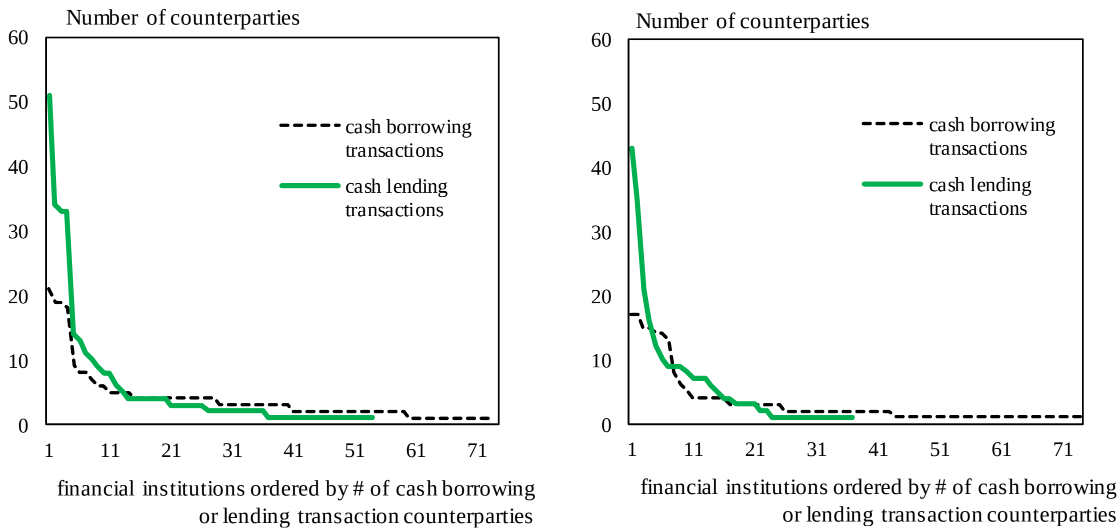


Figure 5 shows the distribution of the number of counterparties for cash borrowing transaction (in-degree) and that of cash lending transaction (out-degree) for each financial institution in the repo market. In Figure 5, the financial institutions are arranged from left to right in the order of the number of counterparties, and the number of counterparties for each financial institution either for cash borrowing or lending transactions is plotted on the vertical axis.

Figure 5: Distribution of the number of counterparties (degree)

(Left: GC repo, Right: SC repo)



(Note) Based on the transaction network as of the end of September 2019.

In the left-hand graph for GC repo transactions, some financial institutions have a large number of counterparties in both cash borrowing transactions and cash lending transactions, while other financial institutions have only a small number of counterparties. In the case of cash borrowing transactions, only four financial institutions have more than 10 counterparties, and the majority of the others have an even more limited number, less than five, of counterparties (although it is not clear from this figure, their transactions are concentrated on a few institutions). This tendency is also observed for the SC repo transactions (the right-hand graph). Thus, in the repo market, transactions are concentrated on a small number of financial institutions that act as hubs in the network, whereas a large number of the other entities conduct most of their transactions with those hubs. The characteristic of the network represented by this degree distribution is called the "long-tail characteristic" and this characteristic of financial market networks has been observed in many previous studies.[13]

Looking at the top few financial institutions in terms of the number of counterparties, there are more counterparties of cash lending transactions than those of cash borrowing transactions in both the GC repo market and the SC repo market. This indicates that some entities are acting as large cash lenders with a large number of cash borrowing counterparties (asymmetry between cash borrowing and lending transactions).

Shortest distance and reachable region

The length of the shortest path connecting any two financial institutions is called the "shortest distance," and the number of other financial institutions that can be reached from one financial institution in the shortest distance n is called the "n-step reachable region" (see Figure 6 for an example). This indicator shows how close the trade relationships linking financial institutions in a network structure are.

Figure 7 plots the reachable region for each financial institution in each of the GC and SC repo markets using actual transaction data as of the end of September 2019. The results show that for most financial institutions, the region that can be reached in three steps (thick solid green line) is close to the maximum region of N steps (thin solid black line). In other words, most of the financial institutions can reach a significant number of other financial institutions in only three steps. This characteristic has also been shown in many previous studies and is called the "small-world characteristic." It is a characteristic that although many financial institutions in the network are not directly connected to each other, most of the financial institutions are indirectly connected through a few financial institutions. Such a structure may contribute to the efficiency of transactions in the repo market if, for example, an entity with needs of cash borrowing can connect with another counterparty with needs of cash lending through a small number of intermediaries. On the other hand, the fact that the entire network is connected over a short distance suggests that, relatively speaking, shocks that occur in one

[13] Such a distribution is also said to follow a power law, in which the probability distribution is expressed as $p(k) = ak^{-\gamma}$. A distribution that follows a power law is also said to have the "scale-free property" because there is no scale, such as the average, in the number of nodes with an arbitrary number of links (Barabási and Albert, 1999). This characteristic has been reported not only for the degree distribution but also for the distribution of transaction amounts. The scale-free property of the degree distribution can be confirmed by examining whether a linear relationship is observed when the degree and its cumulative distribution are plotted on a two-sided logarithmic graph. In fact, for four cases (out-degree or in-degree for GC repos, and out-degree or in-degree for SC repos), linear relationships indicating distributions that follow a power law have been confirmed.

part of the network are likely to spread throughout the entire network.

Figure 6: Shortest distance and reachable region

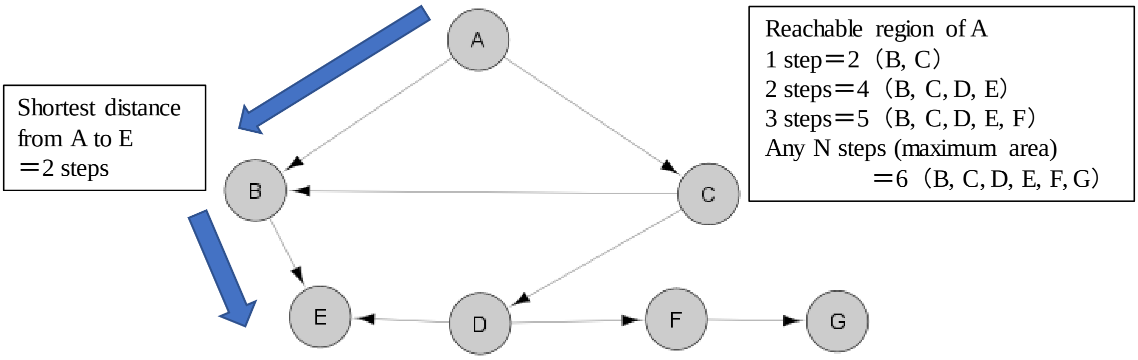
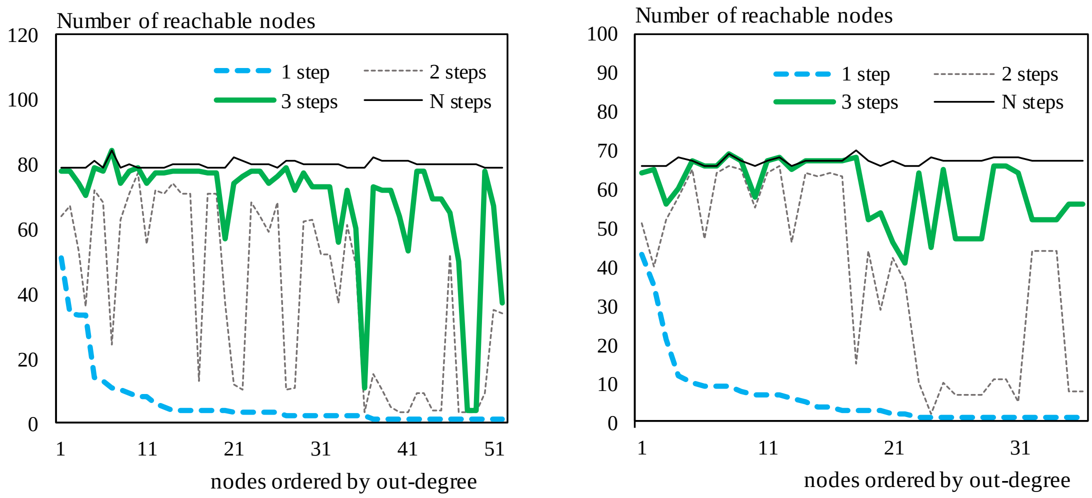


Figure 7: Number of reachable financial institutions

(Left: GC repo, Right: SC repo)



(Note) Based on the transaction network as of the end of September 2019.

So far, we have used the typical network statistics, "degree" and "shortest distance," to examine the characteristics of the repo market.[14] However, these are not enough to explore the efficiency and robustness of the market in depth. Therefore, in the next section, focusing on individual financial institutions and their transaction relationships with each other, we

[14] Prior studies have also examined other characteristics of financial market networks using network statistics such as "clustering coefficients," which measure how closely transaction partners for each financial institution are transacting with each other (see the survey by Iori and Mantegna (2018)). When we calculate the same network statistics for the JGB repo market, although we do not show it graphically here, we can identify features that are common to other financial market networks shown in previous studies.

examine which financial institutions play important roles in the entire network, what roles the important financial institutions play in the network structure, and whether there are continuities in the transaction relationships among financial institutions.

(2) Network structure in terms of centrality and community

If financial institutions that deal with a large number of counterparties and play a central role in the market mediate needs of cash borrowing and cash lending in the market, or if continuous transaction relationships are built around such intermediaries, this can lead to more efficient market transactions through prompt matching of cash borrowing and lending needs (Li and Schürhoff, 2019). On the other hand, as was the case in the repo market during the GFC in the 2000s, if financial institutions that deal with many transactions are hit by negative shocks, market participants' actions to stop or reduce their transaction activities, due to concerns about counterparty risk (including failures to deliver securities), may spread through the network, leading to a decline in the market functioning and liquidity. Therefore, in monitoring the market functioning and liquidity, it is useful to identify financial institutions that play a central role in the repo transaction network and communities that have established close transaction relationships.

In this section, we examine the characteristics of the JGB repo market using a measure of "network centrality," which quantifies the importance of each financial institution -- the extent to which it plays a central role in the network -- based on its relationships with its counterparties, and a "community detection" method, which identifies groups of closely connected financial institutions.

A. Importance of financial institutions by PageRank centrality

We measure the importance of each financial institution on the repo transaction network by using "PageRank" as a measure of network centrality.[15] PageRank was originally developed as a measure of the importance of web pages on the Internet (Brin and Page, 1998), but has also attracted attention as a measure of systemic risk in financial markets (Allen *et al.*, 2020, Yun *et al.*, 2019). The importance of a web page as measured by PageRank is higher (i) the more web pages are referring to it as well as (ii) the higher the importance of web pages referring to it. Since this importance depends not only on one's own status but also on the importance of the other parties, PageRank is suitable for measuring the degree to which individual financial institutions influence the overall network structure. When this measure is applied to the network of repo transactions, the measure of a financial institution is higher (i) the larger its amount of cash borrowing as well as (ii) the larger the amount of cash borrowing of its cash borrowing transaction counterparties. That is, it is an indicator for measuring how much a financial institution influences the entire transaction network, focusing on cash borrowing transactions.[16]

It should be noted that we can also consider a measure that focuses on cash lending transactions rather than cash borrowing ones; such a measure of a financial institution is higher (i) the larger its amount of cash lending and (ii) the larger the amount of cash lending of its cash lending transaction counterparties. In this regard, Saltoglu and Yenilmez (2015) and Kaltwasser and Spelta (2019) use two types of PageRank, that is, (i) "borrower PageRank" that measures the importance of each financial institution in cash borrowing transactions and (ii) "lender PageRank," which measures the importance of each financial

[15] Other indices such as "eigenvector centrality" have been proposed as measures of network centrality. For the present study, we selected PageRank as the most suitable index to capture the degree of influence of each node on the entire directed network.

[16] PageRank for financial institution i is calculated as follows:

$$PageRank_i = (1-\alpha) + \alpha \frac{\sum_{j \in M} w_{ij}\, PageRank_j}{\sum_{z \in N} w_{jz}}.$$

w_{ij} is the net lending amount of node j to node i, M is all nodes connected to node i, and N is all nodes in the network. α is called the damping factor, which is a device to measure the importance of each node based on the overall transaction relationship even if the network is not fully connected. Because PageRank of each institution also depends on the PageRank values of its transaction partners, it is generally calculated iteratively. The damping factor affects the convergence speed of the solution, and it is considered most efficient to set it to 0.85 by Brin and Page (1998), which many subsequent studies have followed. In the present analysis, it was also set to 0.85.

institution in cash lending transactions.[17] This paper also adopts their approach and calculates two types of PageRank in terms of cash borrowing and cash lending.

In addition, to examine the role of important financial institutions as measured by PageRank in the repo transaction network, we identify where each financial institution is located in the hierarchical structure based on the flow of cash in the repo market (i.e., cash lender, intermediary, and cash borrower tiers) using the bow-tie decomposition algorithm (Yang *et al.*, 2011).[18]

Figure 8 illustrates, for each financial institution, its position on the hierarchical structure in the repo market network and its PageRank. Panels (1) and (2) represent the results of analysis of the GC repo market as sizes of nodes for the borrower PageRank and the lender PageRank, respectively, and panels (3) and (4) represent those for the SC repo market. These results show that, for both cash borrowing transactions and cash lending transactions, the middle tier (light blue) includes highly important financial institutions, which indicates these highly important financial institutions play the role of intermediaries between the final cash borrowers and lenders. It should be noted that, looking at the cash lending transactions in the GC market, the PageRank of the financial institutions in the cash lender tier (dark blue) vary; in particular, some of these institutions are lending large amounts of cash (Figure 8(2)). In addition, looking at the SC market, in terms of cash borrowing (i.e., security lending), not only intermediaries but also those in the cash borrower tier (white) (i.e., security lender tier) have high PageRank (Figure 8(3)). This indicates that some financial institutions play an important role as security suppliers in the SC repo market, which aims to lend and borrow specific securities.

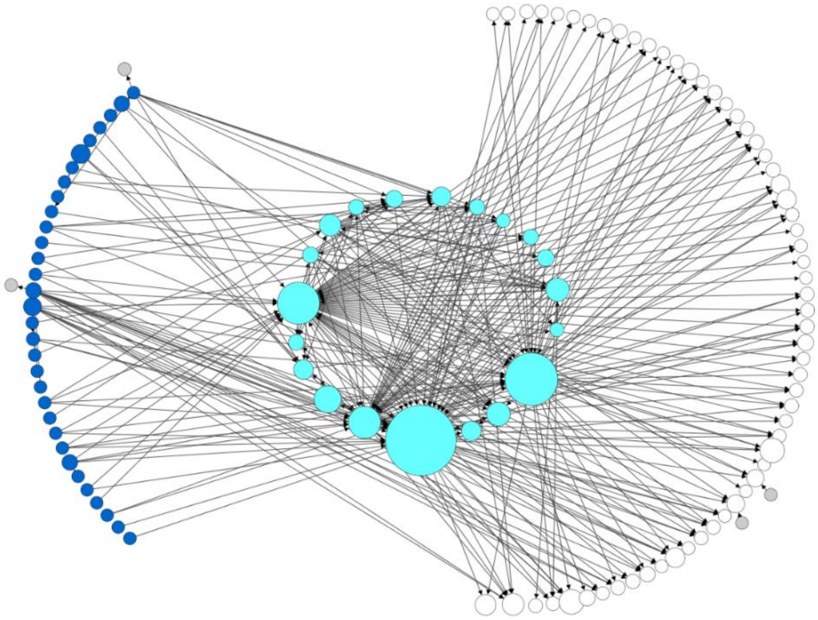
[17] Calculated by replacing w_{ji} with w_{ij} and w_{jz} with w_{zj} in the equation of PageRank in the previous footnote. In other words, the PageRank of node i is determined by the directed link from node i to node j (cash borrowing transaction), not by the directed link from node j to node i (cash lending transaction).

[18] The bow-tie decomposition uses the following algorithm to classify financial institutions mainly into three tiers. (i) The set of financial institutions in which every financial institution is reachable through transaction relationships from every other financial institution is defined as the middle tier (intermediary tier). (ii) The set of financial institutions in which the financial institutions are not included in the middle tier but have transactions that allow cash to flow to the middle tier financial institutions is defined as the upstream tier (cash lender tier). (iii) Among the financial institutions not included in the middle tier, the set of financial institutions that engage in transactions through which cash can flow from middle tier financial institutions is defined as the downstream tier (cash borrower tier).

Figure 8: Hierarchical structure based on flow of cash

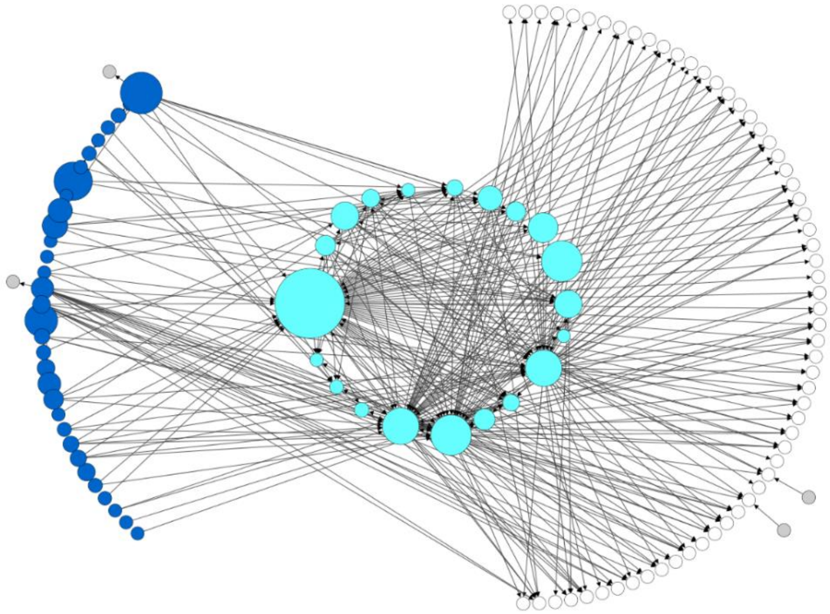
(1) GC repo transaction network structure and borrower PageRank

(cash lenders) ⇒ (Intermediaries) ⇒ (cash borrowers)



(2) GC repo transaction network structure and lender PageRank

(cash lenders) ⇒ (Intermediaries) ⇒ (cash borrowers)

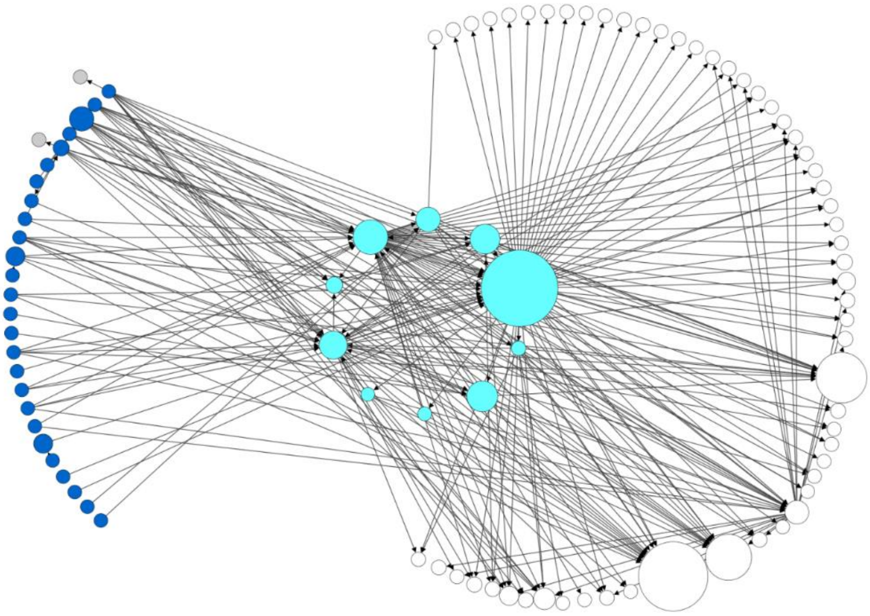


(Note) From left to right, financial institutions are classified into three groups: cash lenders (blue), intermediaries (light blue), and cash borrowers (white). The size of the node in (1) corresponds to the borrower PageRank, and the size of the node in (2) corresponds to the lender PageRank. Based on transactions as of the end of September 2019. Financial institutions are arranged in the same positions in (1) and (2).

Figure 8 (continued): Hierarchical structure based on flow of cash

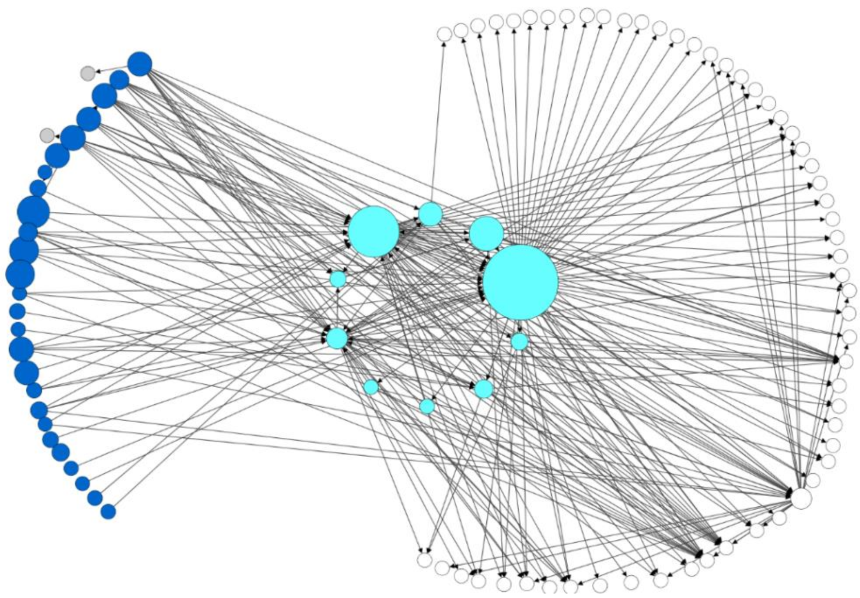
(3) SC repo transaction network structure and borrower PageRank

(cash lenders) ⇒ (Intermediaries) ⇒ (cash borrowers)



(4) SC repo transaction network structure and lender PageRank

(cash lenders) ⇒ (Intermediaries) ⇒ (cash borrowers)



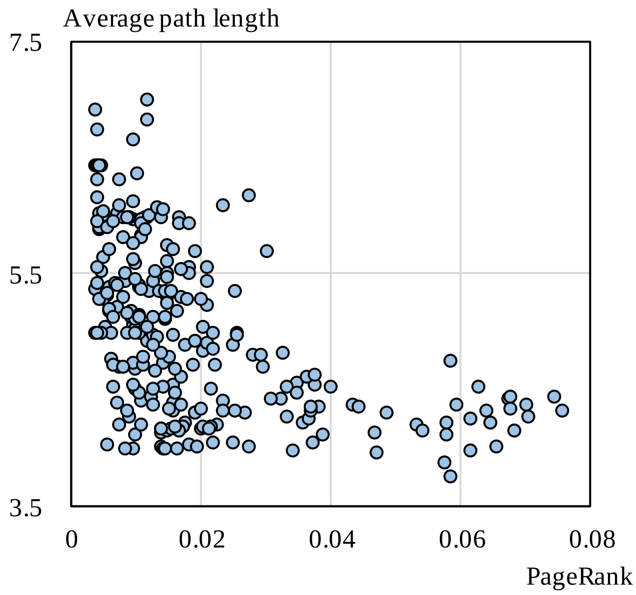
(Note) From left to right, financial institutions are classified into three groups: cash lenders (blue), intermediaries (light blue), and cash borrowers (white). The size of the node in (3) corresponds to borrower PageRank, and the size of the node in (4) corresponds to the lender PageRank. Based on transactions as of the end of September 2019. Financial institutions are arranged in the same positions in (3) and (4).

In addition, we perform some analysis of how the circumstance where financial institutions with relatively high importance play the role of intermediaries contributes to the efficiency of the market. If an intermediary connects cash lenders and borrowers through shorter paths, it is considered that the intermediary contributes to the efficient matching of cash lending needs and cash borrowing needs (Li and Schürhoff, 2019). From the perspective of testing this point for the repo market, we consider the relationship between (i) the importance of the intermediaries and (ii) the average path length of the transaction paths in which they are involved as intermediaries. In detail, for each financial institution in the intermediary tier, (ii) is measured as the average path length of shortest paths connecting pairs of nodes (one each in the cash lender and borrower tiers) that include the intermediary institution. Although the transactions on the shortest path connecting the final cash lenders and cash borrowers are not necessarily the transactions matched by intermediaries, by assuming the transaction path in which it is involved in the intermediation, we treat the indicator in (ii) as a proxy variable to measure the matching power of the intermediary.[19]

Figure 9 plots the relationship between (i) and (ii). These results show that intermediaries with high importance tend to connect the final cash lenders and cash borrowers through shorter paths. This suggests that intermediaries with high importance in the network may contribute to the efficient matching of cash borrowing and lending needs in that they connect the final cash lender and borrower through shorter paths.

[19] Li and Schürhoff (2019) use daily data and CUSIP codes (unique identification numbers assigned to registered securities) to specify the actual process of specific bonds circulating through intermediaries and analyze the matching power of intermediaries. Since the data in this analysis can only capture transactions that are outstanding at the end of the month and do not fully identify bonds of particular issues, they cannot match the lender and borrower as precisely as Li and Schürhoff, so we adopt the treatment described here instead.

Figure 9: Relationship between PageRank and the average shortest path length of transactions mediated by the intermediaries



(Note) The vertical axis is the average path length of transactions in which each financial institution in the intermediary tier is involved in intermediation. The horizontal axis is the average of the "borrower PageRank" and "lender PageRank" of each financial institution in the intermediary tier, for GC repo transactions only.

B. Community detection and continuity of transaction relationships

One class of the network analysis methods is "community detection," which extracts groups of closely connected nodes (communities) that have many internal connections and relatively few external connections. In this paper, we apply one of these methods, the spin glass method (Reichardt and Bornholdt, 2006), to analyze the characteristics of the community structure of the repo market.[20]

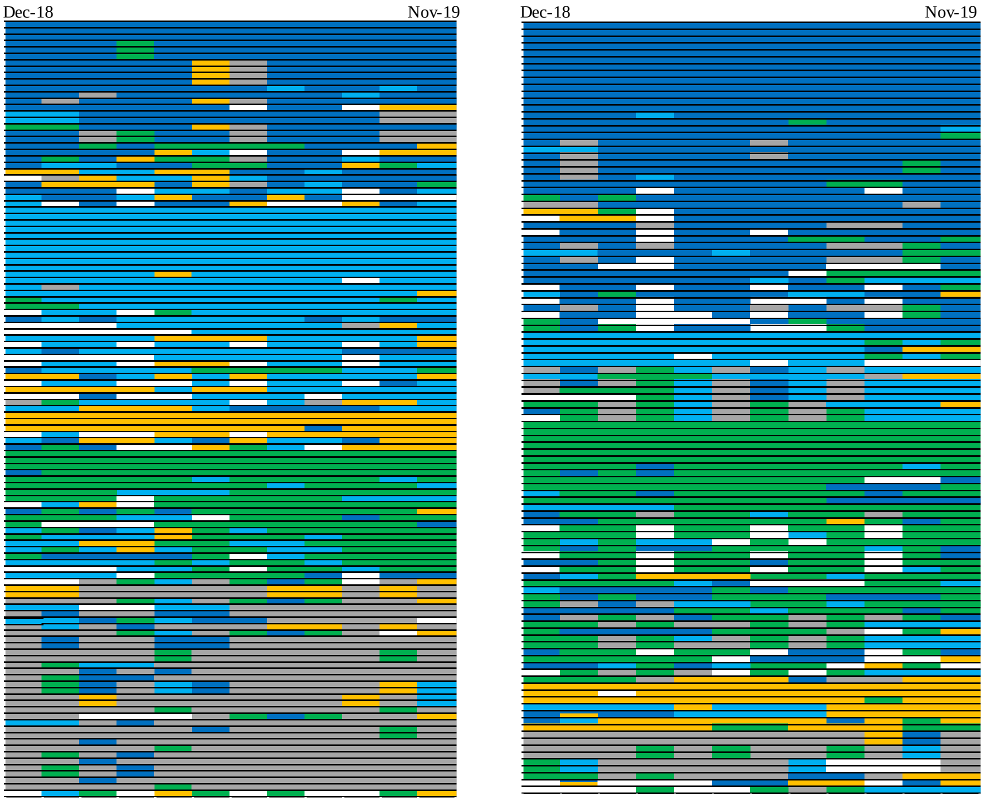
The results are shown in Figure 10, where the detected communities are identified by their central intermediary and color-coded. Specifically, financial institutions are lined up vertically and are color-coded according to the community to which they belong. The

[20] In the spin-glass method, nodes are grouped by community so that there are more links inside the community and fewer links outside the community. Specifically, we consider a score determined as follows. The score is higher if (i) there is a link between any two nodes that belong to the same community or (ii) if there is no link between any two nodes that belong to different communities, while the scores are lower if (iii) there is no link between any two nodes that belong to the same community or (iv) there is a link between any two nodes that belong to different communities. We decompose each node into communities by searching for the grouping of nodes that maximizes the score.

horizontal direction is the time-series direction. In Figure 10, many of the financial institutions have the same color in the horizontal direction, indicating that many of them have continued to conduct transactions within the same community in terms of community formation in the transaction network. Looking at the frequency with which financial institutions move between communities, we observe that about half of them do not move (Figure 11).

Figure 10: Detected communities

(GC repo) (SC repo)



(Note) GC repo (left) and SC repo (right) transactions. Financial institutions are lined up vertically, and the horizontal direction represents the time series, with color-coded communities to which each financial institution belongs at each point in time. Blue, light blue, green, and orange represent communities formed around major intermediaries, and gray summarizes other smaller communities. White indicates that the financial institution had no transactions. Based on the transaction network at the end of each month from Dec. 2018 to Nov. 2019.

Figure 11: Frequency of community transitions

	GC repo	SC repo
from previous month to current month:		
Community unchanged	48%	54%
Community moves	27%	26%
Other	25%	20%

Note: "Other" includes cases where the transaction status changed from "having no transactions" in the previous month to "having transactions" in current month, and *vice versa*. Based on the transaction network at the end of each month from Dec. 2018 to Nov. 2019.

In order to find out what role the existence of such a community structure plays as a market function, we attempt a regression analysis of the background factors of the community structure. Specifically, we conduct a probit regression with a dummy variable indicating whether or not each transaction is conducted within the same community (transaction within the same community = 1) as the explained variable.[21] The explanatory variables are the transaction rate and transaction amount.[22,23]

The results of the probit regression analysis are shown in Figure 12. While the coefficient on the transaction rate is not significant, the coefficient on the transaction amount is significantly positive. This indicates that there is a positive relationship between the size of the transaction amount and the probability of the transaction being conducted within the

[21] For transactions in which the face value of the underlying bond exceeds 5 billion JPY, there is a market practice to split the transaction up into approximately 5 billion JPY units for execution in order to facilitate settlement. In fact, a histogram of transaction value (face value multiplied by market value) shows that the frequency of transactions around 5 billion JPY to 5.2 billion JPY is notably large, suggesting that split transactions are distributed in this range. Although it is not possible from the data to identify whether a transaction is split from a larger original transaction, we have included multiple transactions whose transaction amounts are in this range and that have the same transaction terms (names of parties, repo rates, and transaction period) as a single transaction with the combined transaction amount.

[22] We limited the transaction data used in the estimation to overnight GC repo transactions in order to avoid the effects of differences in transaction period or types of bonds. We also excluded transactions with repo rates of 0% or higher from the data sample for this analysis because they deviate significantly from prevailing short-term interest rates and are considered to be special transactions with nonstandard transaction conditions.

[23] For the transaction rate, the deviation from the Tokyo Repo Rate is used. For the Tokyo Repo Rate the tomorrow-next rate with the last day of the month as the execution date is used in order to correspond to the "Standard Repo Transaction." For the transaction rate, we used residuals from the regression analysis with transaction amounts and dummy variables representing the individual financial institutions, considering the possibility of multicollinearity between the transaction rate and the transaction amount. In the results of the regression analysis for the residuals, the coefficient for the transaction amount was significantly negative. This is consistent with the market's view that small transaction amounts tend to increase transaction rates because operation costs are relatively high.

community, indicating that transaction communities may be formed for the purpose of facilitating large-lot transactions.

Figure 12: Results of probit regression analysis

Dependent variable: Dummy variable (transactions within the same community = 1)		
repo rate	-0.15115	
	(0.20600)	
amount (logarithm)	0.07284	***
	(0.00389)	
constant	-1.49711	***
	(0.08786)	
time dummies	yes	
sample size	20,850	
transaction within the same community	7,989	
transaction between different communities	12,861	
Pseudo-R2 （McFadden）	0.07706	

(Note) *** denotes significance at the 1% level. Figures in parentheses are standard deviations. Robust (heteroskedasticity-adjusted by Huber-White's method) standard errors were used. The sample consists of O/N GC repo transactions with outstanding balances as of the end of each month from Dec. 2018 to Nov. 2019.

In summary, we found that in the repo market transaction network, important financial institutions play the role of intermediaries and continuous transaction relationships are established as communities. In addition, evidence suggested that the repo transaction network may have a structure that contributes to efficient transactions.

On the other hand, some previous studies have pointed out the vulnerability of financial market networks with characteristics similar to those mentioned above, because shocks that occur to highly important financial institutions tend to propagate throughout the network.[24] The argument has also been made that the stability of the entire network can be reduced if it is difficult to trade between different communities because of the cost and time required to

[24] Caballero (2015) and Minoiu *et al.* (2015) point out that closely connected networks are more likely to amplify the impact of any negative shocks, increasing the probability of systemic risk; Yun *et al.* (2019) and Bardoscia *et al.* (2019) point out that the presence of important nodes is likely to diffuse shocks.

change transaction partners.[25] In light of these arguments, it can be said that the repo market has a structure that is conducive to efficient transactions, but it also needs to be careful about its robustness. Although there is a trade-off between the efficiency and robustness of the network structure and it is difficult to theoretically determine the optimal balance between the two, it is important to understand which aspects of the market structure may lead to a decline in robustness. Therefore, quantitatively "visualizing" the structure of the repo market and understanding its characteristics through the analysis presented in this section are considered to be important for monitoring market functioning. It may also be helpful for individual market participants in considering the efficiency and stability of their transactions.

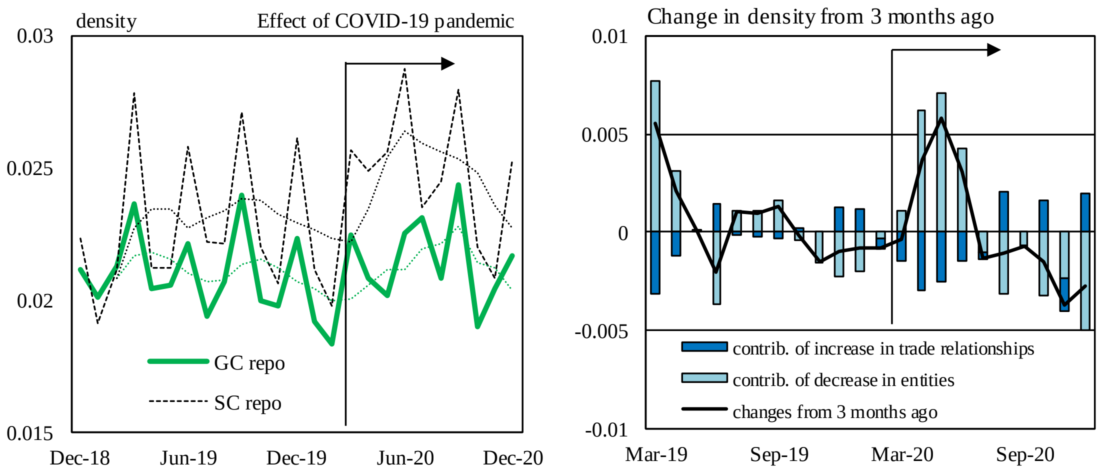
4. Changes in Network Structure under Market Stress

Prior research has reported that the network structure and related indicators behave in a characteristic manner before and after a stress event in financial markets. For example, it has been reported that the number of links in the transaction network decreases and the exposure per counterparty increases in the interbank market during stress, due to movement to narrow counterparties with an awareness of counterparty risk (Beltran *et al.*, 2015, see also Minoiu and Reyes, 2013). It has also been reported that in the transaction network of the JGB market, when interest rates rise sharply, the financial institutions that form the core of the network actively search for new bond buyers, resulting in a sharp increase in transactions between the core financial institutions and financial institutions that normally have few transaction relationships with them (Sakiyama and Yamada, 2016). Others have reported that network structure changed significantly during stress events (in't Veld and van Lelyveld, 2014, Fricke and Lux, 2015).

In this section, we examine the behavior of the network structure of the JGB repo market during market stress. Although we cannot conduct a precise quantitative analysis of the repo market because the data starting period is just from December 2018 and there is not much data available, we attempt to conduct some verification using data from March 2020 onwards, when the repo rate fluctuated significantly following the spread of the COVID-19 pandemic.

[25] Regarding the community structure of the network, Dong *et al.* (2018) show that when there are few links crossing different communities, the robustness of the overall network is reduced as a result of the tendency of network fragmentation.

Figure 13: Network density and decomposition of the contribution of changes



(Note) The thin line on the left is the 3-month moving average. The right figure shows SC repo transactions.

Figure 13 plots the time series of "network density," which represents how transactions are actively conducted in the network, for the transaction networks of GC repos and SC repos. The density of the network is calculated as the ratio of the actual number of transaction relationships to the number of all possible transaction relationships between financial institutions in the network (the number of transaction relationships if all financial institutions transact with each other).[26] Considering the seasonality of the spike at the end of the quarter, we can see that the density has remained high since March 2020, when the impact of the spread of the COVID-19 pandemic began (Figure 13, left). Decomposing the three-month change in density into the change in the number of financial institutions participating in the repo market and the change in the number of counterparties actually conducting transactions (Figure 13, right), we find that while the number of counterparties actually conducting transactions decreased, contributing to a partial reduction in density (dark blue area), the number of financial institutions participating in the repo market decreased (light blue area) and the density has increased in total.[27]

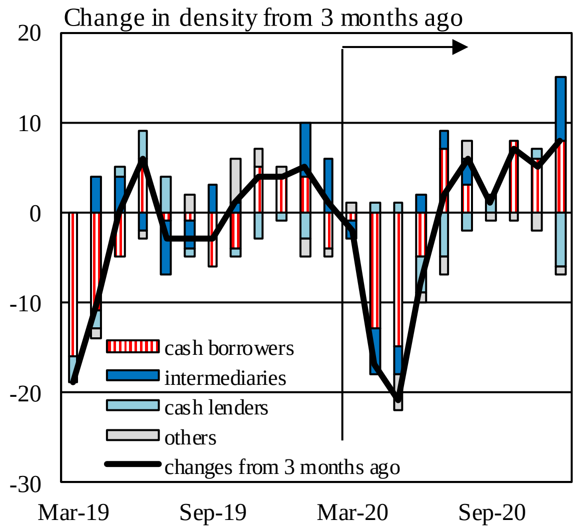
Regarding the SC repo transactions, where the density significantly increased, we broke down the decline in the number of financial institutions by category based on the bow-tie

[26] Density d of a directed network is calculated by $d = \frac{k}{n(n-1)}$, where the number of transaction relationships is k and the number of financial institutions is n.

[27] The decomposition was calculated by $\Delta d = \frac{\partial d}{\partial k}\Delta k + \frac{\partial d}{\partial n}\Delta n = \frac{1}{n(n-1)}\Delta k - \frac{k(2n-1)}{n^2(n-1)^2}\Delta n$.

decomposition used in the previous section ("cash lenders," "intermediaries," and "cash borrowers"). The decline in the number of cash borrowers (i.e., bond lenders) had the main contribution (Figure 14). Based on this, it can be considered as follows. In the SC repo market, during the stress period after March 2020, the number of bond lenders decreased due to an increase in collateral demand and a decrease in market participants caused by the declaration of a state of emergency and the increase in telecommuting. On the other hand, financial institutions did not reduce the number of counterparties with whom they actually conducted transactions to the extent that the total number of whole market transactions decreased, through development of new counterparties (Sakiyama and Yamada, 2016), which is thought to be behind the increase in density.

Figure 14: Breakdown of changes in the number of financial institutions in the network



(Note) SC repo transactions.

Since the data used in this paper cover transactions with outstanding balances at the end of the month, the data fail to capture the short-term trend of transactions executed in mid-to-late March 2020, which is considered to be the most stressed period in the market. The network may have behaved differently during this period than the interpretation given above. To obtain implications for trends of the JGB repo market during times of market stress, it is necessary to reexamine this issue when data accumulation has progressed and data sample size has increased enough that event studies have become feasible.

5. Conclusion

This paper examined the characteristics of the JGB repo market network in Japan. In the JGB repo market, we found that highly important financial institutions in the network act as intermediaries and that continuous transaction relationships were established within groups formed around them. These characteristics suggest that the JGB repo market is efficient but has a network structure in which shocks to a few financial institutions can easily spread throughout the entire market. In order to assess the network structure of the market, it is important to consider whether the market strikes a balance between the aspects that impart transaction efficiency and the aspects that impart robustness. It would be beneficial to continuously monitor the functioning of the JGB repo market in Japan, while keeping in mind these characteristics of the network structure. It is also hoped that the results of this analysis will serve as a reference for market participants when considering the stability and efficiency of transactions through further transparency of the market.

This paper summarizes the basic characteristics of the network structure of the JGB repo market using the network analysis methods. Future research topics include an analysis of the background factors of the network structure and a more in-depth analysis of the behavior of the network structure in response to market shocks as more time-series data are accumulated.

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